The Breakdown of the English Society of Orders: The role of the Industrial Revolution*

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Abstract

We study the role of the English Industrial Revolution in promoting social mobility and ending the society of orders: one based on rigid social categories and regulated by inherited characteristics. We combine two new datasets on individual wealth holdings before and after the Industrial Revolution. Our main finding is that noble and gentry titles as well as surnames explain significantly less of the variation in wealth after the Industrial Revolution. Moreover, these declines are substantially larger in the parts of England most impacted by the Revolution. We also explore the extent to which different characteristics predict being rich. We then study a key facet of this increased social mobility - geographical mobility. We show that people with last names that were more mobile tended to be in the north and working in manufacturing. Moreover, areas that experienced greater outward mobility were those that were; more urbanized; less agrarian; had institutionalized markets; initially more gentry; raised fewer taxes; and were more likely to be the residence of a member of parliament.

Keywords: Social Mobility, Wealth Inequality, English Industrial Revolution.

JEL classification: D31, J60, N63.

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1 Introduction

Modern analyses of social mobility examine how factors like parental income and education, market opportunities and individual preferences interact to create different outcomes (Chetty et al., 2014; Chetty and Hendren, 2018a). Scholarly analysis and policy has also focused on how the character of peers and neighbors, the quantity and quality of public services, social capital and inequality, shape neighborhoods and the potential for mobility.

But there is nothing inevitable about this setting or the ideological and institutional frameworks within which it is nested. Prior to the modern era the dominant models of society were quite different - featuring divinely ordered allocations of people into different parts of a hierarchy. In the feudal Middle Ages, this was often composed of the "three orders": those who work, pray and fight (Duby, 1980). Those who worked were divided into different occupational statuses, indicated by their names - a Smith was a blacksmith, a Miller ground wheat, a Baker turned it into bread, a Cooper forged barrels. Their sons did the same. More broadly, a person's surname, even if not stipulating a specific occupation, was likely predictive of their status which was inherited from their parents. The English fifteenth century judge and political theorist Sir John Fortescue summed up this model of social mobility by stating "A serf can beget in matrimony none but a serf" (Fortescue, 1997, p.60). Later the orders took on more elaborate guises, most famously the "great chain of being" which began with God at the top and worked its way down via the angels to the king, the aristocracy and eventually all the way to the common people above the devil (Tillyard, 1943; Lovejoy, 2009; Laslett, 2000). The dominant theme was that people had been placed by God in their particular station within this chain and should be content with their position. As the Emperor Charlemagne put it "Let everyone serve God faithfully in that order in which he is placed" (quoted by Herlihy (1973, p.623)). As late as 1793, an English commentator remarked that the rich should be in positions of leadership because "This is the order of nature, the decree of God" (quoted by Eastwood (1994, p. 16)). Though the recent literature has studied some types of ascriptive characteristics, such as gender and race, the historical situation was qualitatively very different.

Throughout the Middle Ages, the great chain didn't just represent the ideal social structure. It captured the empirical situation as well, at least in England. Though there were movements and upward mobility could stem from agriculture, trade or holding state or church offices "for the vast majority of people social immobility remained the norm" (Maddern, 2006, p.133). Yet at some point in the early modern or modern periods, this society of orders largely broke down in England. There is little agreement on when this happened or why. In 1577 William Harrison explained that "We in England divide our people commonly into four sorts" (Harrison, 1994, p.). In 1583 Sir Thomas Smith did the same dividing the English population

into; "nobility, or aristocracy proper"; "Gentlemen" divided into Knights, Esquires and gentlemen; "Citizens, Burgesses and Yeomen"; and finally "The fourth sort of men which do not rule" (Smith, 2013, p.66). The 1600 outline of English society by Wilson (1936, p.94) suggested that "the hierarchy of status corresponded roughly with the pyramid of incomes" (Stone, 1966, p.21). Gregory King's famous "social table" of 1688 was based on a hierarchy of "Ranks, Degrees, Titles and Qualifications" (Laslett, 2000, pp.36-37) and "King followed the gradations of gentility from the peerage down ... much as Harrison and Wilson had done" (Wrightson, 1984, p.21). As late as 1701, in his history of his village Myddle, Richard Gough sketched a map of the distribution of pews in his church, a diagram which mapped the social hierarchy of the village onto proximity to the pulpit and religious authority (Gough, 1981, pp.82-83).

In this paper we bring together two new unique datasets to document the importance of the society of orders and the extent to which it broke down in the modern period. We particularly focus on investigating whether this breakdown was higher in parts of England that were more impacted by the Industrial Revolution. Our first dataset consists of all probate records which we digitized over the period 1862 to 1899. The data records estimated gross values of "unsettled personalty" and were collected to handle the possessions of deceased persons who held at least 5 pounds of wealth at death (about 700 pounds today). We use the full 1861 census returns to reconstruct the identity of those who were not probated. Thus we have an approximation of the entire wealth distribution, with people's names, their titles and location.[1] We compare this dataset to a pre-Industrial Revolution proxy for wealth, which we digitize from the hearth tax returns between 1662 and 1674. This tax was proportional to the number of hearths (fireplaces) a household had. We have existing returns for 26 out of 39 historic counties and 343,022 heads of households, which corresponds to close to 100% of the population in the regions we have data for. The returns state not just how many hearths each of these people had but also list the people who were poor and thus not taxed. Additionally, we again know people's names, their titles, and their location by parish.

We measure the nature of the society of orders in a number of ways. In particular, our data enables us to examine many social categories and characteristics of individuals which were potentially relevant features of their occupations and wealth under the society of orders, but not under an ideal modern market economy. These fall into several categories. First, and most significantly, we know whether a person was a noble, or a member of the 'gentry'. The English nobility and gentry were to some extent flexible categories because noble lines died out and titles were given to others, and there was entry into the gentry (Tawney, 1941). Nevertheless, there were strict social norms and conventions which governed the acquisition of these

[1]Probate inventories also exist for the 17th century. However, not in digitized format with sufficient coverage. While Keibek (2017) provides data of the occupational structure for all parishes in England, which was derived from he 17th century probate inventories, his dataset completely lacks individual level information (e.g., names, wealth etc.).

statuses.[2] [3]

Second, we classify people according to their surnames since this is the most obvious characteristic at which status and wealth may persist. The fact that historically so many surnames were connected with specific occupations or ascriptive features (see Dolan, 1972), such as the archaic geographical location of a family, suggests that it is interesting to simply examine a model where we examine the extent to which the variation in wealth is associated with the full vector of individual last names.

Our hypothesis is that the explanatory power of these variables for wealth should be higher before the Industrial Revolution and in particular it should fall more in parts of England more impacted by the Industrial Revolution. We interpret this falling explanatory power as being consistent with increased social mobility (Güell et al., 2015). Empirically, we examine firstly the proportion of the variation in the distribution of wealth which these characteristics explain in 1662-74 and in the second half of the 19th century (henceforth 17th and 19th centuries). Secondly, we investigate the extent to which the attributes predict whether or not a person will be "rich" - in the top decile of the wealth distribution.

We initially study the division of the population between nobles, gentry, and commoners.[4] We find that before the Industrial Revolution being a member of the nobility or gentry explains 17% of the variation in the share of wealth individuals owned, afterwards it explains only 6%, a fall of 2/3. The probability that a noble is rich is 89%-age points higher than for a commoner, prior to the Industrial Revolution. After the size of this effect falls slightly to 88%-age points. The probability that a member of the gentry is rich increases significantly however from 67%-age points to 83%-age points. We interpret the large rise of the coefficient on the gentry as reflecting the flexibility of the upper echelons of the society of orders. As the economy grew new entrants were naturally wealthier than incumbents who were less able to take advantage of the new economic opportunities.[5] Nevertheless, the large fall in the share of the variation explained shows that this flexibility was insufficient to stop the rise of a broader social mobility.[6] The society of orders was sufficiently inflexible to maintain its relative position in the wealth distribution although it remained

[2]With respect to nobility, Cannon, for example, estimates that only 10% of new nobles in the entire eighteenth century did not have direct relationships with pre-existing nobility (Cannon, 1984, p.26). The situation in the nineteenth century is similar: "Only after 1880 did titles and seats in the House of Lords begin to be conferred in substantial numbers upon low born ... and landless manufacturers" (Stone and Stone, 1984, p.207) and see Pumphrey (1959) and McCahill and Wasson (2003) for the data.

[3]The Stones summarize the situation as follows "No amount of land purchase, no amount of house building would confer social respectability upon a man whose wealth was obtained in sordid ways, whose origins were obscure, whose manners and accent were demonstrably vulgar, and whose religion might well be nonconformist" (Stone and Stone, 1984, p.207). For the period after 1880 see Cannadine (1990).

[4]We use the term nobility when we refer to individuals with a peerage rank (duke, marquess, earl, viscount, baron), and we use the term gentry when we refer to lower nobility that does not form part of the peerages.

[5]See Beckett (1986, pp.206-237) on the involvement of the nobility in the Industrial Revolution. Crouzet (1985, pp.148-150) finds that only 9% of his sample of British industrial innovators had noble or gentry parents and only 2.5%, 8 out of 316, where noble or gentry themselves.

[6]A telling example is the grant of knighthoods. The social background of 70% of those who held knighthoods in 1882 can be traced and only 18 had fathers who were in business or trade (Thompson, 1977, pp.39-41).

true that someone with a noble title was almost certain to be rich.[7]

We then use data on employment in manufacturing to break sample into that part of England impacted by the Industrial Revolution and that part not impacted, and repeat the previous exercises. The focus here is on whether the falls we discovered in the explanatory power of the elite characteristics between the 17th and 19th centuries occur more in the parts of England that were more impacted by the Industrial Revolution. This is broadly what we find. Looking at the explanatory power of the nobility and gentry we find the proportion of the variation falls relatively more in the parts of England more impacted by the Industrial Revolution. Moreover, the estimated probabilities that these characteristics are associated with being rich fall more in the Industrial Revolution areas. For instance, the probability that a member of the nobility is rich is 87%-age points higher than that of a commoner in regions impacted by the Industrial Revolution after it happened compared to 97%-age points before. In non-industrial revolution areas there is little change in the explanatory power of nobility.

Are our results consistent with the Industrial Revolution being associated with a "breakdown" in the society of orders? The crucial factor is whether or not 17%, the proportion of variation explained by nobility and gentry before the Industrial Revolution, is large or small. To get some sense of this consider the following exercise inspired by Thomas Wilson's comment cited above that in Elizabethan society "the hierarchy of status corresponded roughly with the pyramid of incomes": take all the 591 nobles in the probate-census sample and relabel them as the richest 591 people. Then take the 25,320 gentry and re-label them as then next richest people. In Table 6 we do this exercise and construct what we call the Maximal R^2. We find this to be 41%. Hence, if the society of orders perfectly matched the wealth distribution this would explain 41% of the variation in wealth. Looked at from this perspective the society of orders was still significantly reflected in the hearth tax returns since our estimated R^2 is 41% of the maximum it could have attained.[8] Doing the same exercise for after the Industrial Revolution we see from Table 6 that our estimated R^2 is less than 10% of the Maximal R^2. A fall of 75%! This does seem to justify the use of the word breakdown.[9] Moreover, Table 6 shows that the difference between the Maximal R^2 and our estimated R^2 falls more in the areas most impacted by the Industrial Revolution.

[7]See Trainor (1990) and Thompson (1994) for overviews of the case study literature on the incorporation of industrial elites into the nobility and gentry. Recent analysis of the probate returns also documents descriptively this persistence of the wealth of the nobility (Bond and Morton, 2022).

[8]That it is not 100% is due to the fact that there were distinct mechanisms of social mobility in the early modern, pre-industrial period. These include such phenomena as the "rise of the gentry" (Tawney, 1941; Heldring et al., 2021); the emergence of the "middling sort" (Muldrew, 2017); the impact of financial innovation (Jha, 2015); and the decline of the aristocracy (Stone, 1967).

[9]The society of orders broke down in other domains. For example, politically the House of Commons came to dominate the House of Lords in the 18th century and particularly after the 1832 Reform Act which passed the Lords after the Prime Minister threatened to make King William IV create enough new lords to pass the measure. This Act was specifically about the enfranchisement of the new industrial cities like Birmingham, Liverpool and Manchester and led to a severe weakening of the political power of the Lords.

The key challenge to our preferred interpretation of our results is measurement error. Our pre- and post-Industrial Revolution proxies for wealth are different, and a drop in the goodness-of-fit may reflect differential measurement error. In Section 4 we develop the econometric theory of measurement error to enable comparisons between datasets, under the assumption that there is no difference in social mobility between our surveys. We find that our post- data would have to be significantly more attenuated than our pre- data to explain our results. In the probate returns, a detailed individual investigation at death into several catgories of wealth yielded a more precise approximation of total wealth, than a counting of hearths. We therefore conclude that while there may be significant measurement error in either survey, in issue we address in robustness checks, our between-survey comparisons are unlikely to be driven by measurement error.

Turning to the analysis of surnames we find that simply using last names explains 9% of the variation in wealth before the Industrial Revolution, which falls to 6% afterwards. Moreover, this decline is much larger in the parts of England most influenced by the Industrial Revolution where the fall is from 11% before to 2% afterwards.

To better understand the role of surnames we group in a number of ways. The Oxford Dictionary of Family Names in Britain and Ireland divides these into several types: locative, relationship, occupational and nickname (Hanks et al., 2016). A locative name refers to a geographical location or origin, e.g.: North, Chapell, Holland. These often had specifically elite status (Clark, 2014, p.76; Mckinley, 2015). A relationship based name takes its origin from a relationship to another person, e.g.: Peterson, Hilson. An occupational name relates to an occupation of the sort we mentioned above, other examples being Carpenter or Cook. A nickname based name is just that and refers to such things as a physical trait or type of behavior, e.g. Brown, Strange, Sharpe. We can also look at the origin or ethnicity suggested by the surnames. For example, we can distinguish those with Norman French names whose ancestors mostly came over with William the Conqueror in 1066 and formed the basis of the subsequent elite; other French names (mostly Huguenots); and Irish, Scottish and Welsh names all of whom were important minorities. Disaggregating surnames into occupational, locative, relational or nickname types we find we find little explanatory power for these categories either before or after the Industrial Revolution. This is also true when we examine surnames based on ethnicity or origin.

With these latter explanatory variables we also investigate the extent to which they explain whether a person is wealthy. There are quite a few interesting findings here. For example, we find that people with occupational last names are less likely to be wealthy both before and after the Industrial Revolution, but this effect vanishes in the areas most impacted by the Revolution. Having a French last name increases the probability of being wealthy before the Industrial Revolution by 47%-age points relative to English origin

last names in the Industrial Revolution areas, an effect which disappears by the 19th century. Finally, while having an Irish last name hardly influences the probability of being wealthy before the Industrial Revolution it is negatively correlated with this afterwards and the effect is quantitatively larger in the regions most influenced by the Revolution.

Though our results cannot be interpreted as causal, they are consistent with the idea that the Industrial Revolution directly increased opportunities and social mobility. That this is so is the theme of Griffin (2013) who uses working class autobiographies to illustrate how industrialization created new opportunities for working and poor people. She emphasizes

> "the throwing open of opportunities for those at the bottom of the social pile. Industrial growth provided the laboring poor with a degree of personal freedom that the poor in the eighteenth century and before had rarely enjoyed" (p.19).

Her even stronger conclusion is that "the Industrial Revolution heralded the advent not of a yet 'darker period', but of the dawn of liberty" (p.20).

Griffin (2013) emphasizes the impact of the Industrial Revolution on geographic mobility as people moved physically, particularly to new sources of employment in factories, towns and mines. To investigate this we build a measure of the extent to which different surnames were "mobile", in particular by measuring the change in dispersion of wealth *within* a family name. An individual surname is "mobile" if it is above the median level of dispersion. A parish is mobile, captured by an indicator variable, if it has above median fraction of people that belong to (future) mobile surnames. We then ask two sorts of questions. First, where did people with mobile surnames tend to end up geographically and what economic sectors did they tend to work in? Second, what were the characteristics of mobile parishes? In particular, what factors seem to be associated with greater outward movement of individuals?

For individuals we find that people with more mobile surnames were more likely to be in the north in the 1861 census and more likely to be working in manufacturing. We interpret this as consistent with Griffin (2013)'s arguments. The increased social mobility we document was related to geographical and economic (sectoral) mobility.

At the parish level we find that parishes which experienced more out-mobility tended to be urban, had an institutionalized market in 1600, were less agrarian with people more concentrated in the secondary sector. We find that initial social structure was important, with mobility being associated with having more gentry and fewer yeoman, a class of wealthier landowning peasants, in 1700. We also find that political characteristics are significant: parishes where a member of Parliament lived are more likely to be mobile. We do not find that parishes that were less feudal, as measured by Heldring et al. (2021) and had enclosed

lands via a parliamentary act and therefore modernized and rationalized property rights, though often at the expense of small landowners (Heldring et al., 2022), were more likely to be mobile.

Our work relates to several important areas of social science. Most research on social mobility has placed it in the context of modern market economies and has tried to estimate various types of transition probabilities between different income bins or social classes (see Jäntti and Jenkins (2015) for a comprehensive overview). Our conceptualization of social mobility is closer to that developed in the literature on equality of opportunity (Niehues and Peichl, 2014; Ferreira and Gignoux, 2015; Hufe et al., 2017). Here, incomes are regressed on a set of characteristics for which people are not held morally "responsible" - such as parental income or factors that influence childhood experience. The coefficients from this regression are then used to calculate the level of income for a person that these characteristics predict. Divergences between this predicted income and actual income is used to construct a measure of equality of opportunity - to what extent has a person been able to overcome the shadow of their characteristics?

What historical research there is for England along traditional social mobility lines comes from the second half of the nineteenth century, after our period of study. Long (2013) and Long and Ferrie (2013) interpret their evidence as being consistent with quite high rates of social mobility, though this finding is disputed by Miles (1993, 1999) and Mitch (1993) who paint a picture of much more stable social classes. None of these studies are able to examine the issues which are our focus, since there is consensus that by their study period the society of orders barely existed and the data for these studies comes from a period after the Industrial Revolution had taken place.

More recently, Clark and Cummins and their collaborators have used the history of surnames as a way of examining historical patterns of social mobility. In particular, they are interested in the extent of elite persistence. They measure this in various ways, typically the extent to which certain surnames are over-represented relative to the population in various institutions, such as Oxford and Cambridge university admissions. They find high levels of elite over-representation which though gradually declining is persistent. Moreover, looking at the time series, Clark interprets his evidence as showing that social mobility rates "were the same before the Industrial Revolution as after" (Clark, 2014, p.14). See Clark and Cummins (2014) for a further development of the argument. We would interpret our findings as showing that the focus on unusual surnames which are over-represented amongst elites does not inform one about the general pattern of social mobility.

The English probate records have also been intensively studied by Cummins who has used them to document the large falls in wealth inequality in the 20th century (Cummins, 2021). Related to our own findings, he has also documented the place of different ethnicities in the wealth distribution (Cummins, 2024) in the 19th century and in particular studied the relative poverty of the Irish (Cummins and Ó Gráda,

2025). None of this work focuses on our main questions or uses a similar econometric approach though Cummins and Ó Gráda (2025) does find that the poverty of the Irish was driven by the North of England, consistent with our results.

Our findings also relate to recent work by Chetty et al. (2014) and Chetty and Hendren (2018a,b) which has examined not just the extent of mobility using new sources of information, but also the contexts that facilitate mobility.[10] Though we are not able to measure quite a few of the things of interest in this research, such as educational inputs and outputs, crime or inequality, many of the variables do have analogues in our sample. In particular Chetty et al. (2014) finds higher rates of social mobility associated with greater tax rates, more manufacturing industry and higher levels of social capital. These are partially consistent with our results. Though we cannot measure historical social capital directly, Putnam (1994) argued that variation in social capital in Italy was caused by different feudal legacies, though we do not find evidence for this connection. Our results on urban areas are consistent with Angelucci et al. (2022).

Though there is little research on the impact of the Industrial Revolution on social mobility, a literature has followed Kuznets (1955) and focused on the impact of the Industrial Revolution on income inequality. This has tended to reproduce Kuznets famous curve suggesting that the Industrial Revolution increased income inequality (see Lindert and Williamson, 1982; Williamson, 1985; Van Zanden, 1995), a finding largely consonant with the recent emphasis of Piketty (2014).[11]

Much less research has been done on wealth inequality. Atkinson and Harrison (1978) was a seminal study using probate records from the twentieth century (see also Harbury and Hitchins (1979)). More recently, Lindert (1986) combined various sources, including pre-Industrial Revolution probate returns to examine the evolution of aggregate measures of wealth inequality in England after 1670. He finds the period of the Industrial Revolution was associated with increased wealth inequality, consistent with (Piketty, 2014, p.344) and the imputations of Piketty and Zucman (2014) and Madsen (2019) (see also the evidence in Roine and Waldenström, 2015). A wide ranging recent survey concludes that "the evidence available for all European areas supports the "stylized fact" that inequality, of both income and wealth, tended to grow from the late Middle Ages to the end of the early modern period" (Alfani, 2021, p.14) (see Waldenström (2024) for a related overview).[12]

Our research design is very different. Since we cannot compare the levels of inequality (for example via Gini coefficients) between our two datasets, our findings are consistent with the increases in wealth

[10] See also Jencks and Mayer (1990), Sampson et al. (2002) and Sampson (2012) for overviews of the related sociological literature on "neighborhood effects".

[11] Other related work has instead focused on the standard of living, mostly real wages, see Allen (2009) for an overview of this literature, but also stature and health.

[12] The higher frequency dynamics are of course much more contentions. Recent estimates by Piketty, for example, suggest more or less constant wealth inequality in the United Kingdom between 1780 and 1900 (Piketty, 2020, 195) and see the discussion in Madsen (2019).

inequality this research identifies. Nevertheless, our results suggest that such increases may have gone along with greater social mobility and new opportunities for people which were less limited by their rank, degree, title or surname.

The paper proceeds as follows: in Section 2 we discuss the new data sources we use in the paper particularly the hearth tax and probate records and the issues involved in using them. Section 3 we lay out our empirical approach to social mobility using rigid categories and ascriptive characteristics. In Section 4 we discuss the econometric issues connected with our empirical strategy in particular establishing that differential measurement error in our data, the most salient concern, is highly unlikely to be creating bias in our results. Section 5 then examines the extent to which the categories and characteristics we measure explain variation in wealth holdings and the probability of being rich before and after the Industrial Revolution and we present a benchmark which justifies our use of the word "breakdown". Section 6 presents some case studies of the nobility and mill owners. In Section 7 we split the sample between areas which were more or less directly impacted by the Industrial Revolution and show how our findings are more stark in industrial areas, consistent with the Industrial Revolution playing an important role in stimulating and facilitating mobility. In Section 9 we then turn to examine the connection between social mobility and geographic and occupational mobility and the correlates of high levels of outward mobility of surnames from a parish. Finally, 10 concludes.

2 Data

For the pre- and post-Industrial Revolution period we create an individual level dataset of wealth, names, social class and location of adult males. We map locations to parishes, small administrative units in England, which are contained in counties. In this section we introduce each dataset, our procedure for digitizing it, our process for assignment of social status, and mapping location information to parishes and counties. In section 2.5 we discuss the coverage of the data and present summary statistics.

2.1 Post-Industrial Revolution records

2.1.1 Principal Probate Registry records and 1861 census

For the post-Industrial Revolution period we use records of the Principal Probate Registry, containing wealth of deceased persons from 1862 to 1899, and link it to the 1861 census of England (Schurer and Higgs, 2015). So-called grants of probates (for deaths with a will) or letters of administration (in case of intestacy) were required to distribute the possessions of deceased persons, if their wealth exceeded a certain

threshold. Up until the 1890s, the threshold was 5 pounds, except for London where it was commonly 10 pounds (Owens et al., 2006). The recorded wealth is the estimated gross value of "unsettled personalty", which essentially refers to all personal wealth except assets subject to legal arrangements such as trusts (which are "settled"), property, shared assets or shared bank accounts, and debts (Rubinstein, 1977b; Owens et al., 2006; Cummins, 2021; Bond and Morton, 2022; Cummins, 2022). Therefore, the recorded wealth includes movable assets, including those held in own businesses, cash, savings on own bank accounts and stocks.

Large parts of the population weren't wealthy enough to pass the 5 pound threshold and thus were not probated. Comparing the probate records to death records for the same years, suggests that 16% of deaths were probated in the considered period.[13] For the remainder of the population we know that their wealth was less than 5 pounds and we draw on the 1861 English census to get information on names, social class, and location of residence. In our main analysis we assume wealth to be zero for unprobated people. In robustness checks we make different assumptions about the distribution of wealth among the unprobated.

While Principal Probate Registry records are available at national level from 1858 until today, this paper uses data from 1862, so that it can be linked to the 1861 census, and up to 1899 because this allows aggregation of deaths of a generation into a cross-section. The "Integrated Census Microdata (I-CeM) Names and Addresses, 1851-1911: Special Licence Access" are available at the UK Data Service (Schurer and Higgs, 2015). We use the 1861 census information on first and last names, parish and county of residence, and age (the latter for linking to the probate only).

2.1.2 Digitization of records

The census data is available in digitized format (Schurer and Higgs, 2015). For probates, scans of all original records from 1858 onward are available and searchable by year and name at https://probatesearch.service.gov.uk/.[14] We scraped probate records by downloading all images for 1858 until today, and using Google Vision to parse the images into boxes with individual probate entries (see Appendix Section VIII.B for an example of a probate entry). We then use Optical Character Recognition to convert each probate entry into a record of an individual. From these entries we could then extract names of deceased, whether they were part of the nobility or gentry, their wealth, the year of death and their addresses using regular expressions. For example, for total wealth, we look for the first pound sign, and extract all characters up to the next white space using regular expressions. We provide a step by step process in Appendix Section III.

We validate our procedure by checking by hand the records of several subgroups. First, we check the

[13] For death records, see Cummins (2021).

[14] https://probatesearch.service.gov.uk/ is managed by Government Digital Services on behalf of the Crown and is part of the Cabinet Office.

richest 100 individuals, the richest 100 members of the gentry and the richest 100 noble individuals. Second, we check the records of *all* 610 noble individuals in the probate records (see below, section 2.3.1, on how we identify these). Third, we can aggregate our dataset of individuals to time-series of measures that have been computed in the economic history literature on this data. We closely line up with their summary statistics. For example, Cummins (2021) finds that 15% of individuals were probated in the early years of the probate registry, compared to 16% for our estimate. The discrepancy likely arises because Cummins (2021) considers a slightly different time-period.

2.1.3 Probate-census linking

We link probate records from 1862 to 1899 to the 1861 census of England. We use these years so that every adult recorded in the census would show up in the probate records if they died with some wealth by 1899.[15] We link the probate and census data in seven steps. Each step progressively eases some secondary characteristics of an individual, such as location, while keeping strict name-matching criteria.

In the first step of the linking procedure, we match people by their first and last name, county, parish and social status (nobility, gentry or commoner). In the second step, we match by the same characteristics, except social status. In step three, we allow for fuzzy matching on first names, while keeping exact matches for the remaining variables plus gender. In steps four and five, we omit parish information and use exact matches on first and last names and county, once with and once without social status. If there are multiple observations in the probate and census with matching characteristics, we link earlier death years in the probate to older people in the census.[16] In steps six and seven, we acknowledge that people may have moved after the 1861 census and match the remaining census and probate observations by names country-wide, once with and once without social status. In this last step we only match individuals if they are unique by names in both datasets so that there is no ambiguity about their county of residence, which is the county when their wealth is measured in the probate data. This is important because of the regional concentration of the Industrial Revolution.[17] Appendix Table V.I shows that most observations are linked through exact matches in steps one and two (33.1% of matched observations) and steps four and five (47.90% of matched observations). Appendix Section V provides further details on the linking procedure.

The final dataset includes 5,190,592 observations after excluding unmatched children from the census

[15] Individuals without wealth who were born after the 1861 census and who died at young adult ages cannot be observed. We do observe wealthy people who die young, irrespective of when they were born. Additionally, we may miss wealthy individuals who were adults in the 1861 census, but died after 1899.

[16] Note that the census information we use in our analysis are the name and county of a person, and only in some auxiliary analyses occupation and parish. Therefore, it does not matter which census observation a probate observation is matched to, if the name and county are the same.

[17] Because our main analysis relies on name and county information, even if we merge an individual from the census to someone with the same name and location in the probate who is not the correct probated individual, we obtain similar results.

data (N=7,244,780), females (N=5,675,610), and observations dropped due to missing values (N=72,558).[18] It includes linked observations (N=764,997), unlinked census observations (those too poor to be probated, N=4,226,812), and those who are probated and unlinked (so as to not lose rich people, N=198,783). This corresponds to a linking rate of probate records of 79.4%.

We therefore have individuals in the census that should have been linked but were not, and their counterparts in the probate dataset. The total linking rate implies that up to 20.6% of unlinked wealthy people have a non-wealth duplicate in our combined dataset. We deal with this issue by introducing an eighth linking step, in which we randomly assign an unmatched probate observation to an unmatched census observation with equal surname and sex, independent of their location across England (see Section 8). This raises the match by 50,367 observations to a rate of 84.6%. Note, however, that we do not expect all probated individuals to be included in the 1861 census because some individuals may have been born after 1861 and died young and wealthy, and others may have moved into the country. Our main dataset contains all probated individuals - linked and unlinked - and all census observations.

2.2 Pre-Industrial Revolution records

2.2.1 The Hearth Tax records

For the pre-Industrial Revolution period we use hearth tax records. The hearth tax was a property tax in England and Wales that was levied twice a year (on Lady Day and Michaelmas) between 1662 and 1689 and charged occupiers proportional to the number of fireplaces or "hearths" they owned. In the first hearth tax collection year of 1662 the tax amounted to 2 shilling a year. Up until 1674, the hearth tax data includes for each township, hamlet or ward, handwritten records of first and last names of the heads of occupying households, their form of address or title, and their number of hearths. In later years names of occupiers were not recorded and, therefore, later years are not used in this paper.[19] The included hearth tax data span the years of 1662 to 1674 and, for each county and parish, we include one data collection date only, e.g., Lady Day 1674.[20]

Hearth tax records survived for most counties, however, not always with full coverage within counties. We combined publicly available records with archival records to create, to our knowledge, the most complete dataset of hearth tax records. Our record collection efforts resulted in a dataset with records from 26 out of 39 historic counties at the time of hearth tax collection. See Appendix Section VIII.B for an example of

[18] We do not know the age at death of individuals recorded in the probate data. They were only probated if they were adults at death. But it could well be that they were not adults yet at the time of the 1861 census.

[19] Names were recorded on local documents but not on the files sent to the Exchequer and centrally archived.

[20] For most counties we have only one data collection date available. For counties with data from multiple dates, we identified the overlap in parishes across years and use the more recent data wave if overlap occurs. Overall, overlap was very small, affecting only 88 parishes.

a hearth tax record.

Hearth tax records have been previously used by historians as a source, for example, for local analysis of economic conditions, literacy or population estimates (Vann, 1974; Arkell, 1982, 1987; Stephens, 1990; Spufford, 2000).[21] We are unaware of any analysis in economics that uses hearth tax data, or any publication at all that combines the hearth tax records from across England to the extent we do.

2.2.2 Digitization of records

The hearth tax data come from five sources: the National Archives of the United Kingdom; county archives; the Hearth Tax Series project by the British Record Society[22], the Roehampton University Centre for Hearth Tax Research[23] and the Hearth Tax Digital by the British Academy and Graz University[24]. All hearth records follow the same format, listing individuals and their number of hearths grouped by place of residence. We digitized the records from 15 historic counties using a digitization company. For counties that we digitized ourselves, we used optical character recognition with manual back-checks. For 11 other counties historic counties we could use records that were already digitized. Appendix Table VI.I lists the sources of the data as well as the methods of digitization for all included records.

2.2.3 Validation: Proxy for wealth

In this section, we try to validate this claim using probate inventories collected between 1518 and 1787 in six English counties.[25] These probate inventories include information on names, location and wealth in movable assets of deceased people for 28,316 individuals. We do not use this data for our main analyses because observations per county-year combination are below 100 (there are two exceptions) and the records available to us do not include counties in the heartland of the Industrial Revolution.[26]

We merge the probate inventory records to the hearth tax records over years, location and names. Of the 1,807 observations in the probate inventories in the eligible year range we can merge 324 observations to the hearth tax data. Figure 1 shows a binned scatter plot (mean probate inventory wealth for each categorical number of hearths) and a linear fitted line of the probate inventory wealth on the number of hearths. The scatter points are closely aligned with the linear fitted line. The correlation between the

[21] There are data projects such as Hearth Tax digital (https://gams.uni-graz.at/context:htx) that continuously digitize more hearth tax data and makes them available to the public. We use some of their data but large parts of our dataset come from own digitization efforts.

[22] See `https://www.britishrecordsociety.org/hearthtax/`.

[23] All hearth tax data originally provided by Roehampton University Centre for Hearth Tax Research was moved to the project Hearth Tax Digital by the British Academy and Graz University (`https://gams.uni-graz.at/context:htx`).

[24] See `https://gams.uni-graz.at/context:htx`.

[25] The counties include Berkshire, Durham, Essex, Kent, Warwickshire and Worcestershire.

[26] Keibek (2017) provides data of the occupational structure for all parishes in England, which was derived from 17th century probate inventories, however, his dataset completely lacks individual level information (e.g., names, wealth etc.).

probate inventory wealth and the number of hearths is 0.24.

2.3 Data processing

2.3.1 Identification of social order status and noble titles

This section describes the identification of nobility and gentry in our records. For the nobility, we performed this process by hand, and extensively validated our work. We describe the process in this section, and Appendix Section VIII provides further details. In Appendix Table VIII.III we provide a full list of the 591 noble titles and individuals extant in the linked probate-census records, with their validation to outside sources, discussed below. In Appendix Table VIII.I we do the same for the 95 noble title and individuals in the hearth tax records. Finally, we discuss titles that were present in our validation sample, but not in our data, in Appendix Table VIII.IV. These are mostly people who passed away before 1861 or held a title not registered in the peerage of the United Kingdom or England. Further, our data include 25,320 members of the gentry in the linked probate-census data and 2,589 members of the gentry in the hearth data.

We code the social orders of *nobility*, *gentry*, and everyone else is referred to as *commoners*, representing the society's social classes at the time. The coding is based on the identification of particular titles for nobles and positions of the gentry, so that we do not only have information about the social order, but also the noble rank or position of the gentry. The noble ranks in the Peerages of England, Great Britain and the United Kingdom back then (until today) include Duke, Marquess, Earl, Viscount and Baron. Positions of the gentry include Baronet, Esquire, Gentleman and Knight. Female noble ranks and members of the gentry existed and were recorded as well, but females were excluded from this analysis.

The probate records reported names, together with their wealth, separately from the remaining information on date of record, date of death, address and so on. When a person was noble or a member of the gentry, the noble title or gentlemanly title was typically recorded with the name, i.e. separately from the rest of the information, and including the form of address, e.g. "The Right Honourable Archibald George Stuart Earl of MORAY" (record: year 1872, p.574) or "DOUGLAS. William Esq" (record: year 1869, p.176). As these examples show, the name of the peerage as well as last names were recorded in capital letters. Appendix section VIII.B provides examples of original records of individuals from all three social orders.

In the 1861 census, nobility titles and gentry designations were rarely recorded. If a noble title was recorded typically the rank was recorded as the first name and the title then specified as the last name, e.g. Baron Clyde was recorded as first name "Baron" and last name "Clyde". As described below all of the

nobility was essentially recorded in the probate data, so that it does not pose a problem when nobles were recorded without their titles, simply by their first and last names, in the 1861 census.

The hearth tax records list names in a dedicated column. For noble individuals, titles were often recorded instead of their names (e.g. "Duke of Buckingham"), which were sometimes accompanied by their form of address (e.g. "the Most Honourable"), and often nobles were referred to as Lord rather their full title (e.g. "The Lord Arlington" for the Earl of Arlington). When names of nobles were not recorded, we added this information to the data after manual online research on the title holder in that year. For members of the gentry their title was typically recorded following the individuals' name in the same column, e.g. "Abraham Langton Esq" for an esquire or "Anthony Kendale gent" for a gentleman.

The identification and cleaning of social order variables included the following main steps. First, we used regular expressions to identify records mentioning the noble ranks of Duke, Marquess, Earl, Viscount and Baron, or the gentlemanly titles of Baronet, Esquire, Gentleman, Knight and Sir. This included spelling variations and abbreviations as, for example, gentlemen or esquire were often recorded as gent or esq. The results of the regular expression were screened and the code adjusted in order for the nobility to capture all potential nobility observations and for the gentry, given that there are so many more than nobles, to maximize true positives while minimizing false positives in subsample validation exercises.

In a second step, all noble titles were manually checked in order not to allow for any margin of error from automated coding. When nobles were only recorded with their titles we added their first and last names manually.

In a third step, we validated the list of noble people from our data against external sources. Our main source of external validation is "Burke's genealogical and heraldic history of peerage, baronetage and knightage 1861" (Burke, 1861), which we supplemented with the wealth of information on the Peerages of England, Great Britain and the United Kingdom on Wikipedia, which is digitized from Cokayne (1898). For nobles in these external lists that we had not identified so far, we conducted more background research on whether we would expect them to show up in our data or not. For example, a noble might have moved out of the country and died there, or a title was abeyant at the time of hearth tax collection or went extinct in the 19th century.

In a fourth step, we searched for noble titles that we would expect to find in our data but haven't so far, typically by searching for the first and last name of the unobserved noble or for the number of hearths if that was known from an external source. When there was a match, e.g., by name, we validate that this is a correct match using available information on wealth and parish. Appendix Section VIII.C lists all noble titles from the external sources and indicates whether we observe the title in our data and if not, the reason for it.

2.3.2 Wealth cleaning

Exemptions to the hearth tax were granted to poor people, if the poor had no more than two hearths, after they had petitioned for exemption. Information on exempted households were recorded in all but three counties—Norfolk, Westmorland and Worcestershire—and only partially recorded in one county—the former hundred Bradford South in Shropshire. The Appendix Table VI.II describes in detail how exemptions were recorded and poor households identified in each county. We assigned households zero hearths if they were exempted and had no more than two hearth or missing hearth information. In robustness checks we (i) drop counties for which information on exemptions were not recorded, and (ii) use the original hearth values before poor correction.

We paid particular attention to the wealth values of nobles and the richest in the data. If a noble person was missing wealth information, we went back to the original records to be sure that the information wasn't lost in the digitization process, and corrected it if needed. In both datasets we back-checked the wealth values, names and location of the 100 richest nobles, gentry and commoners to be sure these were correctly coded.

While in the probate data each individual had just one record (there were exceptions of reassessments), in the hearth tax multiple records may refer to one individual if that individual occupied multiple places. For example, it was not uncommon for nobility to have a residence both in the country-side and a city. While having multiple homes was rare for commoners, it did sometimes occur, and we captured it by collapsing observations if the exact same first name, last name and social status was mentioned in consecutive records, i.e. two lines following directly upon each other within the same parish (reduction by N=2,970). For nobles, we collapsed over previously cleaned and checked noble titles throughout the country, reducing the number of noble observations from 104 to 95. For gentry, we used a fuzzy matching technique based on first name, last name, and gentry status to identify the same individuals across the country, and collapsed over those, reducing the number of gentry observations from 3429 to 2708.

2.3.3 Mapping

We map the location information of the hearth tax, probate, census, and all auxiliary data used in the analysis to a geo-referenced dataset with parish and county information from 1851.[27]

The probate data typically contained addresses of deceased individuals. Using the Google Maps API, we got latitude and longitude for these addresses and selected as a parish the nearest 1851 parish centroid.

[27]This dataset is the underlying data of the ArcGIS shapefile "1851EngWalesParishandPlace.shp" (Satchell et al., 2016). This dataset includes information on ancient parishes and counties as of 1831, allowing us to take account of changes in county borders due to the *Counties (Detached Parts) Act 1844*.

In instances where individual level location information was not matched using the Google Maps API, we use regular expressions to extract counties and parishes. These parish county combinations were then mapped onto our 1851 dataset of parishes and counties. The mapping followed the same strategy as the geo-referencing of the census and the hearth tax data, which we describe jointly below. The 1861 census data include the variables county and parish. The hearth tax records list individuals and their number of hearths place by place for a county or a hundred as an ancient subdivision of countries. The recorded places are typically parishes, and sometimes wards or hamlets within parishes and in rare cases whole hundreds.

To map the probate and census data we use our 1851 county and parish dataset. To map the hearth tax data we first use the 1831 location information of ancient parishes and counties and then convert the mapped data from 1831 to 1851. The mapping was conducted in two steps. First, the county and place information in the probate, census, and hearth tax data were directly merged to the county and parish information in our 1851 dataset of parishes. Second, in case of unsuccessful merges, the data were then manually mapped. Often differences in the spelling of location information rendered merges unsuccessful, which could easily be fixed. For remaining unsuccessful merges a more detailed research was conducted. This used the structure of the data, e.g. which places were recorded before and after, as well as information on ancient parishes, hamlets and wards provided at websites such as genuki.org.uk. More details on the mapping are provided in Appendix Section IX.

The 1851 parish and county data include 42 counties and 10,365 parishes. In the final dataset, the post-Industrial Revolution data cover all counties and 10,108 parishes.[28,29] For 305,243 observations (5.9%), we were not able to map to a parish, but we do have county information, which is relevant for the main definition of industrialization.[30]

Because the large historic county of Yorkshire was split into three counties (East, North and West Riding of Yorkshire) and county borders changed with the *Counties (Detached Parts) Act 1844*, the 26 historic counties we have hearth tax data for map to 32 counties in 1851 (of a total of 42 counties in 1851).[31] In these counties we don't observe all parishes. The hearth tax data span 3,917 of the 10,365 parishes in our 1851 dataset of parishes. 19,512 hearth tax observations (5.7%) could not be mapped to a parish, but we do have county information for them.[32]

[28] Those are distributed across the country. Most of the 257 unmapped parishes are in Lincolnshire (27 parishes), second most in Hampshire (18 parishes), and third most in Northamptonshire (17 parishes).

[29] We have no data for the Isle of Wight, which became independent from Hampshire and its own county in 1890.

[30] 226,664 (74.3%) of those observations are in the census without a matching probate observation. The large majority of observations in the post with unmapped parishes are in Lancashire (11.1%), the second largest share in the West Riding of Yorkshire (9.5%), and the third largest share in London (6.7%).

[31] This implies that we have low numbers of observations in counties that we only observe due to the border changes. For example, we have 188 observations for Dorset from 3 parishes due to border changes. The count of 32 excludes Cambridgeshire which we dropped because information on names was not available.

[32] The quality of the place recording varied by county. 29.0% of the observations that could not be mapped are in Kent, 25.1% are in Middlesex and 7.8% are in Devon.

2.3.4 Occupations

Occupations of individuals are recorded in the census and we use them to measure employment in the manufacturing sector and thus the extent of industrialization at the county-level. The census data include 5-digits HISCO classifications of occupations, however, often HISCO codes were not consistent with the occupation recorded and the level of aggregation was either too detailed or too broad for our purposes. Therefore, we classified occupations into groups (e.g., agriculture, mining, construction, manufacturing, etc.) and skill levels (i.e.high, medium and low) based on keywords in the occupations variable, and then define sectors based on the occupational groups. We describe this process in Appendix Section IV. We can code 86.0% of the 5,190,592 observations in the linked probate-census data this way to occupations groups, skill levels and sectors.[33]

2.4 Other data sources

2.4.1 The Oxford Dictionary of Family Names in Britain and Ireland

The Oxford Dictionary of Family Names in Britain and Ireland contains detailed information on variants of names, name origins and name categories of over 45,000 surnames that have more than 100 bearers currently and those that had more than 20 bearers in the 1881 census (Hanks et al., 2016). For each surname, we scrape and extract its variations in spelling, its geographical origin (N=88), and whether the name describes a location, a relationship, an occupation, or a nickname.

We merge the geographical and descriptive characterization of names to our data. In the pre-Industrial Revolution dataset 75.6% of names are of English origin and in the post-Industrial Revolution dataset 80.1% are of English origin. The next most common name origins are Scottish (pre: 11.8%, post: 14.1%), Irish (pre: 6.1%, post: 8.7%), Norman (pre: 7.4%, post: 8.1%), and Welsh (pre: 1.8%, post: 3.5%).[34] The remaining origin categories account for below 1.5%. In both datasets the majority of surnames are locational (pre: 37.5%, post: 42.1%), followed by relational (pre: 30.9%, post: 34.5%), nickname based (pre: 19.4%, post: 20.5%), and occupational (pre: 16.7%,, post: 16.1%). See Appendix section VII for more details on the Oxford Dictionary name data. Additionally, in Appendix section VII.A.1 and VII.A.2 we visualize the distribution of name types and name origins, in bar graphs pre-/post- Industrial Revolution and in map format.

[33] We can code occupation groups and sectors for 82.4% of the probate observations linked to the census and 90.7% for census observations not linked. For probate observations without a census link we do not know occupations. But note that to define industrializing counties we do not need to rely on probate data at all and use population figures from the census (see Section 2.6).

[34] Note that one name can have multiple origins. Name origins are missing for 21.6% in the pre-period and 13.0% in the post-period.

2.4.2 Sources of geographic mobility

We compile a dataset with parish-level characteristics in the 17th century for our analysis of the sources of geographic mobility. We group these characteristics in five categories: (i) economic structure, (ii) initial conditions, (iii) social structure, (iv) political variables and (v) feudal legacy. The category of economic structure includes information at parish level on cities and towns (Youngs, 1981b,a), markets or fairs held around 1600 (Letters et al., 2003), and fractions of the population employed in the primary, secondary and tertiary sector around 1700 (Keibek, 2017, made available by the Cambridge Center for Population History).[35] The category of initial conditions includes information on parish level data on tax revenue in 1525 and tax revenue per capita in 1525 from the Tudor lay subsidies analyzed by Sheail (1968). The category of social structure includes information at parish level on the number of nobility and gentry around 1700 (Adams, 1700), and the number of yeoman around 1700 (Keibek, 2017, made available by the Cambridge Center for Population History). The category of political variables includes information at parish-level on the number of members of parliament around 1700 (Adams, 1700), the share of Catholics in 1603 (Bossy, 1975) and the fraction of elections between 1701 and 1831 that were contested (Cannon, 1973). Lastly, the category of feudal legacy includes an indicator whether a monastery owned part of a the land in a parish in 1535 (Heldring et al., 2021) and the number of Parliamentary enclosure acts passed between 1750 to 1830 based on the Domesday of English enclosure acts and awards (Tate and Turner, 1978).[36] See Heldring et al. (2021) and Heldring et al. (2022) for a description of the data and their sources in greater detail.

2.5 Sample

2.5.1 Coverage

Through the linking of the probate and census data, we observe virtually all adult male individuals and their wealth in the entire country in the post-Industrial Revolution period. The linked dataset contains 5,263,062 adult males, however, 50,483 of those observations have missing wealth information (0.96% of linked data; 4.9% of probate data), 17,031 have missing county information (0.33%) and 4,956 observations have missing last names (0.10%), resulting in a final post-Industrial Revolution dataset with 5,190,592 males. In Appendix Section X.A we report these statistics county by county.

The hearth tax data comprise 397,574 households, from which we exclude 32,279 female headed house-

[35]The data include anonymized records for people passing away. We subsetted the data to the year range 1688-1715 and computed fractions for individuals in that range.

[36]Heldring et al. (2021) describe monastic ownership in a parish. The original data source is the Valor Ecclesiasticus commissioned by Henry VIII in the 1530s. We digitized a transcript of the surviving original returns made by the British Record Commission (Caley et al., 1810, 1814, 1817, 1821, 1825, 1831).

holds.[37] Of the 365,295 male heads, the number of hearths are missing for 7,924 observations (2.17%), surnames are missing for 14,249 observations (3.99%) and county information is complete, resulting in a final pre-Industrial Revolution dataset of 343,123 males. In Appendix Section X.A we report these statistics county by county. For counties with full coverage, we cover about 100% of the population[38]

Figures 2 and 3 illustrate the regional coverage of the post-Industrial Revolution and pre-Industrial Revolution data. The figures outline the country border of England and Wales and map the average individual level wealth for each parish in England that we have data for. The thicker black outline indicates counties that were more industrialized, as measured by whether more than fifty percent of the population was employed in manufacturing in the 1861 census. The post-Industrial Revolution data cover 97.5% of parishes and therefore span the whole country. The pre-Industrial Revolution data cover 37.8% of parishes, with most coverage in the southeast, southwest and north. Although the pre-Industrial Revolution data cover all parts of the country, we exclude counties and parishes, respectively, that are not observed in the pre-Industrial Revolution period from the analysis in robustness checks. We will discuss the regional wealth concentration in the following section.

2.5.2 Descriptive statistics

Mean wealth in the total post-Industrial Revolution sample is 635 pounds, in the sample of probated individuals it is 3,417 pounds. The richest counties in the late 19th century, measured by their mean wealth in the total sample, are located close to London and include Middlesex (1,326 pounds), Surrey (1,072 pounds), Sussex (1036 pounds) and Kent (845 pounds). The poorest counties were Staffordshire (294 pounds), Durham (323 pounds) and Cornwall (350 pounds). The regional wealth distribution is presented Figure 2, mapping mean wealth at parish level. Yellow and light green indicate poorer parishes and dark green and blue indicate wealthier ones. Besides the concentration of wealth outside of London, mean wealth is high in the Northern parts of the heartland of the Industrial Revolution, which is indicated by the thick black outline and which includes Cheshire, Lancashire, West Riding of Yorkshire (Northern parts), Bedfordshire, Derbyshire, Nottinghamshire, Staffordshire and Warwickshire.

[37] The gender of household heads is determined based on first names. For 14% of observations first names could not be assigned because either their first name was missing or because the first name could refer to a female or male. Because predominantly males were recorded as household heads in the data, we only drop observations for which we are sure that they are females.

[38] We use population estimates from the Cambridge Group for the History of Population and Social Structure (`https://www.campop.geog.cam.ac.uk/research/projects/transport/data/population1680.html`), which are based on the 1680 Compton Census and to a lesser extent hearth tax data. We compare these estimates to the number of observations in the hearth data for counties that we have data for, using 4.6 persons as an average household size as also suggested by the Cambridge Group for the History of Population and Social Structure, and accounting for the the fact that we exclude female headed households. This comparison suggests that we observe 57% of households in these counties. Because we have data for 49% of parishes in these counties (the raw data comes parish by parish), we would have expected a share of around 49%, and 57% is even larger.

Figure 4 shows that essentially all wealth is held by the 10% richest people in the country, irrespective of the assumptions made about wealth of unprobated individuals. The least wealth that unprobated people may own is zero and the maximum is 5 pounds. If we assign everyone the lowest possible value, the richest decile owns 98.2% of wealth and the second richest 1.8%, whereas, if we assign to everyone the highest possible value, the richest decile owns 97.5% of wealth.[39] In Appendix Section X.B we provide average wealth and percentiles of wealth by county, and average wealth per decile of the wealth distribution. We also present wealth shares and averages when using only probate data, i.e. excluding poor people from the census.

The data contain 591 noble individuals and 25,320 members of the gentry (see Appendix Table X.V). Among the 200 richest individuals 10.5% are noble and 43% are part of the gentry. Among the richest 100 households 14.0% are noble and 37% are part of the gentry. The richest noble person is William Wentworth-Fitzwilliam, Earl Fitzwilliam, with a wealth of 2,799,999 pounds. The richest person from the gentry is Sir Andrew Walker, Baronet, with 2,876,782 pounds. Overall the richest person is Herman de Stern, of Stern Bankers, who was worth 3,544,978 million pounds at death (see Table 7 for a list of the richest 10 people in the probate records).

In the pre-Industrial Revolution period, the mean number of hearths is 2.37. The richest counties in the late 17th century, measured by the mean number of hearths per household, are located in the south of England and include London (4.8 hearths), Middlesex (4.0 hearths) and Sussex (3.7 hearths). The poorest counties are Northumberland (0.85 hearths), Lancashire (1.16 hearths) and Durham (1.27 hearths) in the north of the country. The regional distribution of wealth, measured by mean wealth at parish level, is presented Figure 3. Yellow and light green indicate poorer parishes and dark green and blue indicate wealthier ones. The map shows a clear geographical wealth gradient. Most parishes in the north have a mean number of hearths of no more than 2, whereas parishes in south mostly have a mean number of hearths of more than 2. The wealthy parishes in the south are not solely cities but are spread across the countryside, too. In Appendix Section X.B we provide average wealth and percentiles of wealth by county, and then average wealth, and wealth shares, per decile of the wealth distribution.

Figure 5 shows the share of wealth by decile. The richest decile owns 35.5% of wealth whereas the poorest decile owns 0% of wealth.[40] The hearth tax data contain 95 nobles titles and there are 2,589 households of the gentry (see Appendix Table X.VIII for these statistics).[41] Among the 200 richest households 21.9%

[39] In today's Great Britain the richest 10% of individuals own 48.6% of wealth and the second richest decile owns 19.8% (Office for National Statistics, 2022a).

[40] For comparison, between April 2018 and March 2020, the wealthiest 10% of households in Great Britain held 43% of wealth (Office for National Statistics, 2022b).

[41] Some nobles own more than one estate and we collapse the estates associated with one noble title and assigned the location of the main residence to the observation. Female and male title holders were counted as one. For example, the Countess of Devonshire and the Earl of Devonshire would jointly count as one title.

are noble and 55.2% are part of the gentry. Among the richest 100 households 34.0% are noble and 48.1% are part of the gentry. The richest noble title is the Duke of Buckingham with 281 hearths. The richest person from the gentry is Esquire Richard Lucy with 88 hearths.

2.6 Measurement of Industrialization

The unit of observation in both of our cross-sections and our analysis is the individual. Based on the individual's place of residence, we group them geographically to parts of the country where the Industrial Revolution was concentrated and where it was not concentrated. Our main definition for industrializing regions is based on employment in manufacturing in the 1861 census. For our main analysis, we identify counties to be industrialized if more than 50% of the population is employed in manufacturing, as identified by the census. This classification includes Bedfordshire, Cheshire, Derbyshire, Lancashire, Nottinghamshire, Staffordshire, Warwickshire, and West Riding of Yorkshire. We vary this cutoff as part of our robustness analyses below.

3 Empirical approach: Social orders, ascriptive characteristics and comparisons

Our empirical strategy rests fundamentally on the simple idea, developed by Güell et al. (2015) and other contributions cited in the introduction that if social mobility is perfect, rigid characteristics (such as social status) or fully unalterable (or 'ascriptive') characteristics should not be predictive of a person's wealth. Conversely, if wealth is fully determined by, say, one's parents' social standing, then wealth can be fully explained by ascriptive characteristics.

We therefore compare the predictive power of ascriptive characteristics across our cross-sections of hearth tax records (which we label 'pre', like above) and probate plus census records ('post'). Our simplest comparison is of goodness of fit in a simple linear model, following Güell et al. (2015). We start by estimating the following linear model, using OLS:

$$Y_{ip} = \alpha + X_{ip}\beta' + \epsilon_{ip} \tag{1}$$

Where Y_{ip} is the fraction of total wealth owned by individual i in $p \in pre, post$. We estimate separate models for 'pre', and 'post'. X_{ip} is a vector of social order indicators, or ascriptive characteristics, and ϵ_{ip} is an error term. We estimate heteroskedasticity robust standard errors, either unclustered (for characteristics that vary at the individual level, such as social status) or clustered at the last name level (for ascriptive

characteristics derived from last names). From this regression we compute the R^2. We then randomly re-assign the ascriptive characteristics one hundred times, re-estimate this model, and get the average R^2_{random}. We obtain the Informational Content of Ascriptive Characteristics (ICAC) from the difference between the two:

$$ICAC = R^2 - R^2_{random} \tag{2}$$

We then adjust this difference for the number of degrees of freedom by multiplying by an adjustment factor, analogous to the adjustment made to obtain an adjusted R-squared.[42] We label this difference the adjusted R-squared ICAC coefficient, analogously to Güell et al. (2015).[43]

After making 'pre'-'post' comparisons of the ICAC coefficients we focus on parts of England where the Industrial Revolution (IR) took place. To do so, we split each cross-section into two parts, defined by whether the share of the population employed in manufacturing is above 50%. We estimate a similar linear model, using OLS:

$$Y_{ipr} = \alpha + X_{ipr}\beta' + \epsilon_{ipr} \tag{3}$$

Where the dependent variable, ascriptive characteristics, and the error term are now also indexed by $r \in IR, nonIR$. We estimate separate models in the four samples defined by p, r: IR/non-IR 'pre', and IR/non-IR 'post'. With the four adjusted R-squared ICAC coefficients that we obtain from these models, we construct the adjusted R-squared ICAC *differences* coefficient:

$$ICAC_{differences} = (ICAC_{IR,post} - ICAC_{IR,pre}) - (ICAC_{nonIR,post} - ICAC_{nonIR,pre}) \tag{4}$$

As before, we adjust this measure for the different degrees of freedom in pre/post and IR, nonIR. The $ICAC_{differences}$ coefficient captures the change in goodness of fit of a vector of ascriptive characteristics in the heartland of the Industrial Revolution, to the change in the rest of the country.

We estimate two versions of Equations (1) and (3). They vary by the dependent variable and which estimates we report. The first version uses the percent wealth owned by individual i and reports the $ICAC$ and the $ICAC_{differences}$ coefficients. The second version uses an indicator as the dependent variable, which is equal to one if an individual is 'wealthy', meaning being in the top decile of the wealth distribution. For this version, we report point estimates from individual point estimates of our vector of characteristics.

[42] We compute the adjustment factor as $N/N-K$, where N is the number of observations in a regression, and K the number of fixed effects. This factor can be easily obtained by taking the difference of two adjusted R-squareds.

[43] Güell et al. (2015) label their measure the Informational Content of Surnames. We extend their approach of surnames to ascriptive characteristics more broadly.

For example, reporting the point estimates for being a member of the nobility captures the conditional probability of being wealthy if noble. We compare these probabilities over time, just as we do with goodness of fit.

The preceding analysis is at the level of the individual. We also estimate a model at the level of the parish, to understand the determinants of geographical mobility. For this analysis, we estimate the following linear model, using OLS:

$$Y_{gc} = \alpha + X_{gc}\delta' + \gamma + \varepsilon_{gc} \tag{5}$$

Where Y_{gc} is a dependent variable for parish g in county c. X_{gc} is a potential correlate of Y_{gc}. γ is a vector of county fixed effects. ε_{gc} is an error term.

Before reporting results, we now discuss inference, and the potential effect that measurement error has on our results.

3.1 Randomization Inference

To assess the statistical significance of the adjusted ICAC difference coefficients, we conduct a randomization inference procedure. For each set of fixed effects, we randomize the industrial location status of each observation, preserving the original proportion of industrial location versus non-industrial location observations in the pre- and post-period datasets. We also preserve the number of fixed effects within the new pre-IR sample defined by the randomization of industrial location, as well as in the post-IR, pre-nonIR, post-nonIR samples. Following the randomization of industrial location status and the subsequent definition of our four randomized subsamples, we repeat our main regressions and calculate the adjusted ICAC difference coefficient. We repeat this process 600 times, generating a distribution of ICAC difference coefficients. Using this distribution, we compute two-tailed p-values by computing the fractoin of randomized coefficients whose absolute value is greater than the ICAC difference coefficient generated with the correct assignment of industrial location. The resulting p-value reflects the likelihood of observing an adjusted ICAC difference coefficient as extreme as our observed coefficient for each set of fixed effects, under the null hypothesis of no relationship between industrialization and the explanatory power of ascriptive characteristics on wealth.

4 Measurement

In this section we discuss the measurement of wealth in our datasets. There are two main sources of measurement error. First, we may measure data in either of our datasets with error due to, for example, record survival. We address this issue in our robustness section. Second, and more importantly, both the hearth tax records and the linked probate-census records contain imperfect measures of an individual's true wealth. While this issue is prevalent in modern and historical studies of wealth alike, it may bias our results in particular if our hearth and probate-census records are differentially affected by this type of measurement error. In this section we expand the standard econommetric theory of measurement error to cover the case of comparison between two datasets. We discuss classical measurement error in wealth, but the main case of interest is correlated measurement error in wealth. We set up a simple econometric framework which yields expressions for the quantities of interest in our results, and we use this framework to provide intuition for what form measurement error would need to take to explain our main findings. In short, our highest-quality data would have to be measured with *more* error than the rest of our data to explain our main finding that social mobility went up over the period of the Industrial Revolution in England. We believe this to be implausible.

4.1 Measurement error

We start with a simple setup. Consider a linear structural model, with a scalar dependent variable measuring wealth, potentially with error, and a scalar independent variable, potentially also measured with error. Consider such a setup for the hearth tax records (as before, we will refer to this cross-section as 'pre') and the probate plus census records ('post'). The general setup is as follows:

$$\begin{cases} \textbf{Structural equation:} & Y_i^{*,j} = \beta^j + \gamma^j X_i^{*,j} + \epsilon_i^j; \\ \textbf{Measurement error 1:} & \underbrace{Y_i^j}_{\text{Observed}} = \underbrace{Y_i^{*,j}}_{\text{True variable}} + \zeta_i^j \\ \textbf{Measurement error 2:} & \underbrace{X_i^j}_{\text{Observed}} = \underbrace{X_i^{*,j}}_{\text{True variable}} + \eta_i^j \\ j \in \{\text{pre}, \text{post}\} \end{cases}$$

It will be useful to use the following notation: $\sigma_Z^2 := \text{Var}(Z)$, $\sigma_{Z,W} := \text{Cov}(Z, W)$. We now state expressions for the probability limit of $\hat{\gamma_j}$ and $\hat{R}_j^2$, the estimated goodness of fit of the regression, when both Y_i^j and X_i^j are measured with (possibly correlated) error.

Proposition 1. *If $\{Y_i^j, X_i^j\}$ is an i.i.d random sample and X_i^j is real-valued (one-dimensional), it follows that:*

$$\hat{\gamma}^j \xrightarrow{\mathbb{P}} \gamma^j \underbrace{\left(\frac{\sigma^2_{X^{*,j}} + \sigma_{X^{*,j},\eta^j}}{\sigma^2_{x^{*,j}} + \sigma^2_{\eta^j} + 2\sigma_{x^{*,j},\eta^j}} \right)}_{\textit{Scale distortion}} + \underbrace{\left(\frac{\sigma_{X^{*,j},\epsilon^j} + \sigma_{X^{*,j},\zeta_i^j} + \sigma_{\epsilon^j,\eta^j} + \sigma_{\zeta^j,\eta^j}}{\sigma^2_{X^{*,j}} + \sigma^2_{\eta^j} + 2\sigma_{X^{*,j},\eta^j}} \right)}_{\textit{Location distortion}}$$

Proposition 2. *Under the same assumptions, it follows that:*

$$\hat{R}^2_j \xrightarrow{\mathbb{P}} \underbrace{\tilde{A}}_{\textit{Scale distortion}} R^2_j + \underbrace{\tilde{B}}_{\textit{Location distortion}}$$

where

$$\tilde{A} = \frac{1}{\sigma^2_{x^{*,j}}} \frac{\left(\sigma^2_{X^{*,j}} + \sigma_{X^{*,j},\eta^j}\right)^2}{\sigma^2_{x^{*,j}} + \sigma^2_{\eta^j} + 2\sigma_{x^{*,j},\eta^j}} \left(\frac{[\sigma_{X^{*,j},Y^{*,j}}]^2 + 2(\sigma_{X^{*,j},Y^{*,j}})(\sigma_{X^{*,j},\epsilon^j}) + (\sigma^2_{X^{*,j}})(\sigma^2_{\epsilon^j})}{[\sigma_{X^{*,j},Y^{*,j}}]^2 + 2(\sigma_{X^{*,j},Y^{*,j}})(\sigma_{X^{*,j},\epsilon^j} + \sigma_{X^{*,j},\zeta^j}) + \sigma^2_{X^{*,j}}[\sigma^2_{\epsilon^j} + \sigma^2_{\zeta^j} + 2\sigma_{\epsilon^j,\zeta^j}]} \right)$$

$$\tilde{B} = \frac{(\sigma_{X^{*,j},\epsilon^j} + \sigma_{X^{*,j},\zeta_i^j} + \sigma_{\epsilon^j,\eta^j} + \sigma_{\zeta^j,\eta^j}) \left[2\left(\sigma_{X^{*,j},Y^{*,j}}\right)\left(\sigma^2_{X^{*,j}} + \sigma_{X^{*,j},\eta^j}\right) + \sigma^2_{X^{*,j}}(\sigma_{X^{*,j},\epsilon^j} + \sigma_{X^{*,j},\zeta_i^j} + \sigma_{\epsilon^j,\eta^j} + \sigma_{\zeta^j,\eta^j}) \right]}{\left[\sigma^2_{X^{*,j}} + \sigma^2_{\eta^j} + 2\sigma_{X^{*,j},\eta^j}\right] \left[[\sigma_{X^{*,j},Y^{*,j}}]^2 + 2\sigma_{X^{*,j},Y^{*,j}}(\sigma_{X^{*,j},\epsilon^j} + \sigma_{X^{*,j},\zeta^j}) + \sigma^2_{X^{*,j}}[\sigma^2_{\epsilon^j} + \sigma^2_{\zeta^j} + 2\sigma_{\epsilon^j,\zeta^j}] \right]}$$

We derive these expressions in Appendix section XI.A We now analyze the case where there is no measurement error in the independent variable, but (potentially correlated) measurement error in the dependent variable.

4.2 Classical measurement error in wealth

The simplest case is classical measurement error in wealth. For example, this type of error could result from i.i.d measurement error in the probate-census data as a measure of true wealth. In itself, this type of measurement error is not that interesting, but comparing between surveys provides a useful baseline comparison.

The relevant expressions for $\hat{\gamma}^j$ and $\hat{R}^2_j$ follow from propositions 1 and 2, with the following assumptions: There is measurement error in the dependent variable for 'pre' and 'post' periods. This error is not correlated with the independent variable ($\sigma_{X^{*,j},\zeta_i^j} = 0$) nor with the regression error term ($\sigma_{\epsilon^j,\zeta_i^j} = 0$). There is no measurement error in the independent variable ($\eta_i^j = 0$), and the independent variable is uncorrelated with the regression error term ($\sigma_{X^{*,j},\epsilon^j} = 0$).

Definition: For a variable Z with measurement error, define its **reliability ratio** in period j as:

$$\lambda_Z^j := \frac{\text{Var}(Z_i^{*,j})}{\text{Var}(Z_i^j)}$$

Notice that $0 \leq \lambda_Z^j \leq 1$. In simple terms, the reliability measure represents how well a particular observed variable Z_i^j with measurement error replicates the variance of the true variable $Z_i^{*,j}$.

In the uncorrelated case, the reliability ratio λ_Y^j is a monotone-decreasing transformation of a signal-to-noise ratio. Specifically, notice that it can be expressed as:

$$\lambda_Y^j = \frac{\text{Var}(Y_i^{*,j})}{\text{Var}(Y_i^j)} = \frac{\text{Var}(Y_i^{*,j})}{\text{Var}(Y_i^{*,j}) + \text{Var}(\zeta_i^j)} = \frac{\frac{\text{Var}(Y_i^{*,j})}{\text{Var}(\zeta_i^j)}}{1 + \frac{\text{Var}(Y_i^{*,j})}{\text{Var}(\zeta_i^j)}}$$

This means that the more noise, the less reliable the proxy variable is. Without measurement error ($\text{Var}(\zeta_i^j) = 0$), $\lambda_Y^j = 1$. Conversely, when $\text{Var}(\zeta_i^j) \to \infty$, $\lambda_Y^j \to 0$.

Following the results established in propositions 1 and 2, together with the classical error assumptions:

$$\hat{\gamma}^j \xrightarrow{\mathbb{P}} \gamma^j$$

$$\hat{R}_j^2 \xrightarrow{\mathbb{P}} \lambda_Y^j R_j^2$$

For the point estimates $\hat{\gamma}^j$ we observe the textbook result that classical measurement error yields consistent results. For goodness of fit, this is not true, and the estimated R-squared is subject to an asymptotic attenuation bias.

Theorem 1. *If $\lambda_Y^{Pre} < \lambda_Y^{Post}$ and classical error in the dependent variable,*

$$\mathbb{P}(\hat{R}_{Pre}^2 \geq \hat{R}_{Post}^2 | R_{Pre}^2 \leq R_{Post}^2) \xrightarrow{n \to \infty} 0$$

Proof. See Appendix section XI.B.1 □

The main results of this paper are a reduction in the explanatory power of ascriptive characteristics in the 'post' period (and particularly concentrated where the Industrial Revolution took place). Theorem 1 states that if our pre data is measured with more error than our post data then, as $n \to \infty$, the probability of observing our main result, if using the true wealth data there would be no differences in R-squared, goes to zero. Since we do observe a reduction in explanatory power of various individual characteristics, it follows that the assumption $\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$ cannot hold *if* our results are to be explained by measurement error.

Since we believe that the probate returns are a better measure of total wealth, and therefore $\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$ should hold, we conclude that our results are unlikely to be driven by measurement error.

These results are derived considering a single scalar independent variable. In Appendix Section XI.B.2 we show that the same results holds when X is vector-valued.

4.3 Correlated measurement error

It is more realistic to expect that measurement error in wealth is correlated with certain ascriptive characteristics. For example, it seems reasonable to think that ease of obscuring wealth from assessors differs by wealth levels.

To capture this case, we will allow a correlation between the error measurement of the dependent variable and ascriptive characteristics ($\sigma_{X^{*,j},\zeta_i^j} \neq 0$). Following the results from proposition 1 and 2, for a single scalar independent variable we obtain:

$$\hat{\gamma}^j \xrightarrow{\mathbb{P}} \gamma^j + \left(\frac{\text{Cov}(X_i^{*,j}, \zeta_i^j)}{\text{Var}(X_i^{*,j})} \right)$$

$$\hat{R}_j^2 \xrightarrow{\mathbb{P}} \left(\sqrt{R_j^2 \lambda_Y^j} + \frac{\text{Cov}(X_i^{*,j}, \zeta_i^j)}{\sqrt{\text{Var}(X_i^{*,j})\text{Var}(Y_i^j)}} \right)^2$$

There are two main things to note here. First, the probability limit for $\hat{\gamma}^j$ now has a location distortion. Second, the probability limit for $\hat{R}_j^2$ exhibits both a scale and a location distortion. Particularly, the new term introduced from allowing correlation, namely the location distortions, depends on the term $\text{Cov}(X_i^{*,j}, \zeta_i^j)$, representing the covariance between the independent variable and the measurement error in wealth. This implies that, in addition to attenuation bias, goodness of fit and coefficients may appear lower or greater than population values due to the correlation.

Theorem 2. *If $\lambda_Y^{Pre} < \lambda_Y^{Post}$ and at least one of the following conditions is true:*

i) ***Moderate correlation case:***

$$\Big(Cov(X_i^{*,Pre}, \zeta_i^{Pre}), Cov(X_i^{*,Post}, \zeta_i^{Post}) \Big) \to (0, 0)$$

ii) ***Covariance in the post is much larger than in the pre:***

$$\left| \frac{Cov(X_i^{*,Post}, \zeta_i^{Post})}{Cov(X_i^{*,Pre}, \zeta_i^{Pre})} \right| >> 1$$

then

$$\mathbb{P}(\hat{R}^2_{Pre} \geq \hat{R}^2_{Post} | R^2_{Pre} \leq R^2_{Post}) \xrightarrow{n \to \infty} 0$$

Similar to Theorem 1, Theorem 2 discusses conditions[44] under which the key findings of this paper cannot be attributed to historical variation, but to measurement error. Relative to theorem 1 there are now two conditions that need to be met for the probability of observing our results, provided there are no differences in true goodness-of-fit, to go to zero. The first condition is the same as before, $\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$. The second now either is condition i) which simply states that correlated measurement error disappears, or a condition on the relative sizes of correlated measurement error, condition ii). We focus on the interesting condition, ii).

Like before, we do observe a fall in R-squared in our results, and, as before, we can conclude that this is unlikely to be explained by classical measurement error because we think $\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$ is a reasonable assumption. In this case, however, it can also be the case that $\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$ and that we violate condition ii). This combination of conditions says that if classical measurement error attenuates pre more than post, correlated measurement error will have to be much stronger in post than in pre to generate our observed results (because it attenuates 'post' even more than classical measurement error attenuates 'pre'). Since we expect both classical and correlated measurement error to be stronger in the hearth tax records - e.g. due to the fact that larger houses are a worse measure of total wealth than total probated wealth -, correlated measurement error moves biases the R-squared in the same direction as classical measurement error. This means we can apply the same argument as before: Since we do observe an effect, it would have to be the case that measurement error (both classical and correlated) is stronger post than pre for our results to be explained by measurement. We don't believe this to be plausible, and we therefore conclude that our results are unlikely to be explained by measurement error. For the case where the independent variable is vector-valued, we show similar results in the Appendix section XI.B.4.[45]

Ordinarily it is very hard to sign the bias in goodness-of-fit from (correlated) measurement error, except in the case of classical measurement error in the dependent variable (Greene, 2000). We are able to make some progress in this section because we are comparing between two surveys, and have a benchmark result. In this setup it is possible to identify conditions under which our main results could be explained by (correlated) measurement error. These condition all boil down to conditions on the relative quality of our data. In particular, our hearth tax data would have to be a better measure of total true wealth (or

[44] A rigorous formulation of the theorem conditions and its proof is available in Appendix section XI.B.3.

[45] We can advance a similar reasoning for the γ coefficients. However, our results for individual coefficients are more varied and we therefore do not have a benchmark result.

conversely, our probate-census data would have to be a worse measure of true total wealth) for it to be possible that our results are explained by measurement error. We do not think that this is the case, and we therefore take the theorems in this section as supportive of our preferred interpretation of our main results.

5 Comparison before and after the Industrial Revolution

The starting point of our empirical analysis is a simple comparison of the explanatory power of our ascriptive characteristics before and after the Industrial Revolution. In this section, we report results from the adjusted R-squared ICAC coefficients from a model with social order fixed effects, and last name fixed effects. We then study name type and name origin. We find that the explanatory power of ascriptive characteristics falls over the Industrial Revolution. We supplement this analysis with case studies of the nobility, and the owners of textile mills. Having established these basic patterns, we break down the explanatory power of our ascriptive characteristics by industrial status in the next section.

5.1 Results in tabular format

The society of orders: social status. We start by measuring the society of orders. As introduced in Sections 2.2 and 2.1, we code indicator variables for whether an individual was a member of the nobility or gentry, and the rest we label 'commoners'. In Table 2, Panel I, columns (1) and (2), we report the adjusted R-squared ICAC coefficients of Equation (2) as a first measure of social mobility pre and post the Industrial Revolution. If the adjusted R-squared ICAC coefficient of such characteristics goes down over time, then less can be learned about an individual's wealth from their social rank over time.

In column (1) of panel I we report the adjusted R-squared ICAC coefficient for the pre-Industrial Revolution period. We build this measure up in several steps. We first report the unadjusted R-squared from our estimated regression in row 1. We then report the average R-squared across 100 random re-assignments of the social order indicators. The next row reports the number of observations in the regression, and the number of fixed effects we use (in this case three, for nobility, gentry, and 'commoner'). We then report the adjustment factor for the degrees of freedom in this regression, the R-squared ICAC, which is the difference between rows 1 and 2, and finally the adjusted R-squared ICAC which is this difference multiplied by the adjustment factor. We present the same statistics for every regression going forward. In column (1), the adjusted R-squared ICAC is equal to 0.167, or about 17%. In column (2) we report the same coefficient for the post-Industrial Revolution period. We observe a coefficient of 0.060, or 6%. In other words, the adjusted R-squared ICAC coefficient fell by almost 65% over the course of the Industrial Revolution.

Naturally, this fall cannot at this point be attributed to the Industrial Revolution. Many things changed in England between about 1700 and about 1850, including overseas expansion, warfare, and politics. In the next section, we therefore zoom in on the parts of England where the Industrial Revolution was concentrated.

In Panel II we report estimates from Equation (1). We estimate the probabilities of being wealthy for each social order. We use an indicator variable equal to one if an individual is in the top decile of the relevant wealth distribution to measure whether an individual is wealthy. Before the Industrial Revolution (column (1)) if an individual carries a noble title, the conditional probability of being in the top 10% of the wealth distribution is 89%-age points higher for nobles than for commoners. We return to this statistic in our case study on the nobility below. This probability is similar afterwards, at 88%. In other words, although social orders become much less predictive of wealth as a whole, most noble individuals are rich. Gentry status is more fluid and can be obtained much more during life, often as a consequence of acquiring wealth. We observe that the relative probability of being wealthy goes up for the gentry, from 67% to 83%. We interpret the changes in the relative position of the nobility in more detail below, in section 6.

Below we also examine whether the change from 17% to 6% is quantitatively significant. We now turn to last name fixed effects to measure overall social mobility, including everyone without a title.

Last name fixed effects. We now turn to an overall measure of social mobility across English society: last name fixed effects (Dolan, 1972; Güell et al., 2015), capturing all characteristics that vary by family name. For this exercise, we remove all nobles and gentry from our dataset to focus on mobility of the 'rest' (results are qualitatively similar if we retain them). We report results in Table 3, columns (1) and (2). When we do this we find that together, 59,648 last name fixed effects explain about 9.4% of the observed variation in wealth before the Industrial Revolution, but only 6.6% afterwards (per the adjusted R-squared ICAC). Like with social class indicators, the collective explanatory power of last name fixed effects falls over the Industrial Revolution. Note that the both the level as well as the decline in the R-squared ICAC is smaller for last name fixed effects than for social class fixed effects, despite the difference in the number of indicators. This is because social status varies within family name as well as across, and last name fixed effects do not. In Panel II, we select a few last names to show some patterns of change over time for individual families. We use the name Smith, which is the most common name in our data, as a reference category. We select two very rich last names, Brassey and Rothschild (see table 7). Thomas Brassey was a railway entrepreneur. While his father a well-to-do farmer, Thomas made his fortune by building railways around the world. We do not see any Brasseys in our 'pre'-dataset, post the name Brassey is associated with a 24%-age points higher probability to be wealthy in comparison to individuals with the surname Smith. For the Rothschild family, we even find a 34%-age point higher probability. We study the

Rothschild family in the next section in more detail. We also selected two relatively common names in our 'pre'-records that were poor, with on average just slightly more than one hearth per household, Grainger and Langcaster. We observe that the Grainger family rose, doing slightly better than Smith. Langcaster remains poor (relative to Smith), although we find only insignificant associations. Whereas the previous section studied the relative position of the very top of society, the results in this section show increased social mobility across the wealth distribution over the course of the Industrial Revolution. We provide a case study of owners of textile mills to further study these patterns. In section 7 we study overall social mobility in industrializing parts of England.

We now examine, two other ascriptive characteristics of last name, name type, and name origin.

Locative, and other name types. In Section 2.4.1 we introduced the Oxford Dictionary of Family Names, our source for qualitative information of last names in England. From this dictionary we classify last names in various ways. The first classification we consider is by 'type': locative, relationship, occupational and nickname. A locative name refers to a geographical location or origin, e.g.: North, Chapell, Holland. These have been studied before, and (Clark, 2014, 76) and Mckinley (2015) claim that historically such names held special status. A relationship based name takes its origin from a relationship to another person, e.g.: Peterson, Hilson. An occupational name relates to an occupation of the sort we mentioned above, other examples being Carpenter or Cook. A nickname based name is just that and refers to such things as a physical trait or type of behavior, e.g. Brown, Strange, Sharpe. The Oxford Dictionary of Family allows a name to have multiple origins, and we measure 16 different combinations in our data. We present results using this classification in Table 4 in the same format as above, with panel I presenting the adjusted R-squared ICAC coefficients, and panel II the conditional probability of being wealthy by ascriptive characteristic.

When we compare the adjusted R-squared ICAC coefficients in Panel I, columns (1) and (2), we see that the explanatory power of the 16 indicators for name type (combinations) is 0, both pre and post the Industrial Revolution. In Panel II, we study the conditional probabilities of being wealthy, for the main categories of names (we do not report the coefficients on the combined types). We find that, relative to nicknames, all other types are slightly less likely to be wealthy pre, but the magnitudes are on the order of one percentage point. Post, this difference goes away for locative last names, and remains negative and small. We find that, across the board, too, the type of last name has little effect of ones position in the distribution of wealth.

More prominent than name types have been the national or ethnic origins of names. For example, central in Clark (2014) is the influence of William the Conqueror's Norman/French knights unseating the Anglo-Saxon nobility cementing their social position over subsequent centuries. We have recorded the

origins of last names, and we study these now.

Name origins. From the Oxford Dictionary of Family Names, we record the national origins of last names. We collapse the many origins into a few categories: English, Scottish, Irish, Welsh, Norman, French, and other countries. Names can have combined origins, resulting in 66 origins pre, and 72 post. We report results in Table 5. As before, in Panel I, columns (1) and (2) we study the overall explanatory power of a vector of fixed effects pre and post the Industrial Revolution. We find that ethnic origins of last names have no explanatory power, pre and post. In Panel II, columns (1) and (2), we focus on specific origins. In column (1), where we focus on the pre-period, we find that, consistent with Clark (2014) that Norman and French names are significantly more likely to be in the top decile of the wealth distribution than English origin last names, before the Industrial Revolution. After the industrial revolution, consistent with our goodness of fit measures, these advantages drop by about 46% for Norman last names, and 90% for French last names. Welsh, Irish, and Scottish last names have slightly higher probabilities to be in the top decile before the industrial revolution, although the differences are small (on the order of one percentage point). After the Industrial Revolution, we observe a shift. Scottish last names are now more likely to be rich whereas the Irish are immiserized. Both findings likely reflect selection, in which Scottish are more likely to be in London, and the effect of the Irish is likely driven by low-skilled immigration. We will return to this point when we discuss our results that investigate the industrializing parts of the country separately.

The small explanatory power of name type and origin shows that the explanatory power of last name fixed effects for explaining social mobility is driven by other factors than these simple aspects of family name. In other words, most of the variation explained by last name is accounted for by other factors that determine social mobility at the last name level than just the type of name or even ethnic origin.

5.2 Benchmarking effect sizes

We have so far compared the adjusted R-squared ICAC over time. We have not tried to benchmark its level. We now do so for our social orders result. We ask whether 17%, the proportion of variation explained by nobility and gentry before the Industrial Revolution as measured by the R-squared ICAC, is large or small. We implement a simple exercise in Table 6. For our samples in Table 2 panel I we re-assign our nobility, gentry, and commoner fixed effects as follows: Let the number of nobles in a sample be N and the number of gentry be M. The number of commoners is then n-N-M, where n is the sample size. We now reassign the richest N individuals in a sample to be noble, and the subsequent M richest individuals to be gentry, and everyone else commoners. We then recompute the 'Maximal' R^2 using these fixed effects. We label the resulting estimates the Maximal R^2, and report it in row 2 of Table 6. For instance, for the

hearth tax ('pre') sample we find this to be 41%. Hence, if the society of orders perfectly matched the wealth distribution this would explain 41% of the variation in wealth. Before the Industrial Revolution the society of orders was still prominent: Our estimated R^2 is 41% of the maximum it could have attained. We arrive at this number by dividing our measured R-squared by the Maximal R-squared. We report this ratio in row 3 of Table 6. Doing the same exercise for after the Industrial Revolution we see from Table 6 that our estimated R^2 is less than 10% of the Maximal R^2. This means that expressed as ratios of the Maximal R-squareds the explanatory power or the R-squareds fall off by 75%.

6 Case Studies

We now provide two case studies which we think powerfully speak to our interpretation of the evidence that social mobility went up over the Industrial Revolution. We study the nobility and the owners of textile mills to bolster this interpretation.

6.1 Case study: The nobility

We can ask two questions that help us interpret our findings so far. First, were the nobility among the richest individuals 'pre' and if so, where do they end up? To answer these questions we identify members of the nobility individually prior to the Industrial Revolution, and trace their descendants through their family tree to the post period, to establish whether the holder of a title after the Industrial Revolution was in fact a descendent from the 'pre' title holder. Note that in Table 2 we showed that *as a class* the nobility became less likely to be wealthy, relative to 'commoners'. Here we focus on the richest of the rich. We report results in Table 1. In columns (1)-(5) we collect characteristics of the richest nobles. We went through the 200 richest individuals 'pre', and identified that 48 of those had a noble title. We collect their rank in column (1), their title in column (2), their name in (3), the number of hearths they owned in (4) and their wealth percentile in column (5). The richest noble is also the richest person in the country, the Duke of Buckingham with 281 hearths.[46] In columns (6)-(11) we trace the 48 noble title holders' descendants. In the column (7) we find the current titleholder - if related - and in column (6) their rank within the 'post' wealth distribution.[47] Note that out of 48 members of the nobility, only the Earl of Devonshire is still in the top 200, at place 24, owning 1,8 million pounds. Out of the other title holders, eleven titles are extinct by the time we observe them. Out of the remaining titleholders, their descendants are, with a few exceptions, among the nation's elite, ranked somewhere between the 20th and 10,000th position in the

[46] It stands to reason that the Crown was richer, but they were exempt from the hearth tax.

[47] Titles of descendants might differ from the pre Industrial Revolution titles because some titles holders got promoted to a higher nobility rank. For example, the Earl of Devonshire became the Duke of Devonshire in 1694.

wealth distribution, but they are no longer among the richest of the rich. The startling fact is that while 21.9% of the richest 200 people (34.0% of the richest 100) in England were noble before the Industrial Revolution, this reduces to 10.5% afterwards.

In Table 7 we compile the top 10 richest people in 'post' to study who where the new rich at the top of the wealth distribution. The richest person is Herman de Stern, a banker, and the second richest person is Thomas Brassey, who we studied above. For each individual, we report their profession and whether they themselves or their sons acquired a noble title. We see that among the top 10 richest individuals there was one member of the nobility, the Earl Fitzwilliam, and one gentleman, a brewer. With the exception of the Earl Fitzwilliam, the richest individuals are member of self-made families. The sons of six of the ten individuals acquired noble titles, and one acquired a gentlemanly title (we list these in the table notes). The primary professions of the very wealthy were in banking and trade. This fact was also noted by Rubinstein (1977a) in his case study of the probate records. We return to studying elite professions below. The study of the fall of the nobility out of the very wealthy, and the rise of the 'new' people into the very top is in line with our results on the influence of different characteristics above: While the nobility stay wealthy, they drop out of the very top, and new people move into the top. They try, and succeed, to acquire noble titles (at least their sons do) as a marker of social status after they become successful.

While the nobility as a class significantly loses in terms of importance relative to commoners, being noble is persistently associated with being 'rich', i.e. being in the top decile of the distribution. This observation masks the turnover that the nobility as a class experienced. We study this turnover in Appendix section VIII.E. We show three facts in that section. First, new creations of titles pick up significantly after 1750, averaging out at about 20 per year. Second, this fact does not capture the full extent of the turnover, because existing titles could be re-assigned when an existing holder died without a male heir. This happened frequently. We measure whether a person holding a title in our 'post' dataset either held a new title, or a title recreated, by century. We find that 57% of titles in our 'post' dataset having been (re)created in the preceding century. Third, we document an explosion of titles *per peer*. We find that the number of peers had been largely constant since 1650, while the number of titles increased dramatically. For example, by 1850, there are about 600 peers (we observe 610 in our probate dataset), but about 1500 titles. Famously, Arthur Wellesley, the Duke of Wellington, held all other titles in the peerage of the United Kingdom as well (Earl, Viscount, Marquess, and Baron).[48] The nobility was dynamic, it replenished itself, although it would not be until 1880 that 'new people' consistently become ennobled ((Stone and Stone, 1984, p.207), and see Pumphrey (1959) and McCahill and Wasson (2003)). These are the sons of the newly wealth

[48]He was the Duke of Wellington, Baron Douro of Wellesley in the County of Somerset, Viscount Wellington of Talavera, and of Wellington in the County of Somerset, Earl of Wellington, Marquess of Wellington, Marquess Douro.

documented in 7.

In sum, in this section we brought together some case study evidence to interpret our results using fixed effects above: Even though the nobility replenished itself, presumably with capable and upwardly mobile new members, as a class, they lost ground over the nineteenth century.

6.2 Case study: Millowners

Our results suggest that social mobility did not just go up at the very top, but throughout the wealth distribution. In this section we report a case study of the owners of textile mills to provide more insight. We started with a Parliamentary report of all textile mills in the country in 1838 which we introduced in Heldring et al. (2021). For each mill, we then attempted to identify their owners from supplementary data from Parliament. If an owner was still alive by 1861, when our 'post' measurement starts, we identify them and record their wealth. We then make comparisons between millowners, other individuals with the same surnames as millowners who did not own mills, and everyone else. We report results in Table 8.

In column (1) we report the average wealth of the 61 millowners we were able to identify. Their average wealth is around 7,790 pounds. Imagine that being a millowner was open only to privileged people. Then we would expect people with the same last names as millowners, who were not millowners themselves, to be rich. This is not what we find. While people with millowners names are a bit better off (711 pounds) than people without millowner names (632 pounds), millowners are more than 10 times as wealthy as non-millowners (7,790 pounds). In column (2) we study millowner names before the Industrial Revolution and find that, then too, they are very similar. In fact, people with millowner names are slightly poorer than everyone else. In other words, nothing in a last name will tell you whether an individual will be able to take advantage of the opportunities of the Industrial Revolution.

The two case studies in these sections give some insight into the more general pattern that after the Industrial Revolution, it is harder to predict wealth from ascriptive characteristics. We now study robustness, and afterwards we focus on the parts of England, where the Industrial Revolution took place, and ask whether the reduction in explanatory power of rigid or ascriptive characteristics is stronger there than elsewhere in the country.

7 Comparisons using cross-sectional variation

In this section we compare wealth pre and post the Industrial Revolution (IR), splitting the sample into two parts. The first part covers the heartland of the Industrial Revolution: define from data on the distribution of manufacturing employment in the 1861 census; the second part covers the rest. This gives

us four samples (IR/non-IR 'pre', and IR/non-IR 'post'), and we repeat our previous analyses in these four samples. The main question we will answer is whether the decline in the explanatory power of social orders, last name fixed effects, and other ascriptive characteristics is concentrated in industrializing regions. We find that for the social order characteristics that have some explanatory power this is true: For example, the nobility, while initially somewhat more likely to be rich in the industrializing region, is much less likely to be rich in the industrializing region 'post'. We reach the same conclusion for last name fixed effects. The decline of the society of orders is more pronounced where the Industrial Revolution took place. In an important robustness check, we replace our census based measure of industrialization, with a measure based on geographical regions. We find very similar patterns.

7.1 Results in tabular format

The society of orders: social status. In Table 2 we report results for social status. In Panel I, columns (3)-(6) we report the adjusted R-squared ICAC coefficients, like before. We now, however, split the sample by industrializing and non-industrializing region and also report estimates of the adjusted R-squared ICAC differences coefficient from Equation (4). In column (3) we report estimates for the non-industrializing region 'pre', which we label 'nonIR'. In column (4) we report estimates for the industrializing region 'pre', which we label 'IR'. As before, we have three orders, nobility, gentry, and commoners. In columns (5) and 6) we report the estimates for the 'post' period, again split by 'nonIR' and 'IR'.

We observe a very interesting pattern. Before the Industrial Revolution, social status had a greater explanatory power in (future) industrializing regions (nonIR: 15%, IR: 25%). After the Industrial Revolution, the explanatory power of the social orders falls in both the south and the industrializing north (nonIR: 6%, IR: 7%). The fall in explanatory power is larger in the industrializing north.

In this and the following table we make this point more concretely by presenting the adjusted R-squared ICAC *differences* coefficients defined in Equation (4). Simply put, we compute the difference between 'pre' and 'post' in the industrializing region and subtract the same difference in the non-industrializing region. When we do this, we obtain -0.08 (labeled as 'Adj. ICAC difference' in Table 2). This means that goodness of fit fell by 8 percentage points more in the industrializing region from before to after the Industrial Revolution, relative to the same difference in the non-industrializing region. In other words, social mobility went up disproportionally more where the Industrial Revolution was concentrated. In parentheses, we report a permutation-test p-value of this difference. We observe that the difference is statistically significantly different from zero, with a p-value equal to 0.01.

We see similar patterns in Panel II. Here we again estimate Equation (1) but now in the four subsam-

ples created by our sample split. In columns (3) and (4) we observe that noble status is associated with a significantly higher probability (relative to 'commoners') of being in the top decile of the wealth distribution, 85% in the non-Industrial Revolution areas and 97% in the region most impacted by the Industrial Revolution. After the industrial revolution this increases slightly for the former and falls to 89% in the latter (an increase of 1 percentage points in the former, and a decline of eight percentage points in the latter). The overall decline we observe in goodness of fit in the Industrial Revolution regions is therefore reflected in these probabilities. While still much more likely to be rich, the nobility is now less likely to be among the very wealth relative to ordinary people. For the gentry, they rise across the board, with a one percentage point greater rise in the non-Industrial areas than in the Industrial areas.

Naturally, many types of selection may result in *compositional* differences that explain this effect: Richer nobles may migrate to the south post-IR for example. Note, however, that the *overall* explanatory power of being noble falls too. Below we discuss a robustness check that takes migration patterns into account. We now study our other last name based ascriptive characteristics.

Last name fixed effects. Like before, we now omit titled individuals, and study last name fixed effects, which capture all ascriptive characteristics that vary at the level of the last name. We report results in Table 3. In Panel I, columns (3)-(6) we study the explanatory power of last names. 'Pre', the adjusted R-squared ICAC coefficients are similar in industrializing and non-industrializing regions, around 10% (nonIR: 0.09, IR: 0.10). In the non-industrializing region, it stays about level and 9%, whereas in the industrializing region it falls to zero. This results in an adjusted R-squared ICAC *differences* coefficient that is equal to -0.109. In other words, the explanatory power of last name fixed effects fell disproportionally more in the industrializing region. The p-value for this difference is 0.01. In Panel II, we study our individual last names. Here, patterns by industrializing region are less interesting. 'Post', the predictive power of Brassey is higher in the industrializing region, but the pattern is the reverse for Rothschild. The patterns for Grainger and Lancaster are similar by region and period, and similar overall to our previous comparisons.

Our results for social orders and last name fixed effects constitute the main results of our paper: The English society of orders eroded over the course of Industrial Revolution from the top as social mobility increased. Despite constant re-entry into the nobility and the ambition of 'new' people to acquire titles and join the 'respectable' ranks of society, the orders lose out in relative terms, and more so where the industrial revolution took place. Across society, mobility increases, and more so where the industrial revolution took place.

Locative, and other name types. In Table 4 we report results for name types. In Panel I, columns (3)-(6) we find that the adjusted R-squared ICAC coefficient is essentially zero for all four subsamples.

Like before, this implies that there is no explanatory power in knowing one's last name type for wealth. In Panel II, we reach a similar conclusion. Essentially all conditional probabilities of being wealthy are zero, relative to the base category 'nickname'. In our earlier 'pre'-'post' comparisons, we found more explanatory power for name origin. We now return to this exercise.

Name origin. In Table 5 we study name origins. In Panel I, we find very modest 'pre' adjusted R-squared ICAC coefficients (nonIR: 0.001, IR: 0.002). Since 'post' coefficients are zero we get a small negative adjusted R-squared ICAC *differences* coefficient of -0.001. In other words, the explanatory power of name origins fell more in the the industrializing region than in the non-industrializing region. This result, however, is not statistically significant (p-value: 0.23). In Panel II we study individual origins. The patterns here are less instructive, but we do find, consistent with Cummins and Ó Gráda (2025), the Irish in the North do worse.

Taken together, when we split up our sample in non-IR/IR regions of England, we find that for ascriptive characteristics, with at least some explanatory power, increases in social mobility are concentrated where the Industrial Revolution took place. This result is in line with accounts of the Industrial Revolution that emphasize new opportunities, and the broad slices of English society that were able to take advantage of them (Griffin, 2013). It is less consistent with accounts of limited, or even falling, social mobility. An aspect that is emphasized by both sides is geographical mobility, either as part of new opportunities or as part of labor migrants huddled together in new manufacturing towns. In the final part of our analysis we ask what factors correlated with such geographical mobility. We present results after we discuss robustness of our results so far.

7.2 Benchmarking effect sizes

In Table 6 we again benchmark the adjusted R-squared ICAC coefficients against a 'maximal' counterpart, now broken down by IR/non-IR regions. Columns (3)-(6) report results. In the pre-period, the (future) industrializing North has a maximal R^2 of 0.48, resulting in a ratio of actual R^2 to maximal R^2, reported in row 3, of 0.52. After the Industrial Revolution, this drops to 0.10, a reduction of close to eighty percent. In the South, the ratio drops from 0.37 to 0.09.

8 Robustness

In the Appendix, we report results from a large number of robustness exercises. To facilitate presentation, the Appendix includes a thematic overview table, Table II.I which presents all tables containing robustness checks by 'theme' (e.g. variable definitions) and discuss the main findings. It then refers to

individual tables to verify those findings. In this section, we discuss which robustness exercise we undertake, but do not refer to individual tables. The exception is the most important robustness check, which we present in the paper, and introduce first.

The most important robustness check is varying the assignment of which individuals were impacted by the Industrial Revolution. In the preceding analysis we did this by *location*, which obscures the effect of migration and other compositional changes. In Appendix Section XIII.C, we therefore assign industrialization status by whether a person is employed in manufacturing, or in manufacturing, trade, or banking. We find overall similar results. We provide an example of such an exercise in Figure 6. Here we re-estimate our last name fixed effects regressions county by county, and plot the resulting adjusted R-squared ICAC coefficients by the manufacturing share of employment in the 1861 census. We then fit a linear relationship to this scatter, separately for our pre-period and post-period adjusted R-squared ICAC coefficients, and for the difference between pre- and post-period adjusted R-squared ICAC coefficients. As we observe in Table 3, there is no relationship between the adjusted R-squared ICAC and the (future) manufacturing share before the Industrial Revolution. After the Industrial Revolution, however, the relationship turns strongly negative. This means that social mobility is higher, the higher the share of employment in manufacturing. The difference between pre and post is similarly negative in the manufacturing share. This result is in line with our pre/post results in Table 3 but also shows that our results do not depend on our use of the 1861 census to define which areas were relatively impacted by the Industrial Revolution. We find identical results if we use a simple geographical definition, treating Lancashire, Cheshire and the West Riding of Yorkshire as the focal geography of the Industrial Revolution.

In Appendix Section XII and XIII we undertake robustness checks in several categories. We apply each robustness check to all our main analyses. Please refer to Appendix Table II.I to find individual tables.

First, we vary the way we identify the 'wealthy' indicator which is part of each of our main tables. So far, this indicator has been defined to be equal to one if a person was in the top 10% of the distribution of the relevant sample (e.g. post, North). In the Appendix we show that our results are robust to defining this indicator globally; i.e. wealthy status is assigned using a country wide sample, before splitting the data into subsamples. We then redefine what it means to be wealthy to be an indicator when an individual is in the top 1% or the top 0.1 %. Second, we re-compute R-squared ICAC coefficients, using our indicator for being wealthy, rather than the percentage of total wealth owned. Third, we analyze the consequence of the fact that we do not have hearth tax data for all counties. We construct a sample that keeps for the probate-census data only those counties for which we have hearth tax data. We replicate that analysis for only *parishes* that are in both datasets. Practically, this analysis overlaps fully for most counties for which we have data. Fourth, we exclude cities from our samples. Fifth, we vary the linking procedure between

the probate and census data. We discussed this check in section 2.1.3. It varies the looseness of merging by geography to ensure that everyone gets merged over name (uniquely). Sixth, we provide the tabular version results of the main robustness check above, where instead of defining being industrial from the 18961 census, we define industrial as Cheshire, Lancashire, or the West Riding of Yorkshire. We then vary the inclusion cutoff from 30 to 60% in five percentage point increments. Eighth, we assign a wealth of five pounds to unprobated individuals, rather than zero (five is the midpoint between zero and ten, the probate inclusion cutoff). We also randomly assign a value between zero and ten points to unprobated people. For the hearth, we use a sample in which we do not aggregate hearths over noble titles, but leave individual observations for houses intact. We then exclude counties for which information on poor individuals is missing in the hearth tax. We also provide results assigning observed hearths (if any) to people classified as too poor to be taxed, rather than zero.[49] Ninth, we exclude everyone who is wealthy (top 10% and top 5%).

9 Sources of mobility

We now investigate correlates and sources of increased social mobility. For the poor, Griffin (2013) emphasized the role industrial development played in new opportunities, both in terms of geographic mobility and in terms of job opportunities. Rubinstein (1977a) emphasizes that, for the rich, landowning was replaced by many professions associated with greater industrial development, such as finance, and trade as their source of wealth. In this section we study both hypotheses. We study mobility, first across individuals, and then across parishes. To measure social mobility at the individual level as well as at the parish level, we first construct a measure of social mobility at the family level between our two cross-sections, and we then assign this measure to each individual in our post-dataset. We compute this measure in two steps. We first standardize wealth pre and post by applying a min-max transformation.[50] We then compute the standard deviation of wealth at the level of the family name and compute the post minus pre difference. A higher value of this measure capture higher wealth variability within names and is therefore a measure of social mobility (upward or downward). Finally, we assign an indicator equal to one if an individual is above-median in terms of social mobility, and then assign to each parish an indicator equal to one, measuring high social mobility, if more than fifty percent of its inhabitants were high mobility individuals in the probate-census sample.

We find that those that are more mobile geographically and those with modern occupations are more

[49] Sometimes the hearth tax returns will report a number of hearths, before noting that this person is too poor to be probated. As a rule, we assign poor people zero hearths. In this robustness check, we vary this rule.

[50] This standardization method applies to our wealth measures w the following transformation $w = (w - max(w))/(min(w) - max(w)$.

socially mobile, both for the entire sample, in line with Griffin (2013), as well as a for a subsample of nobles and gentlemen, consistent with Rubinstein (1977a).

9.1 Sources of mobility: Individual-level evidence

We start with our probate-census sample, augmented with the social mobility measure we just described. We relate this measure to three observables at the individual level. We first use the 1861 census to capture an individual's place of birth. We compute an indicator equal to one if an individual was born in the industrial regions but was probated (at death) in non-industrial ones, and vice versa. We label such an individual a 'migrant'. We then simply compute whether a person was probated in industrial regions. Finally, we measure whether an individual was employed in manufacturing according to the census' sectoral classification.[51]. We then restrict to surnames with at least fifty carriers and compute averages of these variables for high and low mobility surnames, defined by a median split. Results are in Figure 7.

We observe that for individuals with family names that are below median social mobility, 7.9 percent are industrial to non-industrial or non industrial to industrial migrants. For above median social mobility individuals, this measure is higher, at 7.9 percent. 31.7 percent of low social mobility individuals are probated in the north, compared to 38.5 percent of high social mobility individuals. Finally, 47.5 percent of low mobility individuals are in manufacturing versus 49.4 percent of high mobility individuals. In sum, individuals from families with higher social mobility are more likely to be geographically mobile, to live in the industrializing north, and more likely to be in manufacturing.

In Appendix section XIV we extend this analysis to the nobility and gentry, for whom we can implement analysis at the individual level. We provide summary statistics of the distribution of wealth and sectoral employment, and we classify occupations into traditional (those employed in agriculture, the army, the government and, for the gentry, the clergy) and those employed in 'new occupations (all occupations not listed previously). We then document that nobles and gentleman who are in the North and nobles and gentlemen who are movers, i.e. they live somewhere different from where they were born, are more likely to be in 'new' occupations.[52]

9.2 Sources of mobility: Parish-level evidence

In this section, we instead use our parish-level measure of high social mobility and ask which historical factors affect it. We present results in Table 9. Each row reports an estimate of δ from Equation (5). The

[51]The census' manufacturing classification includes 'food and beverage', 'construction', and 'manufacturing'. We restrict the the second level manufacturing category.

[52]We also find that average, nobles are wealthier than gentlemen, the North is wealthier than South, movers are wealthier than non-movers, and people with new occupations are wealthier than those with traditional ones.

dependent variable is the indicator variable for being a high mobility parish, and each regression includes county fixed effects, and dependent variables are either standardized (mean zero, unit standard deviation) or are indicator variables. Under the heading 'Economic structure' we study aspects of local economies. We start by measuring whether a parish was (part of) a town or city.[53] We then use data described in Heldring et al. (2021) on whether a market or a fair was held in 1600, as well as the fraction of population in the primary, secondary, or tertiary sectors in 1700 based on our dataset of probate records. We describe this data in our Data Section 2.4.2 above. We find that parishes that are urban, have a market, and are specialized in manufacturing in 1700 are more mobile. More agricultural parishes are less mobile. We probe economic development further by studying a proxy for overall income from the Lay Subsidies tax returns from 1525, described in Heldring et al. (2021). We find that tax revenue in levels correlates negatively, indicating that persistent economic differences three hundred years earlier do not determine social mobility, and reflecting the fact that in the sixteenth century the south was rich, but that economic mobility and activity was concentrated in the north by the time of the Industrial Revolution.

We then focus on social structure. We use data described in Heldring et al. (2022) on the number of members of the nobility, gentry, or yeomanry.[54] Having more 'middle class' gentry is associated with higher mobility, and having more yeomen is associated with less. For a potential mechanism behind this result, see Heldring et al. (2021).

We then turn to political variables. We measure whether a member of Parliament lived in parish, the fraction of Catholics in 1603, the main religious minority, and the fraction of elections between 1701 and 1831 that were contested.[55]. We find that parishes where a member of Parliament lives are more mobile. The latter is likely explained by urban status. Religion is not important.

Finally, we try to directly measure feudal legacy. We discussed in the introduction that the society of orders as present in early modern England had its origins in the feudal structures of the Middle Ages. In Heldring et al. (2021) and Heldring et al. (2022) we discuss two measures of the degree of 'feodality' of a parish. In Heldring et al. (2021) we discuss how parishes where manors were owned by monasteries were less 'feudal' because the abolition of the monastic sector as part of the English Reformation marketized their property and removed archaic copyhold tenure. In Heldring et al. (2022) we discuss how the Parliamentary enclosure movement rationalized informal archaic property rights, potentially assigning property rights and facilitating mobility, but also potentially impoverishing smaller farmers, who then migrated. We use two

[53] We measure this by having official city or borough legal status.

[54] Yeomen were a rank of prosperous farmers. In the hearth tax data, these are not consistently identified, but they are in the earlier probate records.

[55] The number of members of Parliament and Catholics data are discussed in Heldring et al. (2021). The data on contested elections comes from Cannon (1973). We link parishes to their Parliamentary constituencies and assign the value for a constituency to each of the parishes it contains.

indicator variables based on these findings, and find that that these are not significantly correlated

Taken together, we find that mobility is higher in richer, more urban, and heavy-early manufacturing parishes.

10 Conclusion

The modern literature on social mobility makes implicit assumptions about the sociological context in which mobility does, or does not happen. The pre-modern situation in England, referred to by historians as a "society of orders", was very different. In this paper we make the first attempt to conceptualize empirically this society of orders and propose a method for examining its consequences for social mobility. We are particularly interested in change over time and the extent to which this change can be associated with the Industrial Revolution.

Our analysis rests on two new micro datasets, both proxies for true wealth, one for the later 17th century, and the other probated wealth at death in the second half of the 19th century. We operationalize the society of orders using various types of rigid social categories and ascriptive characteristics attached to individuals. We show that the extent to which the most salient of these categories, that of nobility and gentry, can explain the variation in wealth holdings relative to the maximum they could have explained in the 17th century, is very large. We interpret this as being consistent with the persistence of a great deal of the society or orders up until the eve of the Industrial Revolution. Subsequently, however, this explanatory power fell and it fell more in the parts of England which were most impacted by the Revolution. This was true not just of elite titles, but also the explanatory power of surnames. By the 19th century, the predictive power of a person's surname for their wealth fell by a half compared to the 17th century. In the industrial regions, it fell by almost 90%. Our findings are also consistent with an influential argument for the persistence of many aspects of the society of orders until "challenged by the transforming power of the Industrial Revolution" though "what is so remarkable is how long the dikes and levees withstood the rising flood before they finally began to crumble" (Stone and Stone, 1984, p.402).

We finally use the national distribution of surnames to study geographical mobility, defining a "mobile person" to be someone with an above median mobile surname and a "mobile parish" to be one which initially housed surnames which became relatively more disbursed (mobile) subsequently. We find that more, compared to less, mobile people tended to be living in the north and working in manufacturing. We believe these findings are consistent with the evidence and arguments of Griffin (2013) that the Industrial Revolution created new opportunities and broke down many aspects of tradition and thus was associated with greater social and geographical mobility.

At the parish level, greater mobility is associated with several key characteristics including whether or not it was urban, less agrarian, more populated with gentry, had fewer yeoman and was the residence of a member of parliament. These results complement the findings of Chetty et al. (2014) about the correlates of higher social mobility. Interestingly, they illustrate that though the pre-modern world was distinct in some of the ways we discuss in the paper, many of the same mechanisms that we associate with higher mobility today have close analogues in the "world that we have lost" (Laslett, 2000).

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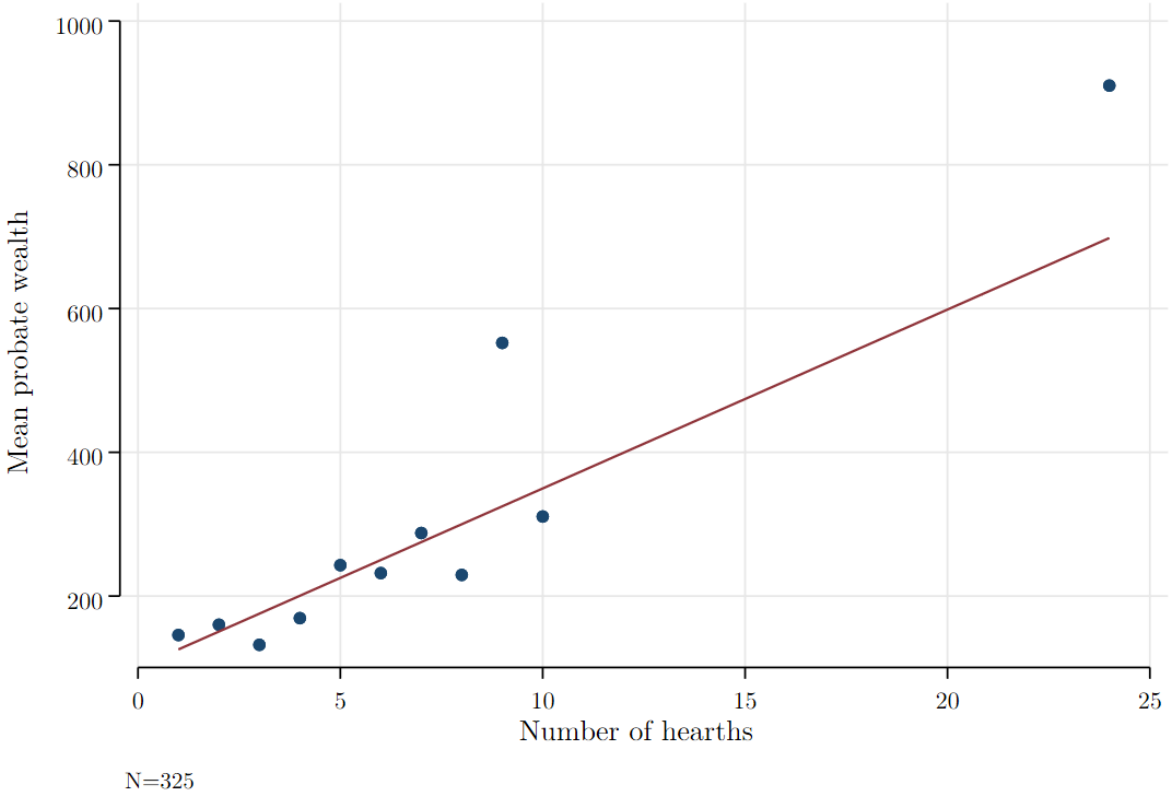
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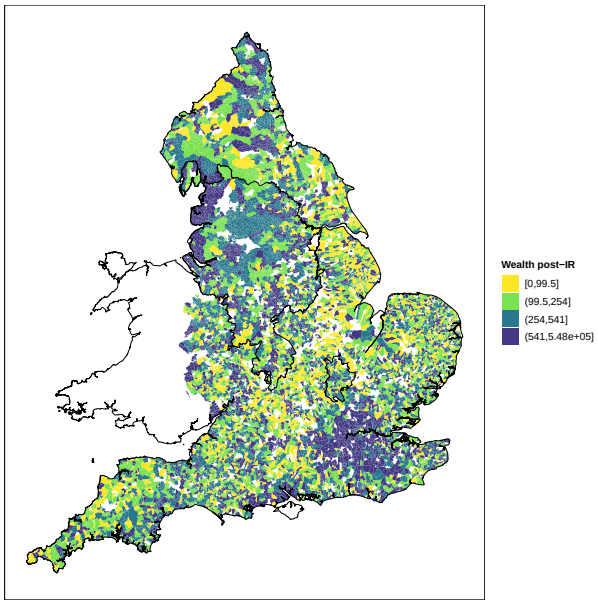
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Figure 1: Relationship of 17th century probate inventory wealth and number of hearths



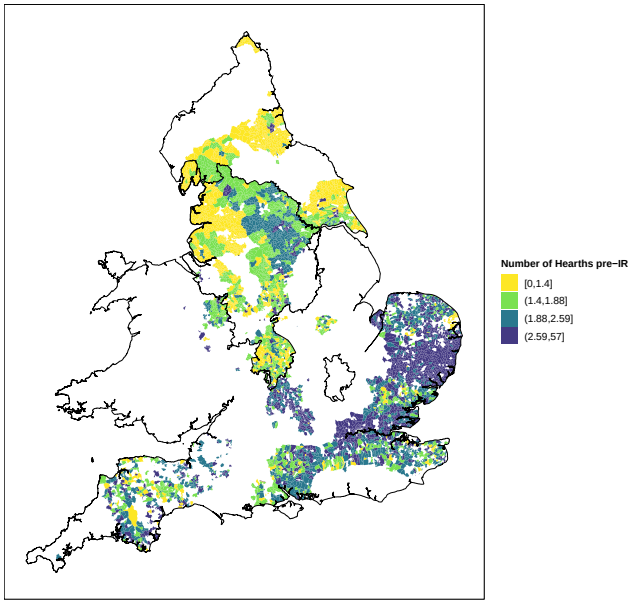
Notes: This figure shows a binned scatter plot (mean probate inventory wealth for each categorical number of hearths) and a linear fitted line of the probate inventory wealth on the number of hearths. The correlation between the probate inventory wealth and the number of hearths is 0.24.

Figure 2: Average wealth post-IR, mapped at the parish level



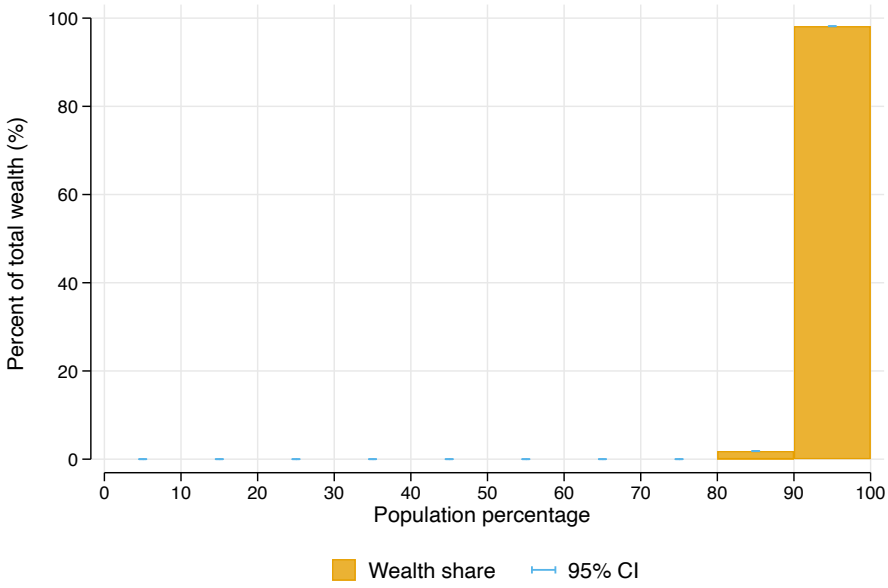
Notes: This figure shows for each parish the average wealth in the linked probate-census data.

Figure 3: Average wealth pre-IR, mapped at the parish level



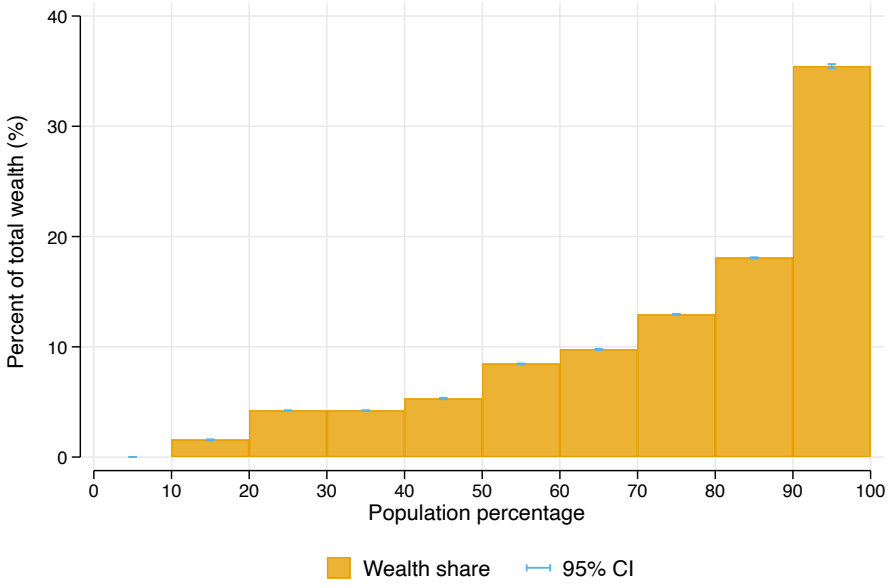
Notes: This figure shows for each parish the average number of hearths owned.

Figure 4: Wealth shares post-IR



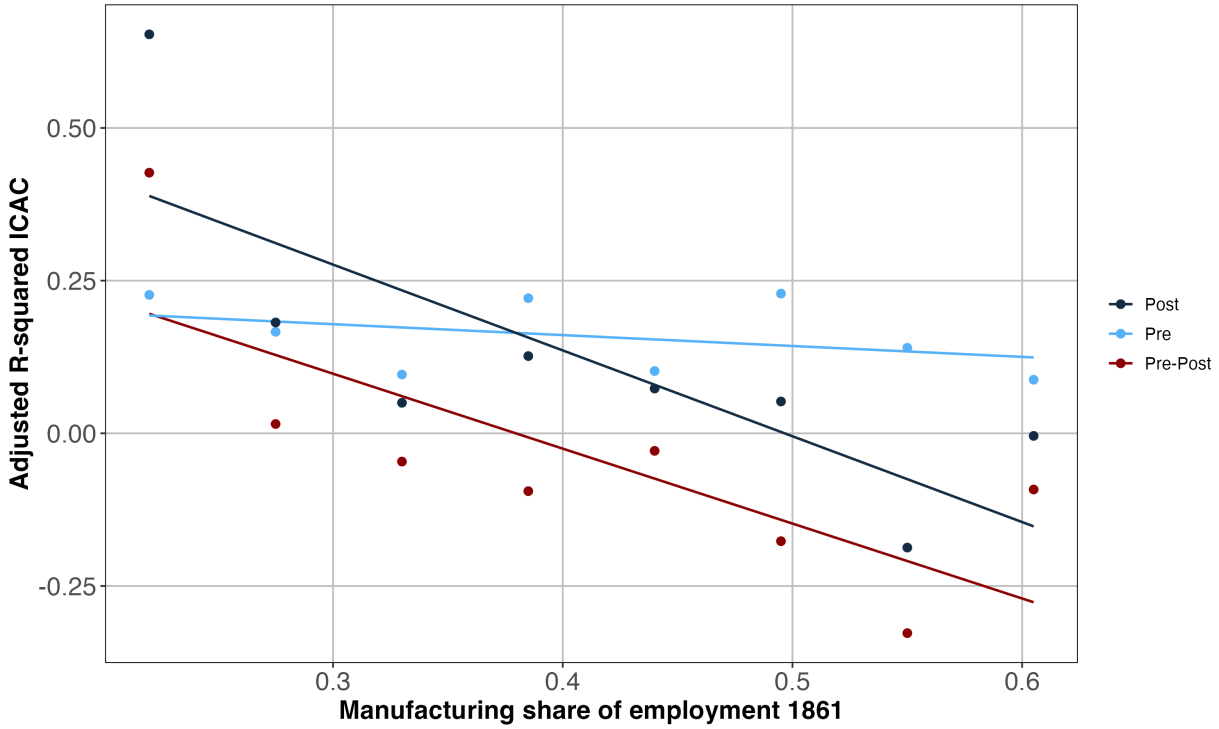
Notes: This figure shows for each decile of the wealth distribution the share of wealth owned in the linked probate-census data.

Figure 5: Wealth shares pre-IR



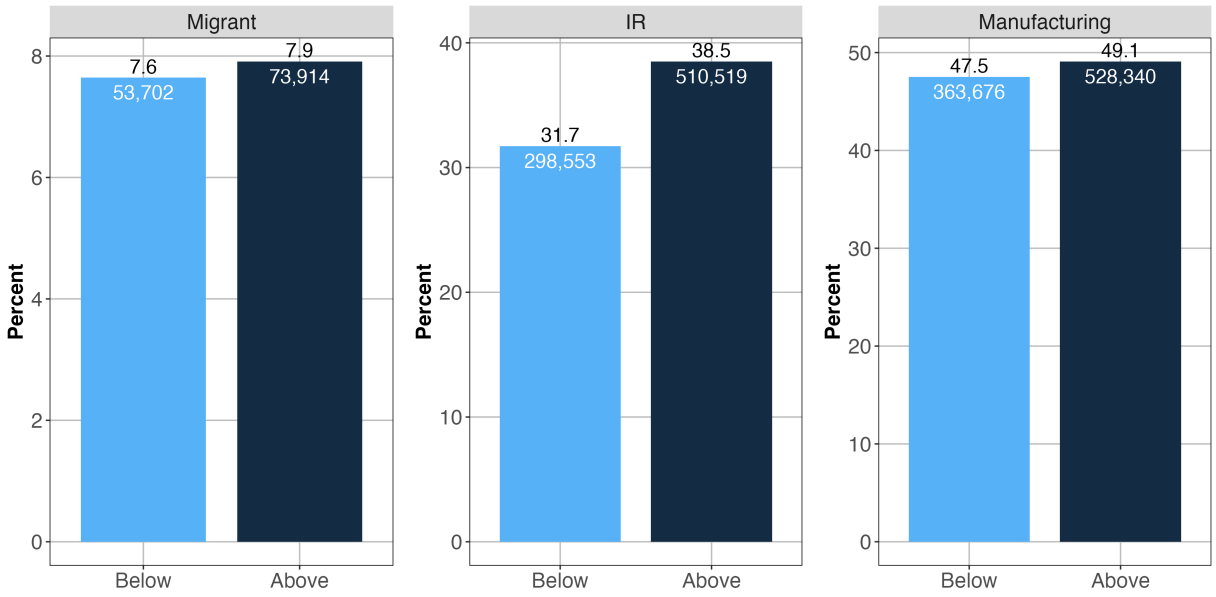
Notes: This figure shows for each decile of the wealth distribution the share of wealth owned in the hearth tax records.

Figure 6: Counties with a higher manufacturing share of employment display higher social mobility



Notes: This figure reports adjusted R-squared ICAC coefficients using a vector of last name fixed effects for ascriptive characteristics by county, and plots these against their manufacturing share of employment in the 1861 census. We report separate scatters and linear fits for our pre-Industrial revolution (hearth tax) sample, our post-Industrial revolution (census-probate) sample, and their difference. A lower adjusted R-squared ICAC coefficient implies higher social mobility.

Figure 7: Share of migrants, probated in industrialized counties, and in manufacturing by delta wealth standard deviation



Notes: This figure shows the share of migrants, probated in industrialized counties, and in manufacturing, for carriers of surnames above or below the median delta standard deviation of wealth. The measure is obtained by standardizing the wealth distribution pre- and post Industrial Revolution, computing the standard deviation by surname, and then subtracting the standard deviation 'pre' from the standard deviation 'post'. Migrants are defined as individuals born in an industrialized county but probated in a non-industrialized one and vice versa. Percentage frequencies on top of the bars. Sample size inside the bars. Surnames with less than 50 carriers 'pre' or 'post' are excluded.

Table 1: Noble people among the top 200 richest people in the hearth tax

Hearth (pre-Industrial Revolution)				Probate (post-Industrial Revolution)					
(1) Rank	(2) Title	(3) Name	(4) Hearths	(5) Rank	(6) Title	(7) Name	(8) Wealth	(9) Percentile	(10) Year
1	Duke of Buckingham	Villiers, George	281	5921	Duke of Buckingham And Chandos	Temple-Nugent-Brydges-Chandos-Grenville, Richard	79942	99,8859	1889
2	Earl of Devonshire	Cavendish, William	260	25	Duke of Devonshire	Cavendish, William	1790871	99,9995	1891
3	Earl of Craven	Craven, William	250	312851	Earl of Craven	Craven, William	800	93,9727	1860
4	Duke of Albemarle	Monck, Christopher	182		Extinct		0	0	
5	Earl of Warwick	Rich, Charles	166		Extinct (See Baron Brooke)		0	0	
6	Earl of Bristol	Digby, George	140	4711	Marquess of Bristol	Hervey, Frederick	90000	99,9092	1859
7	Earl of Chesterfield	Stanhope, Philip	130	6593	Earl of Chesterfield	Stanhope, George	70000	99,873	1866
10	Earl of Northumberland	Percy, Josceline	118	288	Duke of Northumberland	Percy, Algernon	500000	99,9945	1865
11	Marquess of Winchester	Paulet, John	115	3814	Marquess of Winchester	Paulet, John	107044	99,9265	1887
12	Earl of Leicester	Sidney, Robert	114	1169	Earl of Leicester	Coke, Thomas	238419	99,9775	1941
13	Earl of Strafford	Wentworth, William	110	1172	Earl of Strafford	Byng, George	237159	99,9774	1886
13	Baron Brooke	Greville, Robert	110	1638	Earl of Warwick	Greville, George	180203	99,9684	1893
15	Duke of Somerset	Seymour, William	109	1345	Duke of Somerset	Seymour, Edward	202423	99,9741	1885
16	Earl of Bedford	Russell, William	103	213	Duke of Bedford	Russell, William	600000	99,9959	1872
17	Earl of Derby	Stanley, Charles	93	973	Earl of Derby	Smith-Stanley, Edward	250000	99,9812	1869
19	Viscount Strangford	Smythe, Philip	89	72705	Viscount Strangford	Smythe, George	7000	98,5993	1857
21	Earl of Dorset	Sacksville, Richard	85		Extinct		0	0	
22	Earl of St. Albans	Jermyn, Henry	82		Extinct		0	0	
23	Viscount of Irwin	Ingram, Arthur	78		Extinct		0	0	
24	Duke of Richmond	Stewart, Charles	77	243	Duke of Richmond	Lennox, Charles	585373	99,9953	1903
27	Earl of Southampton	Wriothesley, Thomas	75	1642	Duke of Cleveland	Vane, William	180000	99,9684	1864
29	Earl of Arlington	Bennet, Henry	72	1971	Duke of Grafton	Fitzroy, Henry	160000	99,962	1863
31	Earl of Thanet	Tufton, John	71		Extinct		0	0	
31	Earl of Clarendon	Hyde, Edward	71	973	Earl of Clarendon	Villiers, George	250000	99,9812	1870
31	Earl of Peterborough	Mordaunt, Henry	71		Extinct		0	0	
34	Baron Leigh	Leigh, Thomas	70	1234	Baron Leigh	Leigh, William Henry	224841	99,9762	1905
38	Viscount Hereford	Devereux, Leicester	68		Not In Data (Death: 1930)		0	0	
40	Baron Crofts	Crofts, William	66		Extinct		0	0	
45	Earl of Salisbury	Cecil, William	62	723	Marquess of Salisbury	Cecil, James	300000	99,9861	1868
48	Duke of Norfolk	Howard, Thomas	60	4711	Duke of Norfolk	Fitzalan-Howard, Henry	90000	99,9092	1860
52	Baron Wharton	Wharton, Philip	59		Extinct		0	0	
55	Viscount Campden	Noel, Baptist	58	5343	Earl of Gainsborough	Noel, Charles	82998	99,8971	1881
69	Earl of Winchilsea	Finch, Heneage	55	3829	Earl of Winchilsea	Finch-Hatton, Murray	106404	99,9262	1898
69	Viscount Dunbar	Constable, Robert	55		Extinct		0	0	
79	Earl of Middlesex	Cranfield, Lionel	53		Extinct		0	0	
97	Earl of Rutland	Manners, John	48	3702	Duke of Rutland	Manners, Charles	109952	99,9287	1888
107	Earl of Newburgh	Livingston, James	47		Title Holder Is Female		0	0	
115	Lord Fairfax	Fairfax, Henry	46		Not In Data (Emigrated)		0	0	
125	Earl of Lindsey	Bertie, Montagu	45	22331	Earl of Lindsey	Bertie, George	25000	99,5698	1877
130	Earl of Cardigan	Brundell, Thomas	44	2445	Marquess of Ailesbury	Brudenell-Bruce, George	140000	99,9529	1878
143	Viscount Falkland	Cary, Anthony	43	168961	Viscount Falkland	Cary, Lucius	2361	96,7449	1884
143	Baron Teynham	Roper, Christopher	43	53469	Baron Teynham	Roper-Curzon, George	10114	98,9699	1889
149	Baron Sandys	Sandys, William	42	18333	Baron Sandys	Sandys, Arthur	30000	99,6468	1863
161	Duke of York	Stuart, James	40		Recreated (For George V)		0	0	

Notes: This table implements a comparison of noble individuals across our two data sources. It shows that the richest nobility before the Industrial Revolution either lost its wealth, their families went extinct, or their title was recreated for a new family. Only the Earls/Dukes of Devonshire kept their prominent position. We start by selecting noble people among the 200 richest individuals in pre-Industrial Revolution hearth tax records. Each row in this table is for one such individual. We list this individual's rank among the 200 richest people, their title, name, and the number of hearths they had on their house(s). We then trace them in our post-Industrial Revolution data. We indicate their rank in the wealth distribution, the current title of the person holding their title (as sometimes titles of descendants change), whether a link went extinct or was recreated for a different family, the name of the then-current titleholder, their wealth in pounds, and the year in which we observe them.

Table 2: Pre-Post Industrial Revolution Analysis - Social orders

	Panel I: Fixed effect analysis					
Fixed effects:	Social orders					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.167	0.060	0.154	0.245	0.059	0.071
R^2_f	0.000	0.000	0.000	0.000	0.000	0.000
N	343022	5190714	243228	99794	3361853	1828861
$NCat$	3	3	3	3	3	3
Adj. factor	1.00	1.00	1.00	1.00	1.00	1.00
R^2 ICAC	0.167	0.060	0.154	0.245	0.059	0.071
Adj. R^2 ICAC	0.167	0.060	0.154	0.245	0.059	0.071
ICAC difference				-0.079		
Adj. ICAC difference:				-0.079 (0.01)		

	Panel II: Top decile analysis					
Dependent variable:	Wealthy (Yes/No)					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
noble	88.76***	88.45***	85.47***	97.18***	88.11***	88.65***
	(2.81)	(1.14)	(3.64)	(3.38)	(1.28)	(2.60)
gentry	66.77***	82.62***	65.05***	70.70***	82.05***	84.02***
	(0.54)	(0.17)	(0.69)	(0.67)	(0.19)	(0.43)
Constant	8.08***	8.33***	10.24***	2.82***	8.82***	7.43***
	(0.05)	(0.01)	(0.06)	(0.05)	(0.02)	(0.02)
N	343022	5190714	243228	99794	3361853	1828861
$N_{commoner}$	340338	5164803	241211	99127	3339706	1825097
N_{gentry}	2589	25320	1947	642	21658	3662
N_{noble}	95	591	70	25	489	102
Share of Wealthy	8.61	8.74	10.79	3.30	9.36	7.61
Omitted category	Commoner	Commoner	Commoner	Commoner	Commoner	Commoner

Notes: This table compares ascriptive characteristics pre- and post-Industrial Revolution. In this table, we study social orders: Nobility, Gentry, Clergy, and 'Commoners'. Panel I reports the adjusted R^2 from a regression of wealth on a vector of fixed effects, indicated over the panel. We report results in six samples, 'pre' in column (1) and 'post' in column (2), and a combination of 'pre' and 'post' with industrial location in columns (4) and (6) and non-industrial location in columns (3) and (5). Industrial location is defined as residence in a county that has 50% or higher share of jobs in manufacturing. Non-industrial location is residence in a county with less than 50% share of jobs in manufacturing. Each column reports a separate regression, for separate subsamples indicated over each column. In addition we report the number of observations and the number of distinct fixed effects and the adjusted R-squared ICAC difference coefficient capturing the change in goodness of fit of a vector of ascriptive characteristics in industrial versus non-industrial locations. In parentheses we report the p-values of a permutation test designed to test statistical significance of the adjusted R-squared difference coefficient.Panel II reports the point estimates of a regression of an indicator for belonging to the top-wealth decile on the different categories. We indicate the omitted category at the bottom of each column.We report classical standard errors. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significance at the 1% level.

Table 3: Pre-Post Industrial Revolution Analysis - Last Name

	Panel I: Fixed effect analysis					
Fixed effects:	Last Name					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.253	0.108	0.272	0.258	0.142	0.066
R^2_f	0.174	0.047	0.205	0.174	0.057	0.068
N	340338	5164803	241211	99127	3339706	1825097
$NCat$	59254	241698	49293	17273	193836	121533
Adj. factor	1.21	1.05	1.26	1.21	1.06	1.07
R^2 ICAC	0.078	0.061	0.068	0.084	0.085	-0.003
Adj. R^2 ICAC	0.095	0.064	0.085	0.102	0.091	-0.003
ICAC difference				-0.104		
Adj. ICAC difference:				-0.110 (0.01)		

	Panel II: Top decile analysis					
Dependent variable:	Wealthy (Yes/No)					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
Brassey		23.99***			13.06***	35.19***
		(4.30)			(0.00)	(0.00)
Grainger	-7.28*	0.91	-10.22***	-2.11***	2.15***	-1.80***
	(3.99)	(1.04)	(0.00)	(0.00)	(0.00)	(0.00)
Langcaster	-7.28*	-7.59	-10.22***	-2.11***	-7.99***	-6.91***
	(4.19)	(10.83)	(0.00)	(0.00)	(0.00)	(0.00)
Rothschild		33.58***			38.68***	-6.91***
		(6.43)			(0.00)	(0.00)
Constant	7.28***	7.59***	10.22***	2.11***	7.99***	6.91***
	(0.45)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
N	3348	76590	2134	1214	48296	28294
$N_{Brassey}$		38			19	19
$N_{Grainger}$	42	659	27	15	444	215
$N_{Langcaster}$	38	6	23	15	4	2
$N_{Rothschild}$		17			15	2
Share of wealthy						
Omitted category	Smith	Smith	Smith	Smith	Smith	Smith

Notes: This table compares ascriptive characteristics pre- and post-Industrial Revolution. In this table, we study last names in general as well as selected last names: Brassey, Grainger, Lancaster, Rothschild and Smith. Panel I reports the adjusted R^2 from a regression of wealth on a vector of fixed effects, indicated over the panel. We report results in six samples, 'pre' in column (1) and 'post' in column (2), and a combination of 'pre' and 'post' with industrial location in columns (4) and (6) and non-industrial location in columns (3) and (5). Industrial location is defined as residence in a county that has 50% or higher share of jobs in manufacturing. Non-industrial location is residence in a county with less than 50% share of jobs in manufacturing. Each column reports a separate regression, for separate subsamples indicated over each column. In addition we report the number of observations and the number of distinct fixed effects and the adjusted R-squared ICAC difference coefficient capturing the change in goodness of fit of a vector of ascriptive characteristics in industrial versus non-industrial locations. In parentheses we report the p-values of a permutation test designed to test statistical significance of the adjusted R-squared difference coefficient.Panel II reports the point estimates of a regression of an indicator for belonging to the top-wealth decile on the different categories. We indicate the omitted category at the bottom of each column.We report classical standard errors. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significance at the 1% level.

Table 4: Pre-Post Industrial Revolution Analysis - Name Type

	Panel I: Fixed effect analysis					
Fixed effects:	Name Type					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.000	0.000	0.001	0.001	0.000	0.000
R^2_f	0.000	0.000	0.000	0.000	0.000	0.000
N	268959	4513808	188776	80183	2913099	1600709
$NCat$	16	16	16	16	16	16
Adj. factor	1.00	1.00	1.00	1.00	1.00	1.00
R^2 ICAC	0.000	0.000	0.001	0.000	0.000	0.000
Adj. R^2 ICAC	0.000	0.000	0.001	0.000	0.000	0.000
ICAC difference				0.000		
Adj. ICAC difference:				0.000 (0.57)		

	Panel II: Top decile analysis					
Dependent variable:	Wealthy (Yes/No)					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
Locative	-0.84***	-0.00	0.84**	-0.07	0.34**	0.20
	(0.22)	(0.06)	(0.39)	(0.38)	(0.16)	(0.18)
Relationship	-0.97***	-0.40***	-0.67	-0.55	-0.33*	-0.40*
	(0.23)	(0.06)	(0.41)	(0.40)	(0.19)	(0.21)
Occupational	-1.15***	-0.63***	-0.38	-0.82**	-0.77***	-0.10
	(0.25)	(0.07)	(0.42)	(0.40)	(0.26)	(0.26)
Constant	9.15***	9.73***	10.67***	3.64***	10.25***	8.44***
	(0.20)	(0.05)	(0.33)	(0.36)	(0.14)	(0.16)
N	268959	4513808	188776	80183	2913099	1600709
$N_{locative}$	70138	1245136	41813	28325	691451	553685
$N_{relationship}$	53563	932328	39486	14077	639551	292777
$N_{occupational}$	31581	430984	21865	9716	285128	145856
Share of wealthy						
Omitted category	Nickname	Nickname	Nickname	Nickname	Nickname	Nickname

Notes: This table compares ascriptive characteristics pre- and post-Industrial Revolution. In this table, we study name types: Names referring to a location, relationship to another person, occupation and nicknames. Panel I reports the adjusted R^2 from a regression of wealth on a vector of fixed effects, indicated over the panel. We report results in six samples, 'pre' in column (1) and 'post' in column (2), and a combination of 'pre' and 'post' with industrial location in columns (4) and (6) and non-industrial location in columns (3) and (5). Industrial location is defined as residence in a county that has 50% or higher share of jobs in manufacturing. Non-industrial location is residence in a county with less than 50% share of jobs in manufacturing. Each column reports a separate regression, for separate subsamples indicated over each column. In addition we report the number of observations and the number of distinct fixed effects and the adjusted R-squared ICAC difference coefficient capturing the change in goodness of fit of a vector of ascriptive characteristics in industrial versus non-industrial locations. In parentheses we report the p-values of a permutation test designed to test statistical significance of the adjusted R-squared difference coefficient.Panel II reports the point estimates of a regression of an indicator for belonging to the top-wealth decile on the different categories. We indicate the omitted category at the bottom of each column.We report classical standard errors. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significance at the 1% level.

Table 5: Pre-Post Industrial Revolution Analysis - Name Origin

	Panel I: Fixed effect analysis					
Fixed effects:	Name Origin					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.002	0.000	0.001	0.003	0.000	0.000
R^2_f	0.000	0.000	0.000	0.001	0.000	0.000
N	268959	4513808	188776	80183	2913099	1600709
$NCat$	66	72	64	54	72	67
Adj. factor	1.00	1.00	1.00	1.00	1.00	1.00
R^2 ICAC	0.002	0.000	0.001	0.002	0.000	0.000
Adj. R^2 ICAC	0.002	0.000	0.001	0.002	0.000	0.000
ICAC difference				-0.001		
Adj. ICAC difference:				-0.001 (0.23)		

	Panel II: Top decile analysis					
Dependent variable:	Wealthy (Yes/No)					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
norman	4.50**	2.45***	3.15	1.10	1.98	3.08*
	(1.87)	(0.51)	(3.85)	(2.76)	(1.41)	(1.82)
french	28.19***	2.88***	21.66**	56.75***	3.29*	-1.25
	(4.83)	(0.83)	(9.94)	(20.40)	(1.68)	(2.00)
welsh	2.45***	0.70***	1.74	0.40	1.43***	-0.77**
	(0.70)	(0.13)	(1.67)	(0.95)	(0.47)	(0.38)
irish	1.16**	-3.49***	0.71	0.15	-2.41***	-4.58***
	(0.50)	(0.09)	(0.52)	(0.55)	(0.59)	(0.38)
scottish	1.14	4.58***	0.58	1.19	4.85***	3.32***
	(1.07)	(0.14)	(1.59)	(1.76)	(0.47)	(0.51)
Constant	8.17***	9.38***	10.49***	3.25***	9.91***	8.50***
	(0.06)	(0.02)	(0.12)	(0.10)	(0.06)	(0.06)
N	268959	4513808	188776	80183	2913099	1600709
N_{norman}	221	3253	198	23	2666	587
N_{french}	33	1231	28	2	1038	193
N_{welsh}	1601	52028	1300	764	33881	18147
N_{irish}	3184	118337	106	17	65223	2026
$N_{scottish}$	19	43062	19	1	31283	172
Share of wealthy						
Omitted category	English	English	English	English	English	English

Notes: This table compares ascriptive characteristics pre- and post-Industrial Revolution. In this table, we study name regional origin: Norman, French, Welsh, Irish, Scottish and English. Panel I reports the adjusted R^2 from a regression of wealth on a vector of fixed effects, indicated over the panel. We report results in six samples, 'pre' in column (1) and 'post' in column (2), and a combination of 'pre' and 'post' with industrial location in columns (4) and (6) and non-industrial location in columns (3) and (5). Industrial location is defined as residence in a county that has 50% or higher share of jobs in manufacturing. Non-industrial location is residence in a county with less than 50% share of jobs in manufacturing. Each column reports a separate regression, for separate subsamples indicated over each column. In addition we report the number of observations and the number of distinct fixed effects and the adjusted R-squared ICAC difference coefficient capturing the change in goodness of fit of a vector of ascriptive characteristics in industrial versus non-industrial locations. In parentheses we report the p-values of a permutation test designed to test statistical significance of the adjusted R-squared difference coefficient.Panel II reports the point estimates of a regression of an indicator for belonging to the top-wealth decile on the different categories. We indicate the omitted category at the bottom of each column.We report classical standard errors. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significance at the 1% level.

Table 6: Benchmarking social orders R^2

Fixed effects:	**Fixed effect analysis** Social orders					
	pre	post	pre nonIR	pre IR	post nonIR	post IR
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.167	0.060	0.154	0.245	0.059	0.071
Maximal R^2	0.408	0.629	0.406	0.482	0.627	0.686
ratio R^2-Maximal R^2	0.407	0.094	0.374	0.517	0.093	0.102

Notes: This table reproduces the R-squared from Table 2 in row 1. In row 2, we report an R^2 from a regression in which we re-assign the nobility and gentry labels. If the sample for a column contains N nobles and M gentlemen then we reassign to richest N people to be noble and the next M richest people to be gentry, and re-estimate the R^2. In row 3 we report the ratio of row 1 to row 2.

Table 7: Richest people in the probate data

Name	Rank	Wealth	Share	Profession	Ennobled?
Herman de Stern	1	3,544,978	0.108	Banker	Y
Thomas Brassey	2	3,200,000	0.097	Railway investor	Y
Hugh Calmont	3	3,121,931	0.095	Stockbroker, merchant	N
Giles Loder	4	2,900,000	0.088	Merchant	Y
John Gretton	5	2,883,640	0.088	Brewer	Y
Sir Andrew Walker, baronet	6	2,876,782	0.087	Brewer	Y
Richard Thornton	7	2,800,000	0.085	Merchant	N
William Wentworth-Fitzwilliam, Earl Fitzwilliam	8	2,799,999	0.085	Landowner	N
Lionel Rothschild	9	2,700,000	0.082	Banker, politican	Y
William Foster	10	2,587,681	0.079	Industrialist	N

Notes: This table displays a ranking of the ten richest people in the probate data with their names and professions, their personal wealth (in pounds), their share of total wealth (in percent), their profession (taken from Rubinstein (1977b) or the Oxford Dictionary of National Biography) and an indicator whether either the person or their son got ennobled (taken from the Oxford Dictionary of National Biography). de Stern's son was made an earl. Brassey's son was made an earl. Loder's son was made a baronet. Gretton's son was made a baron. Walker's son was made a baron. Rothschild's son was made a baron.

Table 8: Average wealth by millowners, people with millowner names and people without millowner names

	(1) Probate		(2) Hearth	
	Mean wealth	N	Mean wealth	N
Millowners	7790.0	61		
People w/ millowner names	711.3	166770	2.2	7832
People w/o millowner names	631.9	5023761	2.4	335190
p-value: Millowners vs. people w/ millowner names	0.00			
p-value: Millowners vs. people w/o millowner names	0.00			
p-value: People w/ vs. w/o millowner names	0.00		0.00	

Notes: This table displays average wealth of millowners from the 1838 Parliamentary survey of textile mills in the Probate as well as average wealth of people who have and who do not have the same last name as a millowner in both our data sources. It further displays the p-values of t-tests with the null hypothesis that average wealth is the same for millowners and people with a millowner last name, millowners and people without a millowner last name and people with and without a millowner last name.

Table 9: What are the correlates of high social mobility parts of England?

	High Mobility Parish (Yes/No)
Economic structure	
City or town (yes/no)	0.0814***
	(0.0099)
Market or fair held 1600 (yes/no)	0.0939***
	(0.0190)
Fraction pop. in primary sector 1700	-0.0772***
	(0.0185)
Fraction pop. in secondary sector 1700	0.1207***
	(0.0268)
Fraction pop. in tertiary sector 1700	0.0198
	(0.0227)
Initial conditions	
Tax revenue 1525	-0.0121***
	(0.0040)
Tax revenue per capita 1525	-0.0146***
	(0.0039)
Social structure	
Number nobility 1700	0.0047
	(0.0038)
Number gentry 1700	0.0224***
	(0.0043)
Number yeomen 1700	-0.0900***
	(0.0197)
Political variables	
N. members of parliament	0.0141***
	(0.0040)
Fraction catholics	-0.0150
	(0.0094)
Fraction elections contested 1701-1831	0.1392*
	(0.0736)
Feudal legacy	
Monastic ownership of part of parish (yes/no)	-0.0030
	(0.0072)
Parliamentary enclosure 1750-1830 (yes/no)	-0.0005
	(0.0070)

Notes: Every point estimate is from a separate regression of an indicator equal to one if a parish is a high social mobility parish on the relevant variable, and county fixed effects. Parishes have high social mobility if more than 50% of inhabitants carry a surname with a delta wealth standard deviation higher than the median. Delta wealth standard deviation is obtained by standardizing wealth 'pre' and 'post', computing the averages by surname, and subtracting the standard deviation 'pre' to the standard deviation 'post'. All variables are either binary, or standardized.