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

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**Abstract**

New technologies swept through Britain during the Second Industrial Revolution, destroying old jobs and creating new ones. We know little about how workers reallocated. Using 170 million full-count British census observations (1851–1911), I construct new task-level data on occupation and investigate English bootmaking as it mechanized. 153,000 artisanal jobs disappeared as skills became obsolete; 140,000 specialized jobs emerged. Incumbent artisans did not take the new jobs, nor were they displaced. Instead, entry collapsed - young men stopped entering the old trade. New jobs went primarily to young workers, though not in the same locations. Young cohorts absorbed the adjustment.

**JEL codes:** O33, N33, J24, J61, J62

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# Introduction

The fear that new machines will destroy employment is perennial (Keynes, 1930; Mokyr et al., 2015). However, while new technologies do destroy jobs, they have - historically - also created them (Acemoglu and Restrepo, 2019; Schumpeter, 1942). In this paper I ask: when a new labour-saving technology is adopted, how is a workforce reallocated out of declining occupations into the new, emerging ones?

With the advent of generative AI there has been a surge of new research on one dimension of this question. A large literature has focused on workers who hold exposed jobs, measuring which occupations the new technologies are most likely to displace (Frey and Osborne, 2017; Webb, 2020; Eloundou et al., 2024), and exploring the costs of labour displacement to incumbents (Bessen et al., 2025). A much newer and smaller literature studies the creation dimension, by tracking the emergence and growth of new kinds of work (Autor et al., 2024, 2026).

Since the impact of technological change on workers is jointly determined by the dynamics of job destruction and job creation, this paper documents both margins of a complete technological transition. I follow the mechanization of the English bootmaking industry over the latter half of the 19th century, quantifying the number of jobs lost to, and created by, innovation. To do so, I construct new task-level occupational data from the occupational strings of 1.3 million full-count English census records. This new, more granular data on occupation renders visible the structural shift which took place in tandem with mechanization: approximately 153,000 artisanal jobs were destroyed, while 140,000 new, more specialized jobs were created. With the structural shift exposed, I can then identify the margins along which the workforce reallocated.

The historical record offers three particular advantages for studying this process. Firstly, creative destruction has been ongoing for nearly three centuries, leaving a rich record of labour displacement and reinstatement. If we want to understand the dynamics through which societies have reallocated workers out of declining occupations and into emerging ones, we can look to previous experience. Secondly, the historical record captures the entire life-cycle of a technological shock. The impact of generative AI may prove to be profound, but we are observing only its earliest years, and the creative side of the transition is at this stage opaque. Historical episodes make it possible to consider both sides of the creative destruction dynamic. Finally, only long-run data can show whether labour-saving technological change affects successive cohorts differently.

## New Evidence

We do not know whether technological unemployment spread through England in the wake of Britain's industrial revolutions. The extent to which the new machines displaced workers has never been quantified.

A small recent literature studies labour displacement in historical context. The most direct evidence is from studies of single industries. Feigenbaum and Gross (2024) follow the automation of telephone operation in the United States and find that incumbent operators were pushed out of the labour market or into lower-paying work, and that subsequent cohorts of young women found employment in other sectors. Ager et al. (2026) find that the mechanization of milking displaced young women from farm work in postwar Norway, and they moved to cities and better-paid employment. Cavounidis et al. (2023) argue that occupations facing anticipated obsolescence pay a premium. They follow teamsters across matched full-count United States censuses (1880–1930) as the motor truck was adopted, finding that wages rose as employment fell and the occupation grew older. They conclude that workers who remained in the dying trade were compensated for doing so. Other papers take a broader but less direct approach: Kogan et al. (2021) link nearly two centuries of patent data to occupations and administrative worker records, and find that technological exposure is associated with declining wages and employment opportunities for incumbent workers. Atack et al. (2019) use the 1894 Hand and Machine Labour Study to show that mechanization destroyed old tasks while creating new ones.

Even in Great Britain, the first country to industrialize, the impact of mechanization on labour displacement and reinstatement has not been well explored. British workers at the time were deeply concerned that new technologies would lead to labour displacement: there is narrative evidence of this in the Luddite uprisings, the Swing Riots (Caprettini and Voth, 2020), and wider union activity. Leading intellectuals of the time, including Karl Marx and David Ricardo, were alarmed. Nonetheless, we do not know whether widespread labour displacement took place. Scholars hold radically diverging views. David Landes, for instance, claims that the adoption of 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 possible only because there is so little data to bring to bear on the question.

This paper proposes a solution which makes it possible to quantify job loss and job creation

in 19th-century England. The approach is informed by research on routine-biased technological change, 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., 2024). I develop a new, micro-occupational categorization structure using text recorded in individual-level English census observations, as digitized by the Integrated Census Microdata project (ICeM) (Schurer et al., 2022). This uncovers how the adoption of new technologies reshaped the occupational structure.

Having constructed new data on occupation in 19th-century England, I apply this approach to one industry, the English bootmaking industry, as it mechanized. I focus on bootmaking for two reasons. Firstly, it was one of the largest industries in the country, employing approximately 220,000 people, nearly a fifth of whom were women. This yields a total of 1.3 million observations of individuals working in the bootmaking industry over the six English census returns taken between 1851 and 1911. Secondly, the industry mechanized over the latter half of the 19th century, which coincides with the period for which we have excellent, individual level census records. Mechanization was precipitated by the introduction of the bootmaking sewing machine in 1857, and continued through the early twentieth century. I assign 97% of English bootmakers during the period to the sub-industry micro-occupations they performed.

Analysis at this new level of granularity reveals two findings. Firstly, the structural shift which accompanies mechanization becomes visible for the first time. Approximately 153,000 artisanal bootmaking jobs were lost as new technologies rendered skills obsolete, while another 140,000 jobs, demanding new skills, were created. Given the substantial increase in labour productivity brought about by mechanization, the near replacement of lost artisanal employment by the new, more specialized jobs implies a large expansion in output. Secondly, there was a spatial component to the structural shift. At the national level, the countervailing forces of decline and growth were very nearly matched. At the sub-national level, that was not the case. Instead, while the older, artisanal jobs declined in every county in England, the new jobs emerged very heavily concentrated - nearly half of the new jobs - 44% - were generated in Leicestershire and Northamptonshire alone.

## Results

Having established the scale and geography of job destruction and creation, I ask how workers adjusted to this structural shift. Firstly, I find that incumbent bootmakers (male) experienced little displacement. They did not simply transition out of the contracting ar-

tisanal bootmaking jobs into the new, more specialized jobs in the bootmaking industry. Nor were they pushed out of the trade. Instead, incumbent artisanal bootmakers largely remained where they were, both in terms of geographical location and in terms of occupation, and aged in place. The experience of female bootmakers (accounting approximately for a fifth of the trade), on the other hand, was starkly different. They did experience displacement. I document this gendered pattern in Section 5.

Secondly, young men stopped entering the artisanal side of the trade. This margin of adjustment - the decline of entry - drove the contraction of artisanal bootmaking. I show evidence that young men would have incurred costs had they continued to enter into the declining industry, and that the collapse of entry rates was therefore a response to the contraction of the industry rather than a response to opportunities elsewhere.

Thirdly, I find that the margin of adjustment on the opposing side - in new jobs - was also via young cohorts. The new jobs in bootmaking were taken up predominantly by young workers, and predominantly by those born in the places in which the new opportunities emerged. However, although jobs both disappeared and emerged for young people, and the two nearly counterbalanced in aggregate, there was a spatial mismatch. For young people, jobs in artisanal bootmaking disappeared everywhere in England, while the new opportunities emerged in only a few counties. In this way, technological change can tilt access to opportunity, opening new routes into employment for some while closing them for others.

I propose two forms of obsolescence, distinguished by the pace of technological change. The first operates through displacement: when a shock is swift and comprehensive, as in the automation of telephone operation (Feigenbaum and Gross, 2024), incumbents are displaced. The second operates through entry collapse, what population ecologists sometimes describe as "recruitment failure". [1] When a technology diffuses slowly and demand for older forms of labour persists, incumbents can stay where they are, and the adjustment falls on the flow of new workers that would have replaced them. There is early evidence that generative AI may be operating on this margin (Brynjolfsson et al., 2025; Hosseini Maasoum and Lichtinger, 2025). However, that evidence, like the exposure literature it extends, observes only the destruction side of the ledger. The creation side is at least as important. Here, when adjustment is via young cohorts, what matters is whether the young people shut out of contracting occupations are able to find new opportunities. In this particular case, the two sides of the transition did not share a geography, illustrating

[1] In population ecology, "recruitment failure" describes a population in which adults persist, but too few juveniles replace them. For example, a forest can look healthy while ageing underneath.

the way in which an adjusting labour market can nevertheless strand workers in place.

The paper is organized as follows. Section 1 reviews the historical setting and context. Section 2 introduces the data and the construction of the key variables, including the micro-occupational classification and linked panel datasets. Section 3 presents the new evidence revealed by the more granular data, showing how the occupational structure changed in tandem with mechanization. Section 4 presents the empirical strategy, Section 5 shares results, and Section 6 discusses two forms of obsolescence and argues the case for observing both margins of a transition. Section 7 concludes.

# 1 Historical Context

Bootmaking was the single largest craft industry in 19th century Britain, and the fifth most important occupation.[2] It was an industry responsible for directly employing nearly a quarter of a million people, a fifth of whom were women[3], and bootmakers made up 2.9% of the working population in England in 1851[4]. Indirectly, it provided a household income for just over a million people. 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.[5]

The mechanization of the English bootmaking industry was precipitated by the introduction of the bootmaking sewing machine in 1857, 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 the occupational structure and on workers in the 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 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 deal with the process of mechanization in Britain (Church, 1968; Menuge, 2001).

[2] In order, the largest industries are: domestic workers, agriculture, general labourers, coal mining, bootmakers, and dressmakers.
[3] Appendix A provides more detail on recording female labour force participation.
[4] Appendix K provides more detail.
[5] 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).

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 mechanized 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 mechanized was in "finishing": affixing the sole of the 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 mechanized 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 recognized 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 as 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 catalyzing the further mechanization 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 following the introduction of the machine. This is a small sample, and geographically limited, but illustrative of the labour displacing impacts of the new machine. The displacement was 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 mechanized. 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 mechanization of the boot making industry in England followed a similar trajectory. An important difference, however, can be found in resistance from organized 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 destroyed his workshop (Horn, 2005). 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 organized 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. 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). 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.[6]

Nonetheless, by the 1860s the sewing machine revolution was well underway across the

[6]The full letter is reproduced in Appendix B.

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 a new general purpose technology. To understand the impact of this technological shock on labour displacement and reinstatement 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"[7], and indeed these elements of the work are often present in the 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: Occupation in 19th-century English census data

| Year | Occupation | Occode | HISCO | Task |
|---|---|---|---|---|
| 1861 | CORDWAINER | 663 | 80100 | Cordwainer |
| 1861 | BOOT AND SHOE MAKER - MASTER EMPLOYING 4 MEN 4 WOMEN and 5 APPS | 663 | 80100 | Maker |
| 1861 | BOOT AND SHOE BINDER | 663 | 80100 | Binder |
| 1861 | BOOT AND SHOE RIVETTER | 663 | 80100 | Riveter |
| 1861 | BOOT SEWING MACHINIST | 663 | 80100 | Machinist |

*Notes:* This table reports five individual-level observations from nineteenth-century British census data (ICeM) for demonstration purposes. Names and identifiers are omitted in accordance with ICeM terms of use. Columns 1-3 report variables as recorded in the ICeM dataset. The new *Task* variable classifies the primary activity described in the original occupational string.

When the GRO received the census enumerators' books for the decennial census taken in 1851, the records contained nearly a million unique character strings describing occupation. For the bootmaking industry alone there were more than 60 000 descriptions. The GRO realized that they could not track occupation at the level of granularity at which they had it, so they devised a taxonomy of approximately 800 industries, and clerks employed

[7] Woollard (1999). Farr sets out the classification in the 1851 census report

by the GRO then assigned each individual observation to the correct industry. From that point onwards, analysis of structural change in this period has predominantly been conducted at the industry level of occupation[8].

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), which has substantially expanded the frontiers of research on British occupational structure over the latter half of the 19th century. When they digitized the data, they retained the industry level categorization of occupation. This left the more granular information on occupation available, but still sealed in the strings.

## 2.1 Micro-occupations: classification

I construct a sub-industry level "micro-occupation" 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 occupation variable, which indicates the type of work the individual did within their industry. The process is 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.[9] There are approximately 220,000 bootmakers observed in each decennial census for England, resulting in a total of $\sim$1.3 million individual level observations. I then extract all the unique textual descriptions of occupation in this industry: there are 60,426 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.[10] 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, given the highly skewed distribution of the strings. I extract the "task" words available in those strings. These are now identi-

[8]See Appendix C for an example of the dictionaries.
[9]See Appendix D for more detail on this process.
[10]see Appendix E for the categories.

fied categories of bootmaker "tasks". The remaining unique character strings, those not accounted for by the initial sweep, are then extracted and tokenized.

Finally, once the categories - or types of task - have been discovered, the character strings are parsed and assigned to the new "task" categories. The topic modeling process results in the construction of a dictionary, with topic categories assigned to keywords and their spelling variations. From this point, assigning strings to task categories based on the presence of the keywords in the string is straightforward. For example, in Table 1, the third observation includes the keyword "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.

Strings in which more than one occupation is declared are rare. In the bootmaking industry, of 1.3 million individual observations, 32,336 (2.45%) contain two or more keywords. When several keywords exist within one description, 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.[11]

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 a year then an additional task category is added to the set. The process is reiterated until the set of keywords is sufficient to meet the threshold.

## 2.2 Census Linking

The empirical analysis uses six linked datasets, summarised in Table 2. Forward links of the entire population from 1851, 1861 and 1881 underlie the analysis in Section 5.1, Section 5.2 and Section 5.4. Individuals in the base year are followed to the next census

[11] 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. The hierarchy of keywords used, together with sensitivity checks, is available in Appendix E. The hierarchy is set to maximize granular information.

wave, and their occupational and locational outcomes are observed. The 30-year links from 1851, 1861 and 1881 underlie the within-household analysis in Section 5.3, following sons of bootmakers and carpenters from their fathers' households in the base year through to their adult outcomes in 1881, 1891, or 1911.

Table 2: Linked Datasets

| Link | Direction | Linked obs. | Used in |
|---|---|---|---|
| 1851 → 1861 | Forward | 5,080,879 (33%) | Section 5.1, 5.2, 5.4 |
| 1861 → 1881 | Forward | 3,654,999 (21.4%) | Section 5.1, 5.2, 5.4 |
| 1881 → 1891 | Forward | 9,193,037 (40%) | Section 5.1, 5.2, 5.4 |
| 1851 → 1881 | Forward, 30 yr | 2,504,307 (16.2%) | Section 5.3 |
| 1861 → 1891 | Forward, 30 yr | 2,684,401 (15.7%) | Section 5.3 |
| 1881 → 1911 | Forward, 30 yr | 4,705,047 (20.5%) | Section 5.3 |

*Notes.* Linked observation counts correspond to the litmus-calibrated probabilistic specification, the headline specification for the empirical analysis. The base population for each link is the entire set of all individuals born in England. More detail is available in Appendix F. The 1871 returns are not included in the ICeM data, so the 1861–1881 link is constructed as a direct 20-year link.

I follow the linking methodology developed in Vipond (2026b). The same substantive findings emerge when the analysis is rerun on two alternative linking specifications - the well-known ABE deterministic linking specification (Abramitzky et al., 2021) and a basic deterministic specification. This paper's findings are therefore not driven by the choice of linking algorithm. [12]

Match rates are higher in later time periods. Across all panels the rate of false positives is low, reflecting the disambiguating power of the parish-level birthplace information available in the British historical census data. Match rates are higher for men than for women, reflecting surname change at marriage, and higher for panels covering a shorter time span.

Women are included in the three primary linked panels, but not in the 30-year links, in which the analysis follows male children specifically. Women are often dropped from longitudinal data constructed by record linking algorithms, as their change in name at marriage makes them more difficult to track. However, as I show in Vipond (2026b), marriage is an infrequent event in a woman's life, and as a result most women do not change their surname in any given decade[13]. Approximately 70% of women do not change their

[12] Appendix F reports the results from rerunning the main analysis on the alternative linked panels, explains the census linking specifications used in this paper, and provides balance tests for selection bias

[13] Many women are married and stay married, many women who are widowed do not re-marry, and some women stay single.

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 means that the constructed panel data excludes women who married in the period. It is possible that labour market outcomes for these women might be meaningfully different than expected outcomes for other women, and the results in this paper cannot be assumed to apply to that segment of the population. However, here the exclusion of newly married young women is likely to understate the magnitude of the results. These are the women most likely to have left the labour market on marriage, so excluding them removes the group with the highest baseline exit.

### 2.3 Family Units: Birth Order

To analyze intergenerational responses to technological change, I reconstruct family units directly from the census returns. Making use of the relationship to head variable, together with surname, household identifier, address, and parish, I identify every household headed by a bootmaker, and all sons co-resident with that head, for each census year. For each 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.

These reconstructed families have 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.

## 3 New Evidence

The new, granular data on occupation reveals structural change that was entirely obscured at the industry level of analysis. I find that approximately 153,000 old, artisanal bootmaking jobs disappeared as the industry mechanized, while 140,000 new, more specialized jobs emerged. At the national level, the countervailing forces of job loss and job creation nearly netted out. However, that was not true at the regional level. The older, artisanal jobs disappeared in every English county following mechanization, while the new jobs were 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 1.3 million individual level observations of English bootmakers from 1851-1911 into micro-occupations, it is now possible to assess the impact of mechanization on the occupational structure of the bootmaking industry at both the industry level and the new "task" level.

The first finding is the extent to which the "task" level of analysis reveals changes in the occupational structure which were almost entirely masked at the industry level. If we assess the impacts of mechanization on total employment in the bootmaking industry - at the industry level - we see only minimal impact. See Figure 1A, below. Prior to mechanization, in 1851, the English bootmaking industry employed approximately 222,000 workers. By 1911, post-mechanization, it employed approximately the same. This may seem to suggest little impact.[14]

However, the new "tasks" level of analysis makes it possible to pry open this black box. Panels B and C of Figure 1 show the evolution of "old" and "new" tasks in the English bootmaking industry over time. I define the "old" tasks as those which, together, were responsible for the employment of 97% of all English bootmakers prior to mechanization (in 1851 and 1861). These were the "Shoemakers", "Cordwainers", "Cloggers", "Binders", and "Closers". As mechanization set in, the old jobs monotonically declined. In total, 153,000 artisanal bootmaking jobs disappeared over the period.

Simultaneously, a set of new, more specialized jobs emerged. In total, 140,000 new jobs emerged over the period, in work including but not limited to: sewing machinists, riveters, operators, and the foremen and managers in the factories. A more modern production process was displacing the older, artisanal one[15].

At the national level, the countervailing forces of job creation and job loss as the English bootmaking industry mechanized very nearly balanced out. Given the large increase in productivity associated with mechanization, far fewer workers would have been required to produce a given number of boots. Since the number of bootmakers did not fall to a fifth of its 1851 level, production must therefore have increased - substantially. This takes us into Jevons' paradox territory (Jevons, 1865). The fall in the cost of boots appears to have generated a sufficiently large increase in demand to offset much of the labour-saving

[14]These results are based on the expanded cleaned dataset, see Appendix D. The raw historical census data returns a count of 220,000 bootmakers in 1851 and 213,000 in 1911.

[15]The findings require that changes in the occupational descriptions are reflecting real differences in work performed, rather than merely shifts in nomenclature. Appendix G provides supporting evidence.

effect of the new technology. Although job loss and job creation nearly balanced out at the national level, this was not at all the case at the more regional level. The following section turns to the geography of creative destruction at the county level.

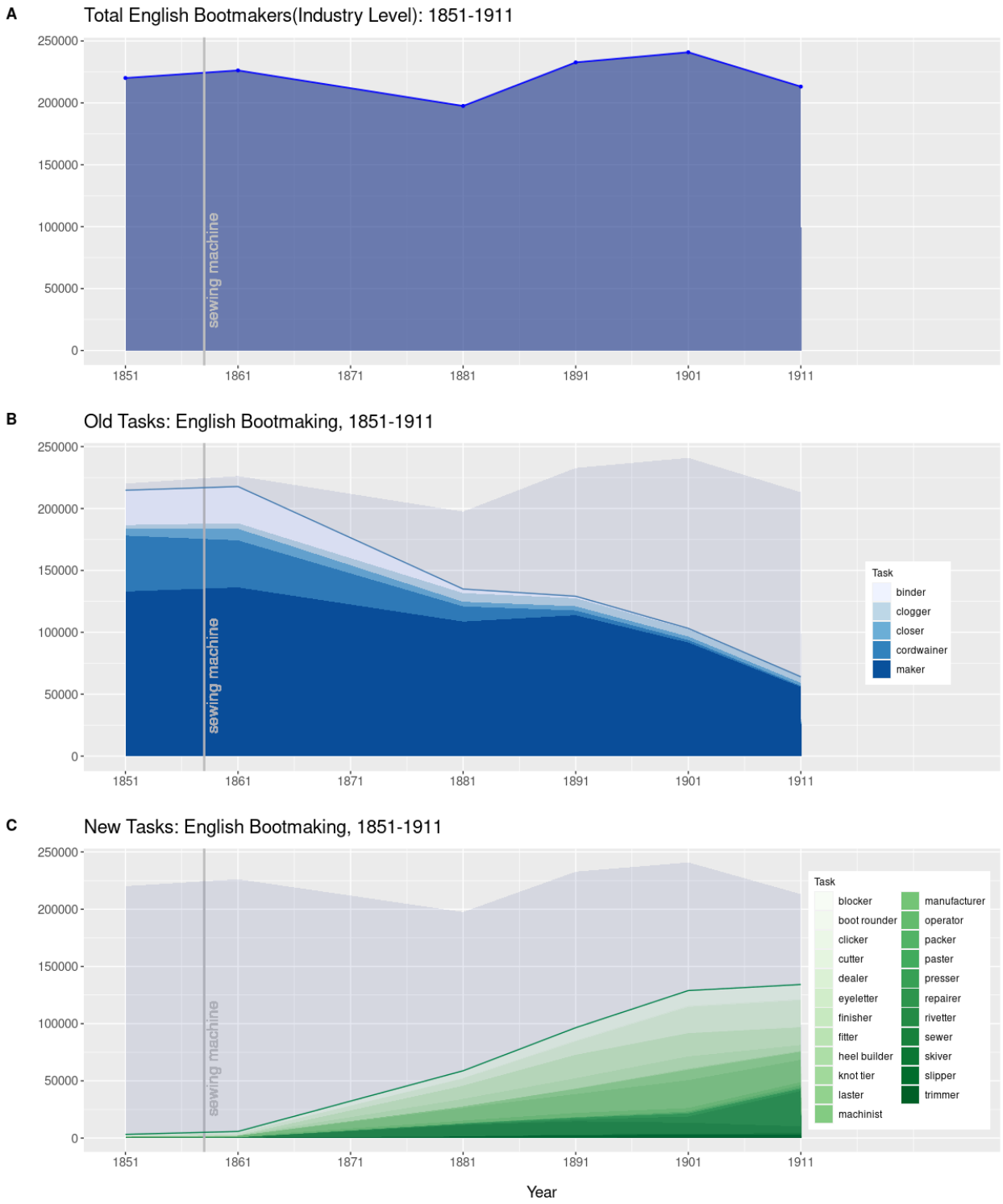



Figure 1: Number of Bootmakers Employed - Industry and Task Level, 1851-1911

*Notes:* This figure reports employment in the English bootmaking industry aggregated at the industry level (Panel A) and disaggregated to the task level (Panels B and C). Panel A shows that total employment in bootmaking remained relatively stable over the period of mechanization. Panel B shows a sustained decline in traditional artisanal tasks, with approximately 153,000 jobs disappearing nationally. Panel C shows the emergence of roughly 140,000 new, more specialized tasks associated with mechanized production. Rates of change are reported in Appendix G. Tasks with fewer than 50 observations are excluded.

## 3.2 Geography

My second finding is that the industry relocated spatially. The new task level of analysis shows that artisanal jobs disappeared in every county in England, while the new jobs emerged primarily in only a few counties. Figure 2 illustrates the total change in the number of bootmakers employed in "new" and "old" tasks, by county, between 1851 and 1911.

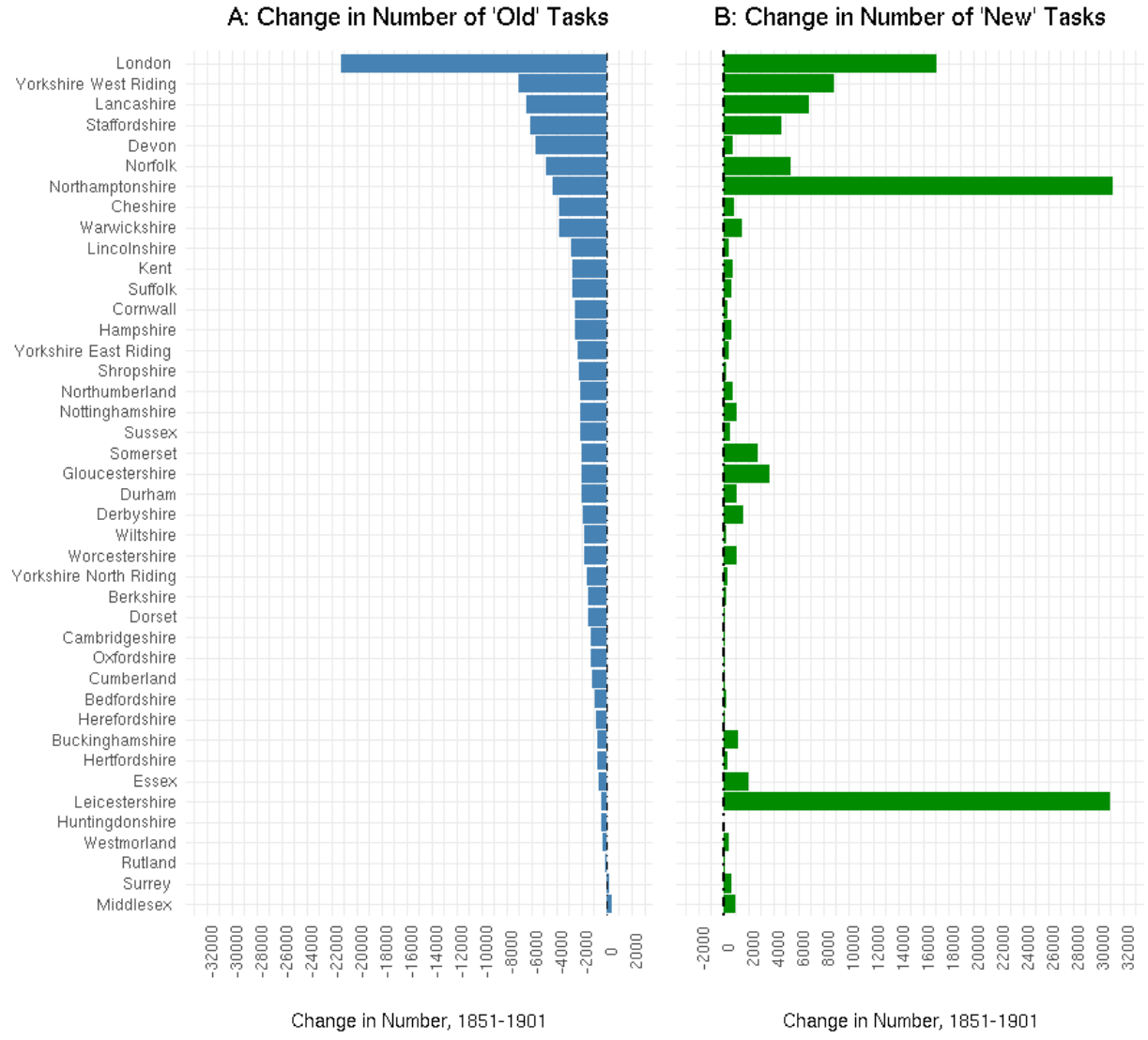



Figure 2: Change in Number of Bootmakers Employed in Old and New Tasks

*Notes:* This figure reports county-level changes in the number of bootmakers employed, by task category, between 1851 and 1911. Panel A shows the change in the number of workers employed in traditional artisanal bootmaking tasks. Panel B shows the corresponding change in employment in newly emerging, more specialized bootmaking tasks.

The overall picture is one in which the older and more general types of work declined in every county in England, while employment in the new and more specialized tasks emerged in only a select few. The result is that the balancing of countervailing forces which we saw at the national level did not take place at the more local level. In most counties the bootmaking industry as a whole went into decline. In two counties — Northamptonshire and Leicestershire — the loss of employment in the older tasks was more than compensated by the surge in new opportunities, and the bootmaking industry flourished.

Interpreted geographically, the net result was a tectonic shift in the location of the industry. Nearly half of the new jobs were generated in Northamptonshire and Leicestershire alone, and those two counties became the enclaves of English bootmaking.[16]

# 4 Empirical Strategy

Now that the new, more granular data on occupation has made visible the structural change which took place as the English bootmaking industry mechanized, it becomes possible to ask how workers were re-allocated away from the old and declining forms of work, and into the new.

On the one hand, artisanal bootmaking jobs contracted, substantially. Here, the natural question is: who bore the burden of this loss? On the other side of the creative destruction coin, many new jobs emerged. Here, the question has to be: who gained the new opportunities? Section 4.1 investigates who bore the burden. This proceeds in three steps: Section 4.1.1 examines exit among incumbents, Section 4.1.2 entry into the declining trade, and Section 4.1.3 asks whether the collapse of entry into artisanal bootmaking was driven by mechanization. Section 4.2 investigates who took up the new opportunities.

## 4.1 Job Loss: Artisanal Bootmaking

In principle, the contraction of artisanal jobs could have operated through one of three margins. Incumbents could have been pushed out of the trade. Young workers could have been deterred from entering, or - given that so many new jobs were created - incumbents could have transitioned out of the old jobs and directly into the new.

[16] The new types of work which emerged as the industry mechanized reflect a shift from craft to factory production. Many of the new jobs were connected to factories and larger enterprises, eg: foremen, supervisors, operators, and factory workers. The British Business Census of Entrepreneurs (BBCE) identifies employers and proprietors between 1851–1911, and details how many workers each employed (Van Lieshout et al., 2021). Using this data, I find that the large bootmaking companies became increasingly concentrated in the counties where the new kinds of work emerged: Leicestershire, Northamptonshire, and London. Appendix G provides more detail.

In practice, the third was rare: approximately 3% of female incumbents and 6% of male incumbents moved directly into the new, more specialized occupations (Appendix H1). The contraction must therefore have operated primarily through the other two margins. Section 4.1.1 measures exit among incumbents, and Section 4.1.2 measures entry among young workers coming of working age to establish which of the two accounted for the contraction in artisanal bootmaking. Section 4.1.3 then asks whether the shift was driven by mechanization.

### 4.1.1 Exit

I investigate whether mechanization pushed incumbent workers out of the bootmaking industry. To do so, I estimate a difference-in-differences design which compares changes in the exit rates of bootmakers pre and post shock to the exit rates of workers in other industries. The question is whether bootmakers left their trade at unusually high rates once mechanization set in, compared with what happened elsewhere. I estimate the specification separately by sex, as male and female labour markets differed sharply in baseline exit rates[17].

Let $t$ denote a baseline census year and let $t'$ denote the subsequent census in the corresponding window $\tau$ (1851–1861 or 1861–1881). Restricting to individuals successfully linked from $t$ to $t'$, define

$$Exit_{ic\tau} \equiv 1\{Occ_{i,t'} \neq Occ_{i,t}\}, \tag{1}$$

an indicator equal to one if individual $i$ reports an occupation at $t'$ that differs from their baseline occupation at $t$. Stacking the two windows, I estimate

$$\begin{aligned} Exit_{ic\tau} = \delta_c + \theta\, Boot_{i\tau} + \phi\, Post_{\tau} + \beta\,(Boot_{i\tau} \times Post_{\tau}) \\ + \gamma' X_{i\tau} + \kappa'(X_{i\tau} \times Post_{\tau}) + \varepsilon_{ic\tau}. \end{aligned} \tag{2}$$

$Boot_{i\tau}$ indicates that individual $i$ is an incumbent bootmaker at baseline within transition window $\tau$; $Post_{\tau}$ indicates the post-mechanization window $1861 \rightarrow 1881$, with $1851 \rightarrow 1861$ as the pre window; $\delta_c$ are county fixed effects defined by baseline county of residence; and $X_{i\tau}$ is a vector of baseline demographic characteristics (age, marital status). Including both $X_{i\tau}$ and $X_{i\tau} \times Post_{\tau}$ allows the relationship between observables and exit to differ

[17] Pooling men and women would obscure differences in baseline occupational mobility.

across windows. Age matters most: young workers exit at much higher baseline rates, so any shift in the age composition of bootmakers would otherwise contaminate $\beta$. The coefficient of interest, $\beta$, captures the differential change in the probability of exiting one's baseline occupation among incumbent bootmakers relative to non-bootmakers. I estimate by OLS, so $\beta$ is read directly as a percentage-point change in the exit rate. Estimates are reported in Table 3[18].

The windows differ in length, ten years against twenty. I therefore interpret $\beta$ as an effect on cumulative exit over the census interval, with $\phi$ absorbing the common increase associated with the longer window. Standard errors are clustered by baseline county. Because the data cover the full population, the rationale for clustering is design-based, and the clustering level follows the level at which the shock varies (Abadie et al., 2023). The treatment was not uniform across bootmakers: mechanization undermined the trade in most counties and expanded it in a few, so two bootmakers in the same county received a more similar shock than two in different counties. Because the design contains a single treated occupation, I complement the clustered standard errors with a design-based placebo procedure, assigning treatment to each comparison occupation in turn, re-estimating, and ranking the bootmaker coefficient in the resulting distribution. Occupation- and two-way-clustered standard errors are reported in Appendix H4.

Since the aggregate DiD may conceal age heterogeneity in where adjustment occurred, I estimate the same difference-in-differences specification separately by baseline age band. For each age band $a$, I estimate:

$$\begin{aligned} Exit_{ic\tau} = \delta_{c,a} + \theta_a Boot_{i\tau} + \phi_a Post_\tau + \beta_a \left(Boot_{i\tau} \times Post_\tau\right) \\ + \gamma_a' X_{i\tau} + \kappa_a' \left(X_{i\tau} \times Post_\tau\right) + \varepsilon_{ic\tau}, \qquad i \in a. \end{aligned} \tag{3}$$

The sample in equation 3 is restricted to individuals in baseline age band $a$. The coefficient $\beta_a$ is therefore the within age band difference-in-differences estimate: it captures the cross-panel change in the bootmaker–non-bootmaker exit gap for individuals in age cohort $a$. $\beta_a$ is the change in the exit rate, vis-à-vis comparators, expressed in percentage points. Displacement of established artisans would be visible among prime-age incumbents, whereas an effect concentrated among the youngest would instead indicate adjustment near the entry margin. All specifications control for baseline marital status and allow its association

[18]Identification requires that bootmakers would have followed the comparison-group trend absent mechanization. Appendix J relaxes this assumption, using the distribution of trends across untreated occupations to bound the missing bootmaker counterfactual.

with exit to differ across the pre and post-mechanization periods.

Geography poses the same risk as age. A national average could hide regional displacement. I therefore estimate the bootmaker–non-bootmaker exit gap county by county, separately for each panel. If displacement were real but localized, it should be visible at this level of analysis. County-level estimates are reported in Appendix H5.

#### 4.1.2 Entry

Having examined the incumbent margin, I turn to entry. The question is whether young men and women continued to enter the artisanal bootmaking trade at the same rates as previous cohorts. The constructed panel data allows me to measure this directly. For each transition window I take all the young people aged 10–18 at baseline, and follow them forward to the next census. The entry rate is then the share of that cohort observed in a given occupation at endline. This is computed separately for men and women. I compare the share of young people entering into artisanal bootmaking both prior to and post mechanization.

Since entry rates are shares of a single cohort, they mechanically sum to one across occupations. A fall in bootmaking's share is therefore necessarily a statement that young people went elsewhere. This distinguishes entry from exit. Exit is cumulative, so a longer window mechanically raises exit rates for all workers. A raw comparison across windows of unequal length is - for exit - uninterpretable without a comparison group. However, entry is measured on a cohort fixed at baseline, so a longer window does not mechanically raise the share ending up in any particular trade. As with exit, a national rate could average over counties where entry collapsed and counties where it held up. I therefore compute entry share by county, for both windows, and report how it shifts.

Because entry into the new machine occupations moved in the opposite direction over the same period, I treat it separately in Section 4.2. Any pooled measure of entry into "bootmaking" would net the two against each other. I report the change in levels and in proportional terms.

#### 4.1.3 The Cost of Entering a Declining Trade

Having established that the decline in artisanal bootmaking was driven by a collapse in entry rather than a rise in incumbent exit, I turn to ask why young men stopped entering. Two explanations are possible. Mechanization may have sent the artisanal trade into decline, meaning that entering it carried poor outcomes. Alternatively, young men may have

been drawn away by expanding opportunities in other industries, and in this case the timing is merely coincidental. To distinguish between them, I investigate whether persisting in the trade would have been costly. If it was, the push explanation is the more plausible account. If it was not, the pull explanation stands.

As entry into artisanal bootmaking slowed, one group of young men continued to enter: the sons of bootmakers. Occupational inheritance in the trade was strong and stable. Roughly a quarter of the young sons of bootmakers observed in 1851 became bootmakers themselves, and the corresponding shares hold for the 1861 and 1881 cohorts[19]. The sons who became bootmakers were also spatially anchored: they migrated away from their county of origin at lower rates than their non-bootmaker brothers. This may have been because they inherited capital (in the form of the shop, or tools), or social capital (in terms of customer and supplier relationships), but whatever the cause, they were exposed to the local trajectory of the trade.

As discussed, from 1861 onwards the shock of mechanization created sharply divergent local labour markets. The bootmaking trade went into steep decline in most English counties, and expanded in only a few. Bootmakers' sons who followed their fathers therefore entered very different local markets: some entered a flourishing industry, while others entered a deteriorating trade. Because these local trajectories were shaped by the broader processes of mechanization and industrial concentration, exposure to local decline is plausibly exogenous to the individual son.

I take a family fixed effects design. I identify all the families who had a bootmaker as head of household. I restrict the sample to families in which there were at least two sons, one of whom went into bootmaking, and one who did not. I compare the outcomes for the sons who became bootmakers against the outcomes for their brothers, in places in which the bootmaking industry was flourishing, and in places in which it was in decline.

I take two transition windows, 1851–1881 and 1861–1891, identifying sons in the household at the baseline census wave, and follow them forward thirty years. Unlike the exit and entry designs, this specification does not compare a pre and post mechanization window. Both windows span the mechanization period. [20] The identifying contrast is between counties in which the trade declined and in which it grew, and the two windows apply that contrast to two successive cohorts of entrants.[21]

[19] Appendix L provides more detail. Occupational inheritance was not unusual in 19th-century England.

[20] Although the sewing machine had been introduced into English bootmaking by 1857, diffusion remained extremely limited in 1861.

[21] The 1871 English census has not been digitized. Sons observed at baseline require roughly twenty years to

Brothers share the household environment, class position, and the county in which they were raised, so the comparison absorbs family and county-level characteristics common to siblings. The identifying variation is whether the brother gap is larger where the local trade declined than where it expanded. If persisting entry into the deteriorating local labour market incurred costs, then sons who followed their fathers into the trade should have fared worse than their brothers in declining counties, but done as well as their brothers where the bootmaking trade was flourishing. That is, if the trade itself was deteriorating, entry should have carried a penalty.

I classify counties according to changes in local bootmaking employment over the relevant census panel. Counties in which the local bootmaking population increased by at least 20 percent are classified as *Growth* counties, while counties in which it declined by at least 20 percent are classified as *Decline* counties. The main specification compares these two groups, dropping the counties in between. I report robustness to alternative cutoffs and to a continuous treatment measure. Counties are classified by realized employment change over the window. Sons of bootmakers account for a minority of entrants into the trade, limiting the extent to which their own entry decisions can determine county classification.

To check whether outcomes between brothers diverged in places in which the local bootmaking trade went into decline, I estimate the following within-family specification:

$$Y_{if} = \delta_f + \theta B_{if} + \beta \left( B_{if} \times \text{Decline}_c \right) + X'_{if}\gamma + \varepsilon_{if}, \tag{4}$$

where $Y_{if}$ is an adult outcome for son $i$ in family $f$; $\delta_f$ is a family fixed effect; $B_{if}$ equals one if the son became a bootmaker. $\text{Decline}_c$ equals one if bootmaking declined in the family's county, with Growth counties the reference category. The vector $X_{if}$ includes age and birth order. Standard errors are clustered at the county level.

I estimate the specification on four outcomes: migration away from the county of origin, marriage, household headship, and the number of co-resident children under 18. Migration serves a different purpose from the others. It establishes the geographic embeddedness that motivates the design, rather than measuring a cost of persistence. Marriage and headship are the substantive outcomes: in this period household formation required the economic means to support it, so delayed or foregone family formation is a measure of a young man's material prospects.

reach ages at which adult outcomes are observable, so from an 1861 baseline the next available endpoint is 1891. The windows are determined by data availability.

The coefficient $\theta$ is the within-family brother gap in Growth counties, and $\beta$ is the additional gap in Decline counties. I also report the implied total brother-gap in declining counties, $\theta + \beta$. This measures the cost of persistence: how much worse bootmaker sons fared, relative to their own brothers, when they followed the paternal trade in a contracting local market. Following the paternal trade also meant different kinds of work across these local trajectories: in growing counties, bootmaker sons increasingly entered the new mechanized occupations, while in declining counties they overwhelmingly entered the older artisanal jobs (Appendix M3).

The design allows sons who entered bootmaking to differ from their brothers, but requires that these differences are not systematically related to the local trajectory of the trade. I assess the plausibility of this assumption in two ways. Firstly, I check whether birth order differs across county types, and show that the results are robust to allowing its effect to vary across local trajectories. Secondly, I implement a placebo design using the sons of carpenters. Sons who entered their father's trade were substantially less likely to leave their county than their brothers, so the estimated penalties could in principle reflect the cost of remaining in a declining local labour market rather than the cost of remaining in a declining trade. Carpenters provide a useful comparison: they were an artisanal trade with a similar succession structure, and carpenter sons were also geographically anchored relative to their brothers. I therefore estimate the same specification on carpenter families, retaining the local trajectory of the bootmaking industry as the source of cross-county variation. If the penalties reflected the cost of being geographically anchored in a contracting local labour market, similar penalties should appear among carpenter sons.

## 4.2 Job Creation: New Jobs in Bootmaking

The contraction of the artisanal trade was only one side of the transition catalyzed by mechanization. The technological shock also created new jobs. While the decline side asks who bore the burdens of creative destruction, the creation side asks who benefited from the new opportunities.

Descriptive statistics suffice here. As discussed in Section 4.1.2, entry rates are shares of a single cohort and sum to one across occupations, so the mean change is zero by construction and there is no informative benchmark to difference against. I ask three questions. Firstly, where did the new jobs emerge? I compute each county's share of all new bootmaking employment in England in 1881. Secondly, who filled them? For each worker in the new occupations I compare county of birth to county of employment, and report

the share employed in their county of birth. I compute the same share for workers in the surviving artisanal occupations. This asks whether the new jobs drew workers from outside the adopting counties to a greater degree than the trade they were replacing. Finally, which workers within those local labour markets took them? I plot the mean age of workers in each machine-era occupation across census years from 1851 to 1911, alongside the mean age in each artisanal occupation. A generational reallocation would show the new occupations persistently younger than the old.

# 5 Results

Following the structure of the empirical strategy, Section 5.1 shows that mechanization did not displace most incumbent bootmakers. Section 5.2 documents that the contraction of artisanal employment occurred along the entry margin. There was a collapse of entry. Section 5.3 shows that continued entry into the bootmaking industry carried a penalty, giving young workers reason to switch away from artisanal bootmaking. Finally, Section 5.4 turns to the creation side of the transition, and documents who took up the new specialized jobs in the bootmaking industry.

## 5.1 Incumbents

Given that so many new jobs emerged at the same time as the artisanal jobs declined, a natural first question is whether incumbents simply transitioned directly out of the old jobs and into the new ones. Because the new work was spatially concentrated, many incumbents would have had to move for this to happen. The descriptive data answers this directly. Figure H1 tracks the men and women recorded as bootmakers in 1861 through to 1881, during the first period of mechanization. Very few incumbents transitioned into the new jobs: roughly six percent of men and four percent of women.

The same flowchart shows what share of incumbents left the industry altogether. For men, 36 percent left bootmaking in this period. In contrast, nearly 89 percent of the women exited the industry. These figures seem substantial, and raise the question of whether incumbents were pushed out of the industry by labour-displacing mechanization. That is, were they displaced?

If mechanization pushed existing workers out, we should observe a sharp rise in exit rates among incumbent bootmakers relative to workers in other industries. Table 3 reports estimates from the linear probability difference-in-differences. In levels, male bootmakers

exhibit lower exit rates than men in other industries.[22] In 1851–1861, male bootmakers were roughly 27 percentage points less likely to leave their occupation than the average man, reflecting the stability of artisanal bootmaking prior to mechanization. Female bootmakers were much closer to the average exit rate for women, consistent with the different skill levels involved. The interaction term for men is 0.8–1.0 percentage points and not statistically significant. Mechanization produced no detectable displacement of incumbent men.[23]

Table 3: Exiting Bootmaking

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Boot | $-0.260^{***}$ | $-0.260^{***}$ | $-0.260^{***}$ | $-0.026^{*}$ | $-0.045^{***}$ | $-0.052^{***}$ |
| | (0.008) | (0.008) | (0.008) | (0.014) | (0.014) | (0.014) |
| Post | $0.082^{***}$ | $0.071^{***}$ | $0.081^{***}$ | $0.074^{***}$ | $0.075^{***}$ | $0.105^{***}$ |
| | (0.006) | (0.005) | (0.009) | (0.004) | (0.004) | (0.011) |
| Boot × Post | 0.008 | $0.010^{*}$ | $0.010^{*}$ | $0.123^{***}$ | $0.121^{***}$ | $0.138^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.014) | (0.014) | (0.014) |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline controls | No | Yes | Yes | No | Yes | Yes |
| Post × controls | No | No | Yes | No | No | Yes |
| Baseline exit (bootmakers) | 0.271 | 0.271 | 0.271 | 0.706 | 0.706 | 0.706 |
| Baseline exit (comparison) | 0.538 | 0.538 | 0.538 | 0.740 | 0.740 | 0.740 |
| Observations | 2,476,147 | 2,476,147 | 2,476,147 | 708,923 | 708,923 | 708,923 |

*Notes:* The sample stacks two transition windows, $1851 \to 1861$ (pre-mechanization) and $1861 \to 1881$ (post-mechanization), estimated separately by sex. The sample is restricted to individuals aged 15 and older at baseline. Occupations assigned a HISCAM score of zero are excluded. Baseline controls are age band and marital status; "Post × controls" adds their interactions with Post $* \tau$. Baseline exit rates report the mean of Exit $* ic\tau$ in the $1851 \to 1861$ window separately for bootmakers and the comparison group. Standard errors are clustered by county of baseline residence. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

For women, the picture is starkly different. Female bootmakers' exit probabilities rose 13.8 percentage points relative to women in other industries. This provides evidence that female bootmakers experienced substantial technological labour displacement. However, as women constituted less than 20 percent of the artisanal bootmaking workforce, this displacement does not account for the large aggregate contraction of the trade.

Occupational structures were shifting across the entire economy in this period. I therefore compare the bootmaking estimate to the distribution of placebo estimates obtained

[22] Appendix H2 provides more detail.
[23] Nor did the shock lead to an increase in bootmakers migrating. See Appendix I.

by assigning treatment to each comparison occupation in turn. Appendix H3 reports the full exercise. The male estimate lies well within the placebo distribution, while the female estimate lies near the extreme upper tail. Mechanization produced no unusual displacement of incumbent men, but substantial and unusually high displacement of incumbent women. Appendix J uses this cross-sectional variation to relax parallel trends. The implied range contains zero for men, but remains positive for women even when the counterfactual spans the central 90% of large untreated occupations.

These aggregate estimates do conceal heterogeneity by age. Table 4 reports the estimates by baseline age cohort. For men, the change is concentrated in the youngest cohort. Young male bootmakers aged 15–24 saw exit probabilities rise by 2.9 percentage points more than non-bootmaker men in the same age band. However, for older male cohorts, the changes are small and not significant. Adjustment is concentrated at younger ages, where workers were closer to the entry margin and more able to switch away from the trade.

Women, on the other hand, show significant excess exit in every band. The changes are striking among prime-age female bootmakers (25–54), with exit probabilities rising by 13.2 to 16.9 percentage points more than for non-bootmaker women. The aggregate female displacement effect is driven by women whose careers were established in artisanal bootmaking.

Table 4: Change in Bootmaker Exit Gap, by Baseline Age Band

| | Men $\beta_a$ (pp) | Women $\beta_a$ (pp) |
|---|---|---|
| 15–24 | $2.9^{**}$ (0.9) | $9.8^{***}$ (1.9) |
| 25–34 | $1.9^{**}$ (0.7) | $16.9^{***}$ (1.8) |
| 35–44 | 0.2 (0.7) | $15.2^{***}$ (1.5) |
| 45–54 | $-1.6$ (1.3) | $13.2^{***}$ (1.5) |
| 55+ | $-0.8$ (1.4) | $8.1^{**}$ (2.7) |
| County FE | Yes | Yes |
| Observations | 2,476,147 | 708,923 |

*Notes:* Linear probability model estimates of $\beta_a$ from Equation 3, the cross-panel change in the bootmaker–non-bootmaker exit gap within each baseline age band. Coefficients are in percentage points. All specifications control for baseline marital status and its interaction with $\text{Post}_\tau$. Standard errors clustered by county of baseline residence are reported in parentheses beside each estimate. The sample is restricted to individuals aged 15 and older at baseline. Occupations assigned a HISCAM score of zero are excluded; occupations unmatched to HISCAM are retained. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

I check that the national estimate is not masking variation in regional responses. Re-estimating the model separately for each of the 42 English counties (reported in full in

Appendix H5) confirms that the national null is not concealing broad-based displacement. Of the six counties significant at $p < 0.05$, signs are mixed: three are positive and three negative. Only Staffordshire survives Bonferroni correction. Most consequentially, Northamptonshire, the largest English bootmaking county and the heart of mechanized boot production, shows no significant excess exit ($\beta = -1.5$pp, $p = 0.21$). There are therefore some localized pockets of male displacement, most clearly in Staffordshire, but they do not account for the aggregate contraction of artisanal bootmaking. The evidence points away from incumbent displacement as the primary mechanism behind that contraction.

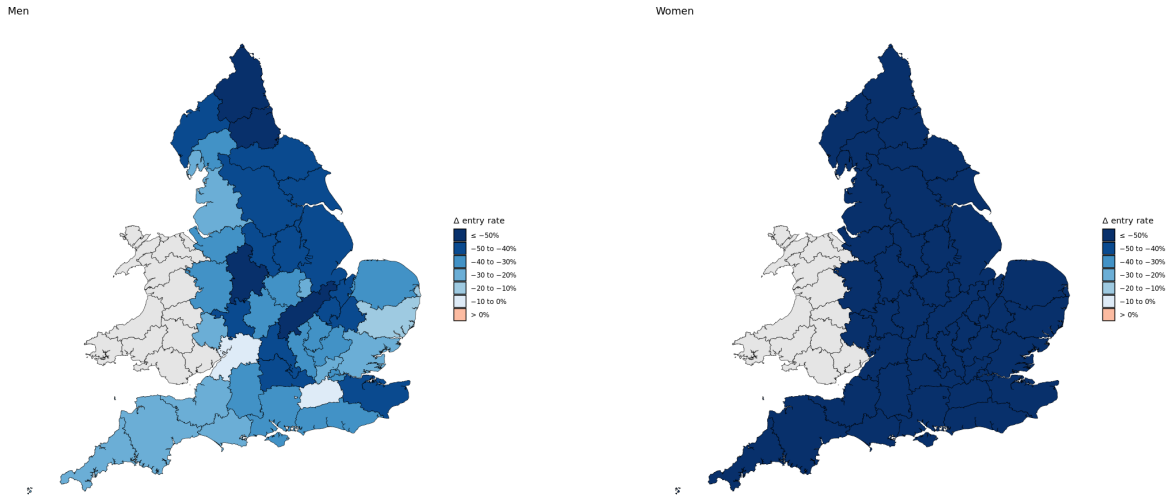
I have shown that female bootmakers experienced a sharp increase in occupational exit as mechanization set in, while male bootmakers did not. Men accounted for more than 80 percent of incumbent bootmakers, so for the incumbent workforce as a whole displacement was limited. Two things are therefore established. Firstly, incumbent artisanal workers did not move directly into the new jobs. Secondly, incumbents as a whole did not experience unusual occupational exit. Nonetheless, roughly 150,000 artisanal bootmaking jobs disappeared. An occupational stock can contract along two margins: either incumbents exit, or fewer new workers enter to replace them. Since increased exit explains relatively little of the overall contraction, I now turn to the entry margin.

## 5.2 Entrants

The collapse in entry is immediately visible in the descriptive statistics. I track the share of young people entering artisanal bootmaking in both the pre-shock and post-shock windows. Prior to the shock, 3.08 percent of all young men in England, aged 10–18 at baseline, had entered the artisanal bootmaking trade by the end of the window. In the first period following mechanization, that fell to 1.81 percent, a decline of about 41 percent. Entry rates for women were lower to begin with, but the contraction was even more severe: 0.75 percent of young women entered the trade before the shock, but this declined to 0.08 percent afterwards, a reduction of around 89 percent.

The collapse was geographically widespread. For men, entry into artisanal bootmaking fell in all 42 English counties, with most declines clustering between roughly 25 and 50 percent. Declines exceeded 50 percent in Northumberland, Staffordshire, Durham, Northamptonshire, Cambridgeshire, and the Yorkshire North Riding. Gloucestershire was the clear exception in magnitude, with entry falling by only 5 percent. For women, the collapse in entry exceeded 50 percent in every county. Figure 3 maps these changes. Northamptonshire is particularly interesting. The artisanal entry rate halved, falling from

20.0 to 8.8 percent, even as the county's bootmaking industry as a whole expanded through factory production.




(a) Men (b) Women

Figure 3: Change in Entry Rates into Artisanal Bootmaking, by County

*Notes.* Each panel maps the relative change in the share of young people aged 10–18 at baseline entering artisanal bootmaking between the 1851–61 and 1861–81 transition windows. Counties are shaded by the percentage change in the entry rate, with darker shades indicating sharper declines. The collapse in entry was broadly distributed across England for both sexes, but was effectively total for women. Absolute entry rates by county are reported in Appendix K2.

The structural consequence of this missing entry is immediately visible in the age composition of the trade. Figure K1 in Appendix K3 shows the stock of artisanal bootmakers in each census year between 1851 and 1911. The male artisanal workforce contracted from approximately 174,000 in 1851 to 60,000 in 1911, a fall of roughly 65 percent, with the bulk of the decline concentrated between 1861 and 1881. Over the same period the share of male artisanal bootmakers under age 30 fell from 44 percent to 29 percent, while the share aged 51 and over rose from 19 percent to 37 percent. The young adult cohort, aged 21–30, saw the steepest proportional decline, falling by 37 percent.

The youngest cohorts collapsed first and most sharply, while older cohorts persisted or grew, even as the total stock shrank. By 1911, men aged 51 and over formed the largest age group in the trade, having displaced the under-30s as the modal cohort. The contraction was therefore borne almost entirely on the entry margin. The female trade followed a different and more extreme trajectory, with the workforce contracting from approximately 33,000 in 1851 to 4,000 in 1911 - an 88 percent decline - concentrated almost entirely between 1861 and 1881.

## 5.3 The Costs of Entering a Declining Industry

The collapse in entry documented above is consistent with two interpretations. Young men may have been deterred from entering a deteriorating trade, i.e. implying that adjustment was a response to mechanization. Alternatively, they may have been drawn away by expanding opportunities elsewhere. The analysis that follows focuses on men, because it exploits intergenerational occupational inheritance, which in this period operated primarily from fathers to sons.

### 5.3.1 Main Results: Within Family Difference-in-Differences

Table 5 reports the main results. Each outcome is estimated separately for the two panel windows, 1851–1881 and 1861–1891 (hereafter the first and second windows). Columns (1)–(2) report migration, which documents the geographic embeddedness channel motivating the identification strategy. Columns (3)–(8) report the substantive consequences of persistence: marriage in columns (3)–(4), household headship in (5)–(6), and the number of co-resident children under age 18 in (7)–(8). Following the empirical strategy, counties are classified as Growth (bootmaker employment increased by at least 20 percent over the panel window) or Decline (decreased by at least 20 percent). Stable counties are excluded from the main specification, with robustness to alternative cutoffs reported in Appendix M.

In Growth counties (the baseline), bootmaker sons are roughly 19–20 percentage points less likely than their non-bootmaker brothers to leave their home county. The Decline interaction is small and not statistically significant: the gap remains 14.5–15.6 percentage points in Decline counties. Sons who inherited the trade were geographically embedded regardless of the local trajectory of the bootmaking trade.

Table 5: Cost of Persistence: Within-Family Difference-in-Differences

| | Migration | | Married | | Head of household | | No. children $< 18$ | |
|---|---|---|---|---|---|---|---|---|
| | 1851–1881 | 1861–1891 | 1851–1881 | 1861–1891 | 1851–1881 | 1861–1891 | 1851–1881 | 1861–1891 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $B_{if}$ | $-0.188^{***}$ | $-0.196^{***}$ | $0.028$ | $0.023$ | $-0.017$ | $-0.012$ | $0.448^{***}$ | $0.261^{*}$ |
| | (0.034) | (0.019) | (0.024) | (0.018) | (0.021) | (0.012) | (0.107) | (0.137) |
| $B_{if} \times \text{Decline}_c$ | $0.032$ | $0.051$ | $-0.093^{***}$ | $-0.072^{***}$ | $-0.055^{**}$ | $-0.038^{*}$ | $-0.240^{*}$ | $-0.220$ |
| | (0.038) | (0.031) | (0.030) | (0.024) | (0.025) | (0.019) | (0.137) | (0.161) |
| Total brother-gap in Decline ($\theta + \beta$) | $-0.156^{***}$ | $-0.145^{***}$ | $-0.065^{***}$ | $-0.049^{***}$ | $-0.071^{***}$ | $-0.049^{***}$ | $0.208^{**}$ | $0.041$ |
| | [0.019] | [0.024] | [0.019] | [0.016] | [0.012] | [0.015] | [0.082] | [0.096] |
| Family FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,329 | 2,816 | 3,329 | 2,816 | 2,859 | 2,454 | 3,329 | 2,816 |
| $R^2$ | 0.540 | 0.538 | 0.459 | 0.457 | 0.508 | 0.500 | 0.488 | 0.487 |

*Notes:* Controls are age and birth order. "No. children $< 18$" is the number of co-resident children under age 18. The sample is restricted to mixed occupation bootmaker-father households. The "Total brother-gap in Decline" row reports $\theta + \beta$, with the standard error of the linear combination in square brackets. Standard errors clustered at the county level in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

In counties where bootmaking was expanding, bootmaker sons were no less likely than their brothers to marry or become household heads. They also had more co-resident children under age 18: approximately 0.45 more children in the first window and 0.26 more in the second.

This relative advantage deteriorated where the local trade contracts. The interaction coefficients for marriage are $-0.093$ and $-0.072$, and those for household headship are $-0.055$ and $-0.038$. In Decline counties, bootmaker sons were about 6.5 and 4.9 percentage points less likely than their brothers to be married, and 7.1 and 4.9 percentage points less likely to be household heads. The number of children follows the same directional pattern. Sons who followed their fathers in counties in which the trade was contracting experienced measurable and repeated penalties in adult life.

Estimating each outcome separately across the two windows serves a second purpose beyond replication. The moderate attenuation from the first window to the second is consistent with the change in entry mechanism. Earlier cohorts may have entered a trade whose decline was not foreseen, and bore the largest costs, while later entrants may have entered with better information. The penalties were largest for the cohort ambushed by the shock.

### 5.3.2 Placebo: Sons of Carpenters

As a placebo test of the causal interpretation, I estimate the same specification on sons of carpenters. This is a comparator artisanal trade, selected for its similar succession structure and demographic profile.

The within-family design absorbs any shock common to brothers, including county-wide decline. But brothers did not share an identical exposure to their county as adults: sons who entered the paternal trade stayed, while their brothers frequently left. The penalties we see in Table 5 could therefore be reflecting the costs of remaining in a struggling place. The carpenter placebo separates these. Carpenter sons, under the same classification, faced the same county-level conditions but were not directly exposed to the bootmaking mechanization shock. If the penalty attached to staying in a declining place, carpenter sons should exhibit it.

The carpenter placebo does not reproduce the bootmaker pattern. The interaction with local bootmaking decline is small and statistically insignificant for migration, household headship, and the number of children in both windows. For marriage, it is positive in the first window and insignificant in the second.

Table 6: Placebo: Carpenter Sons

| | Migration | | Married | | Head of household | | No. children $< 18$ | |
|---|---|---|---|---|---|---|---|---|
| | 1851–1881 | 1861–1891 | 1851–1881 | 1861–1891 | 1851–1881 | 1861–1891 | 1851–1881 | 1861–1891 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $C_{if}$ | $-0.050$ | $-0.100$ | $-0.023$ | $0.025$ | $-0.031$ | $0.043$ | $-0.011$ | $0.659^{**}$ |
| | (0.057) | (0.067) | (0.028) | (0.074) | (0.025) | (0.052) | (0.270) | (0.243) |
| $C_{if} \times \text{Decline}_c$ | $-0.003$ | $0.024$ | $0.054^{*}$ | $0.015$ | $0.035$ | $-0.036$ | $0.351$ | $-0.348$ |
| | (0.059) | (0.069) | (0.031) | (0.075) | (0.028) | (0.053) | (0.276) | (0.256) |
| Total brother-gap | $-0.053^{***}$ | $-0.076^{***}$ | $0.032^{**}$ | $0.040^{**}$ | $0.004$ | $0.007$ | $0.340^{***}$ | $0.312^{***}$ |
| in Decline ($\theta + \beta$) | [0.013] | [0.019] | [0.012] | [0.017] | [0.012] | [0.011] | [0.060] | [0.073] |
| Family FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,356 | 2,920 | 3,356 | 2,920 | 2,935 | 2,562 | 3,356 | 2,920 |
| $R^2$ | 0.541 | 0.565 | 0.436 | 0.425 | 0.517 | 0.497 | 0.468 | 0.499 |

*Notes:* Placebo estimates using sons of carpenter fathers in carpenter-father households. $C_{if}$ indicates entry into carpentry. Counties are classified using the same local bootmaking Growth-vs-Decline measure as in the main specification, with a $\pm 20\%$ cutoff. Stable counties are excluded. Controls are age and birth order. "No. children $< 18$" is the number of co-resident children under age 18. The "Total brother-gap in Decline" row reports $\theta + \beta$, with the standard error of the linear combination in square brackets. Standard errors are clustered at the county level in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

### 5.3.3 Identification Checks and Robustness

The within-family identifying assumption requires that sibling-specific differences do not vary systematically with the local trade trajectory. I test this in several ways, reported in full in Appendix M.

Firstly, I examine the observable composition of bootmaker sons across county types. In both windows, firstborns are more heavily represented among bootmaker sons in declining counties, with the difference particularly pronounced in 1861–1891. Since firstborn

sons do not appear systematically disadvantaged in the absence of exposure to the bootmaking shock, the direction of this selection does not suggest that declining counties increasingly channel less advantaged sons into the trade. I nevertheless allow birth-order effects to vary with local decline. The Bootmaker son $\times$ Decline interactions are essentially unchanged, and if anything become somewhat larger for marriage and headship.

Secondly, I vary the classification cutoff, using $\pm 10$ and $\pm 30$ percent rather than the baseline $\pm 20$ percent. The estimates are highly stable between the $\pm 20$ and $\pm 30$ percent definitions. Under the more inclusive $\pm 10$ percent definition, the marriage and headship interactions attenuate in the 1861–1891 window, consistent with relatively modest changes in bootmaking employment being included in the Growth and Decline groups. Finally, I replace the discrete classification with a continuous-intensity specification using local bootmaker employment change directly. For marriage and headship, greater local contraction is associated with a larger within-family penalty for bootmaker sons.

In counties in which the bootmaking industry was contracting, persistence translated into measurable costs: bootmaker sons were less likely to marry and to head their own households than their brothers. These penalties replicate across both panel windows and survive adjustment for observable within-family selection and alternative measures of local trade decline. The collapse in entry documented in the previous section was therefore neither a coincidence of timing nor a pull from opportunities elsewhere. Young men who avoided the trade were responding to real costs to continued entry.

## 5.4 New Jobs

Mechanization also created new jobs. Alongside the disappearance of roughly 150,000 artisanal jobs, around 140,000 new and more specialized bootmaking jobs emerged. Table 7 sets the two margins side by side. For men, entry into the specialized occupations rose from 0.07 to 0.63 percent of the youth cohort, offsetting nearly half the artisanal decline. Pooled across both segments, entry into bootmaking as a whole fell by 0.72 percentage points against an artisanal fall of 1.28.

Table 7: Entry rates into bootmaking

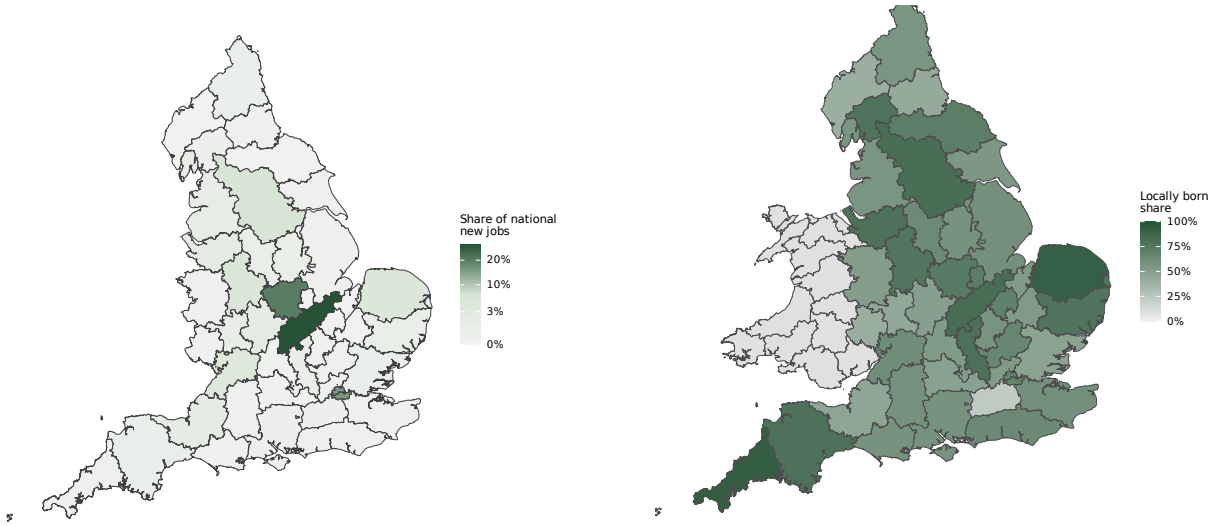
| | Entry rate (%) | | |
|---|---|---|---|
| | 1851–1861 | 1861–1881 | 1881–1891 |
| *Panel A: Men* | | | |
| Pooled | 3.20 | 2.48 | 2.28 |
| Artisanal | 3.08 | 1.81 | 1.08 |
| Mechanized | 0.07 | 0.63 | 1.14 |
| *Panel B: Women* | | | |
| Pooled | 0.81 | 0.42 | 0.82 |
| Artisanal | 0.75 | 0.08 | 0.09 |
| Mechanized | 0.04 | 0.31 | 0.68 |

*Notes:* Sample is linked workers aged 10–18 at baseline. Entries report the percentage of the baseline cohort observed in a bootmaker occupation at endline. Pooled bootmaking spans occodes 663–666. Artisanal and mechanized entry are defined using the task-level classification of Section 3.

The pooled row makes a further point. In levels, the transition nearly netted out: there were nearly 140,000 new jobs created against the 153,000 destroyed. However, England's population grew substantially across this period. For this reason, a stable job count is not identical to a stable opportunity. Population growth meant that, even while the absolute numbers shifted very little, the entry rate into bootmaking as a whole fell from 3.20 to 2.48 percent of the male youth cohort, and from 0.81 to 0.42 percent of the female cohort.

Panel (a) of Figure 4 shows that the new jobs were highly geographically concentrated. As discussed above, a small number of counties accounted for the majority of the new bootmaking employment in England: Northamptonshire and Leicestershire together made up approximately 45 percent, and with London this rose to 65 percent.

Panel (b) shows the share of those jobs taken by people born in the counties where the new work emerged. Overall, around 73 percent of the new jobs were held by people born in the county where they worked, slightly higher than the 68 percent local-born share in the old jobs. The new jobs were therefore filled predominantly by locally born workers. Even where the demand shock was largest, most of the new jobs went to locals. So, while mechanization did create new employment, access was not even.




(a) Share of England's new jobs (b) Share of new jobs held by the locally born

Figure 4: The Geography of New Bootmaking Jobs, 1881

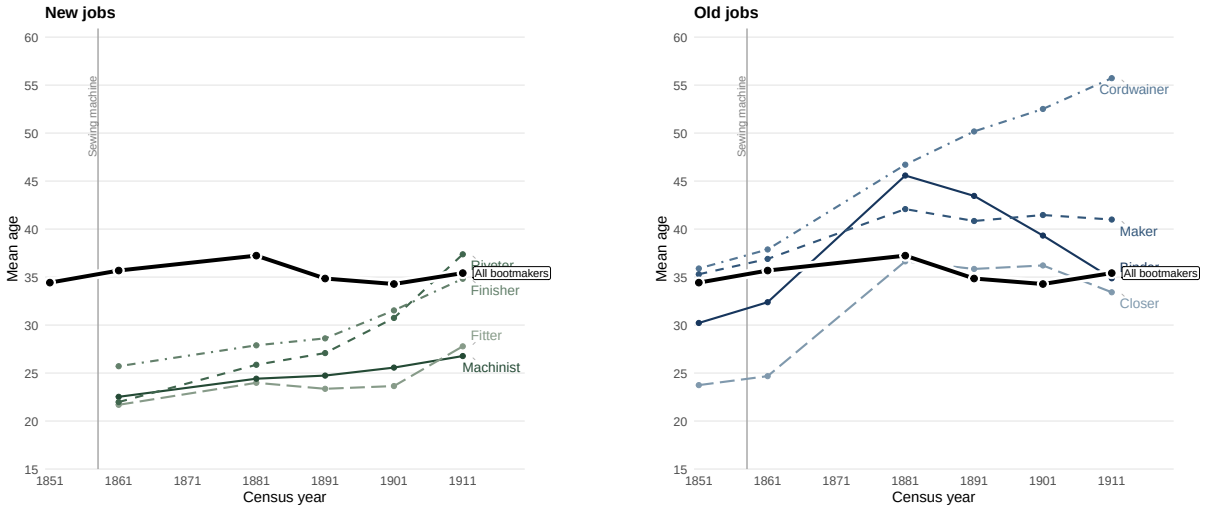
*Notes:* Panel (a) shows each county's share of all new machine-era bootmaking employment in England in 1881. Panel (b) shows the share of workers in those occupations who were born in the county where they worked. Nationally, 73 percent of the new jobs were held by the locally born, against 68 percent in the artisanal occupations. *Source:* ICeM full-count census microdata.

The next question is which workers within those local labour markets took the new jobs. The answer is overwhelmingly younger ones. Figure 5 plots the mean age of workers in each machine-era bootmaking occupation across census years, alongside the mean age in each artisanal occupation. The darker line in each panel shows the overall mean age of bootmakers. Workers in the new occupations are consistently younger than average, illustrating that the new jobs were taken by younger cohorts. On the flip side, workers remaining in the older, artisanal, occupations become substantially older as mechanization sets in, which follows, given the collapse in entry rates.

Mechanization therefore produced a generational reallocation within the industry. Older incumbents remained disproportionately in the artisanal occupations, while younger workers entered the newly created specialized ones. The gap narrows over time, consistent with the new occupations maturing, and their initial cohorts ageing, but it remains clearly visible decades after mechanization began.

Access to the new work was therefore determined by two things: being in the right place, and being young enough to still be choosing an occupation. Neither is a matter of skill. We have had more than a century of skill-biased technological change, and we are used to thinking about education as what mediates access to new opportunities. This was a

deskilling technological change. Access was mediated by geography and by cohort instead.




(a) Machine-era occupations

(b) Artisanal occupations

Figure 5: Mean Age of Bootmaking Workers by Task, 1851–1911

*Notes:* Each line plots the mean age of workers in a given bootmaking occupation in each census year. Panel (a) shows the machine-era occupations. Panel (b) shows the artisanal occupations. The darker line in each panel shows the mean age of all bootmakers. *Source:* ICeM full-count census microdata.

# 6 Discussion

Having completed a full tour of an instance of creative destruction in Victorian Britain, three findings emerge on the destruction side. We saw that: 1) Incumbents did not, for the most part, transition directly into the new jobs; 2) Incumbents faced relatively little displacement, once we note the gendered experience of this; 3) There was a collapse in entry into artisanal bootmaking, which took place across the breadth of England. Taken together, these three findings show that the contraction of artisanal employment operated primarily through the collapse of entry, rather than through incumbent reallocation or displacement. Of course, that accounts only for the destruction side of the transition. On the creation side, around 140,000 new, more specialized jobs emerged in the bootmaking trade. These were heavily concentrated in Northamptonshire and Leicestershire, and went primarily to young people born in the counties in which the new jobs emerged.

These findings bring two broader issues to the fore. One is that they suggest we should expand our view of the mechanisms through which occupational obsolescence occurs. I propose we consider two forms of obsolescence: labour displacement and collapse of en-

try. The other is that, since the impact of labour-displacing technological change is jointly determined by job destruction and job creation, we cannot dispense with the creation side of the ledger.

## 6.1 Destruction: Two Forms of Obsolescence

There are several ways in which the workforce can be reallocated when jobs are destroyed by innovation. Over the last decade, research on the labour market impacts of technological change has focused on identifying which jobs are susceptible to technological obsolescence, and whose jobs (Frey and Osborne, 2017; Goos et al., 2014). This framing can elide exposure and mechanism, implicitly assuming that technologically induced occupational decline operates via labour displacement. That is, the standard view of reallocation is that it operates by dislocating incumbent workers from their jobs. As evidenced above, cohort replacement is another mechanism through which labour can be reallocated out of waning occupations and into the new, emerging ones.

I therefore propose that we consider two forms of obsolescence. The first is the canonical model, in which incumbent workers face labour displacement and have to seek work elsewhere. The second operates via the collapse of entry - a contracting occupation can decline over decades simply as the result of insufficient replenishment.

The distinction between the two can be tied to two features: the rate at which a new technology is adopted, and the persistence of demand for old skills. In the study by Feigenbaum and Gross (2024) on the automation of telephone operation in the United States, implementation was abrupt at the exchange level. When AT&T switched an exchange over to mechanical operation, the cutover made incumbents immediately superfluous. These conditions necessarily result in labour displacement.[24]

On the other hand, at least in historical context, new technologies have often been adopted very gradually (Edgerton, 2007). The steam engine took decades to replace the watermills in England. Steamships took decades to replace sail. Under these conditions, demand for older types of skills persists, and when demand for waning skills survives even as it contracts, it is possible to grandfather older workers through the transition. Obsolescence may then take place on the other margin, through a collapse of entry as young people cease to enter the trade.

[24]The relevant speed here is not the speed of aggregate diffusion. The mechanization of the American telephone network took decades. However, cutovers happened exchange by exchange, and the shock to workers was abrupt at each exchange.

This is also what one might expect. Older workers, with deep investments in human capital and social networks, should find it more costly to leave their occupations. Equally, and for the same reasons, they may be better placed to compete for what remains of a waning demand for labour in a declining industry. I do not argue that all technologically induced occupational decline will take place through entry-driven obsolescence. However, when new technology diffuses slowly, as it often does, the margin of adjustment may well run through young people no longer replacing the workers who leave.

In the bootmaking case, there is supporting evidence that demand for old skills persisted. Artisanal bootmakers served a bespoke market concentrated among wealthier customers, and their density across parishes is positively associated with parish wealth in 1851, in 1861, and still in 1881. Workers in the new mechanized occupations show the opposite pattern: by 1881, their density is negatively associated with parish wealth. The two products were serving different markets, and the artisanal trade retained many of its customers even as ready-to-wear captured new markets and took some of the old. The result was that demand for the old skills did not vanish. Instead, the evidence shows that it narrowed, and survived particularly in the places which could afford to pay for high-quality artisanal footwear. See Appendix O1.

## 6.2 Creation: Both Sides of the Ledger

There has been considerable interest in the labour market impacts of labour-displacing artificial intelligence. Recently, a new discussion has materialized around the possibility that adjustment to technologically driven job loss might in fact fall on the entry margin, with young people made less able to find employment in industries exposed to automation (Brynjolfsson et al., 2025; Hosseini Maasoum and Lichtinger, 2025; Financial Times, 2026). However, whether adjustment falls on incumbents or on entrants, both mechanisms remain on the destruction side of the ledger.

Destruction captures only half the story. At least historically, new jobs, demanding new skills, have emerged to replace jobs made obsolete by innovation. The impacts of creative destruction on workers, their families, and their communities are in this way jointly determined by both job destruction and job creation.

While observing both sides of the ledger is vital, this is not enough. Given that outcomes are jointly determined, understanding where the costs and opportunities of a transition in the occupational structure fall requires a more granular analysis of how the two forces intersect. As new jobs emerge, the questions are: do they emerge sufficiently quickly? Do

they emerge in the same places, for the same people? Aggregate replacement of jobs is not at all the same as replacement of opportunity for individual workers, and particular places, skill groups, or cohorts can be left with sharply diminished opportunities in the shift, or - in the vernacular - left behind.

In the Victorian bootmaking industry, adjustment on both the destruction and creation sides of the ledger pivoted on young workers. There was a collapse of entry into artisanal bootmaking, as young people stopped entering. Simultaneously, young people took up the new and more specialized jobs. The reallocation of the workforce as a whole therefore took place through the younger cohort, as entry shifted away from the waning occupations and towards the new and emerging work. Some doors closed and some doors opened, and they did so for the same cohort. While the two sides of the transition coincided in terms of cohort, they did not coincide in terms of geography, because the new opportunities were extremely spatially concentrated. In this way, technological change can tilt access to opportunity, even within the same cohort, while leaving aggregate employment relatively balanced.

Cohort and geography are two dimensions along which the two sides of creative destruction may or may not align. Skill is naturally another. The mechanization of English bootmaking was a deskilling transition, so the new jobs did not demand substantially higher levels of skill than the old. In other technological transitions, however, they may. Access to the new jobs may also depend on social networks or other barriers to entry. Two papers on technological change in historical context document how technological change shifted access to opportunity along the dimensions of race and gender (Gray et al., 2025; Nedelkoska et al., 2021), but the question as a whole would benefit from more research.

In summary, the incidence of creative destruction depends on the extent to which its two sides align across several dimensions. To study impact on the labour market or political economy, both sides must be observed.

# 7 Conclusion

Creative destruction has been ongoing for more than two centuries. In that time millions of jobs have been made obsolete, and have disappeared. On the flip side, much of the work performed today is new: around 60 percent of employment in the United States is now in job titles that did not exist in 1940 (Autor et al., 2024). This underscores the degree to which maintaining employment has relied on the creation of new work. At the dawn of the Industrial Revolution, there was acute concern that the new machines would steal

jobs. This concern abated considerably over time. Did we destroy so many jobs without causing substantial damage? If so - how? The usual answer is that new jobs were created at least as fast as old jobs were lost.

What is less clear is how workers were reallocated out of waning and into emerging work. This paper follows a major technological transition from onset through to completion. As English bootmaking mechanized between 1851 and 1911, approximately 153,000 artisanal jobs disappeared and 140,000 new, more specialized jobs emerged. Incumbent workers did not simply move from the old jobs into the new ones. Nor, for the most part, were they displaced. Male incumbents experienced very little displacement and continued in the traditional bespoke work for which they had trained, although the experience of female incumbents was markedly different.

Instead, adjustment operated primarily through young cohorts. On the destruction side, as mechanization drove a decline in demand for artisanal labour, there was a collapse of entry into the profession. Young men became substantially less likely to enter, and would have borne meaningful costs had they persisted. On the creation side, the new and more specialized jobs were also taken up predominantly by young workers, and overwhelmingly by those born in the counties in which the new work emerged. Adjustment on both sides of the transition - destruction and creation - therefore operated via young cohorts. However, while bootmaking became a less viable option for young people across most of England, the new opportunities were concentrated in only a few counties. If technological change generated inequalities in this transition, it did so primarily by tilting young people's access to opportunity.

I propose we consider two types of technological obsolescence. When technological change is abrupt, and demand for old skills disappears in concert, adjustment falls on incumbents. They are displaced. However, when change is gradual, and demand for older skills persists, incumbents can remain while entry erodes. The pace of diffusion and the persistence of demand for older skills determine which margin bears the adjustment.

Finally, the impact of technological change on workers, their families, and their communities cannot be understood by reading from the destruction side of the ledger alone. It matters a great deal how many new jobs emerge, where they emerge, and who is placed to take them. The incidence of labour displacing technological change is jointly determined by the forces of both job loss and job creation. In the modern day, understanding the labour-market and political-economy consequences of generative AI requires us to ask not only which jobs will disappear, but what new work will emerge, where, and for whom.

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# Appendix A Female Labour Force Participation

Some definitions of Female Labour Force Participation (FLFP) focus on women being "economically active" (International Labour Organization, 1982). This includes self-employment, and in practice translates into the sale of goods or services in exchange for an income. This framework is most suitable for assessing the records on FLFP in Victorian England.

In 19th century England the most comprehensive record of FLFP emerges from the decennial census records. Householders 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" (Great Britain, Census Office, 1851). 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".

Can we trust the recording of FLFP in the English census data of the 19th century? The controversy over whether the Victorian census records reliably report female employment is long-standing. Higgs and Wilkinson (2016) revisit the historiography of the debate.

Several scholars have argued that the census under-enumerates women's work (Higgs, 1987; Hill, 1993; Horrell and Humphries, 1995; Davidoff and Hall, 2002). Higgs, writing in Higgs and Wilkinson (2016), 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"

The paper then summarizes a few of the arguments put forward in support of the reliability of the census records. Both McKay (1998) and Anderson (1999) note that the census records show higher employment for married women in Lancashire than in other counties. Shaw-Taylor (2007, p. 39) argues that, if married women were well recorded, it is unlikely that unmarried women would have been less well recorded.

In revisiting the debate, Higgs and Wilkinson (2016) set out both Higgs's original views and the counter-arguments. Firstly, he had claimed that women engaged in casual and seasonal work were likely to have been excluded from the census records, and that this would have particularly affected women working in agriculture. He now notes that seasonal labour 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 under-counted women in employment. Finally, his original paper relied on a set of very local studies of the census enumeration books (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, 2012). 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.

Two further defences of the census records of female employment have been put forward elsewhere. Shaw-Taylor (2007) 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, but that does not imply that full-time employment has been under-reported. McGeevor (2014) makes the same point more directly - comparing a Hertfordshire trade directory against the CEBs for the same county, she finds that, of the women in the trade directory who could be identified in the CEBs, over 95% were recorded with an occupation in the census. She too argues that the omission of casual and seasonal work reflects householders following the instruction to record only those "regularly employed."

It is worth noting that much of the earlier debate on these questions took place before the digitized Victorian census data became 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 (2016) note that the availability of the full-count digitized British historical census records through the ICeM project makes it possible, for the first time, to examine women's work systematically at the national level.

# Appendix B Labour Resistance

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

*Northampton Mercury*, 8 April 1865

Dear Sir,

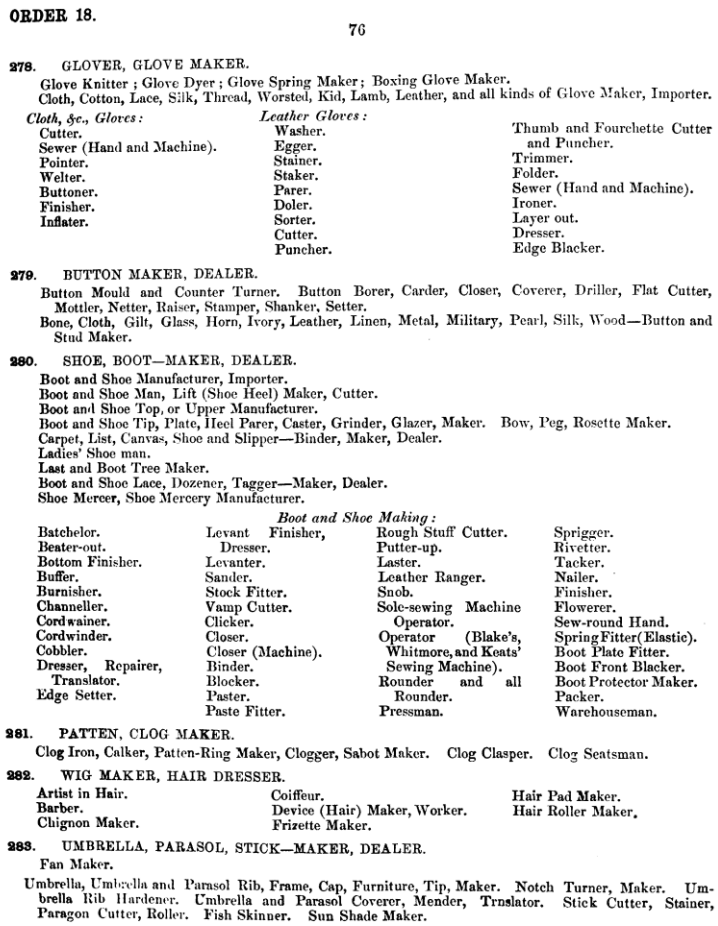
Having read in your journal of Saturday last an article extracted from the *Builder* on the above subject, I wish to make one or two corrections in it. In the first place I beg to say I was the first introducer of the sewing machine into this town in 1857. At that time I was foreman to the London and 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

# Appendix C Dictionaries

The General Register Office (GRO) provided "dictionaries" to aid clerks to assign individual-level census records to the correct industry classification. Figure C1 shows the entry for the bootmaking industry in the 1871 dictionary. Here, we can see listed the numerous micro-occupations performed by bootmakers in 1871. Bootmaking became increasingly specialized over the 19th century as it mechanized, and the evolving complexity of the records reflect this.

The "dictionaries" were compiled from several sources, including trade directories and surveys of manufacturers across the country. These records are therefore a separate source, and they too show a similar evolution of the occupational structure within the English bootmaking industry.



ORDER 18.

76

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, Translator. Stick Cutter, Stainer, Paragon Cutter, Roller. Fish Skinner. Sun Shade Maker.

Figure C1: Dictionary 1871

# Appendix D Construction of the "Bootmakers" Group

## Appendix D.1 Sample Definitions

The group of "English Bootmakers" could be defined in various ways. I use the complete census data for England, 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 results in 1,341,095 observations of bootmakers between 1851–1911. This is the "Standard, all" sample reported in Table D1.

I then remove all individual observations in which "retired", "formerly", or "unemployed" appears in the text description of the occupation. This leaves 1,323,383 observations, reported as the "Standard, employed" sample in Table D1.

Equally, I remove all records in which the person has declared themselves a family member of a bootmaker. This leaves 1,321,456 observations. This is the "Standard, cleaned" sample, and is the main dataset used in the regression analysis.

The four ICeM occupational codes for bootmakers do not capture all bootmakers. Some are erroneously recorded under other occupational codes. I therefore run a search for bootmakers in other occupational codes. After cleaning, this returns an additional 47,569 bootmakers. These can be merged with the standard cleaned group, producing an expanded dataset of 1,369,025 observations. This is the "Expanded, cleaned" sample reported in the final row of Table D1.

The results are highly stable across these alternative definitions of the bootmaking group. Including the additional bootmakers recovered from outside the standard occupation codes increases the estimated decline in "Old" employment only slightly, to 153,107 jobs, while increasing the estimated growth in "New", more specialized employment, to 140,354 jobs.

Table D1: Robustness to Alternative Bootmaking Sample Definitions

| Sample | $N$ | OLD 1851 | OLD 1911 | $\Delta$ OLD | NEW 1851 | NEW 1911 | $\Delta$ NEW |
|---|---|---|---|---|---|---|---|
| Standard, all | 1,341,095 | 214,297 | 63,737 | -150,560 | 3,257 | 136,472 | 133,215 |
| Standard, employed | 1,323,383 | 211,537 | 60,556 | -150,981 | 3,230 | 135,251 | 132,021 |
| Standard, cleaned | 1,321,456 | 211,103 | 60,518 | -150,585 | 3,224 | 135,198 | 131,974 |
| Expanded, cleaned | 1,369,025 | 216,314 | 63,207 | -153,107 | 3,930 | 144,284 | 140,354 |

*Notes:* "Standard" restricts the sample to individuals recorded in bootmaking occupation codes 663–666. "Expanded" additionally includes bootmakers recovered from other occupation codes using the footwear-specific textual search. "Employed" excludes occupational descriptions indicating unemployment, retirement, or former employment. "Cleaned" additionally excludes descriptions flagged as family-linked. Changes are calculated as 1911 employment minus 1851 employment. In all approaches, 97% of individuals are assigned a task. There is a stand-alone "footwear" term in 98% of observations.

In the first part of the analysis, in the New Evidence section, I rely on the expanded cleaned sample. At this stage, the purpose is simply to measure the overall change in the occupational structure of bootmaking, and including the additional bootmakers recovered from outside the standard occupation codes provides a full overview. However, in the regression analysis which follows, I use the standard cleaned sample. Bootmakers recovered from outside the standard bootmaking occupation codes are somewhat more difficult to classify consistently. Their census descriptions more often contain two task descriptions, sometimes within bootmaking but sometimes also outside the bootmaking trade. I therefore restrict the regression sample to the standard bootmaking occupation codes, where I can be more confident that individuals recorded are unambiguously part of the bootmaking workforce.

It is worth noting that the bootmaking group is unusual in being so well captured by the time-invariant industry variables in ICeM. Each census wave taken between 1851–1911 had its own taxonomy of "Industries", set within sectors. When the ICeM project digitized the British census data, they constructed a time-invariant set of categories for occupation. This cuts across the original classification system used in each of the decennial census datasets, and it means that, for some industries, people are split into different time-invariant occupation bins. As an exceptionally large industry, bootmakers had their own category (or several), in each of the decennial census reports. This means that the time-invariant category in ICeM does capture bootmakers quite well.

## Appendix D.2 Topic Modelling

The deterministic approach described above works well, but does leave some relevant observations undiscovered in the text. As discussed, the deterministic approach currently assigns 97% of all observations to a "task". However, I also check the far right-hand tail to discover if there are any important new "tasks" which are undiscovered.

My approach to topic modelling is twofold. I make use of the deterministic approach described in the paper. I also use incremental machine learning; the model I employ is shown in Figure D1.

I take an incremental machine learning approach to topic modelling for two main reasons. Firstly, while the straightforward deterministic model I employ for bootmakers is effective, it does not scale. This limitation becomes apparent as I extend my analysis to task data across all industries. To ensure accuracy, I use the results from the manual deterministic approach as a ground truth for validation. Secondly, I find existing topic modelling methods, which often require setting a number of predefined categories, inadequate. The incremental machine learning approach allows me to generate categories flexibly, and to incorporate knowledge of the occupational structure of the period. In practice, it is essentially supervised learning over multiple iterations.

The micro-occupations for bootmakers are saved separately, to facilitate merging the new data into the constructed panel data.

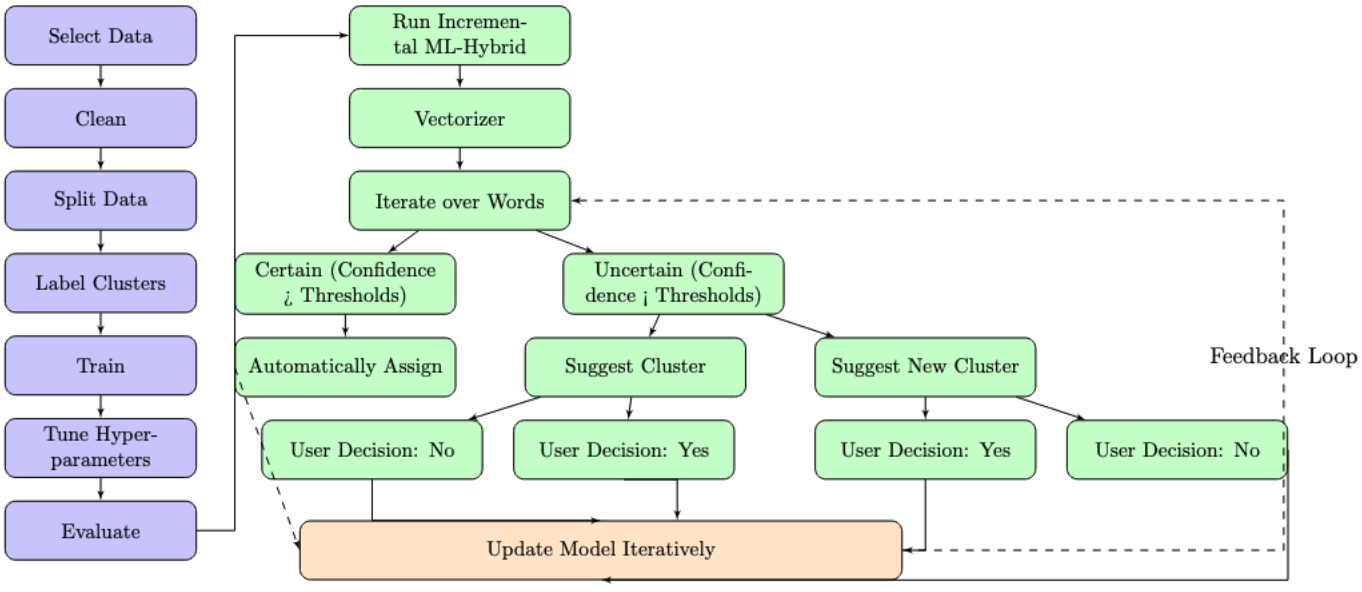



Figure D1: Incremental Machine Learning Model for Topic Assignment

# Appendix E Data Construction - Micro-Occupations

This section provides more detail on the set of micro-occupations. Appendix E.1 provides a table showing the evolution of the set of "tasks" over time. Appendix E.2 provides the hierarchy of keywords imposed during the labeling process and sensitivity tests.

There are four types of keywords which emerge in the “tasks” category. The first group consists of keywords 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”, ”clerk”. 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 type of product being made: 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.

## Appendix E.1 Tasks: Table

Table E1: English Bootmaking Employment by Task, 1851–1911

| Task | 1851 | 1861 | 1881 | 1891 | 1901 | 1911 |
|---|---|---|---|---|---|---|
| Binder | 28,018 | 29,589 | 3,340 | 1,608 | 761 | 267 |
| Blocker | 193 | 141 | 251 | 200 | 146 | 145 |
| Boot rounder | 2 | 0 | 133 | 245 | 487 | 576 |
| Clicker | 572 | 1,182 | 6,424 | 10,670 | 12,376 | 11,826 |
| Clogger | 3,438 | 4,631 | 7,071 | 6,489 | 5,868 | 4,713 |
| Closer | 5,423 | 9,430 | 4,009 | 3,424 | 2,797 | 2,301 |
| Cordwainer | 46,006 | 38,700 | 12,866 | 3,714 | 1,952 | 691 |
| Cutter | 84 | 161 | 703 | 1,056 | 1,348 | 1,149 |
| Dealer | 1,187 | 1,908 | 5,729 | 10,627 | 20,219 | 23,273 |
| Eyeletter | 0 | 1 | 31 | 208 | 335 | 205 |
| Factory | 40 | 180 | 1,257 | 1,713 | 4,486 | 3,861 |
| Finisher | 40 | 181 | 12,258 | 20,380 | 20,083 | 15,392 |
| Fitter | 8 | 320 | 7,584 | 9,152 | 10,696 | 5,266 |
| Foreman | 55 | 82 | 208 | 447 | 743 | 594 |
| Heel builder | 120 | 188 | 17 | 376 | 905 | 971 |
| Knot tier | 0 | 2 | 184 | 250 | 394 | 306 |
| Laster | 85 | 66 | 1,263 | 4,506 | 9,015 | 6,963 |
| Machinist | 3 | 437 | 13,105 | 16,934 | 26,073 | 21,563 |
| Maker | 133,429 | 137,484 | 113,890 | 113,095 | 91,785 | 55,235 |
| Manager | 9 | 22 | 254 | 781 | 1,160 | 1,098 |
| Manufacturer | 886 | 1,365 | 3,231 | 4,212 | 3,988 | 4,078 |
| Operator | 7 | 33 | 107 | 222 | 1,043 | 2,398 |
| Packer | 13 | 22 | 130 | 381 | 864 | 957 |
| Paster | 0 | 3 | 174 | 165 | 168 | 76 |
| Presser | 7 | 11 | 848 | 1,480 | 2,563 | 2,068 |
| Repairer | 253 | 174 | 530 | 1,608 | 5,396 | 30,339 |
| Riveter | 1 | 52 | 10,283 | 11,451 | 9,552 | 5,990 |
| Sewer | 50 | 98 | 497 | 869 | 1,563 | 1,796 |
| Skiver | 1 | 0 | 52 | 87 | 321 | 357 |
| Slipper | 276 | 335 | 1,107 | 2,024 | 2,171 | 2,302 |
| Trimmer | 38 | 30 | 181 | 357 | 745 | 735 |
| **Total** | **220,244** | **226,828** | **207,717** | **228,731** | **240,003** | **207,491** |

*Notes:* Counts are person-level observations in the expanded cleaned English bootmaker sample. Unclassified occupation strings are excluded. Data constructed by author from ICeM British Historical Census data.

## Appendix E.2 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 a machinist rather than a factory worker. The hierarchy is set to maximize the extraction of the most granular information about what type of work individuals were doing. The full ordering is given in Table E2.

Table E2: Hierarchy of Keywords

| | | |
|---|---|---|
| 1. machinist | 12. fitter | 23. repairer |
| 2. factory | 13. paster | 24. cordwainer |
| 3. manufacturer | 14. closer | 25. clogger |
| 4. binder | 15. riveter | 26. slipper |
| 5. dealer | 16. operator | 27. heel builder |
| 6. presser | 17. foreman | 28. boot rounder |
| 7. blocker | 18. cutter | 29. skiver |
| 8. manager | 19. sewer | 30. knot tier |
| 9. clicker | 20. eyeletter | 31. maker |
| 10. finisher | 21. trimmer | |
| 11. laster | 22. packer | |

The frequency with which multiple task keywords appear within the same occupational description differs substantially across the alternative bootmaker samples. To focus on substantively meaningful overlaps, I exclude the generic term "maker" from this exercise. In the standard cleaned sample, 8,437 distinct occupational descriptions contain more than one remaining task keyword. Because some descriptions are observed multiple times, these correspond to 32,336 person-level observations, or 2.45% of the standard cleaned sample. By contrast, among the additional bootmakers recovered from outside the standard bootmaking occupation codes, 8,257 observations contain multiple task keywords, representing 17.36% of that sample. Clearly, occupational descriptions recovered from outside the bootmaking occupational codes (663–666) are much more likely to contain multiple task descriptions.

For this reason, in the regression analysis in Section 5, I use the data in the standard cleaned sample. The heat map below reports the distribution of task dyads within the standard cleaned sample.

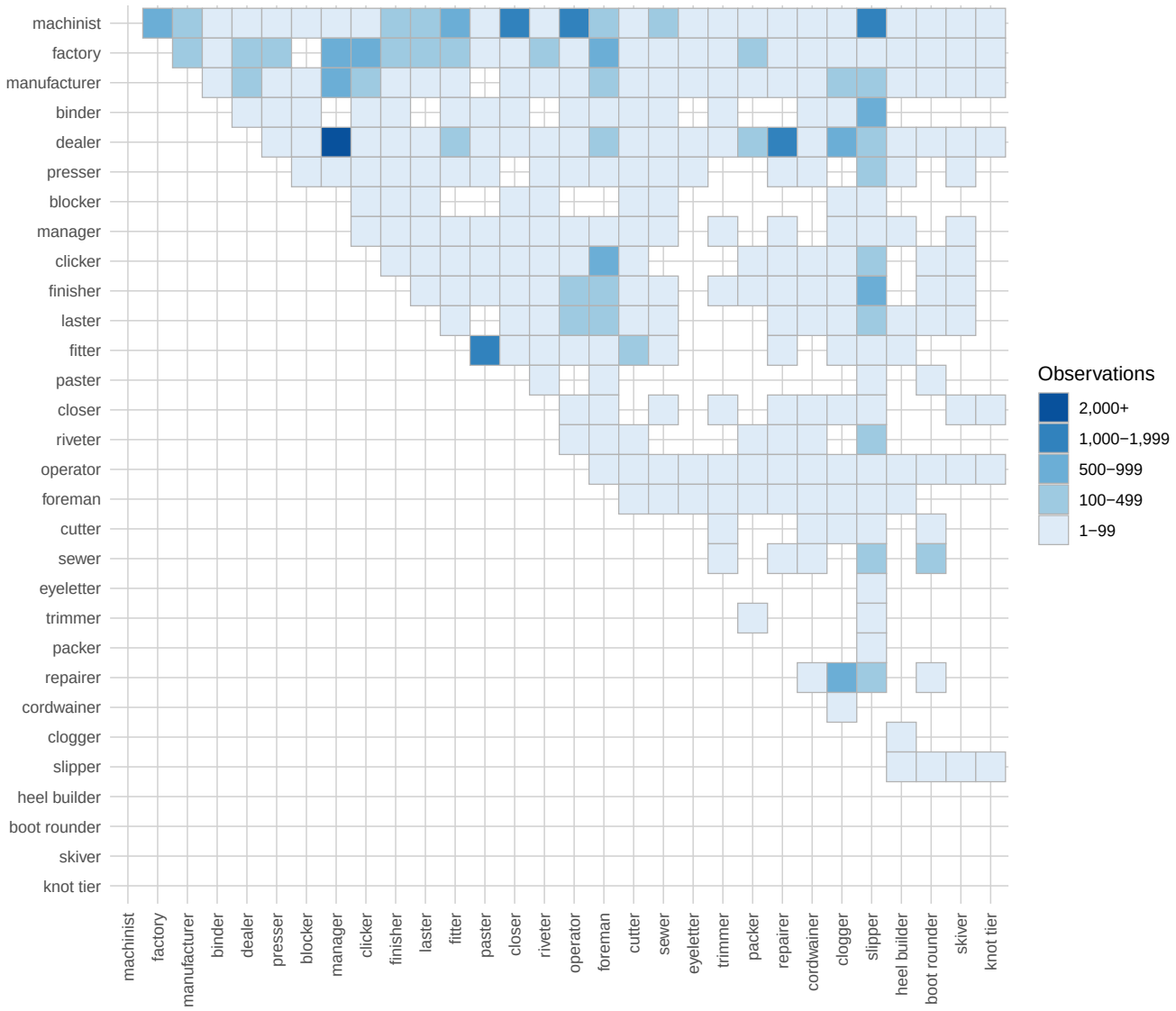



Figure E1: Heatmap of Dyads

The choice of hierarchy can impact on classification. To examine the sensitivity of these choices, I consider an intentionally extreme alternative in which "machinist", which is first in the baseline hierarchy, is moved to the final position. Panel A of Table E3 shows the resulting number of observations classified as machinists. Moving machinist from first to last reduces the number classified as machinists by between 7.4% and 17.5% in the main post-mechanization census years, with a larger proportional difference in 1861 when the number of machinists is still very small.

Importantly, however, these changes predominantly represent re-allocations between detailed task categories, rather than changes in the distinction between "Old" and "New"

work. Panel B reports the employment counts. Even under this extreme reordering, the substantive classification is highly stable. In 1911, for example, moving machinist from first to last reclassifies 950 observations from NEW to OLD, out of approximately 196,000 classified bootmakers. Consequently, the estimated decline in "Old" employment between 1851 and 1911 changes only from 150,585 to 149,635, while the estimated increase in NEW employment changes from 131,974 to 131,024.

Table E3: Sensitivity of Task Classification to Hierarchy Order

| | **1851** | **1861** | **1881** | **1891** | **1901** | **1911** |
|---|---|---|---|---|---|---|
| *Panel A: Observations classified as machinists* | | | | | | |
| Machinist first | 0 | 274 | 12,139 | 16,464 | 24,360 | 19,397 |
| Machinist last | 0 | 185 | 11,153 | 15,246 | 21,450 | 16,005 |
| Difference | 0 | 89 | 986 | 1,218 | 2,910 | 3,392 |
| Difference (%) | — | 32.5 | 8.1 | 7.4 | 11.9 | 17.5 |
| *Panel B: OLD and NEW classifications* | | | | | | |
| OLD: machinist first | 211,103 | 215,310 | 137,615 | 126,449 | 100,820 | 60,518 |
| OLD: machinist last | 211,103 | 215,375 | 138,263 | 126,957 | 101,429 | 61,468 |
| Difference | 0 | 65 | 648 | 508 | 609 | 950 |
| NEW: machinist first | 3,224 | 5,744 | 62,333 | 97,117 | 129,320 | 135,198 |
| NEW: machinist last | 3,224 | 5,679 | 61,685 | 96,609 | 128,711 | 134,248 |
| Difference | 0 | -65 | -648 | -508 | -609 | -950 |

*Notes:* The baseline hierarchy places machinist first. The alternative specification moves machinist to the final position while leaving the ordering of all other task categories unchanged. Panel A reports the number of observations classified as machinists under each hierarchy. Panel B reports the resulting "Old" and "New" counts. The sample is the standard cleaned bootmaker sample. Source: task data derived by author from ICeM data.

# Appendix F Data Construction - Census Linking

This appendix describes the procedure used to construct the linked census panel datasets underlying the analysis in this paper. The panels link individuals observed in one census wave to their records in the next, using full-count individual-level data from the Integrated Census Microdata (ICeM) Project (Higgs et al., 2013). While the methodology is developed in full in Vipond (2026b), this appendix summarises the features relevant to this paper.

## Appendix F.1 Linking the Full Population

The linking uses the full census population. It is not restricted to bootmakers at the matching stage. Instead, the full linked panel is constructed first, and the bootmaker sub-sample is then extracted. Linking the bootmaker sub-sample directly would artificially narrow the set of plausible competing candidates and inflate false positive rates.

The British data record place of birth at the parish, not only the county, level. Vipond (2026b) shows that with parish-level birthplace information, 97.8% of individuals in the 1861 census are uniquely identifiable by name and age alone, against 82.2% at the county level. All three linking specifications described below make use of parish-level birthplace.

All empirical results reported in the body of this paper are estimated on Specification 3 below (litmus-calibrated probabilistic linking). The substantive findings are recovered when the analysis is rerun on Specification 1 (ABE-style deterministic linking) and Specification 2 (Basic deterministic linking). Coefficients are reported in Table F1.

*Specification 1: ABE Linking.* Following Abramitzky et al. (2014), candidate pairs are required to agree on cleaned full name, county and parish of birth, with a $\pm 2$-year birth window. A pair is retained when it is unique within the candidate pool. This is the most widely used baseline in the historical linking literature.

*Specification 2: Basic deterministic linking.* This is the most simple of the three specifications, and is included as a sanity check. Candidate pairs must match exactly on name and both parish and county of birth, with a tolerance band of 2 years around date of birth. There is no probabilistic scoring. Match rates are correspondingly lower than under either ABE-style or the litmus-calibrated specification.

*Specification 3: Litmus-calibrated family probabilistic linking.* Candidate pairs are scored on a weighted sum of sub-scores covering ego variables (name, age, parish of birth, county

of birth) and family-corroboration variables (spouse, parent, and child information where applicable). Sub-score weights are estimated from the data using the Fellegi-Sunter framework. Score thresholds are then calibrated separately for each county using the migration and occupational-change litmus tests of Vipond (2026b), targeting a common false match rate ceiling rather than a common score cutoff. Per-county calibration is necessary because the false match rate at any fixed score varies systematically with county size and surname concentration: a single national threshold would under-discipline large counties and over-discipline small ones.

The 1861–1881 panel spans 20 years, owing to the absence of the 1871 returns from the ICeM data. The age-advance window is set accordingly to 20 years $\pm 2$ in all specifications, and Specification 3's weights and litmus baselines for this panel are estimated on the 20-year gap directly.

## Appendix F.2 Sample Coverage

Figure F1 reports overall match rates at the national level under the three linking specifications, separately by sex. Match rates are higher for the LT Family Linking specification, which uses within-household corroboration to recover genuine matches. Across all three specifications, male match rates exceed female match rates, reflecting the exclusion of women who married and changed their surname in the period. The women who are linked in these panels are: 1) women who were single and stayed single, 2) women who were married and remained married, and 3) women who were married and became widowed.

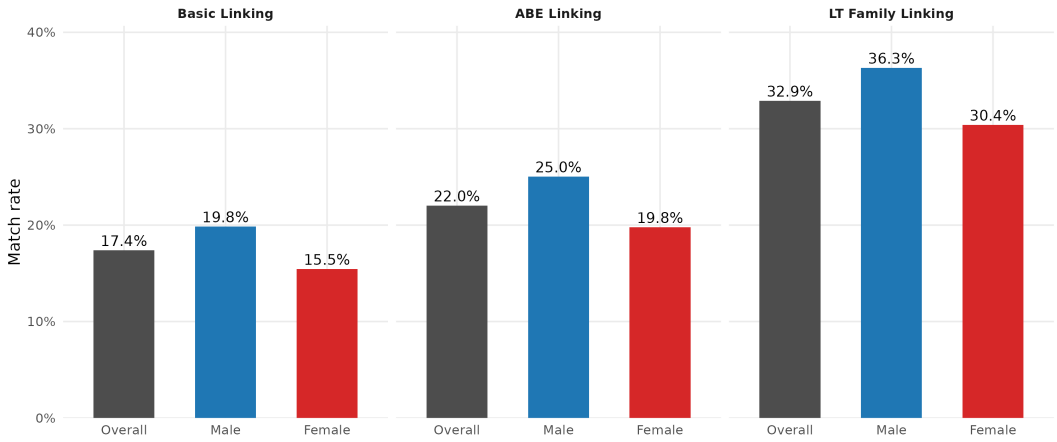



Figure F1: National match rates by linking specification, 1851–1861

*Notes*: Denominator is the 1851 baseline population restricted to the 39 English counties of birth ($N = 15{,}445{,}358$). "Overall" pools both sexes.

Figure F2 disaggregates the national rates to the county of birth, showing overall, male, and female match rates under each of the three linking specifications. Counties are ordered by the LT Family Linking specification's overall match rate. The relative ranking of the three specifications holds across nearly every county and within each sex. The spread of county-level rates has a range under all three specifications, reflecting variation in surname density, surname uniqueness, and the urban-rural composition of each county's 1851 population.

Figure F3 reports the distribution of match rates across occupations under two linking specifications, separately by sex. Each brick represents one occupation code in the 1851 baseline population. The figure allows comparison of the bootmaking match rate (pooled across occupational codes 663–666, in red) against the comparator trades used in the within-family analysis (in blue) and against the broader distribution of artisanal and unskilled occupations (in grey). Under both specifications, the bootmaking rate sits within 1.5 percentage points of its male comparators (carpenters and wheelwrights) and within 2 percentage points of its female comparators (stay and corset makers and straw hat workers). Differential linking quality across trades is therefore not a candidate explanation for the bootmaker-vs-comparator comparisons in the within-family analysis.

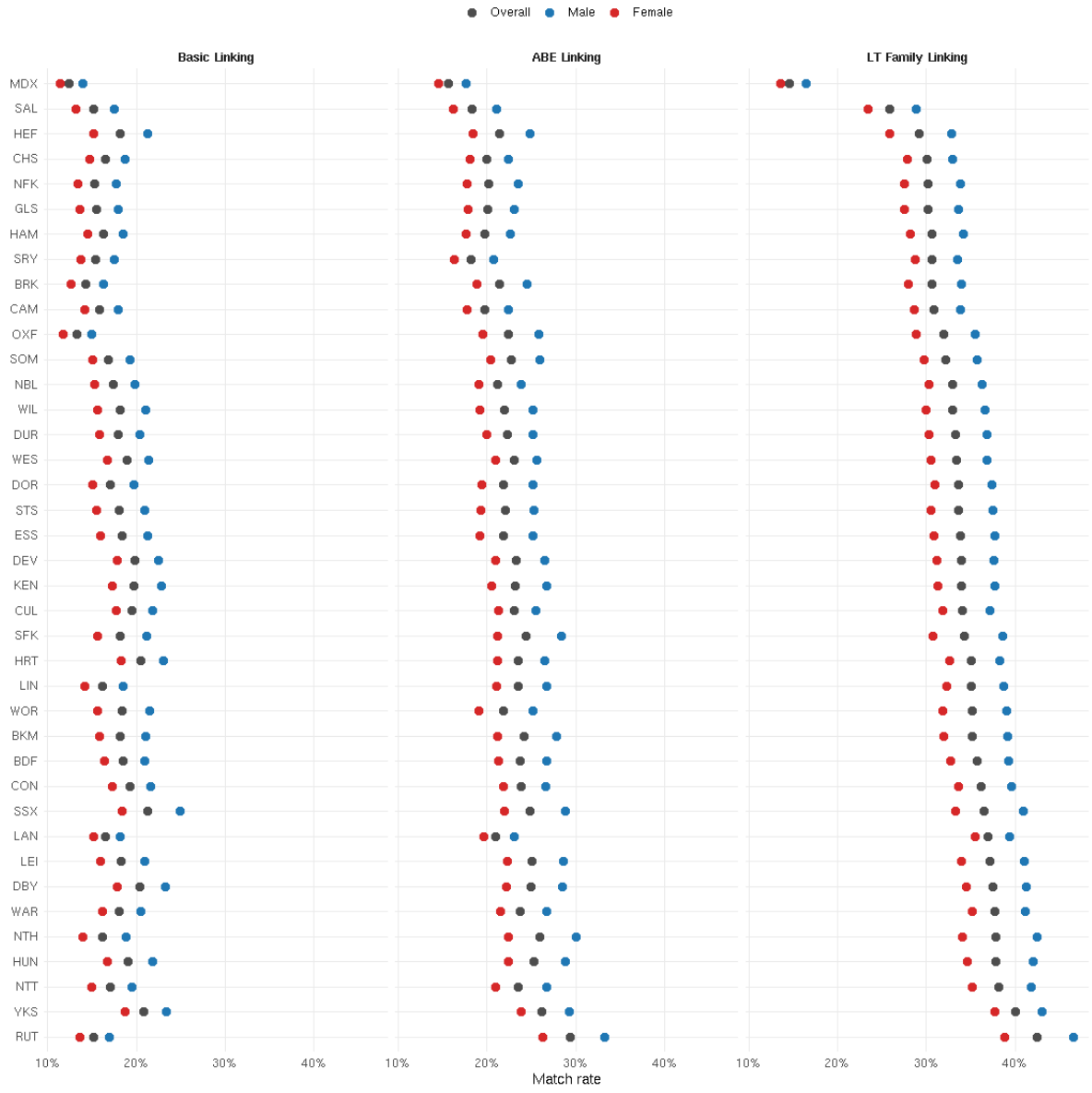



Figure F2: Match rates by county of birth and linking specification, 1851–1861

*Notes*: Each row is one of the 39 English counties of birth. Within each panel, the three points report the overall, male, and female match rates under that specification. Counties are ordered from highest to lowest by the LT Family Linking specification's overall match rate. Denominator: the 1851 baseline population of each county of birth.

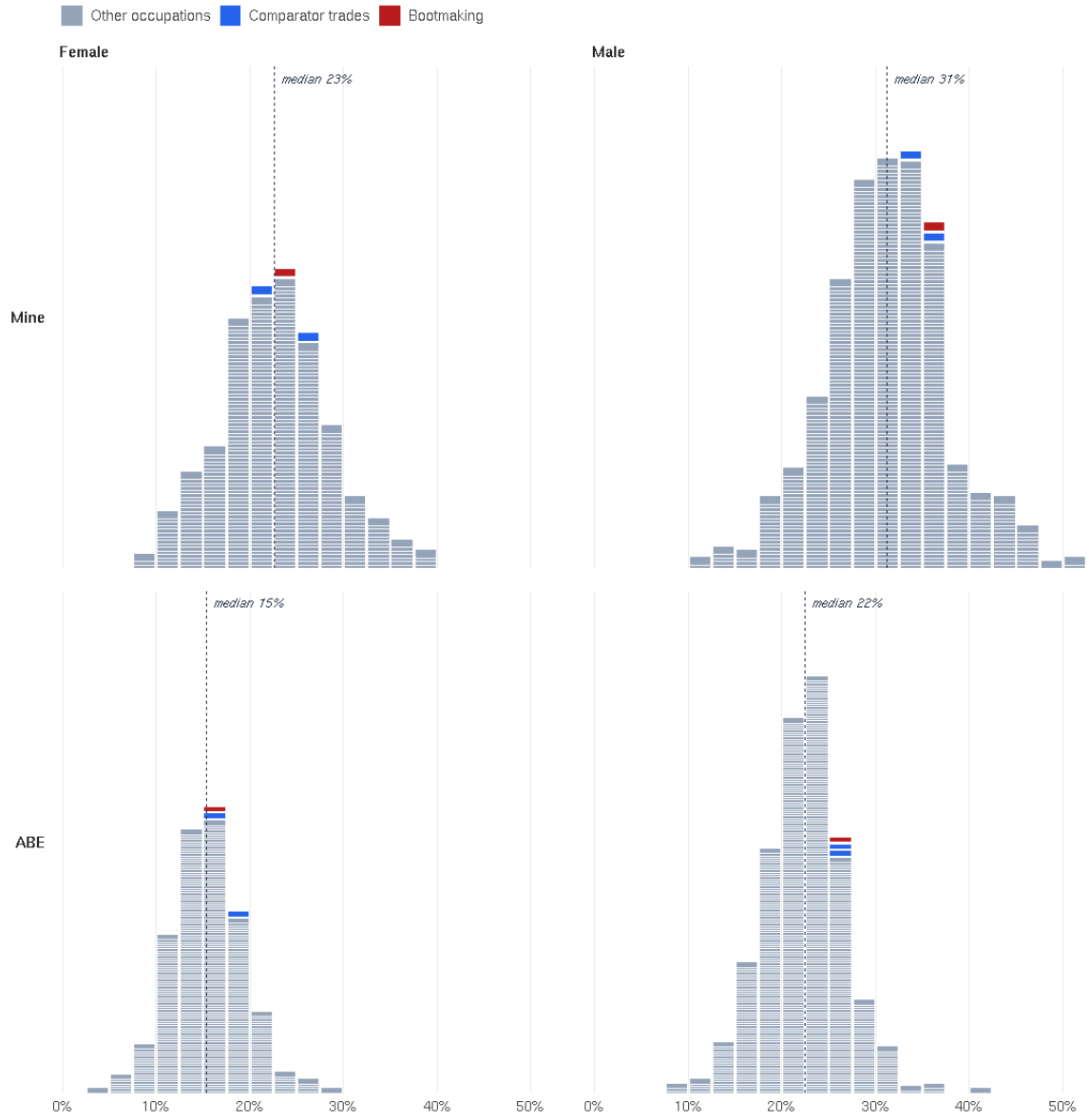



Figure F3: Distribution of match rates across occupations, 1851–1861

*Notes*: Each brick is one occupation code in the 1851 baseline census, restricted to occupations with at least 100 individuals of the relevant sex. The threshold applies to the baseline population, not to the number of successful links. Match rates are computed within sex. The $x$-axis is partitioned into 2.5 percentage-point bins. Bootmaking (occupation codes 663–666, covering boot- and shoemakers, makers, cordwainers, and dealers) is pooled into a single synthetic observation, shown in red. The comparator trades - carpenters and wheelwrights for men, stay and corset makers and straw hat manufacture for women - are shown in blue. The bootmaking pool links at 35.9% (men) and 24.4% (women) under the LT family linker, and at 26.1% and 16.0% respectively under ABE. The blue comparator bricks sit within 2 percentage points of these rates in both sexes and both specifications. The dashed vertical line marks the unweighted median match rate across occupations within each panel: each occupation contributes one observation regardless of population size.

## Appendix F.3 Quality Validation

Linking specifications can produce substantively different results. False positives mechanically inflate observed migration and occupational change rates. The litmus test of Vipond (2026b) addresses this directly, exploiting the fact that migration and occupational change are essentially uncorrelated with the matching variables in the linked dataset. Vipond (2026b) finds that for full-census linking with British historical census data, which benefits from parish-level information on place of birth, the false match rate is relatively low across different census linking specifications.

For Specification 3, the litmus test is applied directly to score thresholds. Figures F4 and F5 plot migration lift and occupational change lift as a function of total match score. Both series remain flat near zero across high score thresholds before elbowing sharply upward as weaker matches begin introducing false positives at scale. The per-county thresholds used in Specification 3 are calibrated to sit well within the flat region of each county's distribution.

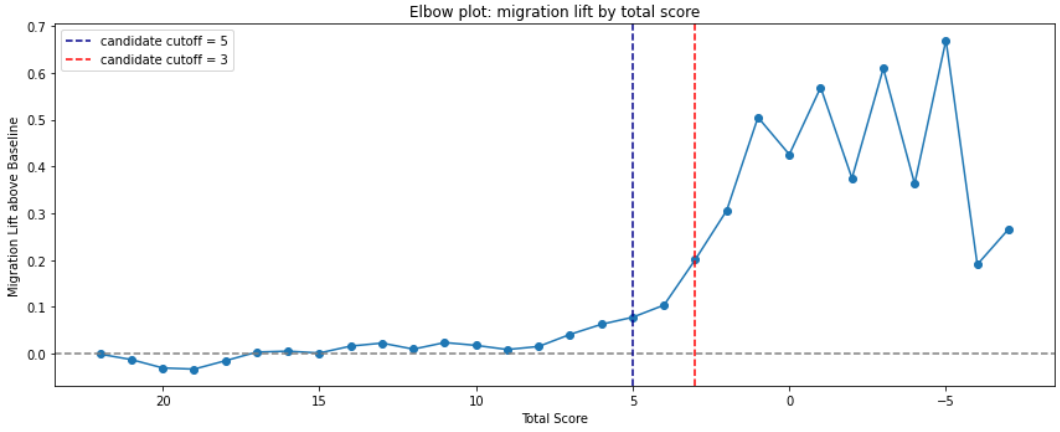



Figure F4: Litmus Test Applied to Probabilistic Linking: Migration

*Notes*: Migration lift above baseline plotted against total match score, for the spouse selection group. The series remains flat near zero for high-scoring matches before elbowing sharply upward as the score threshold is relaxed, identifying the point at which false positives begin flooding in. Vertical dashed lines indicate candidate cutoffs of 5 (blue) and 3 (red). Specification 3 calibrates the cutoff per county within the flat region of the distribution.

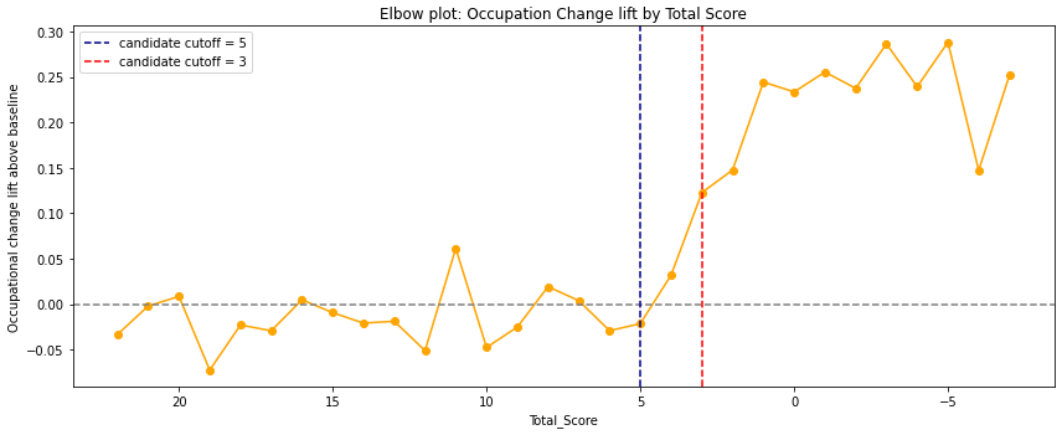



Figure F5: Litmus Test Applied to Probabilistic Linking: Occupational Change

*Notes*: Occupational change lift above baseline plotted against total match score, for the spouse selection group. As with migration, the series is flat near zero for high-scoring matches and rises sharply once weaker matches are included.

## Appendix F.4 Robustness Across Specifications

The headline results of the paper are reproduced under each linking specification in Table F1: incumbent exit estimates from Section 5.1 (Panel A) and entry-margin estimates from Section 5.2 (Panel B). The substantive findings of the paper are qualitatively unchanged across specifications.

Table F1: Robustness Across Linking Specifications

| | Spec 1 ABE deterministic | Spec 2 Basic deterministic | Spec 3 Litmus-calibrated probabilistic |
|---|---|---|---|
| *Result 1: Incumbent Transition* (*Section 5.1*) | | | |
| Bootmaker 1861–1881 (male) | 6.42% | 6.44% | 6.26% |
| Bootmaker 1861–1881 (female) | 3.68% | 3.98% | 3.69% |
| *Result 2: Incumbent Exit DID* (*Section 5.1*) | | | |
| Bootmaker × Post (men) | 0.0119** | 0.0107** | 0.0103* |
| | (0.0053) | (0.0051) | (0.0053) |
| Bootmaker × Post (women) | 0.1382*** | 0.1452*** | 0.1383*** |
| | (0.0174) | (0.0198) | (0.0139) |
| *Result 3: Incumbent Migration DID* (*Section 5.1*) | | | |
| Bootmaker × Post (men) | −0.0065 | −0.0060 | −0.0083* |
| | (0.0051) | (0.0060) | (0.0048) |
| Bootmaker × Post (women) | −0.0021 | −0.0127 | 0.0016 |
| | (0.0113) | (0.0113) | (0.0123) |
| *Result 4: Change in Entry Rates* (*Section 5.2*) | | | |
| Artisanal — men (%) | −42.8 | −43.3 | −41.4 |
| Artisanal — women (%) | −86.8 | −89.2 | −88.9 |
| Mechanized — men (pp) | +0.550 | +0.550 | +0.552 |
| Mechanized — women (pp) | +0.241 | +0.251 | +0.276 |

*Notes.* The table reports the headline results from the empirical analysis using three linked datasets constructed under different linking specifications. Specification 1 follows the ABE-style deterministic procedure of Abramitzky et al. (2014), requiring agreement on cleaned full name, county and parish of birth, and a ±2-year birth window. Specification 2 is the basic deterministic specification, requiring exact agreement on name, parish and county of birth, with a ±2-year birth window and no probabilistic scoring. Specification 3 is the litmus-calibrated probabilistic specification of Vipond (2026b). All specifications use parish-level birthplace information. Headline results in the body of the paper are estimated on Specification 3. For the DID estimates, standard errors clustered at the county level are reported in parentheses. Entry-rate changes compare the 1851–1861 and 1861–1881 panels for linked individuals aged 10–18 at baseline. Artisanal entry changes are reported as proportional percentage changes.

# Appendix G Descriptive Statistics

## Appendix G.1 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, shown in the paper through the analysis of individual level descriptions of occupation in historical 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 C for an example of that material. These dictionaries were constructed from underlying trade directories, and a direct survey of manufacturers in 1881.

Secondly, the new jobs emerge primarily in Northamptonshire and Leicestershire. See the map in figure G2, below. If nomenclature was changing rather than the type of work bootmakers were doing, it would be challenging to explain why the new jobs emerge in such a concentrated fashion. Equally, these new jobs disproportionately emerge in places where there are large bootmaking companies, and indications of factory work. See Figure G1.

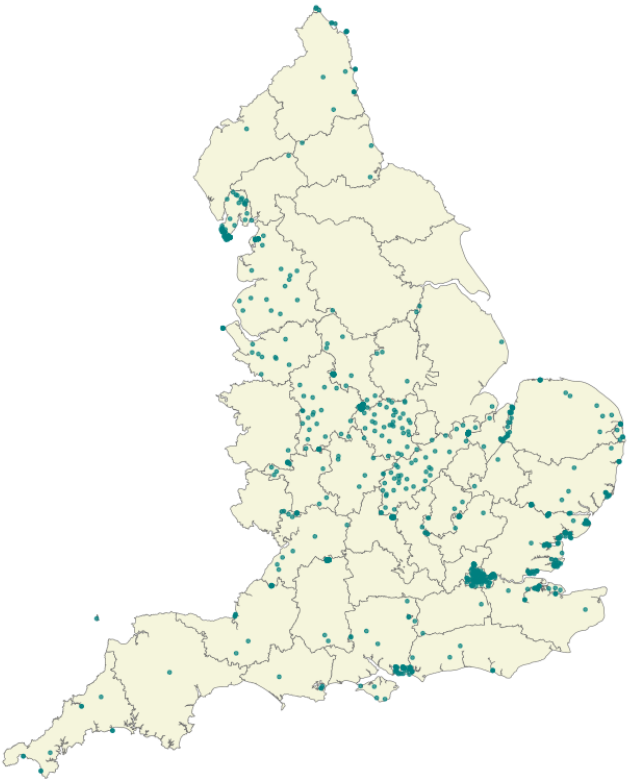


Figure G1: Large Bootmaking Companies

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

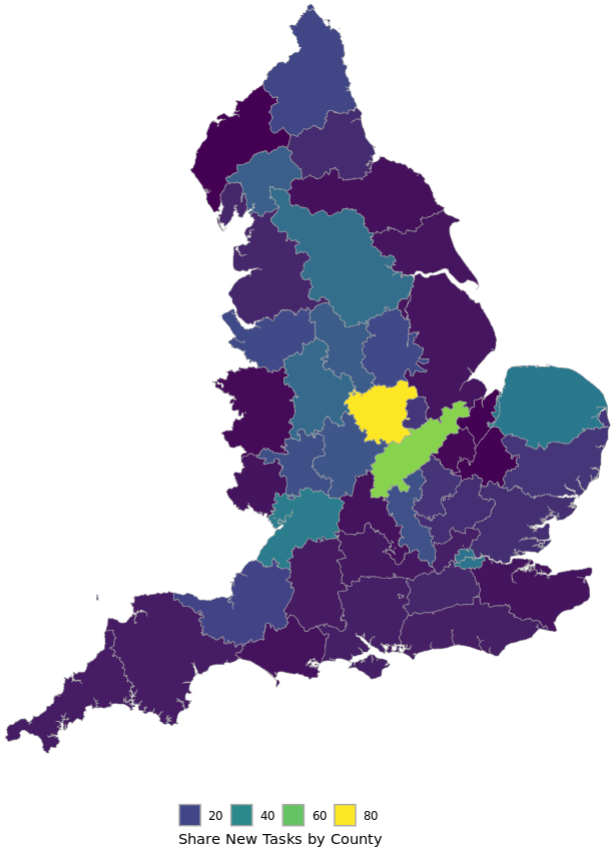



Figure G2: New Bootmaking Tasks

*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 Figure G3, 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.

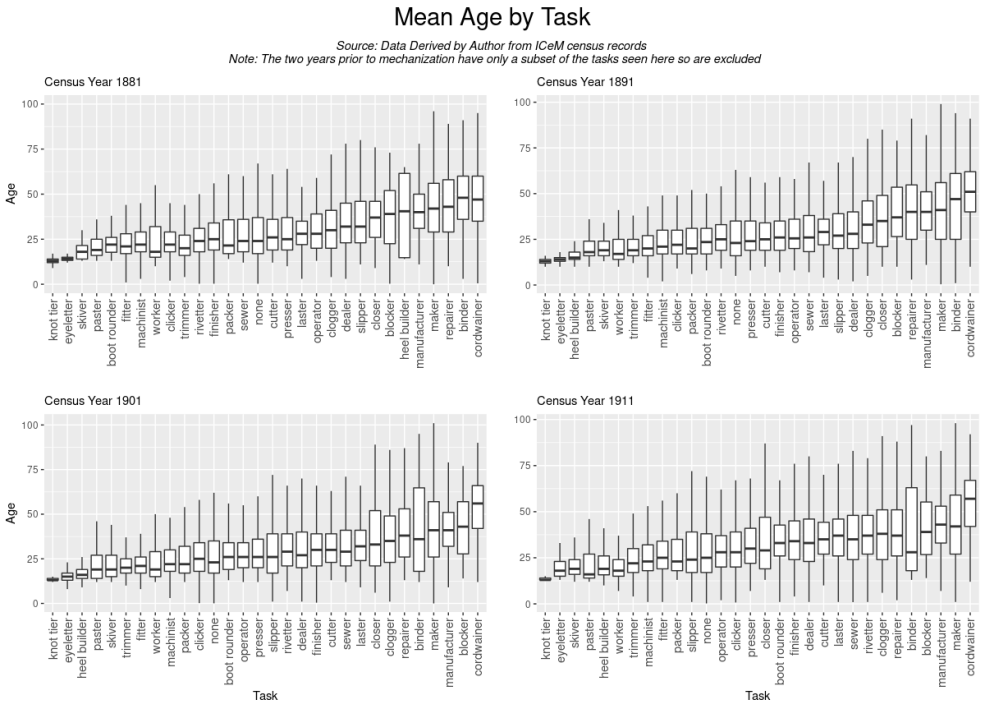



Figure G3: Task by Age, English Bootmakers

Fourthly, the data shows remarkable consistency in accurately reflecting the timing of well-known technological shocks. The bootmaking sewing machine first emerged in 1857, 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 1861. 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 collecting the records, and they did not co-ordinate, so this consistency in the data is remarkable.

## Appendix G.2 Pace of Change

The technological shock of mechanization did not unfold uniformly across the six decades between 1851-1911. The bootmaking sewing machine was not introduced until 1857. In the first decade, between 1851-1861, which is prior to mechanization, there is no clear sign of either job loss or job creation. However, between 1861-1881, the old jobs are in decline in nearly every single English county. Figure G4 shows the number of traditional jobs which disappeared in each county, by census window period. In Panel A, prior to the shock of mechanization, there is little trend. In Panel B, between 1861-1881, in the first period of mechanization, the majority of the loss of the traditional jobs takes place.

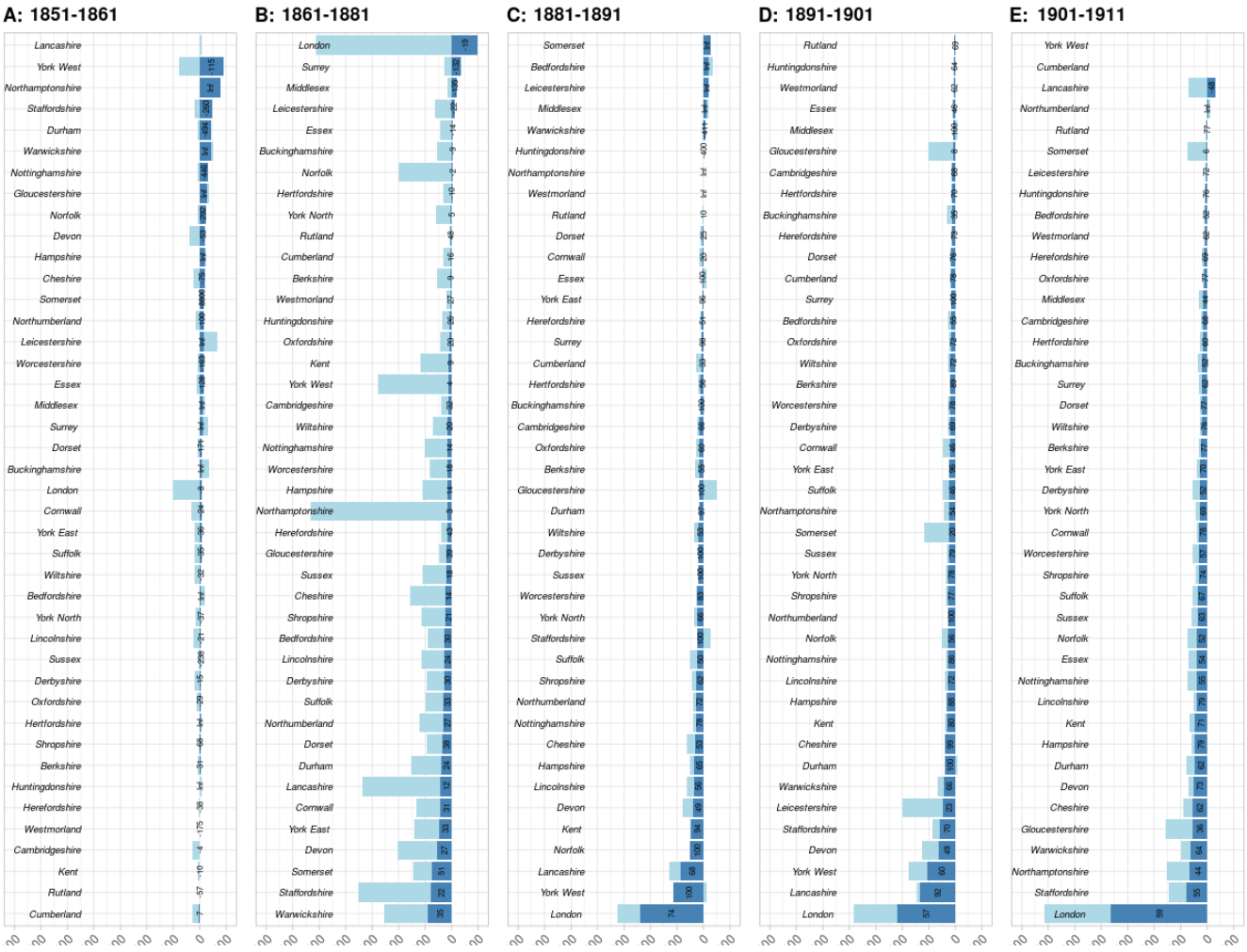



Figure G4: Change in Number of Traditional Bootmakers Employed, by Census Window

## Appendix G.3 Factories

The new types of work which emerged as the industry mechanized reflect a shift from craft to factory production. These jobs were tied to the new production process: for example, foremen, supervisors, operators, factory workers, and some of the new sewing machinists. Here, I check whether the larger bootmaking firms became increasingly concentrated in the places in which the new, emerging jobs clustered.

To do so, I use the British Business Census of Entrepreneurs (BBCE), which identifies employers and proprietors in 1851, 1861, and 1881 and records how many workers each employed (Van Lieshout et al., 2021). Table G1 shows that the shift toward larger-scale production was concentrated in the upper tail of the size distribution. The typical establishment was very small. The median rose from two workers in 1851 to three in 1861, and then remained at three. Mean establishment size changed little between 1851 and 1861 - prior to mechanization - rising from 4.9 to 5.6 workers. However, by 1881 the mean had almost doubled to 11 workers, while the median remained unchanged. The largest recorded establishment employed 2,000 workers. The rise of factory-scale production did not primarily reflect a general increase in the size of bootmaking workshops, but the emergence of a new upper tail of very large establishments.

Table G1: Bootmaking Establishment Size

| Year | Mean size | Median size | Maximum |
|---|---|---|---|
| 1851 | 4.87 | 2 | 507 |
| 1861 | 5.57 | 3 | 750 |
| 1881 | 10.96 | 3 | 2,000 |

The concentration of this change in the upper tail becomes clearer when establishments are grouped by increasingly high employment thresholds. Table G2 reports the share of recorded bootmaking establishments exceeding several fixed size cutoffs. The change is more pronounced further into the upper tail. Establishments employing at least 20 workers were almost equally common in 1851 and 1861, accounting for 3.4 and 3.7 percent of establishments respectively. This rose to 8.6 percent in 1881. The pattern is sharper still among the largest establishments. Those employing at least 50 workers accounted for less than one percent of establishments in both 1851 and 1861, but 3.8 percent by 1881. Finally, the share of firms employing at least 100 workers rose from 0.4 to 1.8 percent.

Table G2: Upper Tail of the Bootmaking Establishment-Size Distribution

| Establishment size | 1851 | 1861 | 1881 |
|---|---|---|---|
| 10+ workers | 8.58 | 10.56 | 14.99 |
| 20+ workers | 3.42 | 3.72 | 8.62 |
| 50+ workers | 0.94 | 0.95 | 3.82 |
| 100+ workers | 0.39 | 0.34 | 1.82 |
| 250+ workers | 0.11 | 0.14 | 0.63 |

*Notes:* Entries report the percentage of recorded bootmaking establishments employing at least the indicated number of workers.

The pre-mechanization establishment-size distribution was extremely compressed. In 1851, the median recorded employer employed only two workers, while the 75th percentile employed four. I therefore divide establishments into four size groups based on the 1851 distribution and hold these cutoffs fixed over time: Q1 contains establishments employing one worker, Q2 those employing two workers, Q3 those employing three to four workers, and Q4 those employing five or more workers. The final group therefore captures establishments above the 1851 75th-percentile size cutoff.

I use these groups to ask whether the cross-county relationship between establishment presence and "New" bootmaking work changed as the industry mechanized, and in particular whether "New" work became increasingly associated with establishments in the upper part of the pre-mechanization size distribution.

$$\begin{aligned}\text{ShareNew}_{ct} = \alpha + \sum_{q=1}^{4} \beta^q \,\text{Firms}_{ct}^q + \sum_{q=1}^{4} \delta_{1861}^q \,\text{Firms}_{ct}^q \times 1[t = 1861] \\ + \sum_{q=1}^{4} \delta_{1881}^q \,\text{Firms}_{ct}^q \times 1[t = 1881] + \gamma \,\text{TotalBootmakers}_{ct} + \lambda_t + \varepsilon_{ct}.\end{aligned} \tag{5}$$

Here, $q$ indexes four establishment-size groups defined from the 1851 distribution and held fixed over time: Q1 contains establishments with one worker, Q2 those with two workers, Q3 those with three to four workers, and Q4 those with five or more workers. The coefficients $\beta^q$ capture the cross-county relationship between the number of establishments in each size group and the share of "New" jobs in the omitted year, 1851. The interaction coefficients $\delta_{1861}^q$ and $\delta_{1881}^q$ measure how this relationship changes in 1861 and 1881 relative to 1851. The year effects, $\lambda_t$, absorb changes in the overall prevalence of "New"

work across census years, while TotalBootmakers$_{ct}$ controls for the scale of the local bootmaking industry. Firm counts are measured per ten establishments, and standard errors are clustered by county.

The regression examines the cross-county relationship between the number of bootmaking establishments in each size group and the share of bootmaking employment accounted for by "New" jobs, and how this relationship changed over time. The dependent variable, ShareNew$_{ct}$, is the percentage of classified bootmaking employment in county $c$ and year $t$ that is in "New" jobs. Establishments are divided into four groups using the 1851 size distribution: Q1 contains establishments with one worker, Q2 those with two workers, Q3 those with three to four workers, and Q4 those with five or more workers. These cutoffs are held fixed across years.

The results are shown in Table G3. There is little evidence that the relationship between establishment presence and "New" work changed between 1851 and 1861 for any of the smaller establishment groups. The Q1–Q3 interaction coefficients are statistically insignificant in both 1861 and 1881. The pattern is different for Q4. The Q4 interaction is small in 1861, before the main period of mechanization, but becomes large and highly statistically significant by 1881. In the preferred specification, ten additional Q4 establishments are associated with a 4.66 percentage-point greater increase in the share of "New" jobs in 1881 relative to the corresponding 1851 relationship. This association is not driven solely by the major factory centres of Northamptonshire and Leicestershire: excluding both counties reduces the coefficient to 2.95 percentage points, but it remains positive and statistically significant. The emergence of "New" work was therefore increasingly associated with the geographic presence of establishments in the upper part of the pre-mechanization size distribution, rather than with the number of smaller establishments.

Table G3: Establishment Size and the Geography of New Bootmaking Work

| | (1) Baseline | (2) Preferred | (3) Excl. Northants & Leics |
|---|---|---|---|
| 1861 | 0.731* | 0.745* | 0.596* |
| | (0.365) | (0.381) | (0.320) |
| 1881 | 13.9*** | 14.0*** | 12.8*** |
| | (2.25) | (2.30) | (1.82) |
| Q1 × 1861 | -0.047 | -0.059 | -0.070 |
| | (0.142) | (0.154) | (0.122) |
| Q1 × 1881 | -3.02 | -3.00 | -2.67 |
| | (2.31) | (2.29) | (1.93) |
| Q2 × 1861 | -0.390 | -0.368 | -0.221 |
| | (0.304) | (0.320) | (0.257) |
| Q2 × 1881 | 2.63 | 2.65 | 1.12 |
| | (3.26) | (3.31) | (2.72) |
| Q3 × 1861 | 0.214 | 0.155 | 0.156 |
| | (0.235) | (0.275) | (0.257) |
| Q3 × 1881 | -4.66 | -4.69 | -0.912 |
| | (3.48) | (3.52) | (2.69) |
| Q4 × 1861 | 0.221* | 0.263* | 0.154 |
| | (0.125) | (0.152) | (0.148) |
| Q4 × 1881 | 4.67*** | 4.66*** | 2.95** |
| | (1.01) | (1.02) | (1.15) |
| Q-group main effects | Yes | Yes | Yes |
| Total bootmakers control | No | Yes | Yes |
| Northants and Leics included | Yes | Yes | No |
| Observations | 130 | 130 | 124 |
| $R^2$ | 0.811 | 0.811 | 0.722 |

*Notes:* The dependent variable is the percentage of classified bootmaking employment in "New" jobs. Establishment-size groups are defined using the 1851 distribution: Q1 = 1 worker, Q2 = 2 workers, Q3 = 3–4 workers, and Q4 = 5 or more workers. Firm counts are measured per ten establishments. The omitted year is 1851. All specifications include the main effects of the Q1–Q4 establishment counts. Column (2) additionally controls for total bootmaking employment; column (3) excludes Northamptonshire and Leicestershire. Standard errors are clustered by county and reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

# Appendix H Incumbent Exit

## Appendix H.1 Descriptive Statistics: Flowchart

Figure H1 tracks the transition of incumbent bootmakers between 1861 and 1881, during the initial period of mechanization. It shows, separately for men and women, the share of incumbent bootmakers who remained in the old artisanal tasks, the share who moved into the new mechanized 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 seen directly. For both men and women, a very small share of incumbent bootmakers transitioned into the new bootmaking jobs. These results are recovered under all three linking specifications, see Appendix F.4.

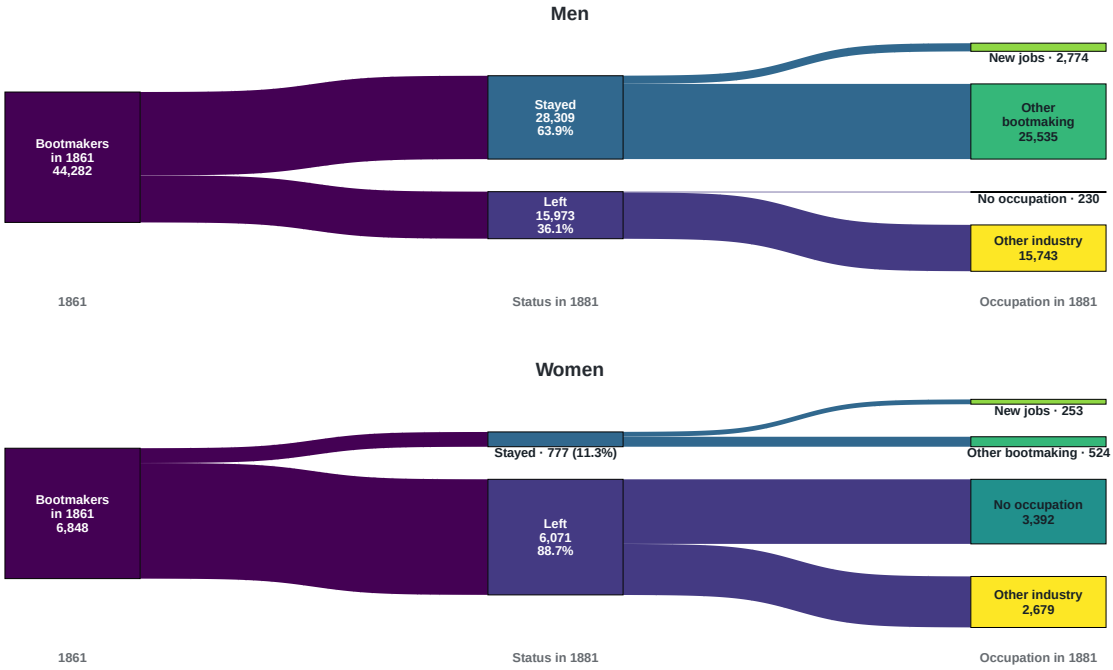



Figure H1: Incumbent Bootmaker Transitions, 1861–1881

## Appendix H.2 Distribution of Exit Rates

This section shows the distribution of exit rates, by gender, before and after the shock. I calculate the exit rates for all industries in both panel datasets, and then construct a weighted kernel density function. This is the probability distribution of exit rates for all

industries in each time period, by gender [25].

$$\hat{f}(x) = \frac{1}{h\sum_{i=1}^{n} w_i} \sum_{i=1}^{n} w_i K\left(\frac{x - x_i}{h}\right) \tag{6}$$

Figure H2, below, shows the distribution of exit rates, for men and women, in both periods. These show the distribution of exit rates as calculated by the kernel density function above. The weighted average rate of exit (across all industries) is shown by the dotted black line. 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, while Panel 2 covers a twenty-year period.

The top panel of Figure H2 shows that male bootmakers have considerably lower rates of exit than men in most other industries. As an industry, it is the fourth most stable available to men. This is not entirely surprising - artisanal bootmaking was a highly skilled trade, often requiring a full 7 year apprenticeship to master. 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 given the longer duration of the second period.

The bottom panel of Figure H2 shows that exit rates for women are universally high. They are naturally higher in the second panel, which covers 20 years (1861-1881), but, compared to men, they are very high in both. 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. 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, as the technological shock sets in, the exit rates of female bootmakers increased substantially. To provide context, two other large female dominated industries are plotted. These show the exit rates for dressmakers and laundresses. Neither of these industries experienced a technological shock during this period, and their position in the distribution did not drastically change.

[25] 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.

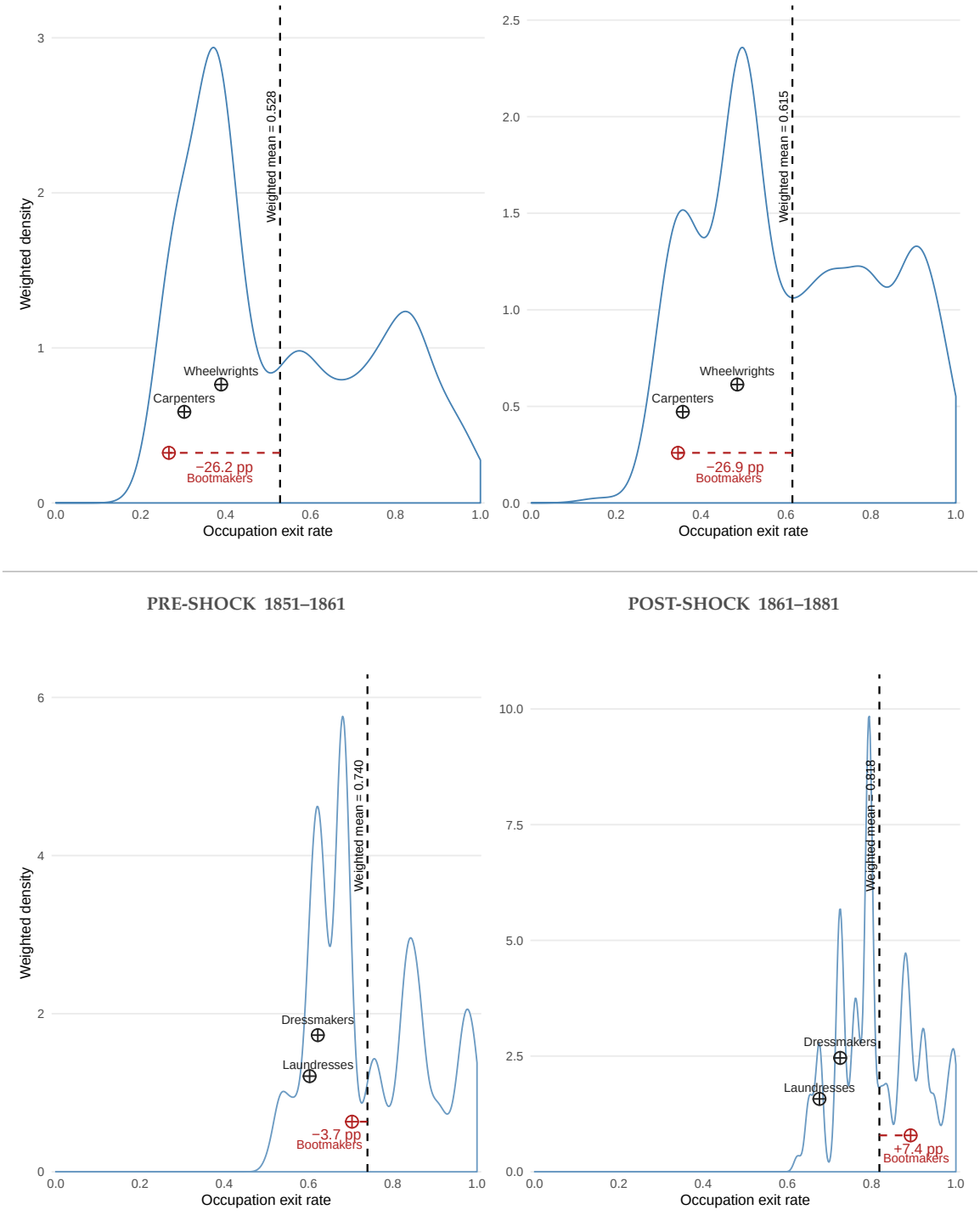



Figure H2: Distribution of Occupational Exit Rates Across All Industries

*Note:* Weighted kernel densities of occupational exit rates across occupations with valid, nonzero HISCAM scores, for individuals aged 15 and above at baseline. Occupational exit is defined as having a different or missing occupation code in the destination census. Top: men. Bottom: women. The dashed line marks the weighted mean. Bootmakers are highlighted in red. Moves between bootmaking occupations (codes 663–666) are not counted as exits from bootmaking.

Table H1 reports the underlying figures. The weighted mean exit rate rises for both sexes between the panels, reflecting the longer second window. What matters is each group's position relative to that moving benchmark. Male bootmakers sit 27.5 percentage points below the cross-industry mean in the first panel and 27.4 points below it in the second: their position is unchanged. Female bootmakers move from 4.3 points below the mean to 7.7 points above it, a shift of 12 percentage points, or roughly one standard deviation of the cross-industry distribution.

Table H1: Bootmaker Position in the Cross-Industry Exit Rate Distribution: Specification 3 (Litmus-Calibrated Probabilistic)

| | Panel 1 (1851–1861) | Panel 2 (1861–1881) | Change |
|---|---|---|---|
| *Men* | | | |
| Bootmaker exit rate | 0.254 | 0.341 | $+0.087$ |
| Cross-industry weighted mean | 0.529 | 0.615 | $+0.087$ |
| Distance from mean | $-0.275$ | $-0.274$ | $+0.001$ |
| Distance ($\sigma$ units) | $-1.23$ | $-1.31$ | — |
| Linked observations | 53,122 | 37,749 | — |
| *Women* | | | |
| Bootmaker exit rate | 0.686 | 0.885 | $+0.199$ |
| Cross-industry weighted mean | 0.729 | 0.808 | $+0.079$ |
| Distance from mean | $-0.043$ | $+0.077$ | $+0.120$ |
| Distance ($\sigma$ units) | $-0.31$ | $+0.78$ | — |
| Linked observations | 7,085 | 6,033 | — |

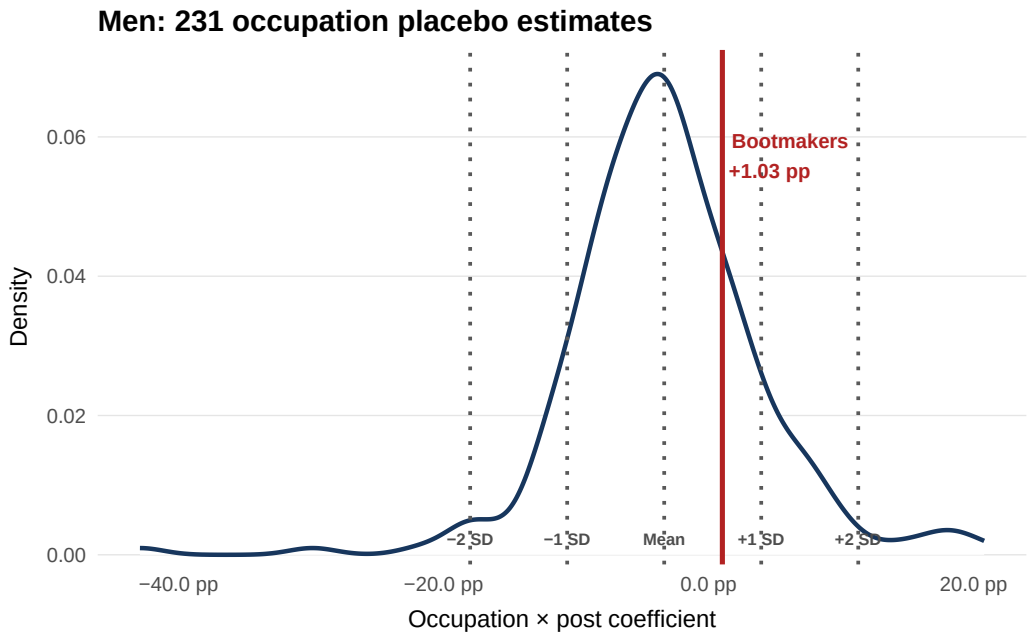
*Notes.* The table reports the position of bootmakers within the cross-industry distribution of exit rates, separately by sex and panel, under Specification 3 (litmus-calibrated probabilistic linking). The weighted mean is calculated across all industries, with weights proportional to industry size in the base year. Distance from mean is the bootmaker exit rate minus the weighted mean. Distance in $\sigma$ units expresses the same distance in standard deviations of the cross-industry exit rate distribution.

## Appendix H.3 Placebo Distribution of Exit DiD Estimates

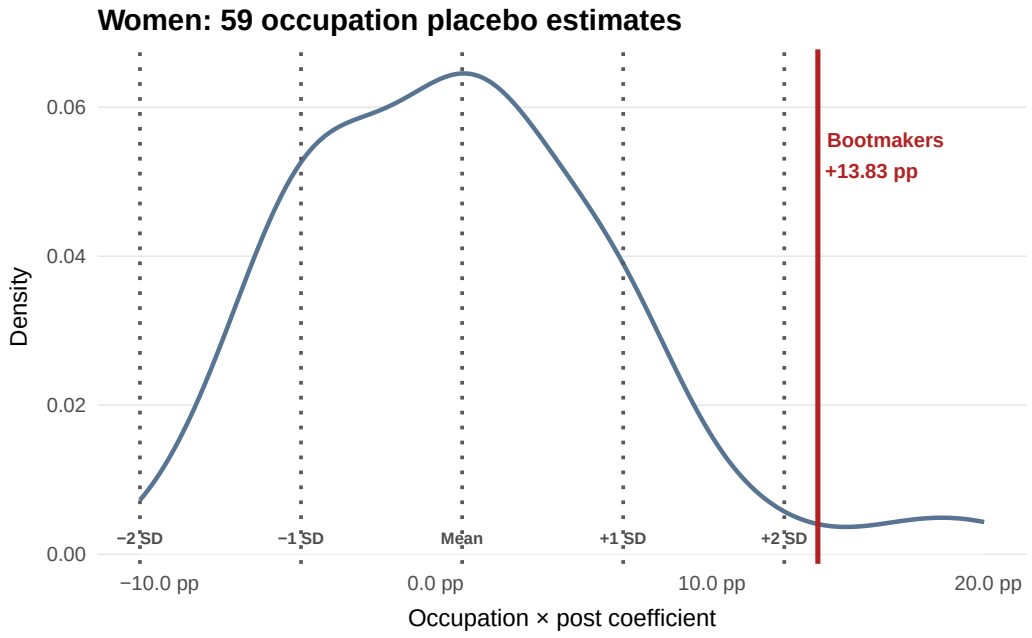
The previous section (H2) located bootmakers within the cross-industry distribution of exit rates, separately in each period. This section does the same for the change over time, using the regression estimates themselves.

Occupational structures were shifting across the whole economy in this period, and exit rates moved for many reasons unrelated to mechanization. A difference-in-differences coefficient for bootmakers is therefore only interpretable against the range of changes occurring elsewhere. I construct that range directly. I repeat the specification in Equation 2 for every comparison occupation in turn, treating each as though it had been affected by mechanization, and record the resulting coefficient. Restricting to occupations with at least 500 workers in each transition window gives 231 placebo occupations for men and 59 for women.

Figure H3 plots the resulting distributions, with the bootmaking estimate marked in red. For men, the estimate sits inside the bulk of the distribution, at around the 78th percentile: 51 of 231 comparison occupations show a larger increase in exit over the same period. For women, it lies in the extreme upper tail, at the 96.7th percentile; only two of 59 comparison occupations show a larger increase in exit.




MEN




WOMEN

Figure H3: Placebo Distribution of Difference-in-Differences Estimates

*Note:* Each distribution plots the difference-in-differences coefficient obtained by assigning treatment to each comparison occupation in turn and re-estimating the specification. The sample is restricted to occupations with at least 500 workers in each transition window. The estimate for bootmakers is marked in red.

## Appendix H.4 Robustness to Alternative Clustering

Standard errors in the main analysis are clustered by county of baseline residence. Although bootmaking is the treated occupation, the treatment was not uniform across it. As Section 4.1.3 documents, mechanization undermined the trade in most counties and expanded it in a few. Two bootmakers in the same county therefore received a more similar shock than two bootmakers in different counties, motivating the use of county-level clustering.

An alternative is to cluster by occupation, pooling ICeM occodes 663–666 into a single bootmaker cluster. I report this for completeness, alongside two-way clustering by occupation and county. Occupation-level clustering is not straightforward in this setting: with only one treated occupation, the cluster-robust variance estimator has a single realization of the treated group. It also treats the shock as common across all bootmakers, despite the substantial geographic variation in exposure to mechanization.

Table H2 reports the preferred specification under all three clustering choices. The substantive conclusions are unchanged. For men, the Boot $\times$ Post coefficient remains small, at 1.0 percentage point, and is statistically insignificant under occupation and two-way clustering. For women, the coefficient remains large, at 13.8 percentage points, and highly significant under every clustering choice. The central finding is therefore robust to alternative assumptions about the correlation structure of the errors.

The complementary placebo exercise, which locates the bootmaking estimate within the distribution of estimates across comparison occupations, is reported in Appendix H3.

Table H2: Exit DiD: Alternative Clustering

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | County | Occ. | Occ.+ Cty | County | Occ. | Occ.+ Cty |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Boot | $-0.260^{***}$ | $-0.260^{***}$ | $-0.260^{***}$ | $-0.052^{***}$ | $-0.052^{**}$ | $-0.052^{**}$ |
| | (0.008) | (0.037) | (0.037) | (0.014) | (0.022) | (0.021) |
| Post | $0.081^{***}$ | $0.081^{***}$ | $0.081^{***}$ | $0.105^{***}$ | $0.105^{***}$ | $0.105^{***}$ |
| | (0.009) | (0.022) | (0.023) | (0.011) | (0.017) | (0.019) |
| Boot × Post | $0.010^{*}$ | 0.010 | 0.010 | $0.138^{***}$ | $0.138^{***}$ | $0.138^{***}$ |
| | (0.005) | (0.015) | (0.015) | (0.014) | (0.012) | (0.009) |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Post × controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean dep. var. (pre) | 0.527 | 0.527 | 0.527 | 0.740 | 0.740 | 0.740 |
| Occ. clusters | — | 747 | 747 | — | 717 | 717 |
| County clusters | 42 | — | 42 | 42 | — | 42 |
| Observations | | 2,476,147 | | | 708,923 | |

*Notes:* Stacked difference-in-differences over two transition windows, $1851 \to 1861$ and $1861 \to 1881$, England, estimated separately by sex. The sample is restricted to individuals aged 15 and older at baseline. All columns report the preferred specification, which includes county fixed effects, baseline age band and marital status, and their interactions with $\text{Post}_{\tau}$. Columns differ only in the level at which standard errors are clustered. Columns (1) and (4) cluster by county of baseline residence, as in the main analysis. Columns (2) and (5) cluster by occupation, pooling occodes 663–666 into a single bootmaker cluster. Columns (3) and (6) cluster two-way by occupation and county. Point estimates are identical across all columns; only the standard errors differ. "Mean dep. var. (pre)" is the sample mean of $\text{Exit}_{ic\tau}$ in the $1851 \to 1861$ window. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

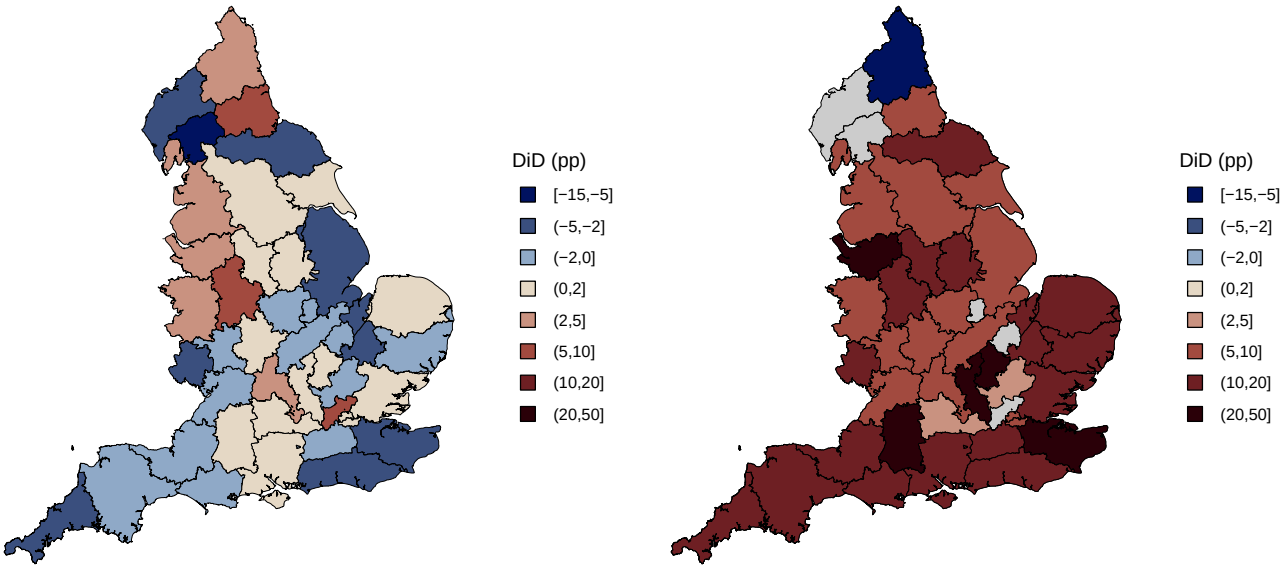
## Appendix H.5 Exit - Regional Level

At the national level, male incumbents experienced very little labour displacement, while women experienced a substantial and significant increase in exit. These aggregates could mask sub-national variation. I therefore re-estimate the baseline specification separately within each English county, by sex:

$$Exit_{i\tau} = \alpha_c + \theta_c \, Boot_{i\tau} + \phi_c \, Post_{\tau} + \beta_c \, (Boot_{i\tau} \times Post_{\tau}) + \varepsilon_{i\tau c}, \qquad \forall \, c. \tag{7}$$

The coefficient of interest is $\beta_c$, the within-county difference-in-differences in the bootmaker exit gap, in percentage points. Counties with fewer than five observations in any group $\times$ time cell are dropped. The exercise produces 42 male and 41 female county-level estimates. Rutland is dropped from the female sample due to insufficient observations, with only one female bootmaker observed in the post-mechanization panel.

Figure H4 maps the resulting estimates separately by sex, using a shared diverging colour scale to allow direct visual comparison across panels.




(a) Men (b) Women

Figure H4: County-Level Exit DiD Estimates, by Sex

*Notes:* County-level within-county DiD estimates of the bootmaker $\times$ post coefficient ($\hat{\beta}_c$), in percentage points. Rutland appears in grey on the female panel because the female sample was too small for stable within-county estimation. *Source:* Data derived by author from ICeM census records, linked using the LT linkage methodology.

For men, the distribution of $\hat{\beta}_c$ remains centred essentially at zero: the mean estimate is $-0.2$ pp and the median $-0.1$ pp. At the same time, the county estimates provide some evidence of geographically concentrated displacement. Of 42 county-level estimates, six are significant at $p < 0.05$. Three are positive: Staffordshire ($+5.5$ pp), Durham ($+5.3$ pp), and Lancashire ($+2.9$ pp). Cheshire also has a positive estimate of $+3.3$ pp, although it falls short of conventional significance ($p = 0.077$). Three significant estimates are negative: Cornwall ($-4.7$ pp), Kent (Extra London) ($-4.2$ pp), and Westmorland ($-11.0$ pp). Only Staffordshire ($p = 0.00048$) survives a Bonferroni correction for the 42 county-level tests. The geography therefore does not indicate broad-based male displacement, but neither does it rule displacement out entirely: there are pockets of economically meaningful excess exit, most clearly in Staffordshire and, more tentatively, in Durham and Lancashire, against a wider distribution of estimates concentrated near zero.

For women, the distribution of $\hat{\beta}_c$ is shifted sharply to the right: the mean estimate is $+12.3$ pp and the median $+10.7$ pp. Of 37 estimable county-level coefficients, 18 are significant at $p < 0.05$, and all 18 are positive. More broadly, 36 of the 37 point estimates are positive. The aggregate female effect is therefore not driven by a small number of anomalous counties. Higher relative exit among female bootmakers after 1861 was geographically widespread, in sharp contrast to the male distribution, which remains centred close to zero and displays substantial heterogeneity in sign.

Figure H5 plots the two distributions of $\hat{\beta}_c$ side by side. The male density is narrow and centred on zero, with most counties not significant (hollow circles). The female density is broader, shifted entirely to the right of zero, and dominated by significant estimates (filled circles).

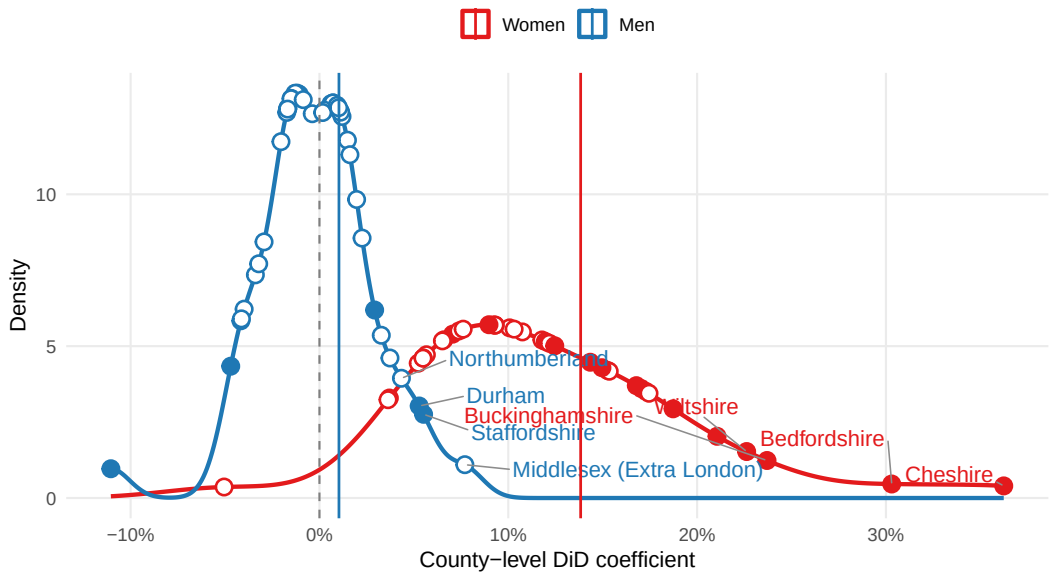



Figure H5: Distribution of County-Level Exit DiD Coefficients, by Sex

*Notes:* Each circle represents one English county's per-county DiD coefficient $\hat{\beta}_c$, plotted on its sex's kernel density curve. Filled circles indicate statistical significance at $p < 0.05$, hollow circles not significant. The dashed vertical line at zero marks the no-effect line, and the solid coloured vertical lines mark the national DiD estimate for men and women. The four right-most counties in each panel are labelled.

# Appendix I Incumbent Migration

Table I1 shows the relative impact of the mechanization of the English bootmaking industry on the migration rates of incumbent bootmakers, as compared to workers in other industries. For both male and female bootmakers, there is no increase in migration rates in the post period.

Table I1: Difference-in-Differences: Migration Rates

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Group | $-0.0072^{*}$ | $-0.0075^{*}$ | $-0.0077^{*}$ | $-0.0274$ | $-0.0097$ | $-0.0153$ |
| | (0.0038) | (0.0039) | (0.0038) | (0.0173) | (0.0129) | (0.0132) |
| Post | $0.0668^{***}$ | $0.0554^{***}$ | $0.0835^{***}$ | $0.0680^{***}$ | $0.0662^{***}$ | $0.0896^{***}$ |
| | (0.0060) | (0.0052) | (0.0095) | (0.0063) | (0.0064) | (0.0109) |
| Group × Post | $-0.0108^{**}$ | $-0.0089^{*}$ | $-0.0083^{*}$ | $-0.0162$ | $-0.0120$ | $0.0016$ |
| | (0.0043) | (0.0045) | (0.0048) | (0.0121) | (0.0122) | (0.0123) |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | No | Yes | Yes |
| Post × controls | No | No | Yes | No | No | Yes |
| Observations | 1,934,459 | 1,934,459 | 1,934,459 | 537,444 | 537,444 | 537,444 |

*Notes:* This table reports difference-in-differences estimates from linear probability models estimated separately for men and women. The sample is restricted to individuals aged 15 and over at baseline. Migration is an indicator equal to one if county of residence differs between the baseline and destination censuses. The coefficient on *Group* × *Post* is the DiD estimate. All specifications include county fixed effects. Columns (2) and (5) add baseline age-band and marital-status controls; columns (3) and (6) additionally interact these controls with the post indicator. Standard errors are clustered at the county level and reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

# Appendix J Parallel Trends

## Appendix J.1 Motivation

The difference-in-differences designs in this paper rely on the parallel trends assumption: absent mechanization, bootmakers' exit rates would have evolved in line with those of workers in other occupations. Standard practice motivates this assumption with pre-trends tests, but a growing literature has shown these tests are neither necessary nor sufficient for parallel trends (Roth, 2023; Rambachan and Roth, 2023). They often have low power and require multiple pre-treatment periods. This is a particular concern in the Victorian census context, where 1851–1861 is the only clean pre-period available.

This appendix proposes an alternative diagnostic, grounded in cross-sectional rather than temporal variation. The diagnostic is developed formally in Vipond (2026a) - here it serves primarily as a robustness check on the parallel trends assumption underlying the paper's main DiD results.

## Appendix J.2 The Diagnostic

The DiD designs in this paper compare bootmakers to workers in approximately 800 other occupations in the English census. The standard DiD estimate summarizes these occupations in a single comparison-group trend, which is used to construct the counterfactual for bootmakers. But the comparison group is heterogeneous: individual occupations experience different changes, and the mean does not capture this dispersion.

Rather than assuming bootmakers would have followed the average trend, I use the range of trends observed across untreated occupations to define a plausible range for what would have happened to bootmakers in the absence of mechanization. Each part of this range implies a corresponding range of treatment effects. When the untreated occupations follow similar trends, the resulting range is narrow. When their trends vary more widely, it is broader.

The logic is illustrated in Figures J1 and J2. Panel B in each figure decomposes the single control trend into the individual trends that comprise it[26]. The mean trend (and therefore the conventional DiD estimate) is identical across the two examples. What differs is the dispersion around it. A wider cross-sectional distribution permits a wider range of counterfactual trends for the treated group and therefore a wider range of treatment effects.

[26]Conventional difference-in-differences summarizes the comparison units in a single comparison-group trend. Here, because the comparison group contains roughly 800 occupations, I can also examine the cross-sectional variation in occupation-specific trends around that aggregate benchmark.

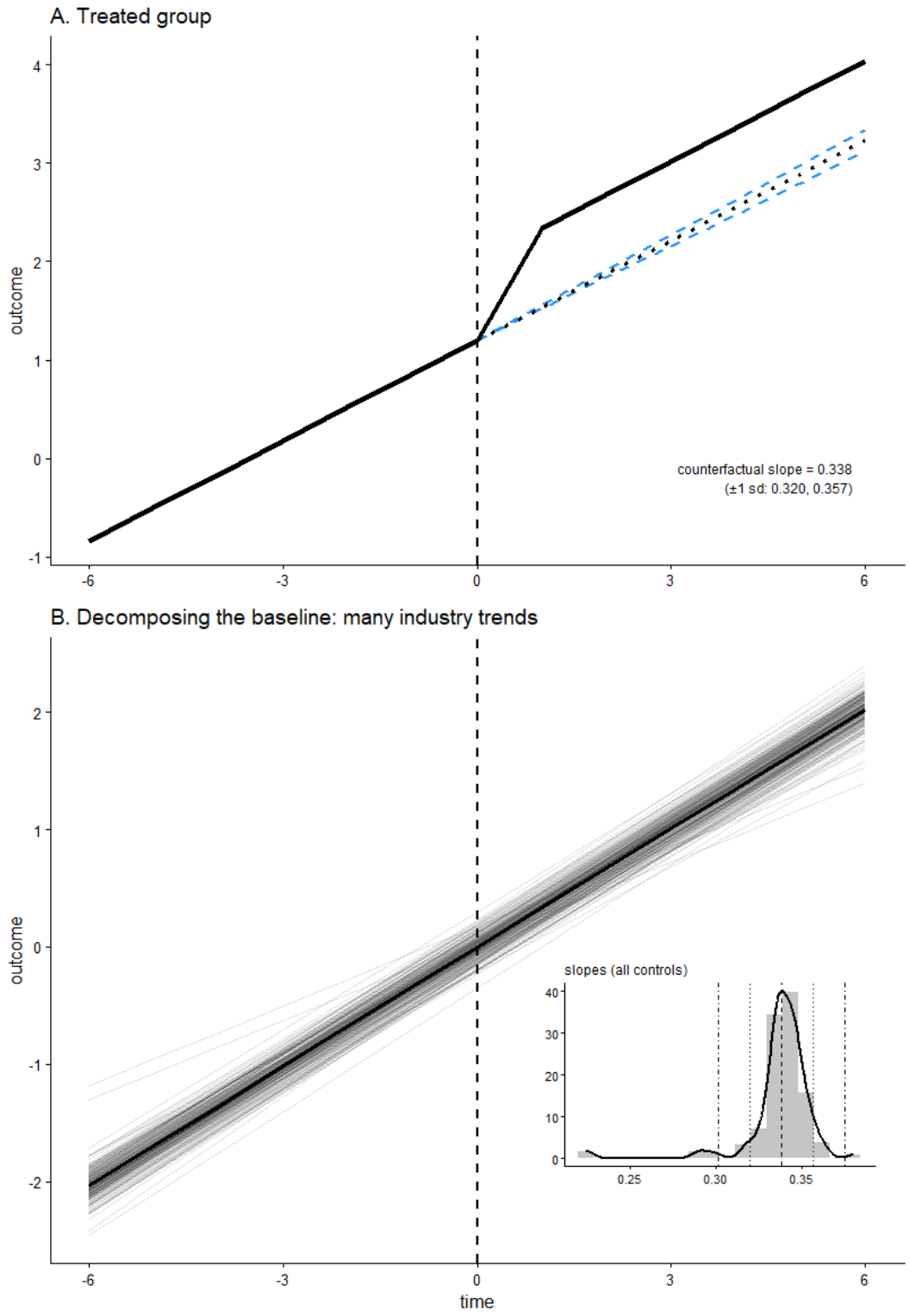



Figure J1: **Cross-section A: Tight Trend Distribution.** Panel A shows the treated group's trajectory together with a range of counterfactual trends derived from the cross-sectional distribution among untreated groups. Panel B decomposes the control trend into the individual trends that comprise it. A tightly concentrated distribution places substantial discipline on the treated group's unobserved counterfactual.

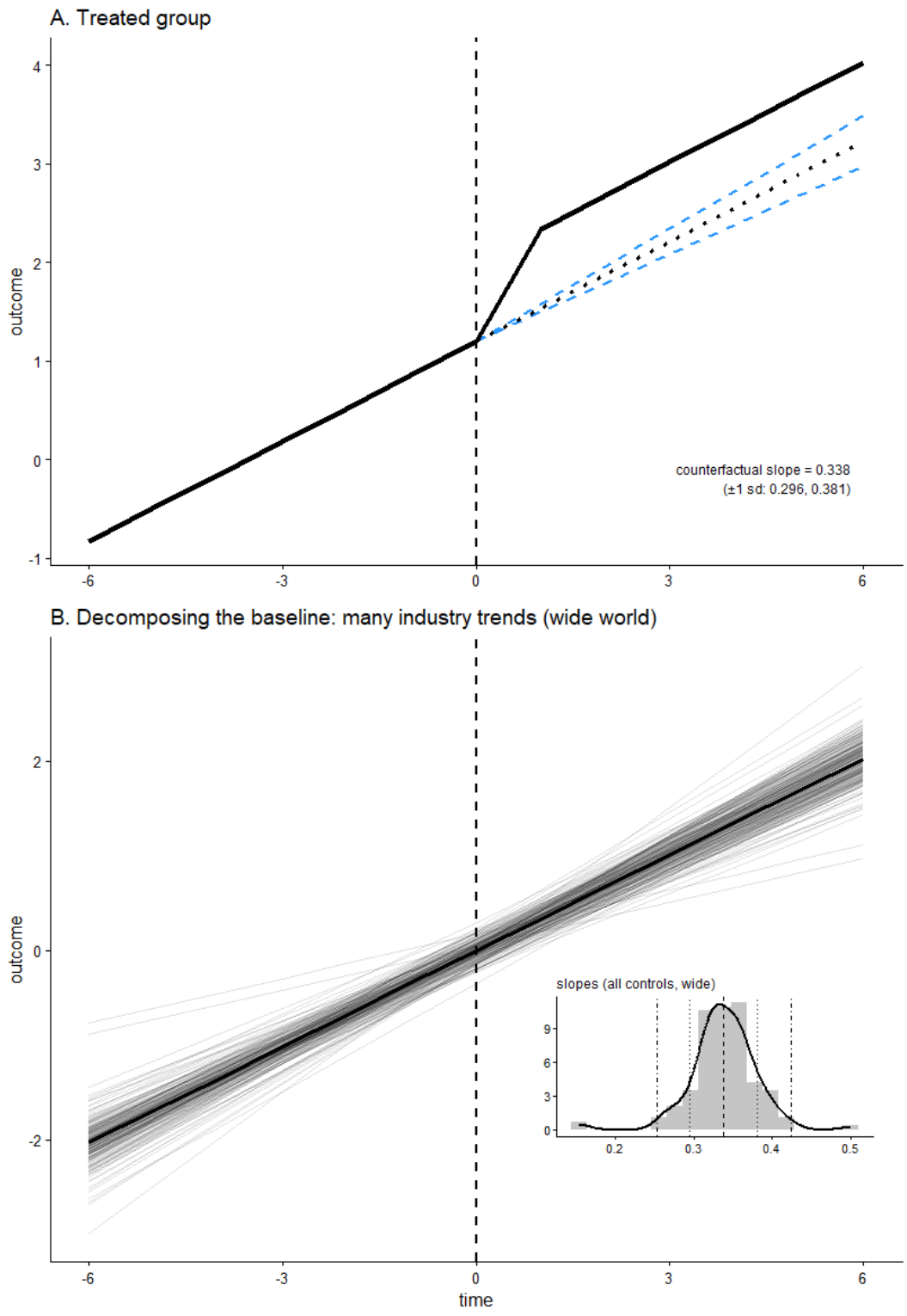



Figure J2: **Cross-section B: Wide Trend Distribution.** The mean untreated trend is identical to Figure J1, but the cross-sectional distribution is substantially wider. The resulting range of plausible counterfactuals is correspondingly wider, producing less precise identification of the treatment effect.

The relationship can be written simply as

$$\hat{\beta}_B = \tau_B + \delta_B, \tag{8}$$

where $\hat{\beta}_B$ is the observed bootmaker DiD, $\tau_B$ is the treatment effect, and $\delta_B$ is the differential trend that bootmakers would have experienced absent mechanization. Conventional parallel trends imposes

$$\delta_B = 0. \tag{9}$$

Instead, I estimate occupation-specific differential trends $\{\hat{\delta}_j\}_{j \in U}$ across the set $U$ of untreated occupations. Each occupation is treated in turn and its differential change is estimated using the same specification as the main DiD, including age bands, marital status, interactions between these controls and period, and county fixed effects.

I then allow the bootmaker counterfactual differential trend to lie between two quantiles of this empirical distribution:

$$\delta_B \in [Q_\delta(q_L), Q_\delta(q_U)]\,. \tag{10}$$

Since

$$\tau_B = \hat{\beta}_B - \delta_B, \tag{11}$$

the corresponding range of treatment effects is

$$\tau_B \in \left[\hat{\beta}_B - Q_\delta(q_U), \hat{\beta}_B - Q_\delta(q_L)\right]. \tag{12}$$

I report three increasingly permissive restrictions on the counterfactual: the interquartile range ($P_{25}$–$P_{75}$), the central 80% of the distribution ($P_{10}$–$P_{90}$), and the central 90% ($P_5$–$P_{95}$). These are sensitivity ranges rather than confidence intervals, and need not contain the conventional DiD estimate: the exercise asks what treatment effects are implied if the untreated bootmaker trend is allowed to occupy different regions of the observed cross-sectional distribution.

This approach is related in spirit to the sensitivity analysis of Rambachan and Roth (2023). In their framework, observed pre-treatment dynamics discipline the magnitude of permitted violations of parallel trends. Here the discipline instead comes from the cross-sectional distribution of differential trends among untreated groups. Widening the permitted region of that distribution relaxes the restriction on the counterfactual and widens the cor-

responding range of treatment effects.

## Appendix J.3 Application to Bootmaking Exit Rates

I apply the diagnostic to the exit-rate analysis at the core of this paper. For each untreated occupation, I estimate the adjusted differential change between the 1851–1861 and 1861–1881 panels using the preferred DiD specification from the main analysis. I do this separately for men and women.

I consider three comparison sets. The first includes every untreated occupation for which the placebo coefficient can be estimated. The second restricts the distribution to large occupations, defined as those with at least 500 observations in each panel. This reduces the influence of coefficients estimated from small occupational samples. The third further restricts the large-occupation sample to a conservative set of core craft occupations — identifiable skilled manual trades such as carpenters, blacksmiths, tailors, dressmakers, cabinet makers, bookbinders and instrument makers. This classification is defined independently of the estimated coefficients. Table J1 reports the resulting treatment-effect ranges.

Table J1: Cross-sectional Sensitivity to Violations of Parallel Trends

| Sex | Counterfactual set | $N$ | DiD | IQR | $P_{10}$–$P_{90}$ | $P_5$–$P_{95}$ |
|---|---|---|---|---|---|---|
| *Panel A: Men* | | | | | | |
| Men | All occupations | 735 | 1.03 | [2.68, 10.17] | [−2.23, 14.57] | [−5.73, 17.91] |
| Men | Large occupations | 231 | 1.03 | [0.50, 8.39] | [−3.64, 11.74] | [−6.54, 13.37] |
| Men | Large core crafts | 52 | 1.03 | [3.10, 8.31] | [−0.55, 13.22] | [−2.60, 16.81] |
| *Panel B: Women* | | | | | | |
| Women | All occupations | 677 | 13.83 | [15.47, 22.00] | [10.91, 24.69] | [7.47, 27.28] |
| Women | Large occupations | 59 | 13.83 | [9.12, 17.32] | [6.60, 19.72] | [4.10, 20.08] |
| Women | Large core crafts | 10 | 13.83 | [7.97, 16.93] | [6.63, 19.11] | [5.48, 19.49] |

*Notes.* Entries are percentage points. The DiD column reports the preferred bootmaker Group × Post coefficient. For each untreated occupation, an occupation-specific differential trend is estimated using the same regression specification. "Large occupations" require at least 500 observations in both panels. "Large core crafts" additionally restricts the sample to an independently defined set of skilled manual trades. The remaining columns report the range of treatment effects implied when the untreated bootmaker differential trend is allowed to lie within the interquartile range, central 80%, or central 90% of the corresponding untreated cross-sectional distribution.

For male bootmakers, the preferred DiD estimate is small, at approximately $+1.0$ percentage point. Once the counterfactual trend is allowed to vary over the central 80% of the untreated distribution, the implied treatment-effect range contains zero under every comparison set. Among large occupations, for example, the range is $-3.6$ to $+11.7$ percentage

points; expanding the permitted counterfactual to the central 90% gives a range of $-6.5$ to $+13.4$ percentage points. The diagnostic therefore corroborates the main paper's finding of little evidence of increased exit among male bootmakers.

For female bootmakers, the result is very different. The conventional DiD estimate is $+13.8$ percentage points. Among large untreated occupations, allowing the bootmaker counterfactual trend to lie anywhere within the central 80% of the observed cross-sectional distribution implies a treatment effect between $+6.6$ and $+19.7$ percentage points. Even when the permitted counterfactual is widened to the central 90%, the implied effect remains between $+4.1$ and $+20.1$ percentage points.

Restricting the comparison set further to large core craft occupations produces a very similar result. The central-80% range is $+6.6$ to $+19.1$ percentage points, and the central-90% range is $+5.5$ to $+19.5$ percentage points. The craft sample is small for women, so I treat this as a comparability check rather than the primary specification. Its similarity to the broader large-occupation distribution is nevertheless reassuring.

The result therefore does not depend on requiring the female bootmaker counterfactual trend to equal the mean trend of the comparison group. Female displacement remains substantial even when the missing counterfactual is allowed to depart considerably from exact parallel trends.

## Appendix J.4 Conclusion

The diagnostic corroborates the paper's main DiD results from a different angle. For male bootmakers, allowing the untreated counterfactual to vary over a broad range of observed occupational trends quickly produces treatment-effect ranges that contain zero. For female bootmakers, the implied range remains positive across all three comparison sets, including when the counterfactual is allowed to span the central 90% of the untreated distribution.

The exercise does not replace the conventional DiD estimate. Instead, it shows how conclusions change when the exact parallel-trends restriction is relaxed and the missing counterfactual trend is disciplined by the cross-sectional experience of untreated occupations.

# Appendix K Entry into Artisanal Jobs

## Appendix K.1 Population Growth and Employment Counterfactuals

The absolute contraction in the number of artisanal bootmaking jobs is reported in Section 3. The counterfactuals here concern shares. They answer a different question: how much of the observed decline in the share of workers employed in artisanal bootmaking is attributable to a growing workforce rather than to disappearing jobs.

The decline in artisanal bootmaking as a share of employment reflects both population growth and an absolute loss of jobs. To separate these, I first construct a fixed-stock counterfactual, benchmarked to 1861. I hold artisanal employment fixed at 219,834 and allow the working population to grow as observed. This shows how far the artisanal share would have fallen through population growth alone; the remaining gap reflects jobs that actually disappeared.

I then construct a fixed-share counterfactual, which asks a broader question. Rather than holding the number of jobs fixed, I hold artisanal bootmaking at its 1861 share of the working population, allowing employment to grow with the workforce. This shows how many artisanal jobs would have existed had the trade continued to absorb the same share of a growing working population. The shortfall therefore captures both jobs that disappeared and jobs that were never created.

Table K1: Artisanal Bootmaking Employment and Population-Growth Counterfactuals

| | 1851 | 1861 | 1881 | 1891 | 1901 | 1911 |
|---|---|---|---|---|---|---|
| *Observed* | | | | | | |
| Working population | 7,339,970 | 8,279,267 | 11,197,484 | 11,854,012 | 13,709,560 | 16,140,166 |
| Artisanal employment | 216,314 | 219,834 | 141,176 | 128,330 | 103,163 | 63,207 |
| Artisanal share (%) | 2.947 | 2.655 | 1.261 | 1.083 | 0.752 | 0.392 |
| *Fixed-stock counterfactual* | | | | | | |
| Employment | – | 219,834 | 219,834 | 219,834 | 219,834 | 219,834 |
| Share (%) | – | 2.655 | 1.963 | 1.855 | 1.604 | 1.362 |
| Share gap (pp) | – | 0.000 | 0.702 | 0.772 | 0.851 | 0.970 |
| Employment gap | – | 0 | 78,658 | 91,504 | 116,671 | 156,627 |
| *Fixed-share counterfactual* | | | | | | |
| Employment | – | 219,834 | 297,320 | 314,752 | 364,021 | 428,559 |
| Employment gap | – | 0 | 156,144 | 186,422 | 260,858 | 365,352 |

*Notes:* Expanded cleaned bootmaker sample. Counterfactuals are benchmarked to 1861. The fixed-stock counterfactual holds artisanal employment at 219,834; the fixed-share counterfactual holds the 1861 artisanal employment share at 2.655 percent. Employment gaps are counterfactual minus observed employment.

The two counterfactuals capture different dimensions of the contraction. By 1881, simply maintaining the 1861 stock would have implied 219,834 artisanal jobs, compared with the 141,176 actually observed: a shortfall of 78,658 jobs.

However, because the working population grew substantially, maintaining the industry's 1861 employment share in 1881 would have required approximately 297,320 artisanal jobs. Relative to this benchmark the shortfall was 156,144 jobs. The second figure contains the first: of the 156,144, some 78,658 are jobs that disappeared, and the remaining 77,486 are jobs that would have had to be created for the trade to hold its position. By 1881 the two components were almost exactly equal, and by 1911 jobs never created accounted for the larger share - 208,725 of a total shortfall of 365,352.

This distinction is particularly relevant for entry. Entry is a question of the employment opportunities available to new cohorts, so that even an industry that maintained a constant number of jobs would be absorbing a progressively smaller share of new workers if the population was expanding. Artisanal bootmaking contracted on both counts. It failed to expand at the same rate as the population. It also lost in absolute terms. The result is that, by 1911, artisanal employment was 156,627 jobs below the fixed-stock benchmark and 365,352 jobs below the level implied by maintaining its 1861 share of the working population.

These are accounting counterfactuals rather than causal estimates. The fixed-stock counterfactual measures the contraction relative to preserving the pre-mechanization stock of jobs, while the fixed-share counterfactual measures the broader loss of employment capacity relative to the trade's pre-mechanization share of a growing workforce.

## Appendix K.2 Entry: County-Level Rates

This appendix presents the change in entry rates into artisanal bootmaking at the county level, separately for men (Table K2) and women (Table K3). The analysis is restricted to the first two linked panels: Panel 1 (1851–1861) and Panel 2 (1861–1881). For each English county, the tables report the share of all linked young people aged 10–18 at baseline who are observed in artisanal bootmaking at endline, together with both the absolute and relative change between the two panels. The denominator therefore includes all linked individuals in the relevant age range, regardless of their baseline occupation. The absolute change measures the percentage-point decline in entry, while the relative change measures the proportional contraction from the Panel 1 entry rate.

Table K2: Change in male entry rate into artisanal bootmaking, by county, 1851–1861 to 1861–1881

| County | P1 (%) | P2 (%) | Δ pp | Δ % | County | P1 (%) | P2 (%) | Δ pp | Δ % |
|---|---|---|---|---|---|---|---|---|---|
| Northumberland | 2.399 | 0.981 | −1.418 | −59.1 | London | 2.672 | 1.585 | −1.087 | −40.7 |
| Staffordshire | 3.168 | 1.372 | −1.795 | −56.7 | Rutland | 3.041 | 1.812 | −1.229 | −40.4 |
| Durham | 2.079 | 0.919 | −1.161 | −55.8 | Warwickshire | 2.239 | 1.336 | −0.903 | −40.3 |
| Northamptonshire | 19.987 | 8.829 | −11.159 | −55.8 | Huntingdonshire | 3.927 | 2.351 | −1.576 | −40.1 |
| Cambridgeshire | 3.296 | 1.578 | −1.718 | −52.1 | Bedfordshire | 3.669 | 2.200 | −1.469 | −40.0 |
| Yorkshire North Riding | 4.194 | 2.090 | −2.105 | −50.2 | Hampshire | 2.617 | 1.596 | −1.021 | −39.0 |
| Yorkshire East Riding | 3.346 | 1.683 | −1.663 | −49.7 | Herefordshire | 2.783 | 1.716 | −1.067 | −38.3 |
| Worcestershire | 2.394 | 1.212 | −1.182 | −49.4 | Norfolk | 5.640 | 3.511 | −2.128 | −37.7 |
| Kent | 2.023 | 1.040 | −0.983 | −48.6 | Cheshire | 3.279 | 2.047 | −1.233 | −37.6 |
| Sussex | 2.974 | 1.577 | −1.398 | −47.0 | Westmorland | 3.500 | 2.291 | −1.209 | −34.5 |
| Nottinghamshire | 3.040 | 1.632 | −1.408 | −46.3 | Wiltshire | 2.536 | 1.678 | −0.858 | −33.8 |
| Derbyshire | 2.554 | 1.376 | −1.177 | −46.1 | Shropshire | 2.986 | 2.048 | −0.938 | −31.4 |
| Berkshire | 2.781 | 1.509 | −1.272 | −45.7 | Devon | 3.697 | 2.592 | −1.105 | −29.9 |
| Yorkshire West Riding | 2.440 | 1.373 | −1.068 | −43.8 | Essex | 2.279 | 1.606 | −0.674 | −29.6 |
| Cumberland | 3.433 | 1.952 | −1.481 | −43.1 | Somerset | 3.475 | 2.507 | −0.967 | −27.8 |
| Hertfordshire | 2.737 | 1.565 | −1.171 | −42.8 | Surrey | 1.745 | 1.270 | −0.476 | −27.3 |
| Leicestershire | 4.497 | 2.581 | −1.916 | −42.6 | Lancashire | 1.761 | 1.313 | −0.448 | −25.4 |
| Dorset | 2.886 | 1.677 | −1.208 | −41.9 | Suffolk | 3.003 | 2.364 | −0.640 | −21.3 |
| Buckinghamshire | 5.040 | 2.968 | −2.072 | −41.1 | Cornwall | 2.659 | 2.131 | −0.528 | −19.8 |
| Oxfordshire | 2.773 | 1.638 | −1.135 | −40.9 | Middlesex | 1.777 | 1.458 | −0.319 | −17.9 |
| Lincolnshire | 2.674 | 1.583 | −1.091 | −40.8 | Gloucestershire | 2.883 | 2.735 | −0.148 | −5.1 |

*Notes.* Each cell reports the share of all linked young men aged 10–18 at baseline observed in artisanal bootmaking at endline. P1 denotes Panel 1 (1851–1861) and P2 denotes Panel 2 (1861–1881). Δ pp is the change in the entry rate (Panel 2 minus Panel 1, in percentage points). Δ % is the relative change as a percentage of the Panel 1 rate. Counties are sorted by Δ %, from the largest decline to the smallest; the right-hand block continues from the left.

The decline among men is universal. All forty-two English counties record a fall in artisanal entry, and most cluster in a relative-decline band of roughly twenty-five to fifty percent. Gloucestershire is the clear exception, with entry falling by only 5 percent. The next-smallest declines are considerably larger: 18 percent in Middlesex, 20 percent in Cornwall, and 21 percent in Suffolk.

Northamptonshire records by far the largest absolute decline, at $-11.2$ percentage points. This unusually large absolute fall reflects the size of the county's pre-existing artisanal base: in Panel 1, almost one in five young Northamptonshire men entered artisanal bootmaking, compared with rates of only a few percent in most counties. By Panel 2 the Northamptonshire entry rate had fallen from 20.0 to 8.8 percent. In proportional terms, however, its 56 percent decline is not unique: Northumberland, Staffordshire, Durham, Cambridgeshire, and the Yorkshire North Riding all record declines of approximately 50 percent or more.

The female collapse is considerably more thorough than the male. In ten counties the female artisanal entry rate falls to zero in Panel 2, and in thirty of the forty-two counties it falls by at least 85 percent. The median female relative decline is approximately $-90$ percent, against a median male decline of approximately $-41$ percent. Northamptonshire

again records by far the largest absolute decline, at $-5.2$ percentage points. As with men, this reflects the size of the county's pre-existing artisanal base.

Table K3: Change in female entry rate into artisanal bootmaking, by county, 1851–1861 to 1861–1881

| County | P1 (%) | P2 (%) | Δ pp | Δ % | County | P1 (%) | P2 (%) | Δ pp | Δ % |
|---|---|---|---|---|---|---|---|---|---|
| Bedfordshire | 1.035 | 0.000 | −1.035 | −100.0 | Yorkshire West Riding | 0.242 | 0.024 | −0.218 | −90.0 |
| Berkshire | 0.739 | 0.000 | −0.739 | −100.0 | Norfolk | 2.646 | 0.268 | −2.377 | −89.9 |
| Cumberland | 0.110 | 0.000 | −0.110 | −100.0 | Lancashire | 0.207 | 0.023 | −0.184 | −88.9 |
| Dorset | 0.855 | 0.000 | −0.855 | −100.0 | Essex | 0.310 | 0.036 | −0.275 | −88.5 |
| Durham | 0.189 | 0.000 | −0.189 | −100.0 | Wiltshire | 0.435 | 0.050 | −0.385 | −88.5 |
| Hampshire | 0.702 | 0.000 | −0.702 | −100.0 | Gloucestershire | 1.668 | 0.197 | −1.471 | −88.2 |
| Rutland | 0.422 | 0.000 | −0.422 | −100.0 | Somerset | 1.504 | 0.200 | −1.304 | −86.7 |
| Westmorland | 0.518 | 0.000 | −0.518 | −100.0 | Surrey | 0.417 | 0.058 | −0.359 | −86.1 |
| Yorkshire East Riding | 0.371 | 0.000 | −0.371 | −100.0 | Suffolk | 1.033 | 0.155 | −0.878 | −85.0 |
| Yorkshire North Riding | 0.116 | 0.000 | −0.116 | −100.0 | Warwickshire | 0.609 | 0.093 | −0.516 | −84.7 |
| Staffordshire | 1.218 | 0.026 | −1.192 | −97.8 | Hertfordshire | 0.348 | 0.054 | −0.295 | −84.6 |
| Sussex | 0.666 | 0.029 | −0.637 | −95.7 | Shropshire | 0.541 | 0.098 | −0.443 | −81.8 |
| Cheshire | 0.839 | 0.038 | −0.801 | −95.4 | Buckinghamshire | 1.577 | 0.294 | −1.283 | −81.4 |
| Devon | 1.260 | 0.082 | −1.178 | −93.5 | Worcestershire | 0.454 | 0.094 | −0.361 | −79.4 |
| Lincolnshire | 0.469 | 0.032 | −0.437 | −93.2 | Nottinghamshire | 0.605 | 0.129 | −0.476 | −78.7 |
| London | 0.891 | 0.060 | −0.831 | −93.2 | Huntingdonshire | 0.804 | 0.178 | −0.626 | −77.9 |
| Cornwall | 0.787 | 0.056 | −0.731 | −92.9 | Northamptonshire | 7.207 | 1.962 | −5.245 | −72.8 |
| Kent | 0.558 | 0.046 | −0.512 | −91.8 | Herefordshire | 0.437 | 0.130 | −0.307 | −70.3 |
| Cambridgeshire | 0.802 | 0.071 | −0.731 | −91.2 | Middlesex | 0.393 | 0.122 | −0.270 | −68.8 |
| Oxfordshire | 0.764 | 0.069 | −0.695 | −90.9 | Derbyshire | 0.357 | 0.125 | −0.232 | −65.0 |
| Northumberland | 0.287 | 0.028 | −0.259 | −90.3 | Leicestershire | 1.011 | 0.402 | −0.609 | −60.3 |

*Notes.* Each cell reports the share of all linked young women aged 10–18 at baseline observed in artisanal bootmaking at endline. P1 denotes Panel 1 (1851–1861) and P2 denotes Panel 2 (1861–1881). Δ pp is the absolute change in the entry rate (Panel 2 minus Panel 1, in percentage points). Δ % is the relative change as a percentage of the Panel 1 rate. Counties are sorted by Δ %, from the largest decline to the smallest; the right-hand block continues from the left.

## Appendix K.3 Entry: Stock and Age Composition

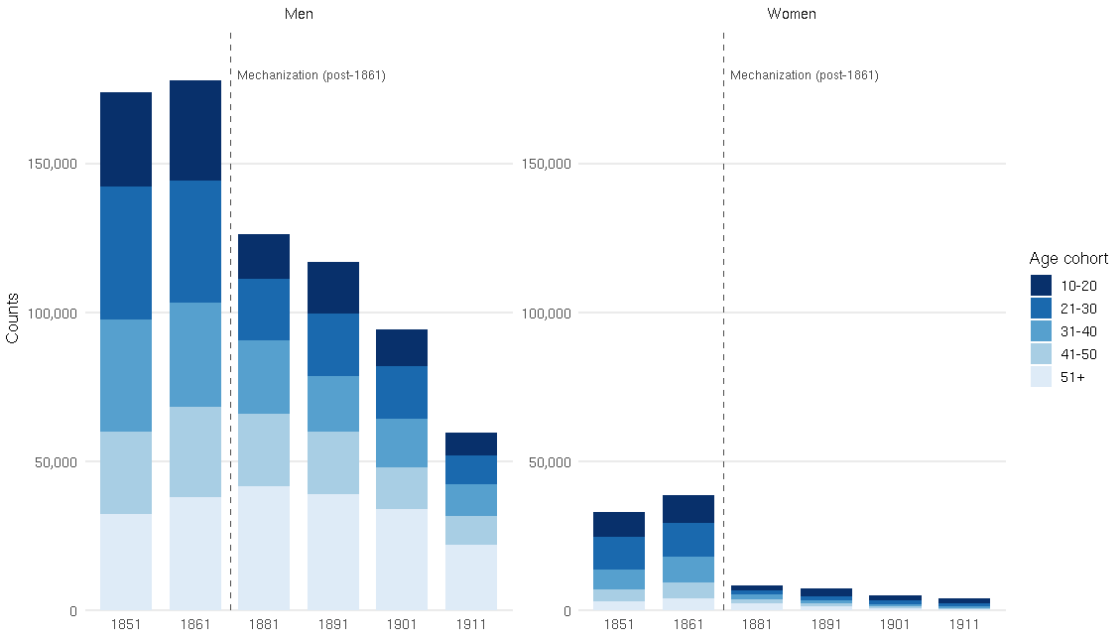



Figure K1: Stock of Artisanal Bootmakers, 1851–1911

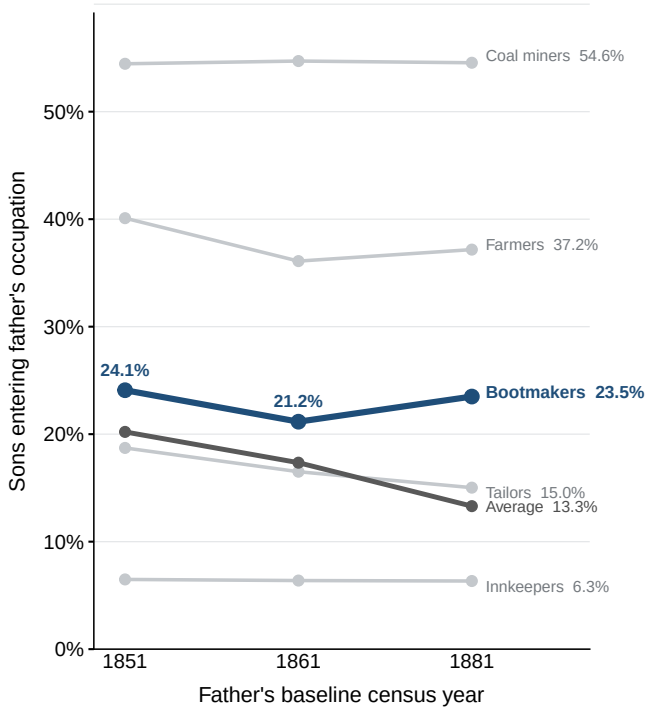
*Notes:* Stock of artisanal bootmakers in England by census year by age-band, by sex. The dashed line marks the onset of bootmaking mechanization after 1861. *Source:* ICeM full-count census microdata.

# Appendix L Sons of Bootmakers

Father-to-son occupational transmission declined substantially across this period. Figure L1 shows the share of sons entering their father's occupation across large, established occupations. On average, occupational inheritance falls steadily across successive cohorts, consistent with the changing occupational structure and the emergence of new forms of work.

Bootmaking is an exception to this broader decline. Around 21–24 percent of bootmakers' sons enter their father's trade: 24.1 percent in 1851, 21.2 percent in 1861, and 23.5 percent in 1881. Bootmaking is therefore not unusual in the level of occupational inheritance, but in its persistence. Despite the transformation of the industry, sons of bootmakers remained about as likely to enter the trade in 1881 as they had been thirty years earlier.

Figure L1: Intergenerational Occupational Transmission




*Notes:* The figure reports the share of linked sons who enter their father's occupation, measured over consistent 30-year intervals for sons aged 18 or younger at baseline. The dark grey line reports the weighted average across established occupations with valid HISCAM scores observed in all three cohorts. Source: ICeM full-count census microdata

# Appendix M Within-Family Difference-in-Differences

## Appendix M.1 Birth Order and Selection

The within-family identifying assumption requires that sibling-specific selection into bootmaking not vary systematically with the local trade trajectory. I evaluate this by examining the distribution of birth order among bootmaker sons across county types. Table M1 reports the share of bootmaker sons in each birth-order rank, separately by county type and panel.

Table M1: Birth-Order Composition of Bootmaker Sons, by County Type

| | 1851–1881 panel | | | 1861–1891 panel | | |
|---|---|---|---|---|---|---|
| Birth order | Growth | Stable | Decline | Growth | Stable | Decline |
| First-born | 40.3 | 45.1 | 46.7 | 37.6 | 46.0 | 49.9 |
| Second-born | 31.7 | 30.5 | 28.0 | 34.7 | 29.9 | 26.9 |
| Third-born | 18.7 | 14.2 | 16.1 | 15.5 | 12.8 | 14.4 |
| Fourth or later | 9.4 | 10.2 | 9.1 | 12.2 | 11.3 | 8.7 |
| Mean birth order | 1.99 | 1.95 | 1.92 | 2.08 | 1.99 | 1.86 |
| $N$ | 421 | 907 | 1,153 | 458 | 719 | 859 |

*Notes:* Table reports the percentage of bootmaker sons in each birth-order rank by county type, separately for each panel. Sample restricted to bootmaker sons in mixed-occupation bootmaker-father households.

There is meaningful variation in the birth-order composition of bootmaker sons across county types. In both panels, firstborns are more heavily represented among bootmaker sons in Decline counties than in Growth counties. That difference is particularly pronounced in 1861–1891: roughly 50 percent of bootmaker sons in Decline counties are firstborn, compared to 38 percent in Growth counties. The pattern is consistent with families in declining trades disproportionately supporting the eldest son into the family occupation.

I therefore re-estimate the main specification on the 1861–1891 panel allowing birth-order effects to vary across county types. Specifically, I add the interaction term $\text{BirthOrder}_{if} \times \text{Decline}_c$ to the regression. This allows the relationship between birth order and later-life outcomes to differ with the local trajectory of the trade. Table M2 reports the resulting estimates alongside the unadjusted estimates from the main specification. The total brother-gap in Decline is of a very similar magnitude after the adjustment.

Table M2: Birth-Order × County Type Adjustment, 1861–1891 Panel

| | Migration | | Married | | Head of household | |
|---|---|---|---|---|---|---|
| | Main | Adjusted | Main | Adjusted | Main | Adjusted |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Bootmaker son × Decline | 0.051 | 0.049 | −0.072*** | −0.082*** | −0.038* | −0.045** |
| | (0.031) | (0.031) | (0.024) | (0.025) | (0.019) | (0.019) |
| Total brother-gap in Decline | −0.145*** | −0.146*** | −0.049*** | −0.054*** | −0.049*** | −0.053*** |
| | [0.024] | [0.025] | [0.016] | [0.017] | [0.015] | [0.015] |
| Family FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth order × Decline | No | Yes | No | Yes | No | Yes |
| Observations | 2,816 | 2,816 | 2,816 | 2,816 | 2,454 | 2,454 |

Notes: Odd-numbered columns report the main within-family difference-in-differences specification. Even-numbered columns additionally interact birth order with the Decline indicator. The first row reports the Bootmaker son × Decline interaction. The second reports the total brother-gap in Decline counties, equal to the sum of the Bootmaker son coefficient and the interaction coefficient. Standard errors are in parentheses, and standard errors for the linear combination are in square brackets. Sample restricted to mixed-occupation bootmaker-father households. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimates remain stable. The Bootmaker son × Decline interaction changes from 5.1 to 4.9 percentage points for migration, from $-7.2$ to $-8.2$ for marriage, and from $-3.8$ to $-4.5$ for headship. The corresponding total brother-gaps in Decline counties also change very little: from $-14.5$ to $-14.6$ percentage points for migration, $-4.9$ to $-5.4$ for marriage, and $-4.9$ to $-5.3$ for headship. The marriage and headship penalties actually strengthen modestly after the adjustment, while the migration result is essentially unchanged. The compositional shift documented in Table M1 does not account for the estimated penalties.

The changing birth-order composition would still matter if firstborn and later-born sons generally had substantially different adult outcomes. Table M3 compares outcomes of firstborn and later-born sons who did not themselves enter bootmaking, pooling across county types. Absent differential exposure to the bootmaking shock, birth order is not associated with large differences in later-life outcomes. In the 1851–1881 panel, firstborn sons are 0.9 percentage points less likely to be married and 1.4 percentage points less likely to migrate, but 1.6 percentage points more likely to be household heads. In the 1861–1891 panel, firstborn sons are 2.1 percentage points more likely to be married, 3.2 percentage points more likely to be household heads, and 1.2 percentage points more likely to migrate. These differences are small relative to the estimated penalties associated with entering bootmaking in declining counties. Together with the birth-order adjustment above, this suggests that the results are not driven by changing selection of firstborn versus later-born sons into the trade.

Table M3: Outcomes by Birth Order among Non-Bootmaker Sons

| | 1851–1881 | | | 1861–1891 | | |
|---|---|---|---|---|---|---|
| Birth order | Married | Head | Migrated | Married | Head | Migrated |
| First-born | 82.7 | 94.2 | 39.4 | 85.8 | 96.2 | 42.1 |
| Later-born | 83.6 | 92.6 | 40.7 | 83.7 | 93.0 | 40.9 |
| First-born difference | $-0.9$ | 1.6 | $-1.4$ | 2.1 | 3.2 | 1.2 |

Notes: Table reports mean outcomes among sons in mixed-occupation bootmaker-father households who did not themselves enter bootmaking, pooling across county types. First-born sons have birth order one and later-born sons have birth order greater than one. Entries are percentages. The final row reports the first-born minus later-born difference.

This is important for the direction of selection. As artisanal bootmaking declines, families increasingly send their firstborn sons into the trade. However, in the absence of the mechanization shock, firstborn sons in fact tended to have slightly better adult outcomes than their brothers. This makes it unlikely that the outcomes we observe were the result of families increasingly sending their least qualified sons into the trade in Decline counties. On the contrary, the penalties are observed despite families increasingly sending their firstborns.

## Appendix M.2 Sensitivity Tests

The main specification classifies counties according to changes in local bootmaking employment over each panel. I test the sensitivity of the results to this choice by varying the Growth/Decline cutoff and by replacing the categorical measure with the continuous change in county bootmaking employment.

I first test whether the results depend on the cutoff used to classify counties as Growth or Decline. The main specification uses a $\pm 20\%$ cutoff. Table M4 re-estimates the specification using thresholds of $\pm 10\%$ and $\pm 30\%$, alongside the baseline $\pm 20\%$ definition.

Table M4: Sensitivity to Growth and Decline Cutoffs

| | ±10% | | ±20% | | ±30% | |
|---|---|---|---|---|---|---|
| | 1851–81 | 1861–91 | 1851–81 | 1861–91 | 1851–81 | 1861–91 |
| Migration | 0.046 | 0.055* | 0.032 | 0.051 | 0.046 | 0.048 |
| | (0.036) | (0.030) | (0.038) | (0.031) | (0.043) | (0.031) |
| Married | −0.104*** | −0.013 | −0.093*** | −0.072*** | −0.107*** | −0.071*** |
| | (0.027) | (0.034) | (0.030) | (0.024) | (0.035) | (0.024) |
| Head of household | −0.055** | 0.011 | −0.055** | −0.038* | −0.077*** | −0.039* |
| | (0.023) | (0.021) | (0.025) | (0.019) | (0.025) | (0.019) |
| Family FE | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: Table reports the Bootmaker son × Decline interaction from the within-family difference-in-differences specification under alternative thresholds for defining Growth and Decline counties. The ±20% cutoff is the main specification. Controls include age and birth order. Standard errors clustered at the county level are reported in parentheses. Sample restricted to mixed-occupation bootmaker-father households. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results are stable across the ±20% and ±30% definitions. In the 1851–1881 panel, the marriage and headship interactions are similar across all three cutoffs, with the estimated marriage penalty ranging from 9.3 to 10.7 percentage points and the headship penalty from 5.5 to 7.7 percentage points. In the 1861–1891 panel, the ±20% and ±30% estimates are also nearly identical, while the ±10% specification attenuates sharply for marriage and headship. This is consistent with the narrower cutoff admitting counties with relatively modest changes in bootmaking employment into the Growth and Decline groups, weakening the contrast in local trade trajectories. The close correspondence between the ±20% and ±30% estimates suggests that the baseline results are not driven by the particular choice of the 20 percent threshold.

The categorical specification imposes a discrete classification on what is fundamentally a continuous variation in change in local bootmaker employment. As an alternative, Table M5 reports estimates from a specification that interacts $\text{BootmakerSon}_{if}$ with the continuous county-level percentage change in bootmaker employment, $\Delta_c$.

Table M5: Continuous Intensity Specification

| | Migration | | Married | | Head | |
|---|---|---|---|---|---|---|
| | 1851–81 | 1861–91 | 1851–81 | 1861–91 | 1851–81 | 1861–91 |
| $B_{if}$ | $-0.140^{***}$ | $-0.138^{***}$ | $-0.052^{***}$ | $-0.032^{**}$ | $-0.055^{***}$ | $-0.036^{***}$ |
| | (0.013) | (0.016) | (0.014) | (0.014) | (0.010) | (0.011) |
| $B_{if} \times \Delta_c$ (10 pp) | $-0.003^{***}$ | $-0.003^{***}$ | $0.005^{***}$ | $0.002^{**}$ | $0.002^{*}$ | $0.001^{***}$ |
| | (0.0007) | (0.0007) | (0.0008) | (0.0008) | (0.0010) | (0.0004) |
| Family FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,263 | 4,388 | 5,263 | 4,388 | 4,509 | 3,803 |

Notes: Estimates from a continuous-intensity version of Equation (4), replacing the categorical county classification with the continuous percentage change in county bootmaking employment, $\Delta_c$. The interaction coefficients and standard errors are rescaled to report the change in the bootmaker-son gap associated with a 10-percentage-point increase in county bootmaking employment change. Controls include age and birth order. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For marriage and headship, larger local declines in bootmaking are associated with larger penalties for bootmaker sons, consistent with the categorical results. Migration is different. The migration gap is largest in Growth counties, smallest in Stable counties, and intermediate in Decline counties, so a single linear interaction does not describe that pattern well.

Table M6 shows what the Growth, Stable, and Decline categories correspond to in terms of actual changes in county bootmaking employment, which provides useful context for the results in Table M5.

Table M6: County Bootmaking Employment Change by Category

| Panel | County type | Sons | Mean %Δ | Median %Δ | Range |
|---|---|---|---|---|---|
| 1851–81 | Growth | 843 | 136.0 | 69.5 | 25.3 to 389.8 |
| 1851–81 | Stable | 1,934 | −8.9 | −11.3 | −16.4 to 17.8 |
| 1851–81 | Decline | 2,486 | −33.6 | −37.3 | −44.8 to −21.4 |
| 1861–91 | Growth | 907 | 159.8 | 98.9 | 34.6 to 509.0 |
| 1861–91 | Stable | 1,572 | −1.4 | −2.1 | −19.6 to 19.1 |
| 1861–91 | Decline | 1,909 | −41.6 | −40.9 | −57.7 to −27.0 |

Notes: Table summarizes the percentage change in county bootmaking employment underlying the Growth, Stable, and Decline classification used in the main specification. Categories use the baseline ±20% cutoff. Sons reports the number of sons in mixed-occupation bootmaker-father households in each category.

## Appendix M.3 Occupational Composition of Bootmaker Sons

The occupational content of following the paternal trade differed sharply across local trajectories. Table M7 reports the composition of bootmaking employment among bootmaker sons in the main Growth and Decline samples, separating the older artisanal occupations from the new, more specialized occupations associated with mechanized production.

Table M7: Occupational Composition of Bootmaker Sons, by County Type

| | 1851–1881 panel | | 1861–1891 panel | |
|---|---|---|---|---|
| | Growth | Decline | Growth | Decline |
| Artisanal | 67.4 | 92.8 | 47.4 | 85.6 |
| Mechanized | 31.7 | 6.2 | 50.4 | 12.3 |
| Unclassified | 1.0 | 1.0 | 2.2 | 2.1 |
| Bootmaker sons | 417 | 1,153 | 458 | 859 |

*Notes*: Entries in the first three rows report the percentage of bootmaker sons entering each type of bootmaking occupation. The sample is restricted to bootmaker sons in mixed-occupation bootmaker-father households in the main Growth and Decline samples. Growth and Decline counties are defined using the baseline $\pm 20\%$ cutoff. Artisanal and mechanized occupations use the task-level classification described in Section 2.1.

In the 1851-1881 panel, 31.7 percent of bootmaker sons in Growth counties entered mechanized occupations, compared with only 6.2 percent in Decline counties. By 1861-1891, the corresponding shares were 50.4 and 12.3 percent.

The descriptive split shows that occupational inheritance itself was being transformed by mechanization. In Decline counties, following a father into bootmaking continued to mean entering the old artisanal trade: 92.8 percent of bootmaker sons entered artisanal occupations in the first window, and 85.6 percent in the second. In Growth counties occupational inheritance increasingly brought sons into the new mechanized branch of the industry. The mechanized share rose from 31.7 percent in 1851–1881 to 50.4 percent in 1861-1891. By the second window, following a father into bootmaking in a Growth county was about as likely to mean entering mechanized as artisanal work. The family design therefore compares the consequences of inheriting the same paternal industry under different technological regimes: one in which the industry successfully reorganized around the new technology, and one in which sons continued overwhelmingly to enter a contracting artisanal trade.

# Appendix N Job Creation

## Appendix N.1 County-Level Entry into Mechanized Bootmaking

The expansion of mechanized bootmaking entry is universal. All forty-two English counties record an increase in male mechanized entry. Outside Northamptonshire and Leicestershire, however, absolute levels remain modest: only Norfolk exceeds one percent in Panel 2.

Table N1: Change in male entry rate into mechanized bootmaking, by county, 1851–1861 to 1861–1881

| County | P1 (%) | P2 (%) | Δ pp | Δ % | County | P1 (%) | P2 (%) | Δ pp | Δ % |
|---|---|---|---|---|---|---|---|---|---|
| Leicestershire | 0.312 | 7.182 | +6.870 | +2,199.7 | Staffordshire | 0.144 | 0.762 | +0.618 | +429.9 |
| Bedfordshire | 0.023 | 0.509 | +0.487 | +2,163.7 | Sussex | 0.037 | 0.175 | +0.138 | +377.1 |
| Buckinghamshire | 0.043 | 0.769 | +0.725 | +1,676.9 | Shropshire | 0.045 | 0.205 | +0.160 | +352.6 |
| Nottinghamshire | 0.030 | 0.501 | +0.470 | +1,552.1 | Suffolk | 0.067 | 0.281 | +0.214 | +319.6 |
| Warwickshire | 0.027 | 0.427 | +0.400 | +1,476.8 | Lancashire | 0.036 | 0.150 | +0.114 | +318.7 |
| Norfolk | 0.089 | 1.135 | +1.046 | +1,176.1 | Middlesex | 0.056 | 0.230 | +0.175 | +314.7 |
| Gloucestershire | 0.063 | 0.751 | +0.688 | +1,089.1 | Yorkshire North Riding | 0.061 | 0.251 | +0.190 | +310.6 |
| Devon | 0.019 | 0.227 | +0.208 | +1,086.2 | Hertfordshire | 0.036 | 0.109 | +0.073 | +205.3 |
| Yorkshire West Riding | 0.031 | 0.369 | +0.337 | +1,080.4 | London | 0.175 | 0.528 | +0.353 | +201.2 |
| Berkshire | 0.018 | 0.207 | +0.189 | +1,059.6 | Dorset | 0.039 | 0.098 | +0.058 | +148.4 |
| Lincolnshire | 0.016 | 0.181 | +0.164 | +1,015.0 | Kent | 0.055 | 0.122 | +0.067 | +120.0 |
| Cheshire | 0.060 | 0.654 | +0.595 | +997.3 | Yorkshire East Riding | 0.066 | 0.113 | +0.047 | +70.3 |
| Wiltshire | 0.026 | 0.265 | +0.239 | +908.3 | Cornwall | 0.000 | 0.090 | +0.090 | — |
| Northumberland | 0.021 | 0.209 | +0.188 | +877.9 | Cumberland | 0.000 | 0.136 | +0.136 | — |
| Cambridgeshire | 0.020 | 0.197 | +0.177 | +869.6 | Durham | 0.000 | 0.128 | +0.128 | — |
| Worcestershire | 0.036 | 0.348 | +0.311 | +854.4 | Hampshire | 0.000 | 0.146 | +0.146 | — |
| Essex | 0.021 | 0.192 | +0.171 | +800.7 | Herefordshire | 0.000 | 0.037 | +0.037 | — |
| Northamptonshire | 1.303 | 10.090 | +8.787 | +674.2 | Huntingdonshire | 0.000 | 0.507 | +0.507 | — |
| Somerset | 0.050 | 0.385 | +0.335 | +672.8 | Oxfordshire | 0.000 | 0.222 | +0.222 | — |
| Surrey | 0.020 | 0.137 | +0.117 | +597.3 | Rutland | 0.000 | 0.340 | +0.340 | — |
| Derbyshire | 0.043 | 0.256 | +0.213 | +491.0 | Westmorland | 0.000 | 0.802 | +0.802 | — |

*Notes.* Each cell reports the share of all linked young men aged 10–18 at baseline observed in mechanized bootmaking at endline. P1 denotes Panel 1 (1851–1861) and P2 denotes Panel 2 (1861–1881). Δ pp is the absolute change in the entry rate (Panel 2 minus Panel 1, in percentage points); Δ % is the relative change as a percentage of the Panel 1 rate. Counties with a positive Panel 1 rate are sorted by Δ %, largest gain first. Counties with no mechanized entry in Panel 1 follow alphabetically. For these counties the relative change is undefined and is reported as a dash.

Northamptonshire and Leicestershire dominate the absolute expansion. By Panel 2, mechanized bootmaking absorbs 10.1 percent of young Northamptonshire men and 7.2 percent of young Leicestershire men. In Northamptonshire the absolute mechanized expansion ($+8.8$pp) offsets a large share of the contemporaneous artisanal collapse ($-11.2$pp), leaving total bootmaking entry lower by approximately $2.4$ percentage points. The next cohort of young men therefore shifted strongly toward a different form of bootmaking, but the factory expansion did not fully replace the decline in artisanal entry. The exception to this is in Leicestershire, where the mechanized expansion ($+6.9$pp) substantially exceeds the artisanal loss ($-1.9$pp), producing a net increase in male bootmaking entry of approximately $5.0$ percentage points.

For most of England, the mechanized expansion is too small to offset the artisanal collapse. Only two counties record a net increase in male bootmaking entry across the period: Leicestershire ($+5.0$pp) and Gloucestershire ($+0.5$pp). The remaining forty counties record net declines. The factory model therefore provided a substantial local offset in a small number of counties, but did not generally substitute for the contraction of artisanal entry across England.

Table N2: Change in female entry rate into mechanized bootmaking, by county, 1851–1861 to 1861–1881

| County | P1 (%) | P2 (%) | Δ pp | Δ % | County | P1 (%) | P2 (%) | Δ pp | Δ % |
|---|---|---|---|---|---|---|---|---|---|
| Northamptonshire | 0.314 | 5.533 | +5.219 | +1,660.7 | Bedfordshire | 0.000 | 0.068 | +0.068 | — |
| Leicestershire | 0.248 | 3.543 | +3.294 | +1,326.7 | Berkshire | 0.000 | 0.072 | +0.072 | — |
| Worcestershire | 0.017 | 0.218 | +0.201 | +1,150.6 | Buckinghamshire | 0.000 | 0.073 | +0.073 | — |
| Gloucestershire | 0.040 | 0.478 | +0.438 | +1,103.4 | Cheshire | 0.000 | 0.230 | +0.230 | — |
| Norfolk | 0.152 | 1.779 | +1.627 | +1,070.7 | Cornwall | 0.000 | 0.280 | +0.280 | — |
| Surrey | 0.026 | 0.289 | +0.263 | +1,008.5 | Cumberland | 0.000 | 0.116 | +0.116 | — |
| Warwickshire | 0.025 | 0.269 | +0.244 | +972.8 | Derbyshire | 0.000 | 0.375 | +0.375 | — |
| Nottinghamshire | 0.026 | 0.207 | +0.180 | +685.3 | Dorset | 0.000 | 0.061 | +0.061 | — |
| Devon | 0.023 | 0.144 | +0.120 | +512.2 | Durham | 0.000 | 0.046 | +0.046 | — |
| Staffordshire | 0.077 | 0.460 | +0.383 | +496.3 | Hampshire | 0.000 | 0.070 | +0.070 | — |
| Wiltshire | 0.017 | 0.100 | +0.082 | +473.0 | Herefordshire | 0.000 | 0.000 | 0.000 | — |
| Yorkshire West Riding | 0.028 | 0.149 | +0.121 | +435.5 | Hertfordshire | 0.000 | 0.054 | +0.054 | — |
| Suffolk | 0.044 | 0.233 | +0.189 | +433.5 | Huntingdonshire | 0.000 | 0.000 | 0.000 | — |
| Oxfordshire | 0.027 | 0.139 | +0.111 | +407.8 | Lincolnshire | 0.000 | 0.127 | +0.127 | — |
| Cambridgeshire | 0.029 | 0.141 | +0.113 | +393.7 | Middlesex | 0.000 | 0.122 | +0.122 | — |
| Kent | 0.010 | 0.046 | +0.036 | +374.5 | Northumberland | 0.000 | 0.056 | +0.056 | — |
| London | 0.084 | 0.362 | +0.277 | +328.9 | Rutland | 0.000 | 0.000 | 0.000 | — |
| Somerset | 0.113 | 0.399 | +0.287 | +254.7 | Shropshire | 0.000 | 0.098 | +0.098 | — |
| Lancashire | 0.017 | 0.056 | +0.039 | +237.5 | Sussex | 0.000 | 0.000 | 0.000 | — |
| Westmorland | 0.129 | 0.329 | +0.200 | +154.5 | Yorkshire East Riding | 0.000 | 0.116 | +0.116 | — |
| Essex | 0.031 | 0.000 | −0.031 | −100.0 | Yorkshire North Riding | 0.000 | 0.048 | +0.048 | — |

*Notes.* Each cell reports the share of all linked young women aged 10–18 at baseline observed in mechanized bootmaking at endline. P1 denotes Panel 1 (1851–1861) and P2 denotes Panel 2 (1861–1881). Δ pp is the absolute change in the entry rate (Panel 2 minus Panel 1, in percentage points); Δ % is the relative change as a percentage of the Panel 1 rate. Counties with a positive Panel 1 rate are sorted by Δ %, largest gain first; the Panel 1-zero counties are ordered alphabetically in the right-hand block. Twenty-one counties register no female mechanized entry in Panel 1, so their relative changes are undefined and reported as a dash. Seventeen of these counties record positive mechanized entry by Panel 2, while Herefordshire, Huntingdonshire, Rutland, and Sussex remain at zero. Essex is the only county in which female mechanized entry falls.

The expansion of female mechanized bootmaking entry is more geographically concentrated than the male expansion. Northamptonshire and Leicestershire dominate the absolute expansion. By Panel 2, mechanized bootmaking absorbs 5.5 percent of young Northamptonshire women and 3.5 percent of young Leicestershire women. Norfolk is a distant third at 1.8 percent. In Northamptonshire, the absolute mechanized expansion ($+5.2$pp) almost exactly matches the artisanal collapse ($-5.2$pp), leaving total female bootmaking entry approximately unchanged. This is not incumbent reallocation: the new mechanized jobs were instead taken by young women entering the trade. In Leicestershire, by contrast, the mechanized expansion ($+3.3$pp) greatly exceeds the artisanal loss ($-0.6$pp), producing a net increase in female bootmaking entry of approximately $2.7$ percentage points.

Leicestershire and Derbyshire record clear net increases in female bootmaking entry across the period. In the remainder of England, the expansion of mechanized entry is insufficient to offset the contraction of artisanal entry. As with men, the factory model therefore generated substantial reallocation of entry within the trade in a small number of centres, but was generally only a partial offset to the decline of artisanal bootmaking.

# Appendix O Persistence and the Geography of Wealth

## Appendix O.1 Bespoke Demand and Parish Wealth

I show below that artisanal bootmakers, producing bespoke goods, were over-represented in wealthy parishes in England. In the early 19th century, demand for new boots and shoes primarily came from wealthier individuals, with working-class people often buying second-hand shoes. I hypothesize that demand for bespoke shoes persisted in wealthier areas, and in doing so sustained demand for the older forms of skilled labour specialized in bespoke boots and shoes. To assess this, I regress bootmakers per 10,000 workers on a proxy for parish wealth. I estimate this separately for bespoke bootmakers and, in 1881, for bootmakers working in the new "ready-to-wear" tasks. Wealth is measured by the share of workers in each parish employed in occupations in the top decile of occupational status, which I call top human capital share. I control for workforce size and a measure of urbanisation at the parish level.

$$\text{BootmakerDensity}_i = \beta_0 + \beta_1(\text{Wealth}_i) + \beta_2(\text{WorkforceSize}_i) + \beta_3(\text{Urban}_i) + \epsilon_i \quad (13)$$

The results in Table O1 show a positive correlation between the location of bespoke bootmakers and parish wealth in 1851 and 1861, prior to mechanization. In this period, bootmakers were producing bespoke footwear. By 1881 the pattern had changed: the positive correlation persists for bootmakers working in the old types of bootmaking tasks, although at a smaller magnitude, while it reverses sign for bootmakers working in the new "ready-to-wear" tasks.

There is some research which discusses the demand side of markets during the British Industrialization. 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, finds 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.

Table O1: Bespoke bootmakers and parish wealth

| | *Dependent variable: Bootmakers per 10,000* | | | |
|---|---|---|---|---|
| | Bespoke 1851 (1) | Bespoke 1861 (2) | Bespoke 1881 (3) | Ready-to-wear 1881 (4) |
| Share TopHC | 4.047*** | 4.211*** | 2.034*** | -0.698** |
| | (0.426) | (0.497) | (0.281) | (0.284) |
| Workforce size | 0.009*** | 0.006*** | 0.001** | 0.0002 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | 236.287*** | 242.216*** | 100.703*** | 92.467*** |
| | (10.545) | (11.688) | (6.216) | (6.275) |
| Controls (urban/rural indicators) | Yes | Yes | Yes | Yes |
| Observations | 14,317 | 14,488 | 13,933 | 13,933 |
| $R^2$ | 0.037 | 0.031 | 0.011 | 0.023 |

*Notes:* This table reports OLS estimates from parish-level regressions in which the dependent variable is bootmakers per 10,000. Specifications are estimated separately by census year and bootmaker type: bespoke (artisanal) bootmakers and, in 1881, bootmakers employed in ready-to-wear (mechanized) tasks. Share TopHC is measured in percentage points. Controls include workforce size and urban/rural indicators. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

## Appendix O.2 Why Male and Female Incumbents Diverged

Male and female incumbent bootmakers experienced notably different magnitudes of labour displacement as the English bootmaking industry mechanized. The divergence may be explained by differences in changes in the demand for their labour. The majority of women working in the English bootmaking industry - 95 percent - worked as binders, sewing together the uppers of shoes and boots by hand. The sewing machine comprehensively replaced this work, resulting in demand for it disappearing almost entirely. The labour-market results illustrate that this took place on both margins: roughly nine in ten incumbent female bootmakers left the trade over the post-mechanization window: fourteen percentage points beyond the already-high occupational exit rates of women generally. Meanwhile, female entry into the trade fell by 87 percent. Male bootmakers, however, worked to a different market. They were skilled craftsmen producing bespoke, high-quality footwear, and while mechanization shifted production toward cheaper ready-to-wear goods, demand for bespoke work did not immediately vanish.

# Appendix P Advertisements

This data is based on a small dataset of approximately 100 advertisements, from London papers running between 1855–1885, digitized by the British Newspaper Archives project. Each advertisement provides information on the cost of training on the bootmaking and regular sewing machine. The adverts first emerged in 1860. Figures shown in the tables communicate average prices for each five year period. Prices for the training declined over the twenty year period, and then the adverts disappeared entirely. In all periods tuition on the use of the heavier "bootmaking" sewing machine was more costly. See Table P1, below.

Table P1: Cost of Lessons, in London, to Learn the Sewing Machine

| Year | Price for Lessons |
|---|---|
| 1860–1864 | 6s for the sewing machine, 10s 6d for bootwork |
| 1865–1869 | 5.6s for the sewing machine, 10s 4d for bootwork |
| 1870–1874 | 3.1s for the sewing machine, 8s 7d for bootwork |
| 1875–1879 | 2.3s for the sewing machine |

Note: Data from British Newspaper Archives project.

Taken together, the advertisements provide indirect evidence of a wage premium for machine skills in the early years of adoption. Workers were willing to pay for tuition, which implies they expected the skill to pay for itself. The premium appears to have eroded quickly. The price charged for training fell in every five-year period, and by the end of the 1870s the adverts had disappeared altogether.