NBER WORKING PAPER SERIES

THE BREAKDOWN OF THE ENGLISH SOCIETY OF ORDERS: THE ROLE OF THE INDUSTRIAL REVOLUTION

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Working Paper 34153
http://www.nber.org/papers/w34153

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2025

We would like to thank Daron Acemoglu, Robert Allen, Joshua Angrist, Mattia Bertazzini, Neil Cummins, Steven Pincus, and seminar participants at the 2021 Ridge Virtual Forum, the workshop of Economic History, Montevideo, the University of Chicago, Harvard University, the NBER DAE Summer Institute meeting 2025, Northwestern University, and the University of Warwick for helpful comments. We particularly thank Steven Durlauf for discussion of the empirical approach and inferential issues and Santiago Torres for his analytical help. We would like to thank Mariano Calderon, Santiago Castiblanco, Lorenzo Di Ferdinando, Lauren Futter, Michael Giordano, Isabelle Hauf-Pisoni, Xueyan Li, Daniel Lowery, Parker Whitfill and Cheryl Wu for providing outstanding assistance and feedback. Thanks are also due to Jan Kozak, Thiviya Kumaran, Benjamin Kurtz, Meghana Nuthanapathi, Mariia Paramei, Dominik Wielath, Anna Mayer, Sneha Venu, Cara Chang, Aby James, and Nour Taqatqa for their valuable research assistance. Finally, we would like to thank the Cambridge Group for the History of Population and Social Structure for sharing their data on early probates and the Becker-Friedman Institute for a generous data acquisition grant. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 34153
August 2025
JEL No. D31, J60, N63

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 and occupational mobility. We show that people with surnames that were more mobile tended to be in the north and working in manufacturing. Moreover, areas that experienced greater outward mobility were more urbanized; less agrarian; had institutionalized markets; more gentry; were poorer (as proxied by tax revenues); and were more likely to be the residence of a member of parliament.

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1 Introduction

Modern analyses of social mobility typically examine individual factors or peer and neighborhood effects to understand its drivers. These include parental income and education, market opportunities and individual preferences, the quantity and quality of public services, and social capital (Chetty et al., 2014, 2018; Chetty and Hendren, 2018a). But there is nothing inevitable about the choice for these factors or the ideological and institutional frameworks within which they are nested. For example, prior to the modern era the dominant models of society were quite different - featuring divinely ordered allocations of people into separate parts of a hierarchy, a 'society of orders'. In this paper we examine its breakdown, and therefore the emergence of modern social mobility, and its relation to the Industrial Revolution, using newly collected micro data for England.

In the feudal Middle Ages, society was often conceived of as composed of "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. In the early Middle Ages, the Emperor Charlemagne put it as follows: "Let everyone serve God faithfully in that order in which he is placed" (quoted by Herlihy (1973, p.623)). In 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). 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)).[1] 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

[1] For influential contemporary discussion of the society of orders see Harrison (1994, p.1) for 1577, Sir Thomas Smith (2013, p.66) for 1583, see also Stone (1966, p.21) and Gregory King in 1688 (Laslett, 2000, pp.36-37) who "followed the gradations of gentility from the peerage down ... much as Harrison ... had done" (Wrightson, 1984, p.21).

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 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 Principal Probate Registry records (henceforth 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 (Schurer and Higgs, 2015). Thus we have an approximation of the entire wealth distribution, with people's names and location which we can use to identify their titles.[2] We compare this dataset to a pre-Industrial Revolution proxy for wealth, which we digitize from the hearth tax returns, from 1662 to 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 (that existed until the 19th century) 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.[3]

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. These fall into several categories. First, and most significantly, we know whether a person was a noble, or a member of the 'gentry'.[4] 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 statuses.[5,6]

[2]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 the 17th century probate inventories, his dataset completely lacks individual level information (e.g., names, wealth etc.).

[3]We restrict our analysis to men because the hearth tax is collected at the household level and most heads of households observed were men. Hence, we do not have representative data on female wealth prior to the Industrial Revolution.

[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]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 was similar (Stone and Stone, 1984, p.207), see Pumphrey (1959) and McCahill and Wasson (2003) for the data.

[6]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).

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 simply family status or location (see Dolan, 1972) suggests that they may be significant determinants of social mobility.

Our hypothesis is that the explanatory power of the society of orders and surnames for wealth should be higher before the Industrial Revolution than after and in particular it should fall more in parts of England where the Industrial Revolution had a greater impact. We interpret this reduced explanatory power as being consistent with increased social mobility (Güell et al., 2015). Empirically, we examine the proportion of the variation in the distribution of wealth which these characteristics explain between 1662 and 1674 and in the second half of the 19th century (henceforth pre- and post-Industrial Revolution).

We start with the division of the population between nobles, gentry, and commoners. 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 two-thirds.

We then use data on employment in manufacturing to break our sample into that part of England more impacted by the Industrial Revolution and that part less impacted and repeat the previous exercises. The focus here is on whether the falls we discovered in the explanatory power of the elite characteristics occur more in the parts of England that were more impacted by the Industrial Revolution. This is precisely what we find. Looking at the explanatory power of the nobility and gentry, we find the proportion of the variation explained falls by eight percentage points more in the parts of England that were impacted more by the Industrial Revolution, compared to the fall in less impacted parts.

Measures of nobility and gentry capture status at the very top of society relative to everyone else. Using surnames enables us to understand social mobility in the full population. To focus just on this, we remove anyone who is part of the nobility or the gentry from our sample (this removes less than 1% of the full sample, and results are similar when we include these individuals). We then estimate the explanatory power of a full vector of 59,254 distinct surnames pre-Industrial Revolution and 241,698 distinct surnames post-Industrial Revolution. We find the full vector of surname fixed effects explains 10% of the variation in wealth before the Industrial Revolution, which falls to 6% afterwards. This average effect sharply differs by geography. Before the Industrial Revolution, the explanatory power of surnames is similar in areas that will be industrializing (10%) and in areas that will not (9%). After the Industrial Revolution, the explanatory power of surnames falls to 0% in industrializing parts of the country. In sharp contrast, it stays constant at 10% in the areas of the country less impacted by the Industrial Revolution. These results complement the breakdown of the society of orders at the top: Social mobility increases for the entire population.

Surnames capture several family level characteristics. Two of these have received particular attention

in the literature: name 'types' and the migratory/ethnic origin of names. To better understand the role of surnames we group them to understand these factors. The Oxford Dictionary of Family Names in Britain and Ireland first divides surnames 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. The Dictionary also provides an 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 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. The low explanatory power of these factors is consistent with 20th century evidence in Cummins (2024).

Are our results consistent with the Industrial Revolution being associated with a "breakdown" in the society of orders? The crucial factor is whether 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 1600 comment that in Elizabethan society "the hierarchy of status corresponded roughly with the pyramid of incomes" Wilson (1936, p.94): Take the the richest 95 people in the hearth tax sample and relabel as noble (to match the 95 nobles in our sample). Then take the 2,589 next richest people and relabel them as gentry (to match the number of gentry in our data). In Table 3 we do this exercise and construct a 'Maximal' R^2 - the R^2 if the social orders perfectly corresponded to the wealth distribution. We find this to be 40.8%. 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 40.7% of the maximum it could have attained.[7] Doing the same exercise for after the Industrial Revolution we see from Table 3 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.[8] To implement the corresponding exercise for surnames, we need

[7]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).

[8]The society of orders broke down in other domains. For example, politically the House of Commons came to dominate the

to allocate a vector of surname fixed effects (with varying numbers of holders) to maximize goodness-of-fit. We do so by assigning the richest people surnames with just one holder (since there is more variation in wealth at the top), until we run out of single-holder surnames. The next richest two people get a surname with two holders, etc. This achieves the Maximal R^2. We find that our estimated R^2 as a fraction of this Maximal R^2 falls by 64% over the Industrial Revolution. These benchmarking exercises together suggest that (downward) social mobility at the top and (upward) social mobility at the bottom increase dramatically over the Industrial Revolution.

We implement these analyses carefully considering differences in degrees of freedom and measurement between each survey, as well as goodness-of-fit simply arising by chance when using a large number of fixed effects. However, the key challenge to our preferred interpretation of our results is differential measurement error. Our pre- and post-Industrial Revolution proxies for wealth are different, and a drop in the goodness-of-fit may simply reflect differential measurement error of the true underlying wealth distribution, especially if it attenuates our post-Industrial Revolution estimates more. 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 in the presence of classical measurement error in wealth our post- data would have to be significantly more attenuated than our pre- data to explain our results. However, the probate returns are a much more direct measurement of wealth, even if not the whole of it, and were much more bureaucratically collected than the hearth tax, which is a proxy for wealth. We therefore conclude that while there may be significant measurement error in either survey, an issue we address in various robustness checks, our between-survey comparisons are unlikely to be driven by measurement error. For the case of correlated measurement error, we derive sufficient conditions under which our results would be explained by this form of measurement error, and we argue that these, too, are unlikely to be met in our data.

In addition to our basic results, we also investigate the extent to which different attributes predict whether or not a person will be "wealthy" - in the top decile of the wealth distribution. Our basic finding is that the industrial revolution has little impact on the probability that a noble is rich while the probability that a member of the gentry is wealthy increases significantly from 67%-age points to 83%-age points. We interpret the large rise of the coefficient on the gentry as reflecting the flexibility of this tier 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.[9] Nevertheless, the large fall in the share of the

House of Lords in the 18th and 19th centuries, 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.

[9]See Beckett (1986, pp.206-237) on the involvement of the nobility in the Industrial Revolution. Crouzet (1985, pp.148-

variation explained shows that this flexibility was insufficient to stop the rise of a broader social mobility.[10] The society of orders was insufficiently inertial to maintain its relative position in the wealth distribution although it remained true that someone with a noble title was almost certain to be rich.[11]

Though our results cannot be interpreted as causal, they are consistent with a central idea in the recent historiography of the Industrial Revolution, which is that industrialization 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 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 "socially mobile," by measuring the change in dispersion of wealth *within* a surname pre- and post-Industrial Revolution. An individual surname is "socially mobile" if it is above the median level of the change in dispersion. A parish is socially mobile, captured by an indicator variable, if it has an above median fraction of people that belong to (future) socially mobile surnames. We then ask two questions: First, where did people with socially mobile surnames tend to end up geographically and what economic sectors did they tend to work in?; Second, what were the characteristics of socially mobile parishes? In particular, what factors seem to be associated with greater outward movement of individuals?

For individuals, we find that people with more socially 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's arguments. The increased social mobility we documented was related to geographical and economic (sectoral) mobility.

At the parish level we find that parishes which experienced more mobility tended to be urban, had an institutionalized market in 1600, were less agrarian with people more concentrated in the secondary sector and had lower income levels (as proxied by tax revenues). We find that initial social structure was important, with mobility being associated with having more gentry and fewer yeomen, a class of wealthier landowning peasants, in 1700. We also find that political characteristics are significant: parishes where

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.

[10] 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).

[11] 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).

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). Another literature, on equality of opportunity, has taken a different approach by trying to distinguish between those parts of a person's income for which they are responsible as distinct from that part determined by inheritance or parental decisions (Niehues and Peichl, 2014; Ferreira and Gignoux, 2015; Hufe et al., 2017).

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.[12] Neither study is able to examine the issues which are our focus, since there is consensus that the society of orders barely existed in this period and the data comes from an epoch after the Industrial Revolution had taken place.

Clark (2014) and Clark and Cummins (2014) have used the extent to which certain surnames are over-represented relative to the population in various institutions, such as Oxford and Cambridge university admissions, to study elite persistence. They find high levels of elite over-representation which, though gradually declining, are 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). 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.

Focusing on the 20th century, the English probate records have also been intensively studied by Cummins (2021), for example, Clark and Cummins (2015) has used them to document large falls in wealth inequality in the 20th century while simultaneously finding persistence of status among the rich, and middle class. Their work does not focus on our main questions or use a similar econometric approach.

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, but also the contexts that facilitate mobility.[13] Chetty et al. (2014) finds higher rates of social mobility associated with greater tax rates, less manufacturing industry, lower levels of inequality and poverty and higher levels of social capital. The difference between these and

[12] This finding is disputed by Miles (1993, 1999) and Mitch (1993) who paint a picture of much more stable social classes.

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

our results possibly come from the different stages of economic development. For example, the different signs on manufacturing industry. In our period, as we have emphasized, industry was an opportunity. In the current US this variable picks up those areas left behind by more recent structural transformation. Though we cannot measure historical social capital directly, Putnam (1994) argued that variation in social capital in Italy was caused by different feudal legacies, although 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).[14]

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) found the period of the Industrial Revolution was associated with increased wealth inequality, consistent with Piketty (2014, p.344), Piketty and Zucman (2014) and Madsen (2019) (see also the evidence in Roine and Waldenström, 2015). Alfani (2021, p.14) 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" (see also Waldenström (2024)).[15]

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 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 probate and hearth tax records, and the issues involved in using them. In Section 3 we lay out our empirical approach to social mobility. 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 driving our main 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 wealthy before and after the Industrial Revolution, and we present a benchmark

[14]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.

[15]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).

which justifies our use of the word "breakdown". Section 6 presents some case studies of the nobility and entrepreneurs, in particular 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 status, and location of adult males. We map locations to parishes, small administrative units in England, which are contained in counties. We then classify counties by whether they were more or less impacted by the Industrial Revolution. 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 2.6, we discuss the coverage of the data.

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 in 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.[16] 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 status, 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. We end our sample in 1899.

2.1.2 Digitization of records

The census data is available in digitized format (Schurer and Higgs, 2015).[17] For probates, scans of all original records from 1858 onward are available through the UK Government Digital Services.[18] Appendix Section III.A provides an example of a probate record and in Appendix Section III we describe the scraping, digitization and parsing of the data into individual entries. From the probate records, we extract names, noble or gentry status, wealth, the year of death and their addresses using regular expressions.[19]

We validate our procedure by checking by hand the records of several subgroups. First, we check the richest 100 individuals, the richest 100 members of the gentry and the richest 100 noble individuals. Second, we check the records of *all* 600 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 with this data. 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 1861 census would show up in the probate records if they died with some wealth by 1899.[20] 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. Appendix Section V describes the linking procedure in detail.

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

[17] 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).

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

[19] For example, for total wealth, we look for the first pound sign and extract all characters up to the next white space.

[20] 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.

The final dataset includes 5,276,146 observations after excluding unmatched children from the census data (N=7,356,712), females (N=5,717,879),[21] and observations dropped due to missing values (N=73,227).[22] It includes linked observations (N=764,886), unlinked census observations (those too poor to be probated, N=4,312,418), and those who are probated and unlinked (so as to not lose rich people, N=198,842). This corresponds to a linking rate of probate records of 79.4%.[23]

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.[24] In the first hearth tax collection year of 1662 the tax amounted to 2 shillings a year. Up until 1674, the hearth tax data includes for each township, hamlet or ward, handwritten records of first and surnames 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, this paper includes the years 1662 to 1674.[25] For each location, we use the data from one collection date only, e.g., Lady Day 1674.[26]

Hearth tax records survived for most counties, however, though 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. Our final analysis dataset includes 343,022 observations. See Appendix Section VI.A for an example of a hearth tax record. Appendix Table VI.I lists the sources of records used as well as their method of digitization.

Hearth tax records have been previously used by historians as a source, for example, for local analysis

[21] Recall that our analysis is limited to men because hearth tax returns mostly includes males.

[22] 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.

[23] The fact that we have probated individuals in our dataset for whom we could not link the equivalent person in the census means that we 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 52,032 observations to a rate of 84.8%. 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.

[24] Almost all people occupied only one house. We discuss in Appendix Section VI.D how we identify those, and in particular nobles, who occupied more than one house.

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

[26] For most counties we have only one data collection date available. For counties with data from multiple dates, we use the most recent survey. If there are parishes that are covered in an earlier later survey and not a later one, we use the latest available data. This issue affects only 88 parishes.

of economic conditions, literacy or population estimates (Vann, 1974; Arkell, 1982, 1987; Stephens, 1990; Spufford, 2000).[27] 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 Validation: Proxy for wealth

In this section, we try to validate the idea that the hearth tax returns are a useful proxy for wealth by using probate inventories collected between 1518 and 1787 in seven English counties as compiled by Dean et al. (2004).[28] These probate inventories include information on names, location, year 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 mostly below 100 (there are two exceptions) and the records available to us do not include counties in the heartland of the Industrial Revolution.[29]

We merge the probate inventory records from 1662 to 1730—i.e. those recorded in the hearth data in the 1660s might have died only in the 1700s—to the hearth tax records over year, location and name. Of the 13,921 observations in the probate inventories in the eligible year range we can merge uniquely 269 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 probate inventory wealth and the number of hearths is 0.37.[30] We believe this is important evidence that the hearth tax is indeed a valid proxy for the true wealth distribution.

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.II we provide a full list of the 600 noble titles and individuals extant in the linked probate-census records, with their validation to outside sources, discussed below. In Appendix Table VIII.IV we do the same for the 95 noble titled

[27] There are data projects such as Hearth Tax digital (https://gams.uni-graz.at/context:htx) that continuously digitizes 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 our own digitization efforts.

[28] The counties include Berkshire, Cornwall, Durham, Hertfordshire, Kent, Lincolnshire and Worcestershire. We thank the Cambridge Group for the History of Population and Social Structure for providing the data to us.

[29] 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.).

[30] When we allow non-unique matches (i.e. when a probate inventory observation matches to two hearth observations, the probate inventory observation is duplicated and both hearth observations are retained) the sample size increases to 398 and the correlation is 0.29.

individuals in the hearth tax records. Finally, we present titles that appeared in our validation records, but not in our data, in Appendix Tables VIII.III and VIII.V. In the post-Industrial Revolution period these are mostly people who passed away before 1861 or held a title not registered in the peerage of the United Kingdom or England, whereas for the pre-Industrial Revolution period these are mostly nobles in counties we do not have data on. Further, our data include 25,319 members of the gentry in the linked probate-census data and 2,589 members of the gentry in the hearth tax 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. 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 as discussed females are excluded from our analysis. Appendix sections III.A and VI.A provide examples of original records of individuals from all three social orders (nobility, gentry and commoners).

The identification and cleaning of social order variables can be summarized in the following way, and is described in detail in Appendix Section VIII.A. We used regular expressions to identify records mentioning noble ranks. All identified 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 surnames manually. We then validated the list of noble people from our data against external sources. For the post-Industrial Revolution period, our main source of external validation is "Burke's genealogical and heraldic history of peerage, baronetage and knightage 1861" (Burke, 1861). For the pre-Industrial Revolution period, we use 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 listed in these external sources that we had not identified so far, we conducted more background research to understand 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. If we would expect to find a title in our data, but haven't so far, we searched for the unobserved noble in our data, typically by searching for the first and surname or their wealth 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.B 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.

We paid particular attention to the levels of wealth 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 pre- and post-period 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.

2.3.2 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 (Satchell et al., 2016).[31] For the mapping of the probate, we use Google Maps API to get the latitude and longitude of the recorded addresses or location information, and selected as a county and parish the nearest 1851 county and parish centroid. The resulting county and parish information in the probate data, and the county and parish information that existed in the hearth data, were then merged to the geo-referenced dataset with clean county and parish information. Unsuccessful merges were manually fixed.[32] More details on the mapping procedure 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 10,107 parishes.[33,34] For 309,960 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.[35]

The 26 historic counties (of a total of 39 historic counties) we have hearth tax data for map to 32 counties in 1851 (of a total of 42 counties in 1851).[36] 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.[37]

[31] This dataset is the underlying data (i.e. the attribute table) of the ArcGIS shapefile "1851EngWalesParishandPlace.shp".

[32] 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.

[33] 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).

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

[35] 233,002 (75.2%) 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 (11.0%), the second largest share in the West Riding of Yorkshire (9.4%), and the third largest share in London (6.9%).

[36] 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*. 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.

[37] 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.

2.3.3 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. The census data include 5-digit HISCO classifications of occupations, based on a census occupation description. Upon inspection, the HISCO codes were oftentimes not consistent with the occupation recorded in this description. Even when correct, the HISCO level of aggregation was either too detailed or too broad for our purposes. Therefore, we re-classified occupations into groups (e.g., agriculture, mining, construction, manufacturing, etc.) based on keywords in the occupations variable, and then define sectors based on these occupational groups. We describe this process in Appendix Section IV. We can code 84.7% of the 5,276,146 observations in the linked probate-census data this way to occupation groups and sectors.[38]

2.4 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 at the county level. For our main analysis, we identify counties to be industrialized if more than 40% of the population is employed in manufacturing, as identified by occupations in the census and the coding of occupation groups described in Section 2.3.3. This classification includes Bedfordshire, Cheshire, Derbyshire, Lancashire, Nottinghamshire, Staffordshire, Warwickshire, and the West Riding of Yorkshire (Northern parts). We vary this cutoff as part of our robustness analyses below.

2.5 Other data sources

2.5.1 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 its variations in spelling, its geographical origin (N=88), and whether the name describes a location, a relationship, an occupation, or a nickname, and merge it to our data via surnames.

[38] We can code occupation groups and sectors for 82.9% of the probate observations linked to the census and 88.9% 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 county population figures from the census (see Section 2.4).

English name origin is most common with 79.9% and 75.6% in the post- and pre-Industrial Revolution periods. The next most common name origin is Scottish (pre: 11.8%, post: 14.1%).[39] In both datasets the majority of surnames are locational (pre: 37.5%, post: 42.0%), followed by relational (pre: 30.9%, post: 34.4%), nickname based (pre: 19.4%, post: 20.5%), and occupational (pre: 16.7%,, post: 16.0%). In Appendix section VII we visualize the distribution of name types and name origins, in bar graphs and maps, for the pre- and post-Industrial Revolution periods.

2.5.2 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 the 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).[40] 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 the 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 (Dyer and Palliser, 2005) and the fraction of elections between 1701 and 1831 that were contested (Cannon, 1973). Lastly, the category of feudal legacy includes an indicator of 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).[41]

[39] These are followed by Irish (pre: 6.1%, post: 8.7%), Norman (pre: 7.4%, post: 8.1%), and Welsh (pre: 1.8%, post: 3.5%. The remaining origin categories account for below 1.5%. Note that one name can have multiple origins. Name origins are missing for 21.6% in the pre-period and 13.2% in the post-period.

[40] 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.

[41] 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. See Heldring et al. (2021) and Heldring et al. (2022) for a description of the data and their sources in greater detail.

2.6 Sample

2.6.1 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 5,349,373 adult males, however, 50,481 of those observations have missing wealth information (0.94% of linked data; 4.9% of probate data), 17,031 have missing county information (0.32%) and 5,715 observations have missing surnames (0.11%), resulting in a final post-Industrial Revolution dataset with 5,276,146 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 households.[42] 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 343,022 males. In Appendix Section X.A we report these statistics county by county. For counties with full parish coverage, we cover about 100% of the population.[43]

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 fourty percent of the population was employed in manufacturing in the 1861 census. 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.

2.6.2 Descriptive statistics

Mean wealth in the total post-Industrial Revolution sample is 624 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

[42]The gender of household heads is determined based on first names. For 17.1% of observations gender 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.

[43]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.

the total sample, are located close to London and include Middlesex (1,296 pounds), Surrey (1,033 pounds), Sussex (1020 pounds) and Buckinghamshire (843 pounds). The poorest counties were Staffordshire (291 pounds), Durham (320 pounds) and Cornwall (346 pounds). The regional wealth distribution is presented in Figure 2, mapping mean wealth at the parish level. Yellow and light green indicate poorer parishes and dark green and blue indicate wealthier ones. Besides the concentration of wealth in and around London, mean wealth is high in the Northern parts of the heartland of the Industrial Revolution.

Figure 4 shows that essentially all wealth is held by the 10% richest people in the country in the post-period, 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 97.6% of wealth.[44] In Appendix Section X, 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 post-Industrial Revolution data contain 600 noble individuals and 25,319 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 5 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 regional distribution of wealth, measured by mean number of hearths at parish level, is presented Figure 3. 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 the 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. The richest counties 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. In Appendix Section X, we similarly provide descriptive statistics by county and by decile of the distribution of the number of hearths.

Figure 5 shows the share of wealth by decile. The richest decile owns 35.5% of wealth whereas the poorest

[44] 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).

decile owns 0% of wealth.[45] The hearth tax data contain 95 noble titles and there are 2,589 households of the gentry (see Appendix Table X.VIII for these statistics).[46] Among the 200 richest households 21.9% 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.

3 Empirical approach: Social orders, ascriptive characteristics and comparisons

3.1 Measuring social mobility in cross-sections

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 then rigid characteristics (such as being noble) or fully unalterable characteristics (such as surnames) should not be predictive of a person's wealth. Conversely, if wealth is fully determined by one's parents' status, then wealth can be fully or to a large extent be explained by unalterable or rigid characteristics passed on from parents to children.

We therefore compare the predictive power of rigid and unalterable characteristics across our cross-sections of hearth tax records (which we label 'pre', like above) and linked probate-census records ('post'). We refer to both rigid and unalterable characteristics as 'ascriptive' characteristics. Our simplest comparison is of goodness-of-fit in a simple fixed effects model, following Güell et al. (2015). We start by estimating the following 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 ascriptive characteristic indicators, such as social status, 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 ascriptive characteristic level (e.g. the surname level). From this regression we compute the R^2. We then randomly re-assign the ascriptive characteristics one hundred times, re-estimate this model with random characteristics, and

[45] 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).

[46] 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.

get the average R^2_{random}. Analogously to Güell et al. (2015), we obtain our coefficient of interest, the R^2 Informational Content of Ascriptive Characteristics (ICAC) coefficient[47], 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^2.[48] We label this difference the adjusted R^2 ICAC coefficient.

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 40% in the post-period. We estimate a similar fixed effects model, using OLS:

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

Where the dependent variable, the ascriptive characteristic indicators, and the error term are now also indexed by $r \in \{IR, Non-IR\}$. We estimate separate models in the four samples defined by p, r: IR/non-IR 'pre', and IR/non-IR 'post'. With the four R^2 ICAC coefficients that we obtain from these models, we construct the R^2 ICAC *differences* coefficient:

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

As before, we adjust this measure for the different degrees of freedom in pre/post and IR, Non-IR. The adjusted $ICAC_{differences}$ 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 of individual indicators from our vector of ascriptive characteristics.

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

[48] 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.

For example, reporting the point estimates for being a member of the nobility captures the probability of being wealthy if noble, relative to commoners. 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 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, indicating that social mobility is higher than the median, for parish g in county c. X_{gc} are potential correlates 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.

3.2 Randomization Inference

To assess the statistical significance of the adjusted R^2 ICAC difference coefficient, 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-Non-IR, post-Non-IR 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 R^2 ICAC difference coefficient. We repeat this process 600 times, generating a distribution of adjusted R^2 ICAC difference coefficients. Using this distribution, we compute two-tailed p-values by computing the fraction of randomized coefficients with an absolute value greater than the adjusted R^2 ICAC difference coefficient generated with the correct assignment of industrial location. The resulting p-value reflects the likelihood of observing an adjusted R^2 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 econometric theory of measurement error to cover the case of comparison between two datasets. We discuss classical measurement error in wealth and then 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 finding that the adjusted R^2 ICAC coefficient is lower in the post-period, using linked probate census records, than in the pre-period, using hearth tax records. In short, our highest-quality data, from the probates, would have to be measured with *more* error than the rest of our data to explain this result. 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 linked probate-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 linked probate-census data as a measure of true wealth. It may also arise from measurement error in each survey, or errors in transcription.

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^2 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 □

Our results show a reduction in the explanatory power of ascriptive characteristics in the post-period relative to the pre-period. Theorem 1 states that if our pre-data is measured with more error than our post-data ($\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$) then, as $n \to \infty$, the probability of observing our result, if in reality there is no difference in R-squared, goes to zero. *If* our results are to be explained by measurement error the assumption $\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$ would have to reverse. However, we believe that the probate returns are a better measure of total wealth and therefore $\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$ holds, because probates are based on a recording

and assessment of all unsettled assets, whereas the pre-period wealth is a count of hearths. We therefore 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

We now consider the case in which 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 measurement error 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, coefficients and goodness-of-fit may appear lower or greater than population values due to this 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 to variance is larger in post:***

$$\frac{|Cov(X_i^{*,Post}, \zeta_i^{Post})|}{\sqrt{Var(X_i^{*,Post})\,Var(Y_i^{Post})}} > \frac{|Cov(X_i^{*,Pre}, \zeta_i^{Pre})|}{\sqrt{Var(X_i^{*,Pre})\,Var(Y_i^{Pre})}}$$

then

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

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.[49] 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^2 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. With correlated measurement error, however, our results can be explained by measurement error when $\lambda_Y^{\text{Pre}} < \lambda_Y^{\text{Post}}$ but we violate condition ii). To understand this condition, first note from the probability limit of $\hat{R}^2_j$ that correlated measurement error can increase or decrease the difference in limit goodness-of-fit between pre and post depending on whether the covariance terms are positive or negative. To see this, simply note that the first term in R^2 is always positive.

To make progress, we assume that the covariances have the same sign pre and post. Condition ii) then states that correlated measurement error relative to the variance terms in post should be larger than the same ratio pre. If this is the case, we demonstrate in the Appendix, goodness-of-fit will be large in post relative to pre. Consequently, the probability of goodness-of-fit being larger in pre than post tends to zero. The exact size of the covariances is hard to determine. It may be that, say, wealth is measured with less error for nobility post than pre because probated wealth encompasses more asset classes, and therefore $|\text{Cov}(X_i^{*,Post}, \zeta_i^{Post}| > |\text{Cov}(X_i^{*,Pre}, \zeta_i^{Pre}|$. It may also be that at the lower end of the distribution, hearth tax wealth is a better approximation of wealth than probated wealth because the hearth tax records record poverty more systematically; and the opposite comparison of covariances holds. For given variance terms in the denominator, condition ii) is therefore a weak sufficient condition on the form of correlated measurement error that would explain away our results. Clearer, however, is the case with approximately equal covariances pre and post. If this is the case, then the condition is met if the variance terms pre are larger than in post. In our data, this holds. The variance in right hand side variables tends to be

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

similar between pre and post, but in wealth it is slightly lower in post than in pre. This is because there are relatively more poor people in the post than pre, since the nobility stayed largely fixed in size, and the gentry grew less fast than the population. This reduces the variance in wealth because all poorer people have zero wealth and poorer people are closer to the now lower mean.[50] All else equal, this means this condition is met, and the probability limit of observing our result if, in reality, there is no difference between pre- and post goes to zero (if solely due to measurement error). Since, however, we do observe a reduction in goodness-of-fit, we conclude that correlated measurement error can't explain away our results.

For the case where the independent variable is vector-valued, we show similar results in the Appendix section XI.B.4.[51]

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 sufficient 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 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.

4.4 Comparing two cross-sections

In this paper we compare the full cross-section of wealth in the linked probate-census dataset to the hearth tax records. At several points in this paper so far, we have discussed the comparability of the two surveys. Here we collect these points succinctly, before moving to our results.

Both the hearth tax records and the probate records contain imperfect measures of the true underlying wealth distribution. This is the case with any measure of wealth, including more recent administrative record-based measures. However, our two measures are different in various dimensions. First, coverage: The probate-census dataset covers all individuals, the hearth tax covers a subset of the country, and may not cover all individuals. Our approach to this is extensive robustness checking, reported in Appendix section XV. Second, scales: Total wealth in pounds (probate-census) is a different measure than total number of hearths. We report two exercises to address this issue. We report in Figure 1 a direct comparison of

[50] Of course, we need to rescale wealth in pre and post to be unit free for this argument to hold.

[51] 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.

housing wealth to probated wealth in a sample of individuals for which we have both. We also replicate all results using percentile rank of wealth rather than share of wealth as the dependent variable in Appendix Tables XV.V through XV.VIII. Percentile rank is a scale-free measure of wealth and makes the two sources comparable as long as our wealth measures are order-preserving proxies of true wealth.[52] Third, given coverage and scale-related issues, there may still be differential measurement error between our two cross-sections. If measurement error is such that effects in the probate-census dataset are (differentially) attenuated, then our results may be spurious. We studied this possibility in the previous section and concluded that measurement error is unlikely to explain away our results. There are a number of remaining, but less important, measurement and robustness issues. We address these in our robustness section below.

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

In column (1) of panel I we report the adjusted R^2 ICAC coefficient for the pre-Industrial Revolution period. We build this measure up in several steps. We first report the unadjusted R^2 from our estimated regression in row 1. We then report the average R^2 across 600 random re-assignments of the social order indicators. The next two rows report the number of observations in the regression, and the number of

[52] When switching from wealth shares to ranks, a lot of variation is lost. Therefore, goodness-of-fit falls substantially. We nevertheless find that it falls substantially more where the Industrial Revolution took place, consistent with the results in the following sections.

categories we base the fixed effects on (in this case three; two fixed effects, for nobility and gentry, and the constant for commoner). We then report the adjustment factor for the degrees of freedom in the regression, the R^2 ICAC, which is the difference between rows 1 and 2, and finally the adjusted R^2 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^2 ICAC for the pre-period 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^2 ICAC coefficient fell by almost 65% over the course of the Industrial Revolution. In section 5.2, we examine whether the change from 17% to 6% is quantitatively significant.

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 section 7, 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 probability 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 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%-age points, while the probability for commoners remains constant at 8%. In other words, although social orders become less predictive of wealth as a whole, most noble individuals remain wealthy after the Industrial Revolution. Gentry status was more fungible and could be obtained during one's lifetime, often as a consequence of acquiring wealth or by holding political office. We observe that the probability of being wealthy goes up for the gentry, from a 67%-age points to 83%-age points higher probability relative to commoners. We interpret the changes in the relative position of the nobility in more detail below, in section 6.

Surname fixed effects. We now turn to an overall measure of social mobility across English society: surname fixed effects (Dolan, 1972; Güell et al., 2015), capturing all characteristics that vary by surname. 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 2, columns (1) and (2). When we do this we find that together, 59,254 surname fixed effects explain about 9.4% of the observed variation in wealth before the Industrial Revolution, but only 6.3% afterwards (per the adjusted R^2 ICAC). Like with social status indicators, the collective explanatory power of surname fixed effects falls over the Industrial Revolution. Note that both the level as well as the decline in the R^2 ICAC is smaller for surname fixed effects than for social order fixed effects, despite the difference in the number of indicators. This is because

social status varies within surname as well as across, and surname fixed effects do not. In Panel II, we select a few surnames 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 surnames, Brassey and Cavendish (see Table 5). Thomas Brassey was a railway entrepreneur. While his father was 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 22%-age points higher probability to be wealthy in comparison to individuals with the surname Smith. For the Cavendish family, we even find a 45%-age point higher probability in the post-dataset. The Cavendish are an old noble family, however, and pre we find a 91%-age points higher probability of being rich. 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 marginally significant or 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 6. In Section 7 we study overall social mobility in industrializing parts of England.

Locative, and other name types. In Section 2.5.1 we introduced the Oxford Dictionary of Family Names, our source for qualitative information of surnames in England. From this dictionary we classify surnames in various ways. The first classification we consider is by type: locative, relationship, occupational and nickname. The Oxford Dictionary of Family Names allows a name to have multiple types and we measure 16 different combinations in our data. We present results using this classification in Appendix Table XIII.I in the same format as above, with panel I presenting the adjusted R^2 ICAC coefficients, and panel II the probability of being wealthy by ascriptive characteristic.

When we compare the adjusted R^2 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 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 surnames, and remains negative and small. We find that, across the board, too, the type of surname has little effect on one's position in the distribution of wealth.

Name origins. 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 and cementing their social position over subsequent centuries. From the Oxford Dictionary of Family Names, we record the national origins of surnames. 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 Appendix Table XIII.II. 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 surnames have no explanatory power, pre and post. In Panel II, columns (1) and (2), we focus on the impact of specific origins on being wealthy. 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 surnames. After the Industrial Revolution (column (2)), consistent with our goodness-of-fit measures, these advantages drop by about 46% for Norman surnames, and 90% for French surnames. Welsh, Irish, and Scottish surnames have slightly higher probabilities to be in the top decile relative to English surnames 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 surnames are still more likely to be wealthy than English 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 in Section 7.

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

5.2 Benchmarking effect sizes

We have so far compared the adjusted R^2 ICAC coefficients over time. We have not tried to benchmark their level. We first ask whether 17%, the proportion of variation explained by nobility and gentry before the Industrial Revolution as measured by the adjusted R^2 ICAC coefficient, is large or small, given our data. We implement a simple exercise in Table 3. The first panel of this table studies social orders. For our samples in Table 1 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

compute the 'maximal' adjusted R^2 ICAC using these fixed effects. We label the resulting estimates the Maximal Adj. R^2 ICAC, and report it in row 2 of Table 3. For instance, for the hearth tax ('pre') sample we find this to be 40.8%. Hence, if the society of orders perfectly matched the wealth distribution this would explain 40.8% of the variation in wealth. Before the Industrial Revolution the society of orders was still prominent: Our estimated adjusted R^2 ICAC, 16.7%, is 40.7% of the maximum it could have attained. We arrive at this number by dividing our measured adjusted R^2 ICAC by the maximal adjusted R^2 ICAC (16.7/40.8). We report this ratio in row 3 of Table 3. Doing the same exercise for after the Industrial Revolution we see from Table 3 that our estimated adjusted R^2 ICAC is less than 10% of the Maximal adjusted R^2 ICAC.[53] This means that expressed as ratios of the maximal adj. R^2 ICACs the explanatory power of social orders falls off by 75%.

In the second panel of Table 3 we repeat this exercise for surnames. To compute the maximal adj. R^2 ICAC for surnames we assign the surnames with the fewest holders (starting with names only held by one individual) to the richest individuals, and assigning names with more holders, in order, to less wealthy individuals. Since there is more variation at the top of the wealth distribution than at the bottom, this procedure ensures the highest goodness-of-fit possible. We find that the maximal adj. The ratio of the actual to maximal adj. R^2 ICAC before the Industrial Revolution is 0.1. After the Industrial Revolution, it drops to 0.7; a drop of 30%.

The most important message here is that for both social orders and surnames, the extent of pre-Industrial Revolution social immobility is large compared to the maximum it could have attained. We interpret this as being consistent with important elements of the society of orders being still present in the late seventeenth century. The data also shows that the extent of this immobility fell substantially after the Industrial Revolution.

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, not just over the Industrial Revolution, but also in ways consistent with that the Industrial Revolution was playing a key role in facilitating mobility. We study the nobility and the owners of textile mills to bolster this interpretation.

[53] Note that this number is due to both a lower numerator, and a higher denominator. The higher denominator is due to wealth 'post' being more concentrated, cf. Figure 4. If we use the 'pre' maximal adj. R^2 ICAC, the ratio of estimated to maximal adj. R^2 ICAC is 14.7%.

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 nobility title after the Industrial Revolution was in fact a descendant from the 'pre' title holder. We report results in Table 4. In columns (1)-(3) we collect characteristics of the richest nobles in the pre-period. We went through the 200 richest individuals 'pre', and identified that 44 of those had a noble title, and report the top 20 here, and the remainder in Appendix section XII. We collect their rank in column (1), their title and name in column (2) and the number of hearths they owned in (3). The richest noble is also the richest person in the country, the Duke of Buckingham with 281 hearths.[54] In columns (4)-(8) we trace the noble title holders' descendants. In column (4) we list the descendant's rank within the 'post' wealth distribution, in column (5) their title and name, in column (6) their wealth, in column (7) their percentile rank in the 'post' wealth distribution and in column (8) the year they were probated.[55] Note that out of 44 members of the nobility, only the Earl of Devonshire is still in the top 200, at place 25, 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 wealth distribution, but they are no longer among the richest of the rich. The startling fact from this analysis 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 5 we compile the top 10 richest people in the '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 Earl Fitzwilliam, the richest individuals are members 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. 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

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

[55] 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.

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.[56]

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 start 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 attempt 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 6.

In column (1) we report the average wealth of the 59 millowners we were able to identify. Their average wealth is around 9,287 pounds. Imagine that being a millowner was open only to privileged people. Then we would expect people with the same surnames as millowners, who were not millowners themselves, to be rich. This is not what we find. People with millowners names have almost the same wealth (613 pounds) as people without millowner names (625 pounds). However, millowners are more than 10 times as wealthy as non-millowners (9,287 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 surname 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 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.

[56] In Appendix section VIII.C we show the accumulation of titles by peers over time.

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: defined 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, surnames, and other ascriptive characteristics is concentrated in industrializing regions. We find that this is the case for both social orders and surnames: 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. In Table 1 we report results for social orders. In Panel I, columns (3)-(6) we report the adjusted R^2 ICAC coefficients, like before. We now, however, split the sample by industrializing and non-industrializing regions and also report estimates of the adjusted R^2 ICAC differences coefficient from Equation (4). In column (3) we report estimates for the non-industrializing region 'pre', which we label 'Non-IR'. 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 'Non-IR' and 'IR'.

We observe a very interesting pattern. Before the Industrial Revolution, social status had a greater explanatory power in (future) industrializing regions (Non-IR: 15%, IR: 25%). After the Industrial Revolution, the explanatory power of the social orders falls in both the south and the industrializing north (Non-IR: 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^2 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 1). 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 subsamples created by our sample split. In the pre-period, 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, in the region most impacted by the Industrial Revolution, 97%-age points, compared to 85%-age points in the non-Industrial Revolution areas. After the industrial revolution this increases slightly for the former and falls to 89%-age points 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 wealthy 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, relative to commoners.

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 surname based ascriptive characteristics.

Surname fixed effects. Like before, we now omit individuals from the nobility and gentry, and study surname fixed effects, which capture all ascriptive characteristics that vary at the level of the surname. As in our previous analyses, if we find goodness-of-fit values that are close to zero, little can be learned about wealth from one's last name. We report results in Table 2, Panel I, columns (3)-(6). 'Pre', the adjusted R^2 ICAC coefficients are similar in industrializing and non-industrializing regions, around 10% (Non-IR: 0.09, IR: 0.10). In the non-industrializing region, it stays about level at 9%, whereas in the industrializing region it falls to zero. This results in an adjusted R^2 ICAC *differences* coefficient that is equal to -0.103. In other words, the explanatory power of surname 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 surnames. Here, patterns by industrializing region are less interesting. 'Post', the predictive power of Brassey is higher in the industrializing region and the same is true for Cavendish. Yet before the Industrial Revolution the Cavendish family was much more likely to be rich (in the industrializing regions of England), likely due to their primary residence, Chatsworth house, being in the North. Their relative fall in the wealth distribution is consistent with the overall patterns in Panel I. The patterns for Grainger and Langcaster are similar by region and period, and similar overall to our previous comparisons.

Our results for social orders and surname 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. More broadly across society, mobility increased, and both effects are stronger where the industrial revolution took place.

Locative, and other name types. In Appendix Table XIII.I we report results for name types. In Panel I, columns (3)-(6) we find that the adjusted R^2 ICAC coefficient is essentially zero for all four subsamples. As before, this implies that there is no explanatory power in knowing one's surname type for wealth. In Panel II, we reach a similar conclusion. Essentially all 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 Appendix Table XIII.II we study name origins. In Panel I, we find very modest 'pre' adjusted R^2 ICAC coefficients (Non-IR: 0.001, IR: 0.002). Since 'post' coefficients are zero we get a small negative adjusted R^2 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, see also Cummins (2024).

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 and "dark satanic mills." In the final part of our analysis we ask what factors are correlated with such geographical mobility. We present results after we discuss robustness of our results so far.

7.2 Benchmarking effect sizes

In Table 3 we again benchmark the adjusted R^2 ICAC coefficients against a 'maximal' counterpart, now broken down by IR/non-IR regions. As before, we start with social orders, in the top panel. Columns (3)-(6) report results. In the pre-period, the (future) industrializing part of England has a maximal adj. R^2 ICAC of 0.48, resulting in a ratio of estimated adj. R^2 ICAC to maximal adj. R^2 ICAC, reported in row 3, of 0.51. After the Industrial Revolution, this drops to 0.10, a reduction of close to eighty percent. In the rest of the country, the ratio drops from 0.38 to 0.09. In the bottom panel. we repeat this exercise

for surnames. As in the social orders analysis, we observe a larger drop in industrializing parts of England where the ratio of estimated adj. R^2 ICAC to maximal adj. R^2 ICAC, reported in row 6, falls from 0.10 to zero. In the rest of England it stays constant at 0.09. The fall in maximal adj. R^2 ICAC between pre and post is entirely concentrated in the industrializing parts of England.

8 Robustness

In the Appendix, we report results from a large number of robustness exercises, in addition to the ones discussed in section 4.4. To facilitate presentation, the Appendix includes a thematic overview table, Appendix Table II.I which presents all tables containing robustness checks by 'theme' (e.g. variable definitions) and discusses 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 to investigate changes in social mobility by manufacturing intensity, i.e. whether counties more impacted by the Industrial Revolution, measured by employment in manufacturing at county level, see larger reductions in the explanatory power of surnames.[57] We provide the results of this robustness check in Figure 6. In this Figure we re-estimate our surname fixed effects regressions county by county, and plot the resulting adjusted R^2 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^2 ICAC coefficients, and for the difference between pre- and post-period adjusted R^2 ICAC coefficients. As we observed in Table 2, Figure 6 shows no relationship between the adjusted R^2 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. We find identical results if we use a simple geographical definition of Industrialization instead, treating Lancashire, Cheshire and the West Riding of Yorkshire as the focal geography of the Industrial Revolution. Thus, our findings do not depend on our use of the 1861 census to define which areas were relatively impacted by the Industrial Revolution.

In Appendix Section XIV and Appendix XV 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

[57] We cannot do the same analysis for social orders as cells become too small at county level.

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^2 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 robustness check above, where instead of defining being industrial from the 1861 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. Seventh, we conduct robustness checks regarding wealth cut-offs in the probate data. We assign a wealth of five pounds to unprobated individuals, rather than zero (five pounds was the cutoff for being probated in all counties, except London, where it was 10 pounds) or, alternatively, randomly assign a value between zero and five pounds to unprobated people. We also drop observations probated after 1897 (our main sample runs until 1899) because probated wealth includes land from 1998 onward (Turner, 2010; Bond and Morton, 2022).[58] This drops nobles probated in the early 1900s who were included in our sample if otherwise no title holder was observed in the sample period up to 1899. Eighth, we do various robustness checks for the hearth data. We use a sample in which we do not aggregate hearths over noble titles (which aggregates the wealth of female and male noble spouses), but only use the wealth of male title holders. We exclude counties for which information on poor individuals is missing in the hearth tax. And, we provide results assigning observed hearths (if any) to people classified as too poor to be taxed, rather than zero.[59] 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 creating new opportunities, both in terms of geographic

[58] This only includes unsettled realty, i.e. land that is under the full control of the deceased person.

[59] 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 our main analysis. In this robustness check, we vary this rule.

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.[60] We then compute the standard deviation of wealth at the level of the surname and compute the post minus pre difference. A higher value of this measure captures 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 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.[61] 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 surnames that are below median social mobility, 7.7 percent are industrial to non-industrial or non industrial to industrial migrants. For above median social mobility individuals, this measure is higher, at 8.0 percent. 31.6 percent of low social mobility individuals are probated in the north, compared to 38.3 percent of high social mobility individuals. Finally, 47.6 percent

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

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

of low mobility individuals are in manufacturing versus 49.1 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 XVI 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 industrialized counties and nobles and gentlemen who are migrants, i.e. born in an industrialized county, but probated in a non-industrialized one, or vice-versa, are more likely to be in 'new' occupations, consistent with Rubinstein (1977a).[62]

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 7. Each row reports an estimate of δ from Equation (5). The 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. We describe the data used as explanatory variables in our Data Section 2.5.2 above.

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. 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 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 'Initial condition' using the 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

[62] We also find that on average, nobles are wealthier than gentlemen, industrialized counties are wealthier than the non-industrialized, migrants are wealthier than non-migrants, and people with new occupations are wealthier than those with traditional ones.

of members of the nobility, gentry, or yeomanry.[63] 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 the parish, the fraction of Catholics in 1603, the main religious minority, and the fraction of elections between 1701 and 1831 that were contested. 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 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

[63] Yeomen were a rank of prosperous farmers.

the 17th century, is very large. We interpret this as being consistent with the persistence of a great deal of the society of 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 third compared to the 17th century. In the industrial regions, it fell by over 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 socially mobile surname and a "mobile parish" to be one which initially housed surnames which became relatively more disbursed (socially mobile) subsequently. We find that more, compared to less, socially mobile people tended to be living in the industrialized 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 social 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 though they illustrate that the drivers of social mobility in the pre-modern "world that we have lost" (Laslett, 2000) are distinct from the mechanisms that operate today.

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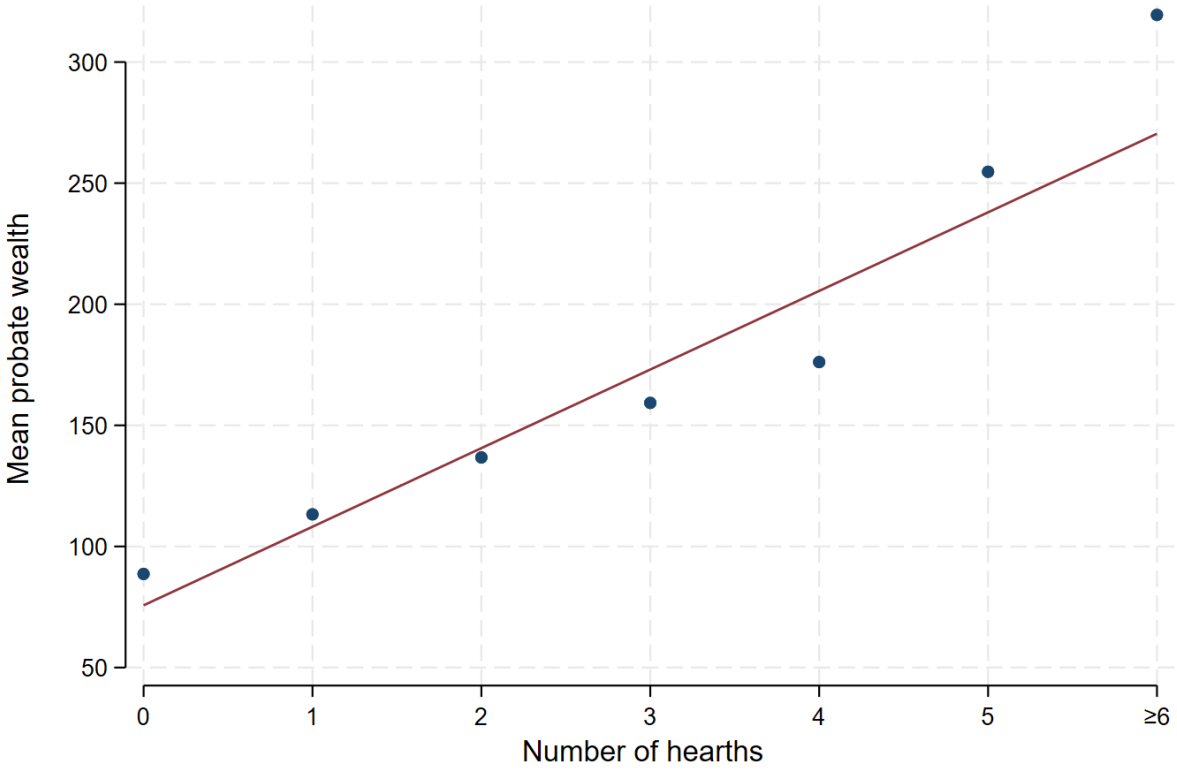
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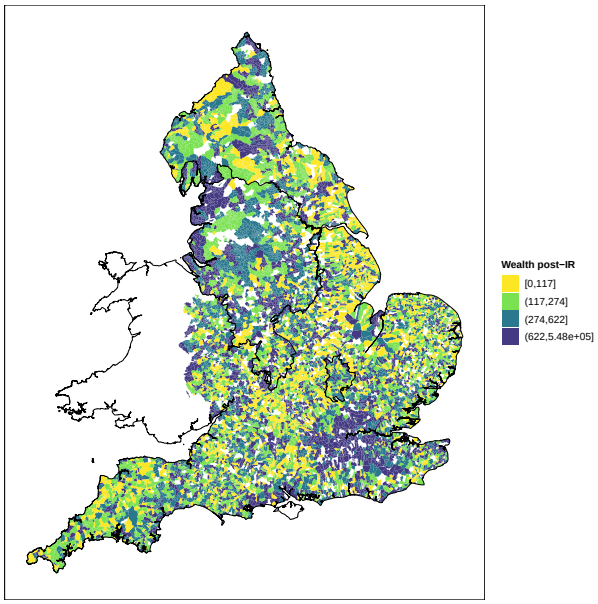
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Figure 1: Relationship of 17th century probate inventory wealth and number of hearths



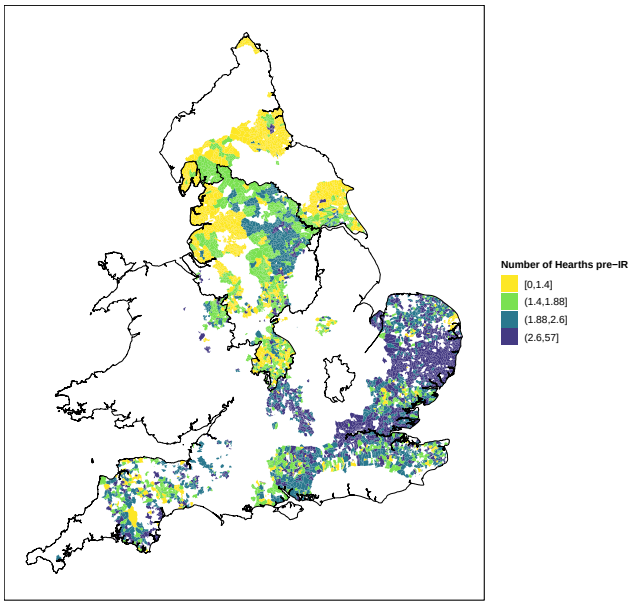
Notes: This figure shows a binned scatter plot (mean probate inventory wealth for each categorical number of hearths) and a linear fitted line of the probate inventory wealth on the number of hearths. The sample consists of 269 matched hearth tax observations to probated wealth from a dataset of probates that cover the hearth tax period. We describe these in section 2.2. The correlation between the probate inventory wealth and the number of hearths is 0.29.

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



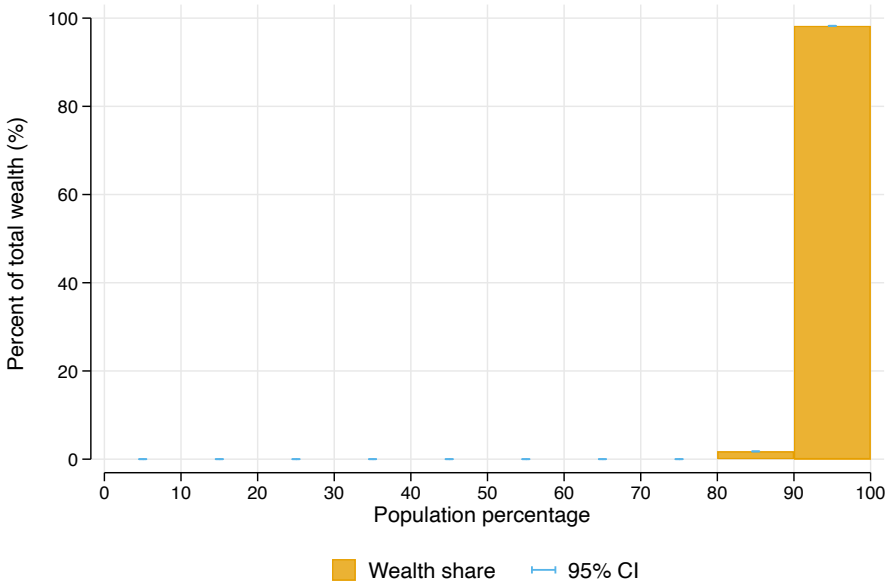
Notes: This figure shows for each parish the average wealth in the linked probate-census data. The black outline within England traces the the union of counties that we identify as 'industrializing' by their manufacturing share.

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



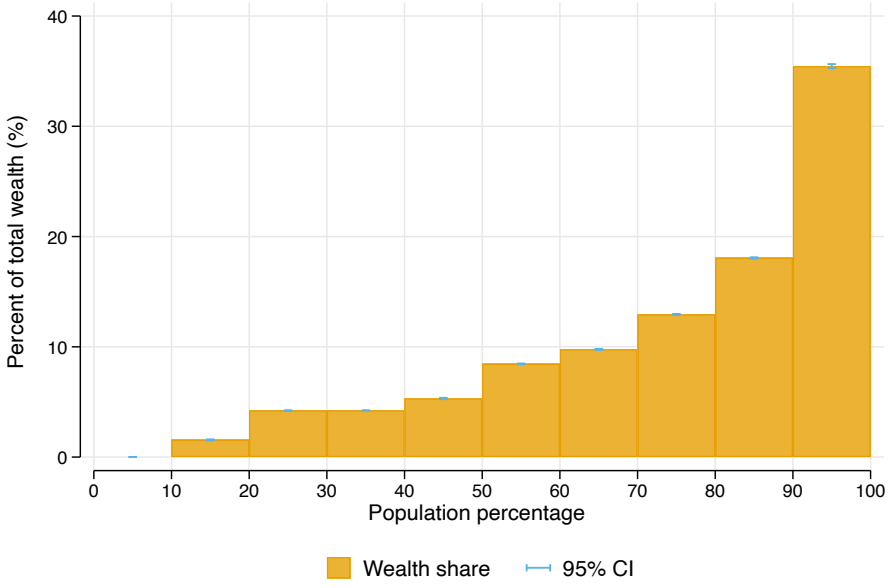
Notes: This figure shows for each parish the average number of hearths owned. The black outline within England traces the the union of counties that we identify as 'industrializing' by their manufacturing share.

Figure 4: Wealth shares post-IR



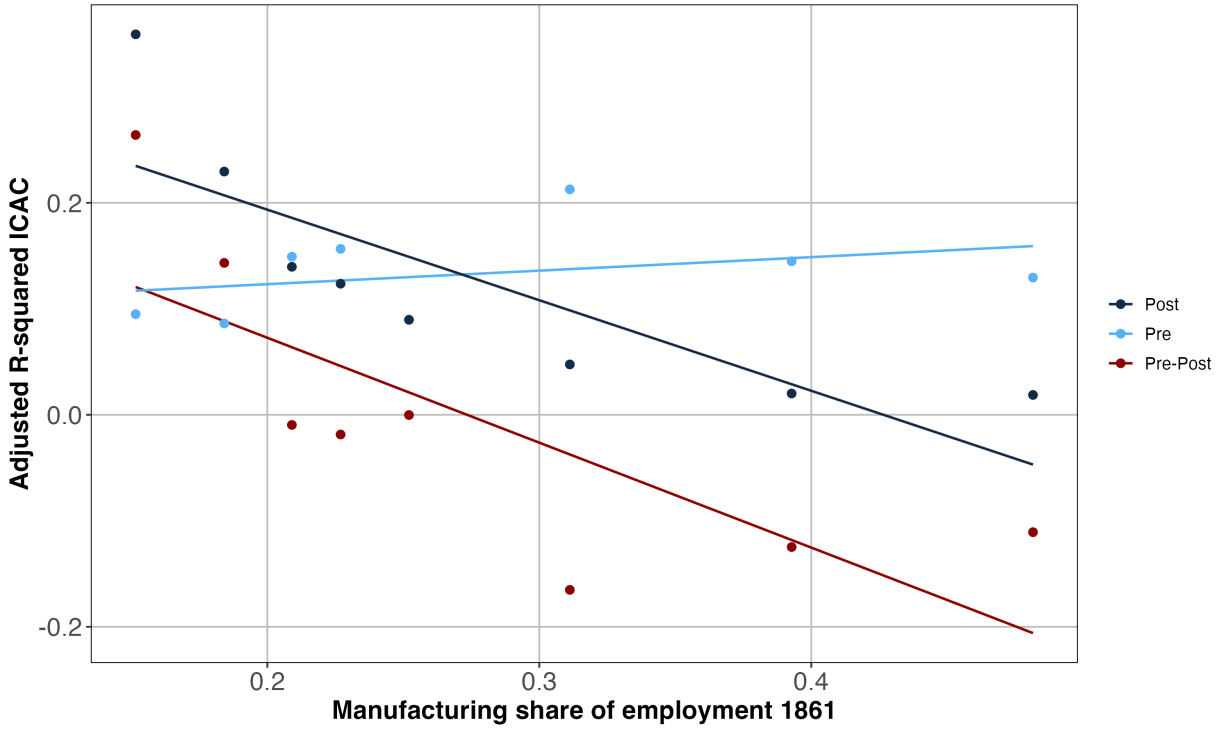
Notes: This figure shows for each decile of the wealth distribution the share of wealth owned in the linked probate-census data.

Figure 5: Wealth shares pre-IR



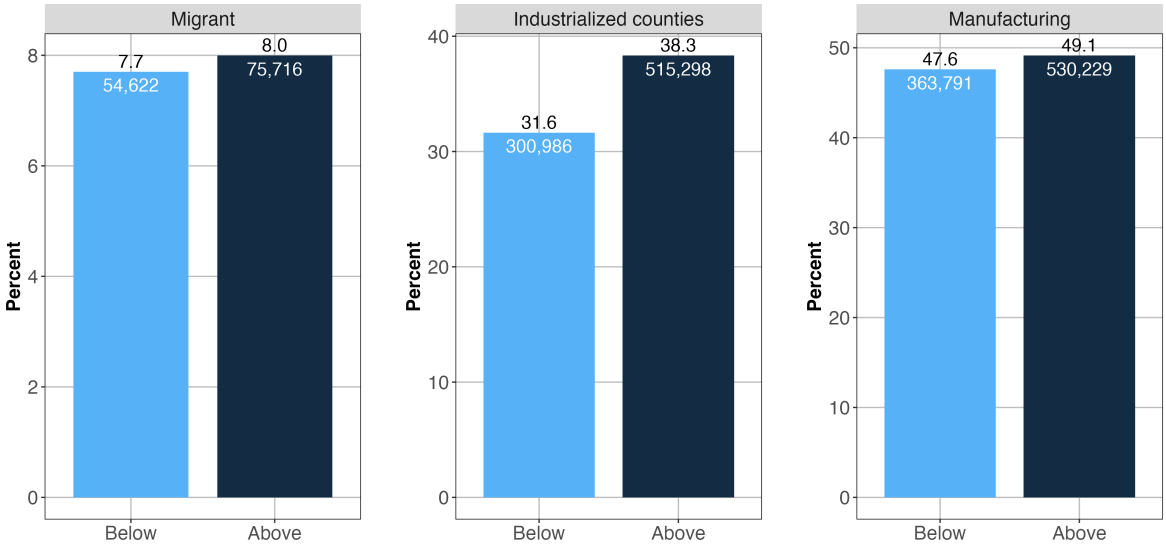
Notes: This figure shows for each decile of the wealth distribution the share of wealth owned in the hearth tax records.

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 surname 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: Pre-Post Industrial Revolution Analysis - Social orders

Fixed effects:	**Panel I: Fixed effect analysis** Social orders					
	Pre	Post	Pre Non-IR	Pre IR	Post Non-IR	Post IR
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.167	0.060	0.154	0.245	0.059	0.071
R^2_{random}	0.000	0.000	0.000	0.000	0.000	0.000
N	343022	5276146	243228	99794	3423984	1852162
$N_{fixed\ effects}$	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)		

Dependent variable:	**Panel II: Top decile analysis** Wealthy (Yes/No)					
	Pre	Post	Pre Non-IR	Pre IR	Post Non-IR	Post IR
	(1)	(2)	(3)	(4)	(5)	(6)
Noble	88.76***	88.47***	85.47***	97.18***	88.13***	88.74***
	(2.81)	(1.12)	(3.64)	(3.38)	(1.26)	(2.58)
Gentry	66.77***	82.75***	65.05***	70.70***	82.20***	84.09***
	(0.54)	(0.17)	(0.69)	(0.67)	(0.19)	(0.43)
Constant	8.08***	8.19***	10.24***	2.82***	8.66***	7.34***
	(0.05)	(0.01)	(0.06)	(0.05)	(0.02)	(0.02)
N	343022	5276146	243228	99794	3423984	1852162
$N_{commoner}$	340338	5250227	241211	99127	3401830	1848397
N_{gentry}	2589	25319	1947	642	21656	3663
N_{noble}	95	600	70	25	498	102
Share of Wealthy	8.61	8.60	10.79	3.30	9.19	7.51
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, 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 40% or higher share of jobs in manufacturing. Non-industrial location is residence in a county with less than 40% 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 2: Pre-Post Industrial Revolution Analysis - Surname

Fixed effects:	**Panel I: Fixed effect analysis** Surname					
	Pre	Post	Pre Non-IR	Pre IR	Post Non-IR	Post IR
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.253	0.107	0.272	0.258	0.141	0.065
R^2_{random}	0.175	0.047	0.205	0.174	0.056	0.062
N	340338	5250227	241211	99127	3401830	1848397
$N_{fixed\ effects}$	59254	246169	49293	17273	197336	123311
Adj. factor	1.21	1.05	1.26	1.21	1.06	1.07
R^2 ICAC	0.078	0.060	0.068	0.084	0.085	0.003
Adj. R^2 ICAC	0.094	0.063	0.085	0.102	0.090	0.003
ICAC difference				-0.098		
Adj. ICAC difference:				-0.103 (0.01)		

Dependent variable:	**Panel II: Top decile analysis** Wealthy (Yes/No)					
	Pre	Post	Pre Non-IR	Pre IR	Post Non-IR	Post IR
	(1)	(2)	(3)	(4)	(5)	(6)
Brassey		22.15***			10.79***	34.58***
		(4.49)			(0.05)	(0.05)
Cavendish	91.38***	44.72***		96.68***	42.40***	49.62***
	(16.19)	(4.18)		(0.07)	(0.05)	(0.05)
Grainger	-8.62**	-0.38	-10.79***	-3.32***	0.53***	-2.47***
	(4.33)	(1.08)	(0.09)	(0.07)	(0.05)	(0.05)
Langcaster	-8.62*	-8.62	-10.79***	-3.32***	-9.21***	-7.52***
	(4.55)	(10.60)	(0.09)	(0.07)	(0.05)	(0.05)
Constant	8.62***	8.62***	10.79***	3.32***	9.21***	7.52***
	(0.05)	(0.01)	(0.09)	(0.07)	(0.05)	(0.05)
N	343022	5276146	243228	99794	3423984	1852162
$N_{Brassey}$	0	39	0	0	20	19
$N_{Cavendish}$	3	45	0	3	31	14
$N_{Grainger}$	42	680	27	15	462	218
$N_{Langcaster}$	38	7	23	15	5	2
Share of wealthy	8.61	8.60	10.79	3.30	9.19	7.51
Omitted category	Smith	Smith	Smith	Smith	Smith	Smith

Notes: This table compares ascriptive characteristics pre- and post-Industrial Revolution. In this table, we study surnames in general as well as selected surnames: Brassey, Cavendish, Grainger, Langcaster, 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 40% or higher share of jobs in manufacturing. Non-industrial location is residence in a county with less than 40% 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: Benchmarking R^2

Fixed effects:	***Fixed effect analysis*** Social orders					
	Pre	Post	Pre Non-IR	Pre IR	Post Non-IR	Post IR
	(1)	(2)	(3)	(4)	(5)	(6)
Adj. R^2 ICAC	0.167	0.060	0.154	0.245	0.059	0.071
Maximal Adj. R^2 ICAC	0.408	0.628	0.406	0.482	0.627	0.686
Ratio	0.409	0.095	0.379	0.509	0.094	0.104
	Surname					
Adj. R^2 ICAC	0.094	0.063	0.085	0.102	0.090	0.003
Maximal Adj. R^2 ICAC	0.949	0.897	0.998	0.997	1.002	1.005
Ratio	0.099	0.070	0.085	0.102	0.090	0.003

Notes: This table contains two panels, corresponding to Tables 1 and 2. In the first rows of each panel, we reproduce the R-squareds from each respective table. In the second rows, we provide a benchmark upper bound, or 'maximal', R-squared. For social orders, 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 the third row of the Social orders panel we report the ratio of the first to the second row. In the second panel, we produce the Maximal R^2 by re-assigning the surnames with the fewest holders as the richest, and then proceeding down in order until we assign the surname with the most holders at the bottom. This assignment produces the highest R-squared since there is more variation at the top end of the distribution of wealth than at the bottom. In the third row of the Surname panel we again report the ratio of the first and second rows.

Table 4: Richest 24 noble people among the top 200 richest people in the hearth tax

Hearth (pre-Industrial Revolution)			Probate-census (post-Industrial Revolution)				
(1) Rank	(2) Title and Name	(3) Hearths	(4) Rank	(5) Title and Name	(6) Wealth	(7) Pctile	(8) Year
1	Duke of Buckingham, Villiers, George	281	599137	Duke of Buckingham And Chandos, Temple-Nugent-Brydges-Chandos-Grenville, Richard	200	89	1861
2	Earl of Devonshire, Cavendish, William	260	25	Duke of Devonshire, Cavendish, William	1790871	100	1891
3	Earl of Craven, Craven, William	250	312828	Earl of Craven, Craven, William	800	94	1860
4	Duke of Albemarle, Monck, Christopher	182	-	Extinct	-	-	-
5	Earl of Warwick, Rich, Charles	166	-	Extinct (See Baron Brooke)	-	-	-
6	Earl of Bristol, Digby, George	140	4712	Marquess of Bristol, Hervey, Frederick	90000	100	1859
7	Earl of Chesterfield, Stanhope, Philip	130	6594	Earl of Chesterfield, Stanhope, George	70000	100	1866
10	Earl of Northumberland, Percy, Josceline	118	288	Duke of Northumberland, Percy, Algernon	500000	100	1865
11	Marquess of Winchester, Paulet, John	115	3815	Marquess of Winchester, Paulet, John	107044	100	1887
12	Earl of Leicester, Sidney, Robert	114	1169	Earl of Leicester, Coke, Thomas	238419	100	1941
13	Baron Brooke, Greville, Robert	110	1638	Earl of Warwick, Greville, George	180203	100	1893
13	Earl of Strafford, Wentworth, William	110	1172	Earl of Strafford, Byng, George	237159	100	1886
15	Duke of Somerset, Seymour, William	109	1345	Duke of Somerset, Seymour, Edward	202423	100	1885
16	Earl of Bedford, Russell, William	103	213	Duke of Bedford, Russell, William	600000	100	1872
17	Earl of Derby, Stanley, Charles	93	973	Earl of Derby, Smith-Stanley, Edward	250000	100	1869
19	Viscount Strangford, Smythe, Philip	89	72698	Viscount Strangford, Smythe, George	7000	99	1857
21	Earl of Dorset, Sacksville, Richard	85	-	Extinct	-	-	-
22	Earl of St. Albans, Jermyn, Henry	82	-	Extinct	-	-	-
23	Viscount of Irwin, Ingram, Arthur	78	-	Extinct	-	-	-
24	Duke of Richmond, Stewart, Charles	77	243	Duke of Richmond, Lennox, Charles	585373	100	1903

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 the richest 20 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 5: 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 6: Average wealth by millowners, people with millowner names and people without millowner names

	(1) Probate		(2) Hearth	
	Mean wealth	N	Mean wealth	N
Millowners	9286.7	59		
People w/ millowner names	612.7	183209	2.1	9391
People w/o millowner names	624.5	5092878	2.4	333631
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	0.63		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 surname 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 surname, millowners and people without a millowner surname and people with and without a millowner surname.

Table 7: What are the correlates of high social mobility parts of England?

	High Mobility Parish **(Yes/No)**
Economic structure	
City or town (yes/no)	0.0813***
	(0.0098)
Market or fair held 1600 (yes/no)	0.0896***
	(0.0190)
Fraction pop. in primary sector 1700	-0.0777***
	(0.0184)
Fraction pop. in secondary sector 1700	0.1225***
	(0.0266)
Fraction pop. in tertiary sector 1700	0.0192
	(0.0227)
Initial conditions	
Tax revenue 1525	-0.0112***
	(0.0040)
Tax revenue per capita 1525	-0.0142***
	(0.0039)
Social structure	
Number nobility 1700	0.0035
	(0.0039)
Number gentry 1700	0.0213***
	(0.0043)
Number yeomen 1700	-0.0945***
	(0.0197)
Political variables	
N. members of parliament	0.0141***
	(0.0040)
Fraction catholics	-0.0150
	(0.0094)
Fraction elections contested 1701-1831	0.1390*
	(0.0735)
Feudal legacy	
Monastic ownership of part of parish (yes/no)	-0.0055
	(0.0072)
Parliamentary enclosure 1750-1830 (yes/no)	0.0026
	(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.