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Smithian Growth in Britain Before the Industrial Revolution, 1500-1800

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Smithian growth in Britain before the industrial revolution, 1500-1800 *

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Abstract

Adam Smith's claim that the division of labour is one of the major engines of economic growth is a foundational concept in economics. Despite this, we lack measures of the scale and growth of Smithian specialisation over the long run. This paper introduces a novel method based on job titles to measure specialisation. We apply this method to document patterns of Smithian specialisation in early modern Britain. National trends in specialisation were closely associated with economic growth. By 1800, the division of labour was over two and a half times as advanced as in the early sixteenth century, with particularly marked changes within English manufacturing, especially in the mechanical subsector, and, to a lesser extent, services. Specialisation was far less advanced in Wales and Scotland. We study several possible explanations for this change with an IV panel analysis. We find that this significant increase in the division of labour was mostly driven by the growth of the domestic market, in line with Adam Smith's predictions. Intensive specialisation was concentrated in Middlesex and was helped by a supply factor, Marshallian externalities. Finally, we explore the connection between Smithian Growth and the Industrial Revolution. We find that early specialisation did not lead to later industrial success. Like Adam Smith himself, Smithian specialisation did not predict the Industrial Revolution.

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1 Introduction

> "The greatest improvement in the productive powers of labour, and the greater part of the skill, dexterity, and judgment with which it is any where directed, or applied, seem to have been the effects of the division of labour."
> (Smith, 1776, Book 1, paragraph 1)

Adam Smith's idea that specialisation allowed by the division of labour is one of the main sources of increases in productivity is a foundational concept in economics (Smith, 1776). In economic history, Smithian growth is generally seen as the principle source of economic growth before industrialisation. Yet, to this day, the theory with which Adam Smith opened his book remains well ahead of measurement: despite its significance, there have been no attempts to directly measure the scale and growth of Smithian specialisation in advance of the Industrial Revolution. In fact, there is a dearth of direct evidence on the evolution of the division of labour over the long run. This paper addresses this fundamental gap by introducing a novel, simple method to measure the division of labour, based on the number of job titles, and uses it to document Smithian growth in the British economy in the two centuries and a half before the onset of the Industrial Revolution, the point when Smith (1776) composed *The Wealth of Nations*.

Our baseline measure detects that on the eve of the Industrial Revolution, England's division of labour was over two and a half times as advanced as it had been in the early sixteenth century. Specialisation was less advanced in Wales, which was about as specialised in the 1770s as England had been in the 1520s. Much of the growth we identify was concentrated in London, England's largest and richest city, which remained its greatest manufacturing hub into the nineteenth century, even as the population of Manchester, Sheffield and the other industrial centers of the north exploded. The increase in the division of labor was greater in manufacturing and services than in agriculture, something Smith also predicted, and within manufacturing it was newer sub-sectors, such as machine and tool making, that outpaced the longer-established textile trades.

Our findings suggest that Adam Smith was right. The increase in the division of labour we uncover closely tracks existing estimates of GDP and urbanisation in England, as Figure 1 shows. The strikingly close relationship between our core measure of specialisation, based on the number of job titles, and these two standard measures of economic development suggests that the division of labor did indeed play the central role in pre-industrial economic growth that Smith believed, and that our measure offers a reasonable proxy for the process that we are interested in.[1]

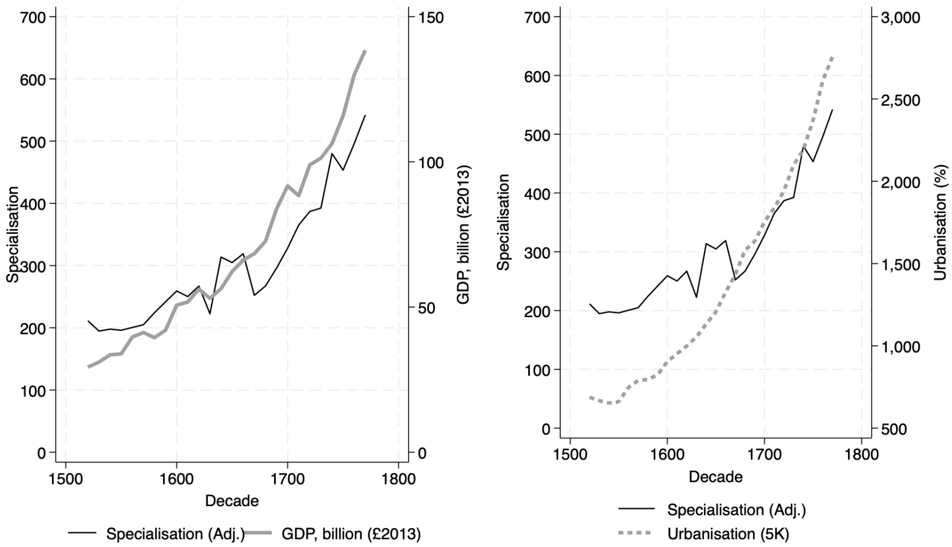


Figure 1: Division of Labour, GDP and Urbanisation in England
Note: We report our overall measure of division of labor based on job titles adjusted for the share of the male population not included in the dataset (see Section 4). GDP and Population are from Broadberry *et al.* (2015); urban populations are from Buringh (2021).

What explains this increase in the division of labor in England? We study several possible determinants of Smithian specialisation with an IV panel analysis of county trends. The size of the domestic market emerges as the main driver, as suggested by Smith (1776) himself (see also Ades and Glaeser, 1999; Atalay *et al.*, 2024 and several others). The close relationship between our new measures of specialisation and market potential is illustrated

[1] The correlation coefficients are 96% for GDP, 90% for GDP pc, and 95/96% for urbanisation, depending on the threshold used. Correlation coefficients between GDP or GDP pc and number of jobs within counties are 83% and 66%, respectively.

in Figure 2. Smithian specialisation encompasses shifts away from domestic production towards reliance on the market as well as the emergence of increasingly subdivided productive processes. Related to this analytical distinction, our method allows us to distinguish between extensive (new occupational categories) and intensive (new job titles within existing occupational categories) changes. We find that a demand factor, structural transformation, significantly contributed to increasing the diversification of the workforce. By contrast, a supply factor, agglomeration economies, mattered for intensive change, in line with the predictions of Becker and Murphy (1992).

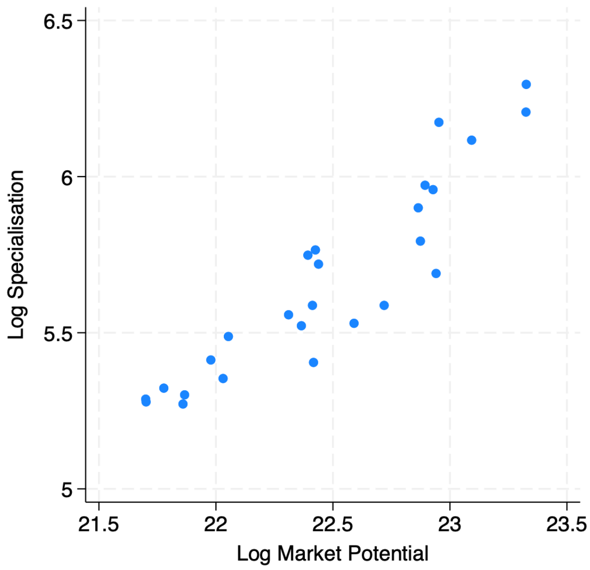


Figure 2: Market Potential and Specialisation in England
Note: We report the natural log of the decadal mean our division of labor based on job titles adjusted for the share of the male population not included in the dataset (see Section 4) for England against the natural log of the decadal average of our measure of Market Potential (see Appendix C).

The relationship between the Industrial Revolution and the economic, cultural and institutional changes that preceded it remains fiercely debated. Recent research has emphasised the crucial role played by skilled artisans in metalworking and machinery in explaining why the Industrial Revolution started in England's northern counties (Kelly *et al.*, 2023; see also Kelly *et al.*, 2014; Zeev *et al.*, 2017; Mokyr, 2021). We offer support to the hypothesis that a local increase in specialisation was part of the process by which the Industrial Revolution began. In the eighteenth century, we document a reversal of fortune, with counties in north-western England witnessing increased division of labour in textiles at the same time as counties in the south and the east saw opposite trends. We also find that from the 1750s onward specialisation became a robust predictor of the location of subsequent industrialisation. However, the previously weak or non-existent relationship between the two variables suggests that Smithian growth in a region was not sufficient to lay the foundations for the Industrial Revolution.

Our baseline estimates are based on over 500,000 job titles drawn from individual-level records made in the probate courts when they registered wills. Adjusting the figures to consider changes in the extent to which the coverage of our data changes across space and over time hardly changes the overall picture. National trends computed with similarly large, but spatially and socially distinct, datasets of apprentices' fathers and masters provide consistent results, too. Our main findings are also robust to the use of an alternative occupational coding scheme, as well as to the use of an array of alternative measures of the division of labour.

The method we introduce operationalises the long-standing idea that Smithian growth could be observed in economic history and is potentially applicable to other contexts. Anecdotal evidence from economic history has frequently been offered to illustrate analyses and models that develop Smith's insights (Young, 1928, 536; Stigler, 1951; Locay, 1990, 965-966; Kelly, 1997, 953-955; Legros *et al.*, 2014). To gauge long-term trends in the division of labour, scholars have so far mainly relied on measures of the size of the market, like population size (e.g. Galor and Weil, 1999) and market integration (e.g. Shiue and Keller, 2007). Becker and Murphy (1992, 1445) drew attention to precisely the multiplication of jobs as a signal of specialisation: "[s]ixteenth century European cities had perhaps a few hundred occupations, whereas a telephone directory for even a small American city now lists thousands of specialized services." Persson (2010), Ades and Glaeser (1999) and Maccelli and van Leeuwen (2025) built on the same insight to map the division of labour in a few selected pre-industrial sites, the United States in the mid-nineteenth century and Italy from the later nineteenth century, respectively. Looking at the number of job titles is an approach that is aligned with recent work on task specialisation, in which job descriptions are used to measure Smithian specialisation in modern economies (Michaels *et al.*, 2019; Atalay *et al.*, 2024).

Our paper contributes to on-going debates on the nature and causes of pre-industrial economic growth. It corroborates the idea that the early modern British economy was characterised by remarkable dynamism rather than Malthusian stagnation, as Smithian specialisation effectively countered the tyranny of decreasing returns (Broadberry *et al.*, 2015; Heldring *et al.*, 2021; Bouscasse *et al.*, 2025). Thus, as seen in Figure 1, progress in the division of labour emerges as a credible explanation of why population growth did not push down living standards in the sixteenth and eighteenth centuries and productivity started growing after c. 1600. Our findings on the centrality of agglomeration economies in London in driving intensive specialisation in particular are consistent with work highlighting the importance of leading cities for economic growth (Wrigley, 1967; Acemoglu *et al.*, 2005; Allen, 2009). The growth of London as a leading specialisation hub offers a potentially useful perspective on the emergence of the 'Great Divergence' (Pomeranz, 2000), which saw Britain forging ahead of China, as well as continental Europe. At the same time, our results on regional trends highlight fundamental discontinuities between Smithian and modern economic growth: like Adam Smith himself, Smithian specialisation did not predict the Industrial Revolution.

2 Measuring specialisation

The division of labour refers to the process whereby workers specialise in increasingly narrow tasks. Smith (1776, 13-14) thought that the division of labour increased labour productivity because of three reasons: a narrow set of tasks implies scope for increased dexterity in performing them, reduces the time needed to move from task to task, and implies that workers develop intimate knowledge of the tools needed to perform tasks, fostering innovation. If there is a match between job titles and tasks performed by workers, an increase in the division of labour will be matched by an increase in the number of job titles, our baseline measure of specialisation. Table 1 illustrates the empirical basis our approach, listing the job titles associated with clock making over time in our main dataset.

Period	**Job Titles Reported**
1550–99	Clock maker
1600–49	Clock maker, clock smith, watch maker
1650–99	Clock maker, clock smith, watch maker, clock worker
1700–49	Watch pillar maker, watch mender, clock smith, watch shagreen case maker, watch engraver, watch chain maker, watch case maker, watch gilder, clock maker, watch maker, clock case maker, watch spring maker
1750–99	Repeating motion maker, watch chain maker, watch shagreen case maker, clock engraver, clock spring maker, watch gilder, watch key, watch wheel finisher, clock case maker, watch tool maker, wall clock maker, watch jeweller, watch finisher, watch glass grinder, watch engraver, musical clock maker, watch piercer, clock smith, watch spring maker, watch pillar maker, watch movement maker, clock worker, watch cap maker, clock maker, watch key maker, watch maker, steel watch chain maker, watch wheel maker, watch case maker

Table 1: Clockmaking Job Titles Reported by Period

In 1550 there was only one job title – 'clock maker' - that fell within this occupational category; by 1780, the same occupational category encompassed eleven different titles, with most of them clearly referring to a particular stage of the production process, like making the watch case, the chain or the spring. The process of specialisation these titles capture reflects well known developments in clockmaking, which was changing from a small artisanal trade dedicated to producing relatively simple and large clocks, to an industry that was producing a diverse range of products, from ever-cheaper pocket watches for the aspiring middle classes to the exactingly precise chronometers that transformed global shipping (Kelly and Ó Gráda, 2016; Cummins and Gráda, 2022). It also illustrates the wide regional variation in this development. In the 1770s, the probate courts in Glamorganshire in Wales still only recorded the death of a solitary 'clockmaker', while London, one of the centres of the industry, they noted the passing of a watch spring maker, a clock case maker, a watch case maker, alongside more generic clock and watchmakers.

Our key identifying assumption is that there was a correspondence between words and things: sets of tasks were differentiated across job titles and stable within them. Is this assumption warranted? On the one hand, ours is a standard assumption in the established literature in labour economics employing a 'task approach', whereby job titles are matched to sets of tasks drawn from job descriptions to answer questions on the changing nature of work (cf. Autor, 2013 for a survey of this literature and Autor *et al.*, 2024 for a recent application). On the other hand, economic historians like Ogilvie (2013) and Whittle (2024) have shown that the relationship between early modern job titles and the tasks people performed was a complex one. Whittle's (2024) analysis of activities described in court records in early modern England highlights how workers were often found performing tasks notionally belonging to other sectors: artisans or builders might also be involved in transport or retail, to give one example. Nevertheless, Whittle's (2024) data does not challenge the basic idea that job titles were associated with meaningful differences in the set of tasks performed by workers: yeomen, for instance, spent a lot more time on agricultural activities than artisans.

Task heterogeneity within jobs would be a problem for the reliability of our trends if the range of tasks associated with given job titles tended to broaden over time. While available evidence falls short of being sufficient to test this hypothesis systematically for our period, present-day data suggests that, in fact, we are likely to underestimate the extent to which the division of labour increased over time: Atalay *et al.* (2024) find that task specialisation within job titles tends to increase with the size of the market.

Smithian specialisation is usually considered as one homogenous process and Smith (1776) himself treated it as such. Upon reflection, however, one can distinguish between two separate dynamics, with different consequences for the diversification of tasks performed by workers, as well as, possibly, different drivers. The first type of specialisation, illustrated by Smith's (1776) famous example of the pin factory, involves allocating different stages of the production process to different workers, so that '[o]ne man draws the wire; another straights it; a third cuts it'. The second one involves a shift from home production to reliance on the market. This second type of specialisation is illustrated by the example of the arrow-maker who realises that he is better off exchanging arrows for food than hunting himself (Smith, 1776).

The tasks performed by the three workers preparing the wire for the pin are very similar to one another and this first type of increased specialisation will not necessarily change task diversity between workers all that much. Indeed, in this case, Smithian specialisation might even contribute to a local decrease in task diversity, if it leads to Ricardian specialisation (Ricardo, 1817) in the products involved. By contrast, manufacturing arrows involves very different tasks compared to hunting prey. The second type of specialisation can generally be expected to increase significantly the differences between individual workers' tasks – an aspect emphasised in Spencer's (1851) and Durkheim's (1933) conceptions of the division of labour.

These two types of specialisation need not to be driven by the same forces. Notably, the relevance of Smith's (1776, 53) famous argument on the size of the market being the key determinant of the extent of the division of labour is obvious in the second case: the specialising arrow-maker depends on the availability of suppliers of food and other necessities for his very survival. However, the link with the size of the market is more indirect in the first case: the division of labour in the pin factory all takes place under one roof, indicating that sub-dividing the production of goods into separate stages need not imply increased reliance on markets (although it might, as with the kind of vertical distintegration emphasised by Young, 1928). The size of the market here enters the picture through a different channel, scale: a sufficiently large demand is needed to absorb increased production.

To explore these two different types of specialisation, we distinguish between intensive changes in the division of labour, stemming from the appearance of new job titles within existing occupational categories, and extensive changes, originating from the emergence of new occupational categories. Our distinction between intensive and extensive specialisation is closely related to Leijonhufvud's (1986) opposition between vertical and horizontal division of labour, which he saw as being grounded in different human capital requirements (low vs. undefined) and technologies (increasing returns vs. minimum efficient scale). Our approach, borrowed from the trade literature, has the merit of having clear and easy-to-apply methodological implications on how to systematically distinguish between the two dimensions of specialisation.

Our strategy requires a taxonomy embodying assumptions on what constitutes a distinct occupational category. These assumptions are, in the last instance, arbitrary. Hence, the line we draw should not be taken as a hard and fast distinction, but as a heuristic tool that supplies insight into how the division of labour changed. In our main analysis, we use the classification system that is widely regarded as the best in the class: Wrigley's (2004) Primary-Secondary-Tertiary (PST) classification. The lowest level categories within PST are 'occupations'. Each of them represents clusters of closely related jobs, so that the occupational category 'chair maker' includes people with job titles such as chair polishers, chair caners, chair stainers and so on. We regard the appearance of a new PST 'occupation' category (e.g. 'chair maker') in an area as an extensive change, and the apperance of new job title (e.g. 'chair bottomer' or 'chair polisher') within a PST 'occupation' category that is already present as an intensive change. For robustness, in Appendix F we examine how our key results are affected by the use of another popular occupation classification scheme, the Historical Intrenational Classification of Occupations (HISCO).

Our analysis centres on three metrics. First, the number of job titles observed in the economy, which offers a simple proxy of the overall division of labour and serves as our basic metric for specialisation. Second, the number of PST occupational categories observed, which is our measure of extensive specialisation. Third, the ratio between the number of job titles and the number of PST occupational categories, which is our measure of intensive specialisation. Each is calculated over a period of ten years to ensure that rare occupations are captured.

The number of job titles, the number of PST occupational categories, and the ratio between the two all suffer from one potential problem: they give jobs equal weight regardless of what share of the workforce they employed. To address this concern, we also examine an array of alternative measures in Appendix H. Following Ades and Glaeser (1999), we compute a Dixit-Stiglitz variety index of the division of labour based on the employment shares of the various jobs and occupational categories. We also consider the probability that three random workers were in three different occupational categories as an alternative way of considering the distribution of occupational titles in the economy. In addition, reflecting also a broader interest in 'new work' (Lin, 2011; Autor *et al.*, 2024), we look at shares of the workforce with occupational titles not mentioned by our sources in previous decades. Finally, we apply a simple PST-based measure of 'occupational distance' (Gathmann and Schönberg, 2010) between two average workers ranging from 0 (same PST occupation category) to 4 (different PST sector, group, section and occupation category), which quantifies the level of diversification of the economy. This approach is similar to that employed by Atalay *et al.* (2024) to measure Smithian specialisation in the present day (see also Li and Sun, 2007).[2]

As should be clear, our method centres on the division of tasks among economic agents. This means that it speaks only imperfectly to the shift from domestic to market production (Locay, 1990). The emergence of new occupational categories is also determined by two other factors: new technological requirements or productivity trends leading certain jobs to become sufficiently rewarded to show up in the probate record. Our sources are entirely silent on the organisation of manufacturing; therefore, we are unable to identify the degree

[2] Quantifying intensive specialisation would require a measure of narrowness of the tasks performed by each occupation. To date, this approach has been untried even with present-day data and would arguably need even more detailed descriptions of the tasks performed by each occupation than measures of diversification/extensive specialisation.

to which tasks were integrated into firms or not (Stigler, 1951; Levy, 1984), or to connect the concentration of production in factories – a phenomenon that was only starting to emerge towards the end of our period - to subsequent innovation (Legros *et al.*, 2014). Our analysis can thus only speak to some of the ways in which Smith's insights have been developed.

3 Data and sources

Our main source is a dataset of probate records constructed from a wide array of court records (Appendix A and Wallis *et al.*, 2018). Our sample includes over 500,000 individuals drawn from 39 English counties (out of 42) and over 40,000 individuals from 12 Welsh counties (out of 13). Southern and northern England are particularly well-covered, and from the second half of the seventeenth century onward Welsh counties are nearly as well-covered as English ones. For every decade used in the analysis, our sample includes more than 10% of adult male deaths in each county. We supplement our main source with two other datasets, based on the registration of apprenticeship contracts. They each contain over 300,000 observations of individuals who were the fathers or masters of apprentices (Appendix B and Wallis, 2025). We use these records to provide a check on our main findings on the long-run patterns of specialisation, and exploit the wide geographic coverage of the apprentice masters dataset in our analysis of the connection between specialisation in the eighteenth century and the Industrial Revolution in Section 8.

One key drawback of these datasets is that they only cover male workers: females did not as a rule record a job title in their wills, and few women appear as mothers or masters of apprentices. Another known issue with probate data, and apprenticeship data to a lesser degree, is that they are biased towards those with wealth and capital: only relatively well-off people left a will and apprenticeship was for skilled work that was less accessible to the poorest families (Keibek and Shaw-Taylor, 2013; Keibek, 2016b, Keibek, 2016a, Wallis, 2025). In consequence, our measures of division of labour unavoidably leave out a large part of the workforce.

Following Wallis *et al.* (2018), in our main analysis, we deal with the wealth and capital bias of the probate sample econometrically by adjusting our measures of the division of labour to account for changes in the shares of deaths covered by wills and in the shares of wills with a job title within counties. We estimate the elasticities of our counts of job titles and PST occupation categories with respect to share of male deaths present in the probate record and the share of probates with a job title using fixed effects panel regressions.[3] The elasticities are then used to predict what the occupational counts would be for each county/decade if coverage were complete, by setting each of the two shares to be equal to 100%. This is our best guess of how the figures would look with perfect coverage.

As with all out-of-sample predictions, adjusted estimates should be treated with caution. Nevertheless, the hierarchy of relative levels and the direction of trends are independent of the choice of constant level (i.e. they would be the same even for, say, constant shares of 16% rather than 100%). To be sure, cross-sectional and inter-temporal comparisons would, of course, still suffer from a bias if the division of labour in the share of the population which did not a leave a will (an average of just over three-fourths of males) behaved differently from that in the share that we observe. Smith (1776) highlighted that the division of labour was both up-skilling, as it made workers more dexterous, and de-skilling, as it divided up the production process into sets of simpler tasks. It is therefore not possible to decide a priori if the division of labour progressed more amongst the poor or the wealthy. Evidence of de-skilling of the workforce in early modern England (De Pleijt and Weisdorf, 2017) would nevertheless suggest that, if anything, a focus on the wealthy should lead us to under-state increases in the division of labour in the workforce as a whole.

Another issue affecting our datasets is that their coverage varies across space and time. Better covered county-decades are bound to show more occupations than worse covered

[3] The method and the estimating equations are presented in Appendix A. We rely on fixed effects panels, including counties' quadratic trends as our only other control. We use a simple log-log OLS, in line with recent applied economic literature's emphasis on the limitations of count regressions (eg. Fry and Farrell, 2023). In fact, count data of the type analysed here behave almost like continuous data (Fox, 1991). We experimented also with Poisson regressions and the results were nearly identical.

ones. Moreover, national trends can significantly depart from local trends if certain jobs are found only in selected areas. In order to address compositional effects in an unbalanced panel, we predict trends in the division of labour in an 'average' county in England and Wales, estimated with fixed effects panel regressions weighted by counties' populations on decadal dummies 3.[4]

The final issue of the probate record that needs to be highlighted is that people at death tended to be older than typical workers, on average by about 14 years (Wallis *et al.*, 2018, 76). We address this age bias by simply back-dating our estimates by two decades so they represent prime age workers.[5] No equivalent adjustment for wealth and age is made to our apprentice master dataset used in Section 8 because the age bias is limited and the dataset systematically excludes agriculture, preventing extrapolation of this kind to the population.

Job titles found in the probate record have been cleaned to avoid counting spelling variations as different jobs (e.g. 'land-surveyor', 'land surveyor' or 'surveyor of land'). For analogous reasons, we ignored differences in job title that refer to a particular employer (e.g. we consider 'shepherd to (Rt Hon) Earl of Lincoln' just as a 'shepherd') or particular place (e.g. we consider 'turner of London' as just a 'turner'). We have deliberately constrained further standardisation to avoid making arbitrary judgements, and keep job titles that may be synonyms (e.g. 'inn-keeper' vs. 'inn-holder') as distinct job titles within a PST occupation category. In addition, we exclude military and official roles, as state dynamics may follow a different logic from those of the market, with possibly looser connections between titles and tasks. The constellation of jobs in the royal household exemplify this: the presence of yeomen of the royal laundry, the robes, the larder, the slaughterhouse, the catery, the avery and their peers are not obviously a reflection of the process Smith was interested in.[6]

4 Counties' populations are averaged over the whole period, given that the weights are fixed. For the sources of counties' populations see Appendix C.

5 For robustness, we replicate our analysis of the determinants of specialisation in Section 6

6 Excluding the military and the state reduced our sample from 564,939 observations including 2,777 unique job titles, to 555,925 observations including 2,329 unique job titles. This understates the overall number of military probate records as we only include those with an address in an English or Welsh county.

We also focus on the first job title reported for the small number of individuals with more than one reported occupation.

4 Trends: nations and counties

We begin by describing trends in specialisation in the simplest form that they exist within our dataset. Figure 3 shows our proxy of overall specialisation, the raw number of job titles, per decade in England and Wales. We detect a continuous increase in the extent of the division of labour, both in England and Wales. However, specialisation was much more advanced in England - which saw a nearly four-fold increase in the number of job titles from 159 to 780 – than in Wales, which ended with 126 job titles, just below where England had started.

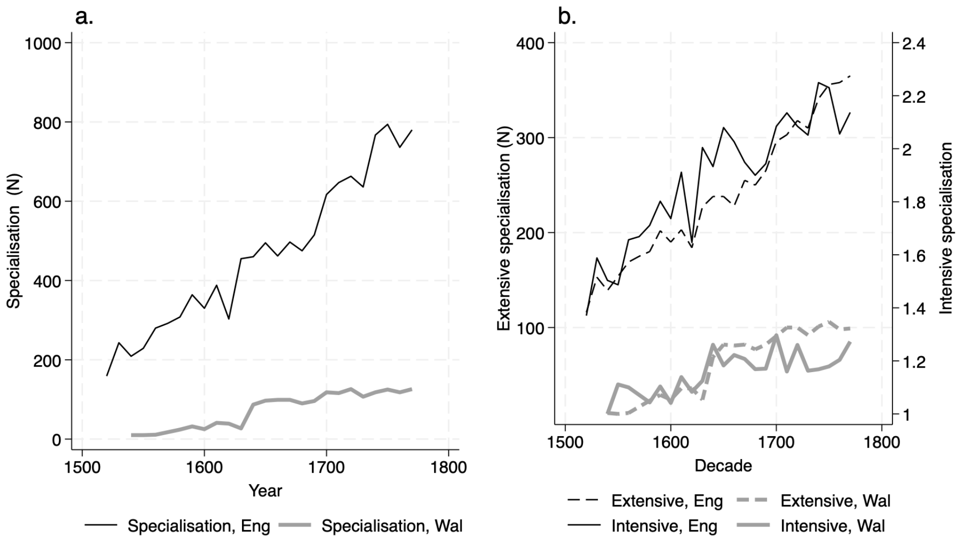


Figure 3: The Division of Labour in England and Wales, 1520-1780
Note: Specialisation is based on job titles. Extensive specialisation is the number of PST occupation categories observed per decade; intensive specialisation is the ratio of job titles to PST occupation categories per decade. Sources: see text.

Specialisation combines both extensive and intensive changes in the division of labour, as we discussed in Section 2. The right hand panel in Figure 3 separates the trends in each kind of Smithian growth, presenting our measure of extensive specialisation alongside our measure of intensive specialisation, the ratio between number of job titles and PST occupation categories. Intensive change tended to track extensive change. Thus, from the perspective of intensive change, too, Wales lagged England: in the latter, in the 1520s, there were 1.37 job titles per PST category; by the 1770s this ratio had gone up to 2.13; at the same time, in Wales the ratio was 1.27, somewhat lower than England's initial level.

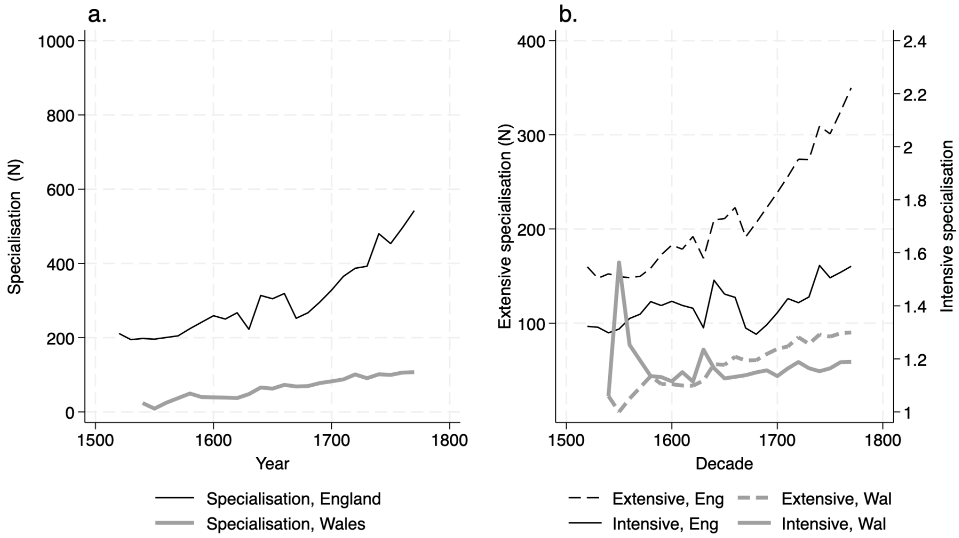


Figure 4: The Division of Labour in England and Wales, 1520-1780, adjusted for partial coverage
Note: Specialisation is based on job titles. Extensive specialisation is the number of PST occupation categories observed per decade; intensive specialisation is the ratio of job titles to PST occupation categories per decade. Estimates adjusted to represent an 'average' county. Sources: see text.

As detailed in Section 3, the estimates reported in Figure 3 are from an unbalanced panel and suffer from two sources of bias. The econometrically adjusted estimates of trends in an average county in England and Wales reported in Figure 4 address these issues and confirm two key results: there was a significant increase in the division of labour, and specialisation was much more advanced in England. Absolute change in the sixteenth century is somewhat slower than for the raw figures, which fits well with recent evidence that productivity growth began to increase around 1600 (Bouscasse *et al.*, 2025). The increase in the number of job titles in England from 1520 to 1780 remains impressive: our prediction suggests this grows by 157%, from 211 to 542, in an average English county. If anything, the contrast with

Wales is even more marked, with the predicted number of job titles, 107, in an average Welsh county in the 1770s being around half of the level in an average English county two and half centuries earlier.

There is, however, one aspect in which the adjusted trends significantly depart from the unadjusted: intensive specialisation is considerably lower in an average county in England. This point is brought into sharp focus in panel b in Figure 4.

Discounting one noisy observation in the 1550s, when the sample size is comparatively small, our adjusted estimates of extensive and intensive change track each other closely in Wales, with both showing only slow change. In England, by contrast, extensive specialisation in an average county grew much faster than intensive specialisation. Indeed, the 19 percentage points growth in intensive specialisation in an average county in England between 1540 and 1770 was not far above the 12 percentage point change in Wales.[7]

The explanation for the differences between the pace of intensive change apparent in our raw and adjusted estimates for England is to be found in the fact that within England intensive change was strongly concentrated in a single county: Middlesex. This was where (most of) London was located. This point is highlighted in Figure 5, which compares average yearly rates of extensive and intensive change in specialisation by county, after adjusting for partial coverage.[8]

Extensive change was uneven but widespread, with average yearly rates of change ranging from 0.12% (in Radnorshire, Wales) to 0.81% (in Flintshire, another Welsh county). On this measure of relative change there is no systematic difference between English and Welsh counties because even if absolute change in the latter tended to be much slower, initial levels were also much lower. Intensive change was much more unbalanced than extensive change: it was much faster in Middlesex than in the other counties, where there were only relatively

7 Using the unadjusted national trends in intensive specialisation, the same differences over time were 42 percentage points in England and 27 percentage points in Wales.

8 Results without adjustments for partial coverage are qualitatively very similar (Figure A14). Maps showing measures of extensive and intensive division of labour for several benchmark years can be found in Figures A7 and A13.

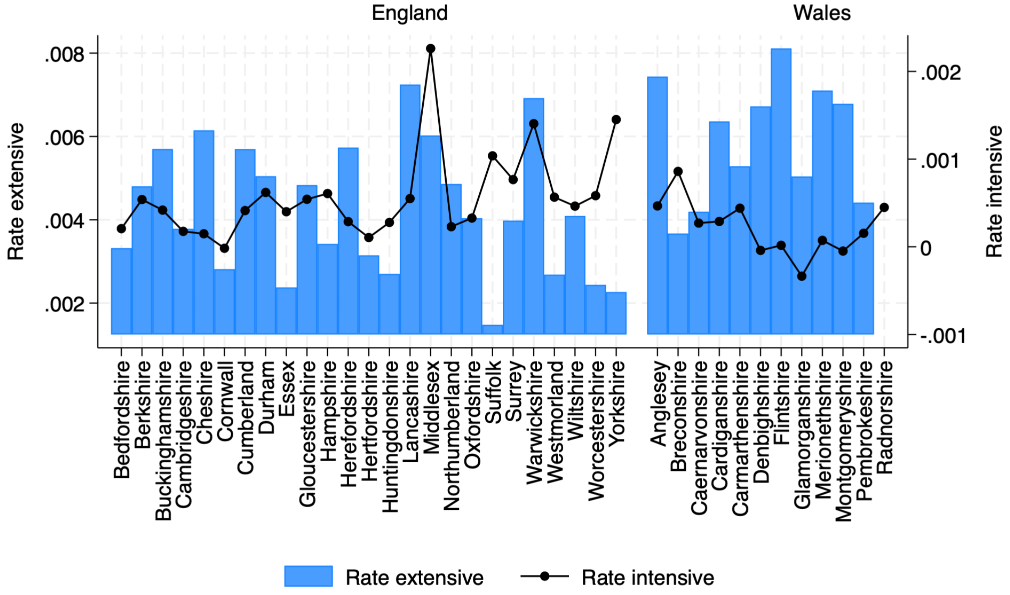


Figure 5: Average yearly rates of extensive and intensive change in Specialisation by county (adjusted for partial coverage)
Note: the figure reports average yearly rates of change in extensive and intensive division of labour by county, computed by regressing the natural log of the variable against decade. Both were adjusted for the share of the male population not included in the dataset (see the text for details). Only counties with at least five decades in observation are included. Sources: see text.

modest differences. Thus, the average yearly rate of change was 0.23% in Middlesex,[9] as compared to an average of 0.04% with a standard deviation of 0.04% in the other counties. The difference between Middlesex and the rest of Britain would be bigger still if one looked at absolute rather than relative change: Middlesex's level of intensive specialisation grew from 1.47 to 1.89 between the 1630s and 1770s. In the other counties of England and Wales, the average level of intensive specialisation was still only 1.26 in the 1770s.

5 Trends: sectors, sub-sectors and regions

Adam Smith did not expect specialisation to affect all parts of the economy equally. We therefore turn in this Section to examine, first, how trends differed across the three main

[9] The yearly rate of intensive change in Middlesex without adjustment for partial coverage is also 0.25%. Reassuringly, our adjusted job title counts in Middlesex, which go from 461 in the 1630s to 1,317 in the 1770s (with 681 in the 1690s), are consistent with Persson's (2010, Table 2.1) counts for London of 111 in 1422 and 721 in 1700.

sectors, agriculture, industry and services, and, second, how specialisation varied between two important subsectors of industry: textiles and mechanical occupations.

Figure 6 presents trends in specialisation by sector.[10] The trends are aggregated from county-level data adjusted for uneven coverage as before.[11] They can thus be interpreted as trends in an average county.

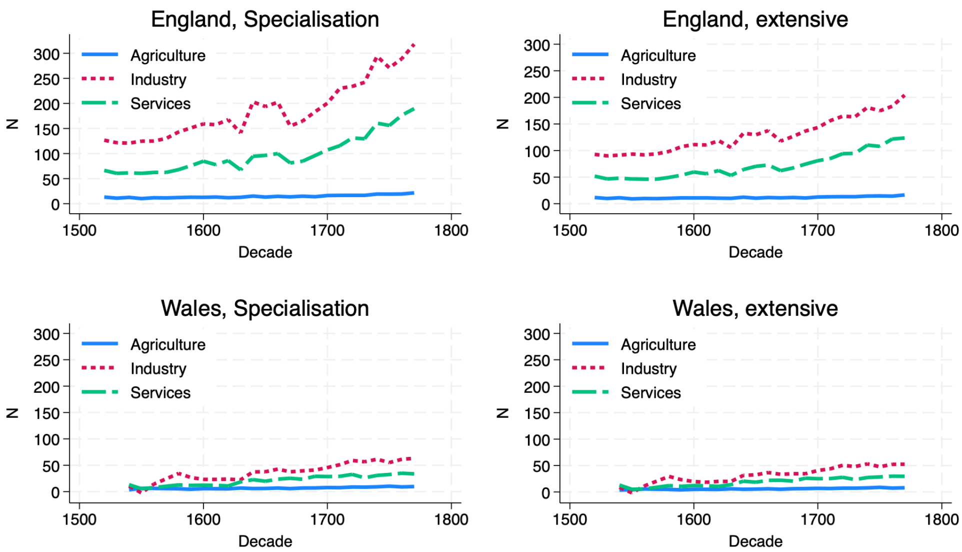


Figure 6: Sectoral trends in specialisation in average county (adjusted for partial coverage), 1520-1780)
Note: The figures are adjusted for the share of the male population not included in the dataset (see the text for details). Sources: see Section 3 and (Wallis *et al.*, 2018)).

Trends by sector strongly support Smith's (1776, 12) insight that '[t]he nature of agriculture ... does not admit of so many subdivisions of labour, nor of so complete a separation of one business from another, as manufactures'. In agriculture there were only a few occupations, with modest differences over time or across countries. Most workers were farmers, yeomen or husbandmen, and there was little if any difference in the range of occupations between counties. The division of labour was concentrated in industry and to a lesser extent

[10] As in Wallis *et al.* (2018), labourers are allocated to industry when they lived in cities and to agriculture otherwise. They account for very few job titles, however, with nearly all simply described as 'labourer'.

[11] However, the dependent variable in Equation 5 (in Appendix A) becomes $ln(y_{it} + 1)$ to include also obervations with no occupations in a given sector. We implement the same adjustment for the same reason in the analysis of sub-sectors below.

in services. It appears that the gap between manufacturing and services narrowed somewhat in the eighteenth century. Both sectors saw much more marked absolute increases in England than in Wales. Moreover, across the three sectors, intensive change was more important in England than in Wales: intensive change explains 39% of the increase in job titles in English agriculture, 42% in industry and 40% in services; the same shares for Wales are 31%, 16% and 20%, respectively.

Smith (1776, 760-761) thought that the division of labour advanced more within occupations that involved working with metals, like clockmakers, than within textile manufacturing: 'There are ... no manufactures, in which the division of labour can be carried further ... than those of which the materials are coarser metals ... [i]n the clothing manufacture, the division of labour is nearly the same now as it was a century ago'. To test this hypothesis, Figure 7 looks at the adjusted number of occupations in an average county in mechanical manufactures and in textile manufactures.

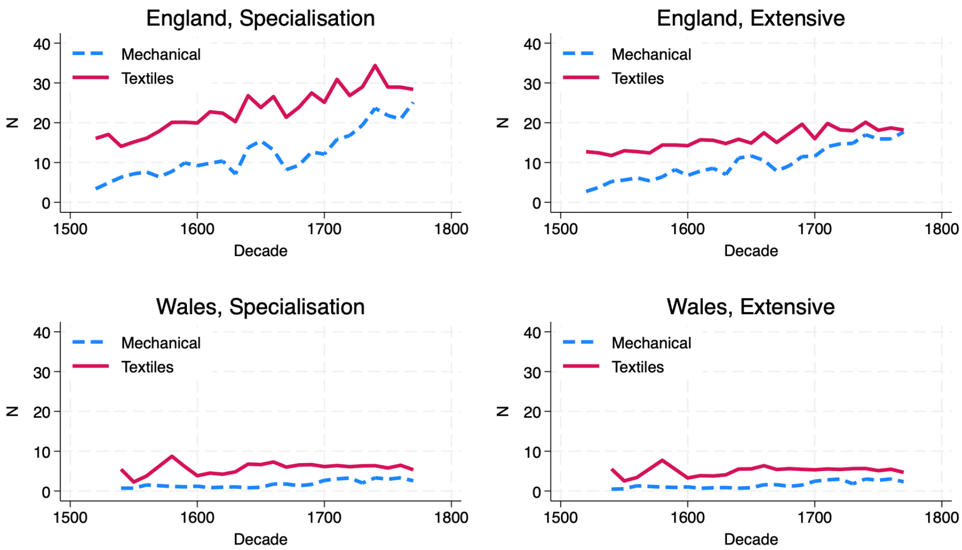


Figure 7: Specialisation in mechanical and textile manufacturing in an average county(adjusted for partial coverage), 1520-1780
Note: Mechanical manufacturing includes all occupations under PST codes 2/52, 2/62 and 2/65; textile manufacturing includes all occupations under PST code 2/20. Sources: 2

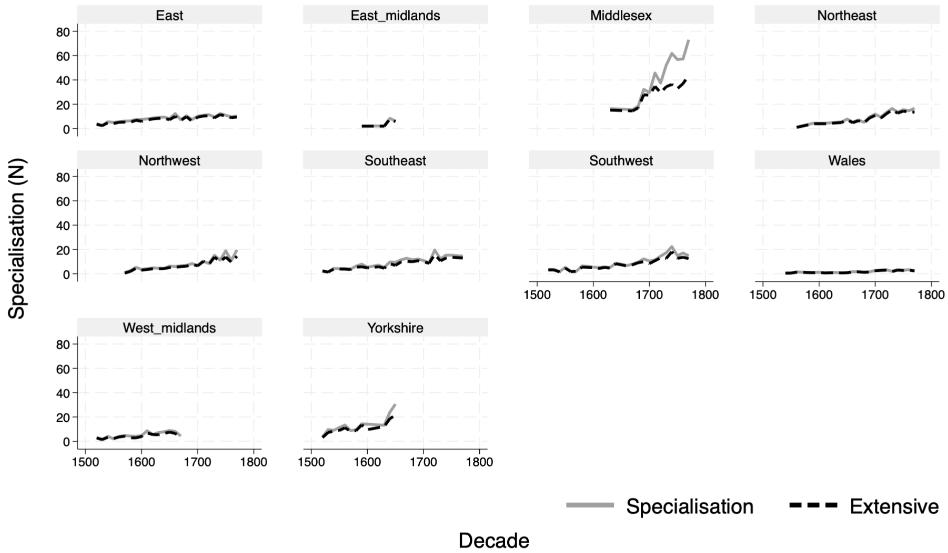
Once again, the absolute increases in number of occupations was far larger in England than in Wales. The division of labour increased much more in mechanical manufacturing, where the number of job titles in the 1770s was over seven times larger than in the 1520s, than in textile manufacturing, where numbers did not even double. While in the 1520s there were many more job titles in textiles than in manufactures (16 vs. 3), by the 1770s there was an only modest difference (28 vs. 25).

In line with Smith's (1776, 760-761) assessment, at a national level the eighteenth century saw hardly any change in specialisation for textiles, and a comparatively rapid increase for mechanical manufactures, especially at the intensive margin. While in the first decade of the eighteenth century the ratio between job titles and PST occupation categories was significantly greater for textiles than for mechanical manufactures (1.57 vs. 1.04), by the 1770s mechanical manufactures had closed most of the gap (the same ratios were 1.56 and 1.42, respectively). That said, for textiles, at least, the aggregate picture of nineteenth-century stability conceals contrasting trends between regions.

To explore how far spatial patterns of Smithian specialisation during the eighteenth century anticipated manufacturing developments during the industrial revolution, in Figure 8 we compare the evolution of mechanic and textile job titles and occupation categories across regions.

The hypothesis of a match between regional patterns of specialisation in the eighteenth century and the geography of the industrial revolution finds stronger support for textile manufacturing than for mechanical manufacturing. In textiles, there is a clear reversal of fortune in the eighteenth century, with a sharp increase in the number of job titles in the northwest – the region where the growth of cotton manufacturing was centred during the industrial revolution – at the same time as numbers were going down in the east, southeast and southwest. However, textile specialisation in the northwest still lagged that of Middlesex, which started witnessing rapid intensive growth earlier, from the second half of the seventeenth century. It is also noteworthy that an upward trend in Yorkshire is visible even earlier, from the mid-sixteenth century.

(a) Mechanical Occupations



(b) Textile Manufacturing

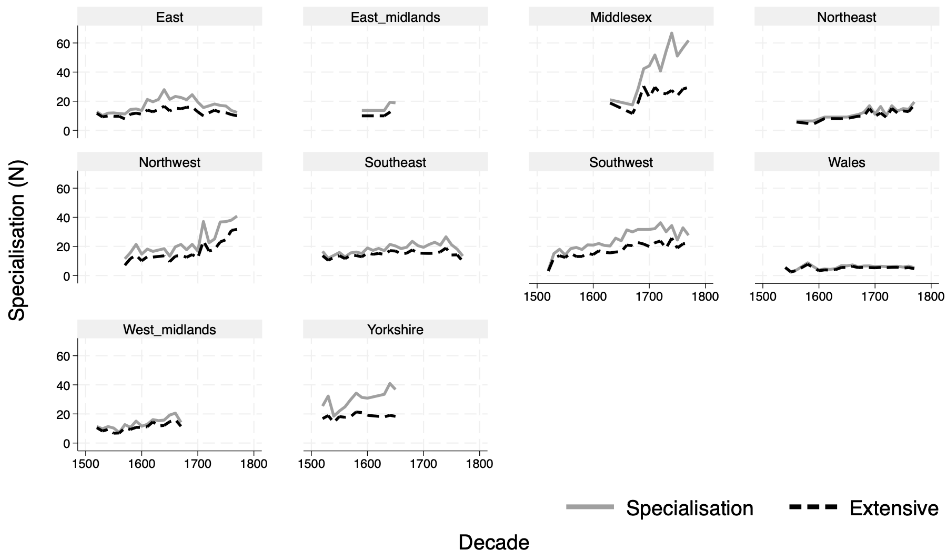


Figure 8: Specialisation in mechanical and textile manufacturing by region, 1520-1780
Note: Mechanical manufacturing includes all occupations under PST codes 2/52, 2/62 and 2/65; textile manufacturing includes all occupations under PST code 2/20. Sources: Section 2

Despite the increasing emphasis on the central role played by the supply of skilled mechanical workers in the industrialisation of northern counties (Kelly *et al.*, 2023), evidence of the same reversal of fortune in this sub-sector is not as strong. In mechanical manufacturing, more markedly than for textiles, the clearest dividing line was between Middlesex, which saw rapid intensive growth from c. 1650, and the rest, which saw only gradual and much smaller increases and much smaller differences between regions.

6 The determinants of specialisation: markets, demand and supply

What explains the growth of specialisation in pre-industrial Britain? In this section, we discuss possible explanations and the data we use in Section 7 to analyse the drivers of Smithian growth.

The best-known hypothesis on the causes of Smithian specialisation is Smith's own: that the division of labour is determined by the size of the market (Smith, 1776, 53). There is no doubt that in early modern times the size of the British market significantly increased: more people traded more wares from further afield. This expansion involved both domestic and international markets.

There are no established measures of the size of the market for pre-industrial Britain. We therefore construct new estimates of domestic market potential based on a gravity model of trade in which its evolution was determined by GDP and trade costs (Head and Mayer, 2014). We rely on Geary and Stark (2015)'s method to estimate counties' GDP. To estimate trade costs, we use Alvarez-Palau *et al.* (2025)'s least cost pathway transport costs between counties' main towns from 1680 and rely on wheat price gaps before (see Appendix C).

Domestic market potential – similarly to our measures of Smithian specialisation (Figure 3) – saw continuous change, signalling a large increase in the size of the domestic market. On a 1 to 100 scale, the mean market potential rose more than fourfold from 20% in the

1520s to 28% in 1600-09, 52% in 1700-09 and 85% in 1770s.

Measures of international markets can be gleaned from available trade figures (Appendix D). Regardless of whether one measures openness of the economy with exports per capita or exports relative to GDP, the size of the international market remained stagnant until the 1640s, but rose continuously thereafter (Figure A18). By the 1770s exports per capita were over five times greater than in the 1640s. Exports grew significantly faster than GDP: their share rose from 1.23% to 3.43% in this period. The exposure of counties to international trade was very heterogeneous, both because only coastal counties and Middlesex were directly involved and because the volume of international trade varied hugely between ports.

The international market began its upward trajectory over a century later than the domestic market. Moreover, while their spatial hierarchies of exposure were similar, differences between counties were particularly marked for international trade, with Middlesex firmly at the top and the Welsh counties at the bottom.

Although Smith emphasised the size of the market, it is clear that other factors may have also mattered for Smithian specialisation in early modern Britain. In Kuznets' (1966) view, the growth of the secondary and tertiary sectors represented shifts towards specialised market-oriented businesses. Since, as predicted by Smith (1776), the division of labour progressed much more in manufacturing and services than in agriculture (Figure 8), it was bound to increase with structural transformation. In London, where there were hardly any agricultural workers from the start, there was no scope for this factor to matter. The rest of the country was different: as documented by Keibek (2017) and Wallis *et al.* (2018), England's share of workers employed in agriculture – though much less Wales' - decreased significantly at the same time as GDP per capita was rapidly rising in the seventeenth century (Broadberry *et al.*, 2015; Appendix D).

Turning to potentially relevant supply factors, Lin (2011) finds that, in the present day, agglomeration economies are a key predictor of the location of new work. Agglomeration economies were becoming increasingly relevant in early modern Britain, albeit in a very uneven fashion. In England, the size of the urban population – here defined, as standard, as the number of individuals living in places with at least 5,000 inhabitants – exploded, at a nearly constant yearly rate of growth of 0.97% from 152,480 in the 1520s to 1,900,300 in the 1770s (Appendix D.3). Around half of England's urban population resided in London. Wales was very different from England: it remained markedly rural, with no urban centres exceeding 5,000 inhabitants before the 1760s.

Two types of agglomeration economies may matter in this context. On the one hand, Marshallian externalities imply agglomeration economies because similar industries benefit from knowledge spillovers and local availability of trained workers, inputs and outputs (Marshall, 1890). On the other hand, Jacobs (1969) argues that the significance of knowledge spillovers increases with the variety of the division of labour. This distinction echoes our distinction between intensive and extensive specialisation: Marshallian (Marshall, 1890) externalities can be expected to mainly matter for intensive specialisation, while one would expect agglomeration economies to mainly foster extensive specialisation through Jacobs' (1969) externalities.

7 The determinants of specialisation: econometric analysis

To examine the effect of changes in the size of national market potential, international trade, structural change and agglomeration economies on the growth of the division of labour in early modern England and Wales, we rely on a standard fixed-effects panel regression specification:

$$\ln(y_{it}) = \alpha_i + \beta_1 \ln(MP_{it}) + \beta_2 \ln(Trade_{it}) + \beta_3 \ln(AgShare_{it}) + \beta_4 \ln(Urb_{it}) + \sum_k \beta_k \ln(x_{k,it}) + \varepsilon_{it} \tag{1}$$

where y_{it} is the number of raw job titles or number of occupation categories or their ratio in county i in decade t and $x_{k,it}$ are two controls for uneven coverage (see Section 3). As all variables are included in log form, we added one added to those that include zero values: counties' international exports and urban population. An analogous specification has been widely used by economic geographers to study the effect of market potential on variables such as GDP per capita (e.g. Head and Mayer, 2011), industrial location (e.g. Basile and Ciccarelli, 2018) or urban population (e.g. Alvarez-Palau *et al.*, 2025).[12]

For robustness, we also explore two alternative specifications. First, we replace *Market potential* with *Market access*, which also includes a term capturing competition between counties (see Appendix C). Second, we follow Head and Mayer (2011) in instrumenting *Market potential* with its 'foreign' part, i.e. excluding the county's own market. This addresses the potential for endogeneity in *Market potential.* If, as posited by Smith (1776), specialisation causes economic growth, the presence of the county's own GDP – one of the inputs of *Market potential* - in the left-hand side implies reverse causality.

Our IV strategy only addresses the most obvious source of endogeneity, neglecting spillover effects across counties. However, when we also exclude adjacent counties in the IV our results are largely unchanged (Appendix I). Moreover, because we lack data on local trends in output per worker within sectors and, until 1680, trade costs, our estimates of *Market potential* ignore their heterogeneity across counties. The measurement errors and thus attenuation bias that follows from this should work against our finding that *Market potential* was the main cause of Smithian specialisation.[13]

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[12] Recent research has highlighted that two-way fixed effects can introduce significant bias in the estimated coefficients (De Chaisemartin and d'Haultfoeuille, 2020; Imai and Kim, 2021 as well as others). In our baseline, we thus prefer to rely on a simple cross-sectional fixed-effects specification (like e.g. Head and Mayer 2011), thus implicitly assuming that we are controlling for the key drivers of changes in specialisation. We report results including also time and time $\times$ county fixed effects in Appendix I.

[13] Another implication is that unobserved variables (such as human capital or infrastructural investment) that might drive uneven changes in both specialisation and *Market potential* through labour productivity or trade costs' are not a threat to our identification, or, at any rate, a relatively mild threat in the case of trade costs. The same point applies to reverse causality through the trade costs channel. When we experimented with an estimate of *Market potential* that neglected unevenness in changes in trade costs also after 1680 we obtained qualitatively identical and quantitatively very similar results to those presented here

Table 2 summarises the variables used in the regression analysis, their expected sign, and their descriptive statistics. The correlation coefficients between explanatory variables, shown in Table A4, are, as expected, high for the domestic market size variables (nearly 0.9 or more) – which are never used together in the same specification - but mostly very low otherwise (with absolute values always significantly below 0.8 and mostly much lower). Hence, multi-collinearity is generally not expected to be a serious concern.

Table 2: Variables used in the regression analysis with their descriptive statistics

Variable	**Description of variable**	**Sign**	**N**	**Mean**	**St. dev.**	**Min.**	**Max.**
Dependent variables							
Occupations	Number of job titles		663	75	59	5	470
Extensive specialisation	Number of occupation categories		663	62	41	5	274
Intensive specialisation	Job titles/Categories		663	1.15	0.11	1	1.75
Explanatory variables							
Market potential	See Equation 6, in M 2011 international $	+	663	656	316	144	1517
Market access	See Equation 7, in M 2011 international $	+	663	18	5	7	30
'Foreign' market potential	Market potential excluding own county's market	+	663	639	309	131	1509
International trade	Value of exports pc + 1, in 2013 £	+	663	11.60	52.89	0	608.83
Agricultural share	Share of agricultural workers (%)	–	663	63.32	15.49	1.84	91.00
Urban population	'000 individuals in places with 5,000+ inhabitants + 1	+	663	14.921	81.714	0	808.770
Share of wills	Share of male deaths with a will (%)	+	663	21.31	8.84	1.00	56.43
Share of occupations	Share of wills with a job title (%)	+	663	63.86	18.92	10.19	91.97

Notes: There are 51 counties and 26 decades, but the panel is unbalanced. Sources: see the text and Appendix F.

Table 3 presents the results of the regression analysis. The values of the R-squared show that the model fits very well with the evolution of number of occupations and extensive Smithian specialisation within counties and to a lesser extent with that of intensive Smithian specialisation. Across the board, first-stage R-squared greater than 99% leave no doubt about the strength of 'Foreign' market potential as an instrument for market potential and explain why the OLS coefficients are nearly identical to the IV coefficients. In all cases, there is a close match between the results that use *Market potential* to estimate the size of the domestic market and those that use *Market access*, in terms of sign, statistical or economic significance.[14]

[14] Even if the size of the coefficients change, as seen in Table 4 below, the quantitative relevance of the factor is same regardless if one use Market potential or Market access.

Table 3: The determinants of Smithian specialisation: panel regression results

Estimator	OLS			OLS			IV (Foreign MP)		
	Occ.	**Ext. Spec.**	**Int. Spec.**	**Occ.**	**Ext. Spec.**	**Int. Spec.**	**Occ.**	**Ext. Spec.**	**Int. Spec.**
Market potential	0.462***	0.418***	0.044***				0.458***	0.414***	0.044***
	(0.066)	(0.056)	(0.015)				(0.065)	(0.056)	(0.015)
Market access				1.049***	0.948***	0.101***			
				(0.156)	(0.140)	(0.033)			
International trade	0.029	0.033	-0.004	0.030	0.034	-0.004	0.030	0.034	-0.004
	(0.035)	(0.033)	(0.008)	(0.038)	(0.036)	(0.008)	(0.035)	(0.033)	(0.008)
Agricultural share	-0.287*	-0.275**	-0.012	-0.380**	-0.359***	-0.020	-0.291**	-0.278**	-0.012
	(0.147)	(0.121)	(0.036)	(0.151)	(0.126)	(0.035)	(0.148)	(0.121)	(0.036)
Urban population	0.020	0.003	0.017***	0.019	0.002	0.017***	0.020	0.003	0.017***
	(0.021)	(0.021)	(0.005)	(0.024)	(0.023)	(0.005)	(0.022)	(0.021)	(0.005)
Share of wills	0.495***	0.444***	0.051***	0.492***	0.441***	0.051***	0.494***	0.443***	0.051***
	(0.042)	(0.045)	(0.007)	(0.043)	(0.045)	(0.007)	(0.042)	(0.045)	(0.007)
Share of occupations	0.566***	0.534***	0.032**	0.626***	0.589***	0.037***	0.569***	0.537***	0.032**
	(0.054)	(0.051)	(0.014)	(0.049)	(0.049)	(0.012)	(0.053)	(0.051)	(0.014)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared (within)	0.850	0.831	0.414	0.846	0.828	0.410	0.850	0.831	0.414
R-squared (within) first stage							0.999	0.999	0.999
F-statistic first stage							66272	66272	66272
Observations	663	663	663	663	663	663	663	663	663

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels respectively. Standard errors clustered by county are in parentheses. All variables are in logs, and 1 was added to zero-valued variables before logging. In IV estimates, Market potential is instrumented with foreign Market potential (excluding the county's own market).

Domestic market size is always highly significant, regardless of the measure or estimator used, indicating that it caused both extensive and intensive Smithian specialisation. In sharp contrast, international trade emerges as irrelevant. A note of caution is in order: this variable's trends are associated with those of urban population (the within counties correlation coefficient between logged variables is 41%) and agricultural share (the within counties correlation coefficient is -33%). While the strength of the associations is hardly very concerning, we cannot entirely rule out multi-collinearity.[15]

Nevertheless, the result that the size of the domestic rather than the international market was the key driver of Smithian specialisation is plausible, given the latter's relatively small share of the national economy. While Britain's openness significantly increased in our period, the lion's share of demand remained domestic: the size of exports relative to GDP remained below 4% throughout (Figure A18). Moreover, the coefficient of international trade only captures its direct effect on Smithian specialisation, and not its indirect role through fostering structural transformation and economic growth.

The effects of the other variables on Smithian specialisation differed between the extensive and intensive margin. Agricultural share, which captures the size of the demand for industrial products and services, mattered for extensive but not for intensive specialisation. This is unsurprising given that intensive specialisation was concentrated in London (Figure 5) where there was no agriculture.

Conversely, the variable most closely related to supply factors (costs and productivity) – urban population – fostered intensive but not extensive specialisation. Since urban population should capture the role of agglomeration economies, that it matters only at the intensive margin suggests that Marshallian (Marshall, 1890) externalities between similar occupations, rather than Jacob's (1969) externalities between diverse occupations, mattered. Our results cast light on the crucial factor that made London especially suited for intensive Smithian

[15] This remark is confirmed by a variance inflation factor for International trade of 20.98 – a value significantly higher than for any other variable (the second one is Urban population with a value of 10.33; the values for other variables are all significantly lower than the 10 points threshold).

specialisation: a high concentration of similar industries benefiting from local availability of trained workers, shared inputs and outputs and fostering knowledge spillovers.

How much did each of the different factors matter for the growth of specialisation that we document? To address this question, we implement a simple decomposition of the shares of the predicted changes in the mean values of the dependent variables between the 1520s and the 1770s accounted for by each of the key determinants, leaving out trivial changes explained by improved coverage and composition effects.[16] Formally, the contribution of each explanatory variable x_k is computed as:

$$\Delta \ln(x_k) = \frac{\hat{\beta}_k \left[\ln(\bar{x}_{k,1770}) - \ln(\bar{x}_{k,1520})\right]}{\sum_{k=1}^{5} \hat{\beta}_k \left[\ln(\bar{x}_{k,1770}) - \ln(\bar{x}_{k,1520})\right]} \tag{2}$$

where the hat denotes estimated coefficients, the bar denotes the mean (after taking the log) and otherwise the notation is the same as in Equation 1. Table 4 presents the results.

[16] i.e. we consider only explanatory variables and not the fixed effects and share of wills and occupations reported in Table 2

Table 4: The determinants of Smithian specialisation: decomposition analysis (%)

Estimator	**OLS**			**OLS**			**IV (Foreign MP)**		
	Occ.	**Ext. Spec.**	**Int. Spec.**	**Occ.**	**Ext. Spec.**	**Int. Spec.**	**Occ.**	**Ext. Spec.**	**Int. Spec.**
Market potential	86.86	87.30	82.89				86.57	87.00	82.67
Market access				82.72	83.14	79.04			
International trade	3.25	4.15	-4.90	3.71	4.73	-5.38	3.38	4.29	-4.85
Agricultural share	7.71	8.21	3.22	11.22	11.81	5.97	7.84	8.35	3.29
Urban population	2.18	0.34	18.80	2.35	0.33	20.38	2.21	0.36	18.89
Predicted/actual change	86.97	87.00	86.64	78.98	78.90	79.66	86.46	86.48	86.29

Sources: Based on the regression outputs in Table 3 and Equation 2. The final row is computed using:

$$\frac{\sum_{k=1}^{5} \hat{\beta}_k \left[\ln(\bar{x}_{k,1770}) - \ln(\bar{x}_{k,1520})\right]}{\ln(\bar{y}_{1770}) - \ln(\bar{y}_{1520})}$$

where y is the dependent variable. Other notation follows Equation 1.

The decomposition analysis produces one very clear result: the size of the national market was far more important than any of the other factors, particularly for extensive specialisation. The contribution of the agricultural share shows that structural transformation also provided a significant impetus for extensive specialisation, while the other two variables mattered little. Agglomeration economies, proxied here by urban population, emerge as an important driver of intensive specialisation. Across specifications, our key variables predict the lion's share of actual changes in the mean values of the dependent variables.

8 From Smithian Growth to the Industrial Revolution

Notoriously, Adam Smith did not notice the dawning of the Industrial Revolution. Did the growth of Smithian specialisation nevertheless anticipate, perhaps even help to generate, industrialisation?

Recent research offers two (not necessarily mutually exclusive) perspectives on the question of how far the drivers of premodern economic growth explain the transition to modern economic growth. On the one hand, Heldring *et al.* (2021) stress continuities with the patterns of commercialisation that emerged in the early sixteenth century. On the other hand, Kelly *et al.* (2023) emphasise how the geography of industrialisation changed during the eighteenth century, as an increasingly integrated national economy allowed greater regional specialisation.

To test these two hypotheses, we examine the relationship between our baseline measure of Smithian specialisation and two measures of early nineteenth century industrialisation: the share of males aged 20–29 employed in textiles in 1851 (used by Kelly *et al.*, 2023) and the share of males aged 20+ employed in industry in 1831 (used by Heldring *et al.*, 2021). We rely on the apprentice masters dataset for this exercise because in the eighteenth century it offers complete coverage for England and Wales (see Appendices A and B). Our baseline measures of Smithian specialisation are highly correlated between both datasets.[17] We exploit the

[17] Pearson's coefficient is 90 % for raw wills figures and 93 % for those adjusted for the partial cover-

panel structure of the dataset by running separate regressions for each of the decades in the eighteenth-century for which full data is available. Each regression estimates how well levels of specialisation in that decade predict industrialisation in the early nineteenth century. We can therefore see how the predictive power of Smithian specialisation developed over the eighteenth century for the first time.

Our specification closely follows that of Kelly *et al.* (2023). We use a semi-parametric spatial regression with a thin-plate spline in longitude and latitude, which is robust to spatial autocorrelation. We control for agricultural wages in the 1760s, market potential in the 1750s, and distance from the nearest carbon strata (which, unlike the nearest coal-field, is exogenous).[18]

The results are reported in Figure 9 and are reassuringly similar regardless of how we measure early nineteenth-century industrialisation (full results are in Appendix E). For both sets of regressions, the predictive power of Smithian specialisation only became statistically significant from the 1750s onward, following a large rise in the size of its coefficient relative to that of the 1740s (by 84% for textile employment in 1851 and by a staggering 169% for industrial employment in 1831, arguably the better measure of the two).

The sizes of our coefficients imply economically significant consequences. By the 1750s, each standard deviation in Smithian specialisation was associated with a change of between a third and a half standard deviations in each measure of early nineteenth century industrialisation. While Smithian specialisation in the 1740s accounted for a mere 3% of the large difference in industrial employment between Cornwall and Lancashire in 1831 (0.15% vs. 31.15%), only one decade later it accounted for a sizeable 13% of the difference. The observed patterns are suggestive of a fundamental discontinuity between Smithian and modern economic growth: it was only from the second half of the eighteenth century - the very eve of the classic period of the Industrial Revolution - that the two started to be closely

age of the probate record. The correlation coefficients are 83 % and 84 % respectively for intensive specialisation.

18 All the controls have the expected sign, even if (as in Kelly *et al.*, 2023) they are not always statistically significant.

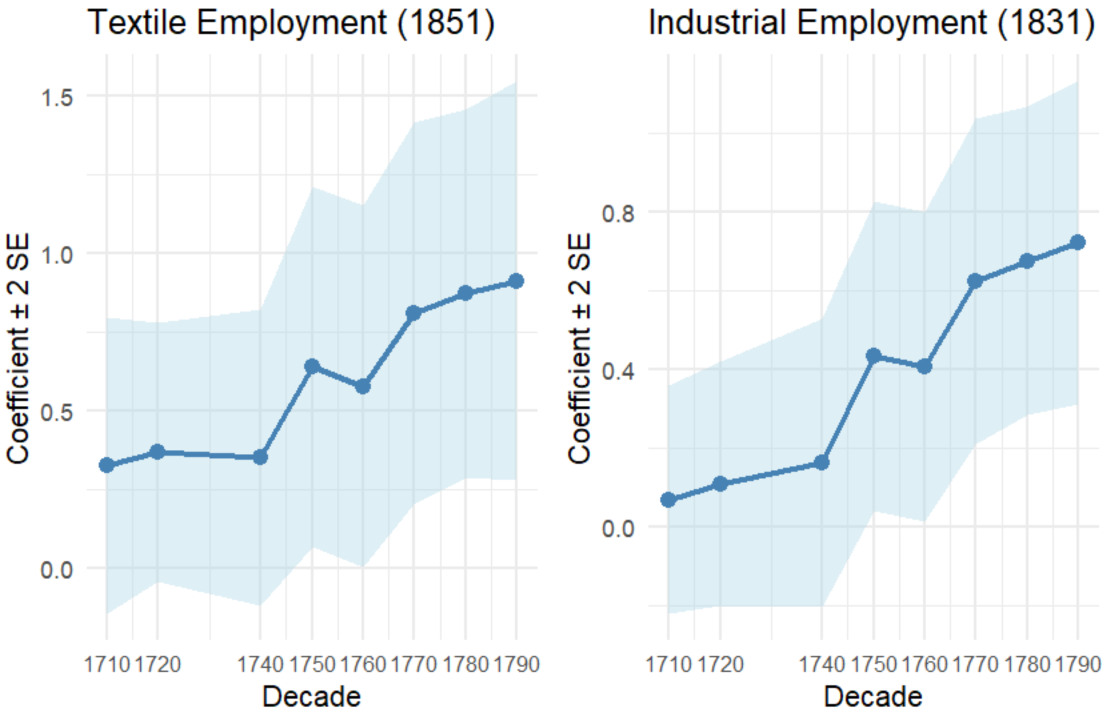

Figure 9: Smithian specialisation and the Industrial Revolution
Note: The unit of observation is the county. All dependent and explanatory variables are logged so that the coefficients refer to pure elasticities (adding one before taking the log to industrial employment to include Huntingdonshire, where the census recorded a value of zero for industrial employment). Each coefficient is computed with a separate regression, with our baseline of Smithian specialisation, the number of jobs, in a particular decade as the explanatory variable of interest. The dependent variables are the employment share of textiles among males aged 20–29 in 1851 (left panel) and the share of males aged 20+ employed in industry in 1831 (right panel) (both in percent). The following controls are included in all regressions: estimates of agricultural wages in the 1760s, market potential in the 1750s and distance from the nearest carbon strata. Sources: See text.

associated. This finding aligns with evidence from regional wages and urbanisation. The Industrial Revolution involved a profound shift in the economic geography of Britain. Our results suggest a fundamental discontinuity between the developments in specialisation and productivity that occurred in the British economy between the sixteenth and mid-eighteenth century and the radical changes that followed.

9 Robustness

We assess the robustness of our analysis in several ways. First, to address the question of whether our methodology is dependent on the specific scheme we use to categorise and order occupations, we test the effect of using an alternative method of occupational coding. In Appendix F, we repeat our analysis of Smithian specialisation and its determinants using HISCO instead of the PST classification scheme. The levels in the number of occupation categories decline as the former scheme is based on broader categories than the latter. However, the trends are very similar.

Second, to address concerns that the results that we see may be the product of the specific dataset based on probate records that we use in our main analysis, we repeat our analysis of trends in specialisation and the determinants of the division of labour using the alternative two apprenticeship datasets with information on job titles that we possess. These are arguably more socially inclusive than the probate record, but are also more chronologically restricted and one of them excludes agriculture (see Appendix B). These yield results consistent with those of the probate dataset and are reported fully in Appendix G. The apprentice masters dataset also suggests that Scotland was more similar to Wales than England in the eighteenth century, providing us with insights into the rest of Britain.

Finally, we consider whether other approaches to measuring occupational diversity might produce different results. The use of alternative measures that consider the quantitative significance of occupational titles does not alter the picture, as shown in Appendix H. We find similar results using a Dixit-Stiglitz variety index of the division of labour (Ades and Glaeser, 1999). The probability that three random workers had three different occupations in an average English county increased continuously and tripled overall. On a scale from 0 (same PST occupational category) to 4 (different PST sector, group, section and occupation), the mean 'occupational distance' between two workers in an English county rose from 1.90 in the 1520s to 3.14 in the 1770s, but grew much less in Wales. The shares of new jobs (job titles or occupation categories absent in Britain in the previous decades) also rose, and workers with new jobs confirm that Middlesex was particularly dynamic (Figure A29).[19]

10 Conclusion

This paper offers the first systematic evidence on patterns of Smithian specialisation in early modern Britain. Drawing on several large datasets of job titles, we develop simple and robust methods to measure the division of labor. We then use these methods to document patterns of both extensive and intensive specialisation over the two and a half centuries before the Industrial Revolution.

Our results provide support to the Adam Smith's hypothesis that specialisation allowed by the division of labour was the main engine of economic growth in early modern Britain and by extension the pre-industrial world. England witnessed a significant and continuous increase in both extensive and intensive specialisation between the 1520s and the 1770s. While progress at the extensive margin was widespread, at the intensive margin it was concentrated in London. The growth in specialisation accelerated after 1600, in line with recent estimates of when productivity growth took off (Bouscasse *et al.*, 2025), and closely tracks estimates of GDP and urbanisation.

Confirming Smith's (1776) expectations, specialisation progressed much more significantly within manufactures and to a lesser extent services than in agriculture. Moreover, within manufacturing, specialisation progressed more in mechanical manufactures than in textiles. Regional patterns highlight a particularly marked increase in specialisation in

[19] Cumulated Computations based on raw figures.

textiles in the north-western counties, anticipating later development during the Industrial Revolution. However, specialisation in both textiles and especially mechanical manufactures was strongly concentrated in England's largest urban centre, London. Our trends are robust to the use of alternative measures of specialisation or alternative sources of job titles.

We provide strong evidence that the size of Britain's domestic market was the main determinant of the division of labour, lending support to another of Smith's (1776) key insights. Other contributory factors differed between the extensive margin, which benefited from an increase in the demand for manufactures and services, and the intensive margin, which was helped by supply factors, particularly Marshallian externalities. However, when we look for connections between our measures of specialisation and industrialisation, we find that a robust relationship between patterns of specialisation and subsequent industrialisation only emerged during the middle of the eighteenth century. The division of labour was an engine of long-run economic growth, but not - by itself - a cause of the Industrial Revolution.

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A Probate Dataset and adjustment

This appendix reports further details on the probate dataset that is used in the main analysis in the paper, and details of the adjustments for bias applied. It also reports maps of adjusted specialisation measures.

A.1 Probate Data

When wills were written and registered, it was common for the occupation or status of the deceased to be recorded alongside their name and location. Wills were important legal documents that managed the disposal of the deceased's estate and ensuring that the individual involved was accurately identified helped to avoid any risk of the will being contested and to distinguish between the different wills being recorded by the court. The majority of the records that survive are enrolled copies of the original wills, made by court clerks. In addition, some estates were settled by administration, granted when no will was made. The probate dataset that we employ in this paper is based on indices of wills and administrations in the records of England's church courts that were mostly constructed by the court officials, archivists and genealogists.

Probate records are one of the largest categories of historical sources that survive in English archives. However, in part because the original records were created by a large number of distinct courts, they are dispersed over a range of different archives, and do not survive for all areas. Full details of the construction of the dataset are given in Wallis *et al.* (2018) and the geographical distribution of probate observations is shown in Figure A1.

We restrict our analysis to counties for which we have wills for at least 10% of male deaths in each decade, and at least 10% of wills in each decade include an occupational descriptor. The number of observations in our dataset for each decade is reported in Table A1. Although the original records cover a variety of geographical areas (archdeaconries, bishoprics, archdiocese), we structure the dataset around the counties that are covered, and for each decade we report the number of counties with records that meet our threshold for inclusion, and the share of estimated national male deaths in that decade that they capture (each county in observation exceeds 10% of deaths within that county).

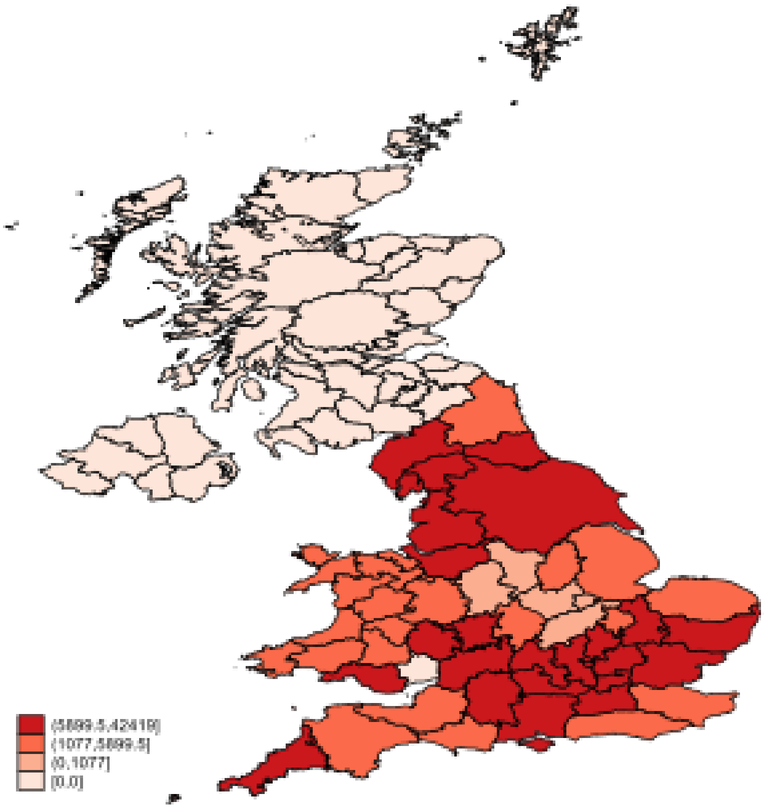


Figure A1: Geographical distribution of the probate observations.
Sources: see text.

Table A1: Male Probate Records by Decade in England and Wales

	England			Wales		
Decade	Obs.	Counties	% Male Deaths	Obs.	Counties	% Male Deaths
1540–1549	3,675	14	4			
1550–1559	10,833	17	8			
1560–1569	7,292	16	7	15	1	0
1570–1579	9,585	16	8	72	2	0
1580–1589	13,016	19	10	42	2	0
1590–1599	17,538	19	12			
1600–1609	17,748	18	12	180	3	1
1610–1619	25,101	22	16	338	4	2
1620–1629	21,779	18	13	252	4	1
1630–1639	23,356	23	12	474	7	2
1640–1649	14,508	18	7	377	6	2
1650–1659	29,461	28	14	242	3	1
1660–1669	27,495	23	13	1,905	12	7
1670–1679	27,616	25	12	2,176	12	8
1680–1689	24,057	20	10	2,426	12	7
1690–1699	24,422	19	12	2,747	12	9
1700–1709	20,975	17	10	2,455	11	8
1710–1719	20,899	16	10	2,939	12	9
1720–1729	27,640	17	12	3,986	12	11
1730–1739	26,032	17	12	3,444	12	10
1740–1749	23,202	16	11	3,133	12	8
1750–1759	16,627	13	8	2,528	12	7
1760–1769	19,819	13	9	3,135	12	8
1770–1779	19,891	15	8	2,996	12	8
1780–1789	15,584	13	6	3,051	11	7
1790–1799	14,559	13	5	3,223	12	8
Total	**513,595**			**42,696**		

A.2 Adjustment for Sample Bias

We discuss several of the issues around selection that affect the probate dataset in the main text. Formally, to estimate the elasticities, we run the following fixed-effects panel regressions:

$$\ln(y_{it}) = \alpha_i + \beta_1 \ln(\textit{Share wills}) + \beta_2 \ln(\textit{Share occupations}) + \beta_{3,i}t + \beta_{4,i}t^2 + \varepsilon_{it} \tag{3}$$

where the outcome variable is the natural logarithm of y_{it}, the number of job titles or the number of PST occupation categories in county i in decade t, *Share wills* denotes the share of male deaths covered by the probate record and Share occupations denotes the share of wills with a job title. To adjust the counts by county and decade, we use the following equation:

$$\ln(\hat{y}_{it}) = \ln(y_{it}) + \hat{\beta}_1 \ln(100\% - \textit{Share wills}) + \hat{\beta}_2 \ln(100\% - \textit{Share occupations}) \tag{4}$$

where $\hat{y}_{it}$ are the adjusted counts, $\hat{\beta}_1$ and $\hat{\beta}_2$ are the elasticities estimated with Equation 3 and otherwise the notation is as before. Finally, to estimate the trend in an average county, we run the following fixed-effects panel regression:

$$\hat{y}_{it} = \alpha_i + \sum_{t=1520s}^{1770s} \beta_t D_t + \varepsilon_{it} \tag{5}$$

where D_t are decadal dummies and otherwise the notation is as before.

A.3 Maps of intensive and extensive Specialisation

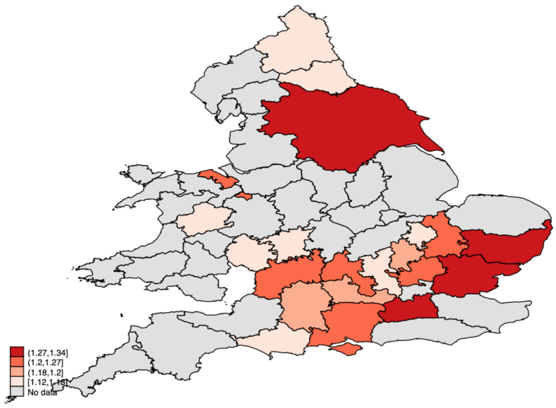


Figure A2: 1560

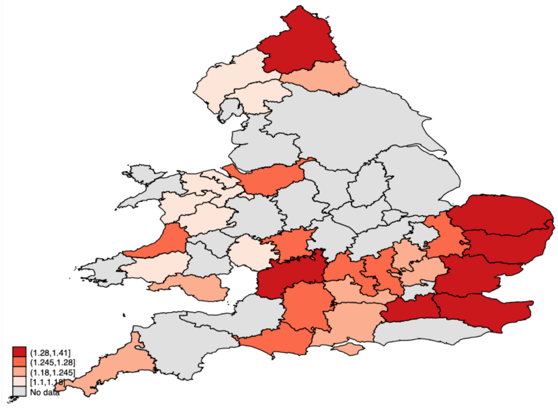


Figure A3: 1610

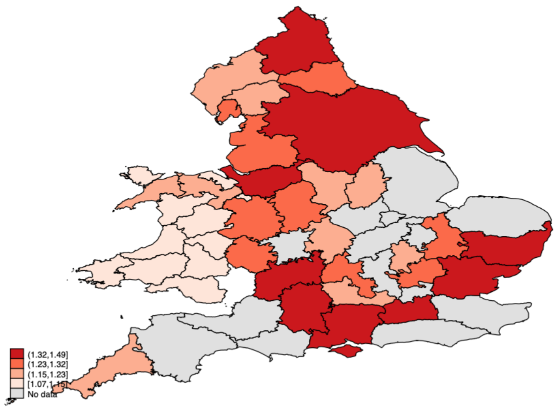


Figure A4: 1650

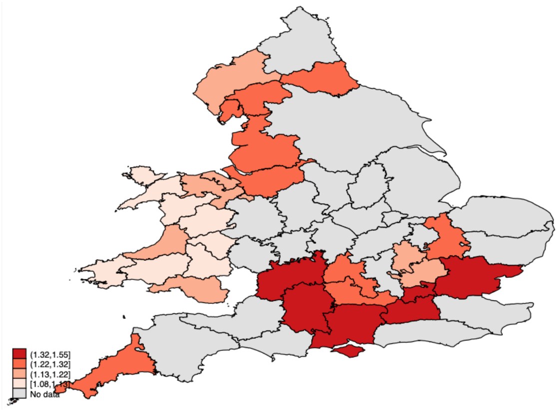


Figure A5: 1700

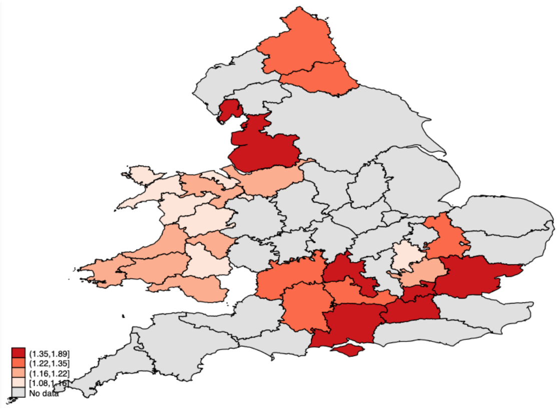


Figure A6: 1750

Figure A7: Maps of Intensive Specialisation in Different Decades

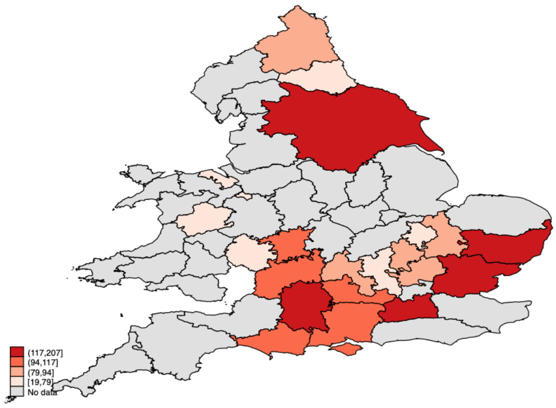


Figure A8: 1560

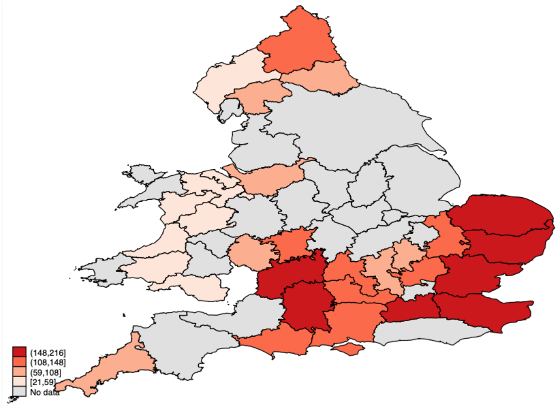


Figure A9: 1610

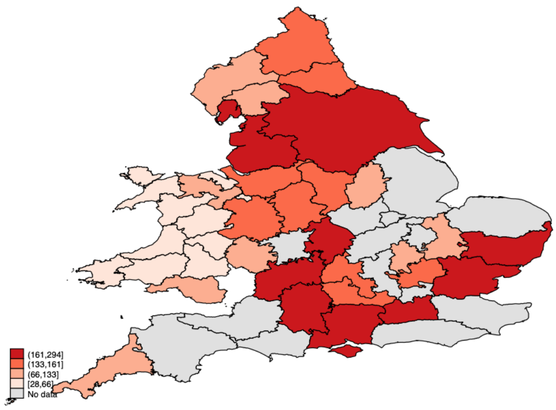


Figure A10: 1650

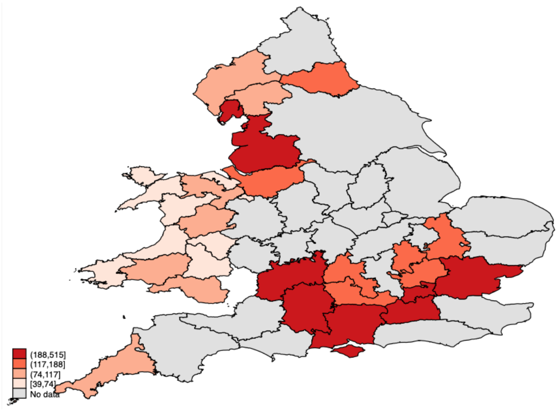


Figure A11: 1700

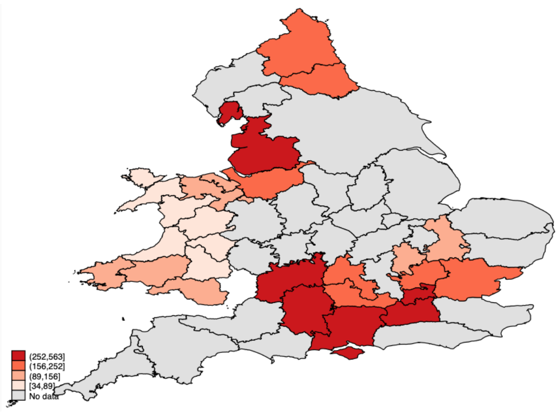


Figure A12: 1750

Figure A13: Maps of Extensive Specialisation in Different Decades

A.4 Results without Adjustment for Sample Bias

We report here the equivalent to Figure 5 without adjustment for sample bias, to confirm the finding holds - with Middlesex's dominance in intensive specialisation being in fact rather stronger - in the absence of this correction.

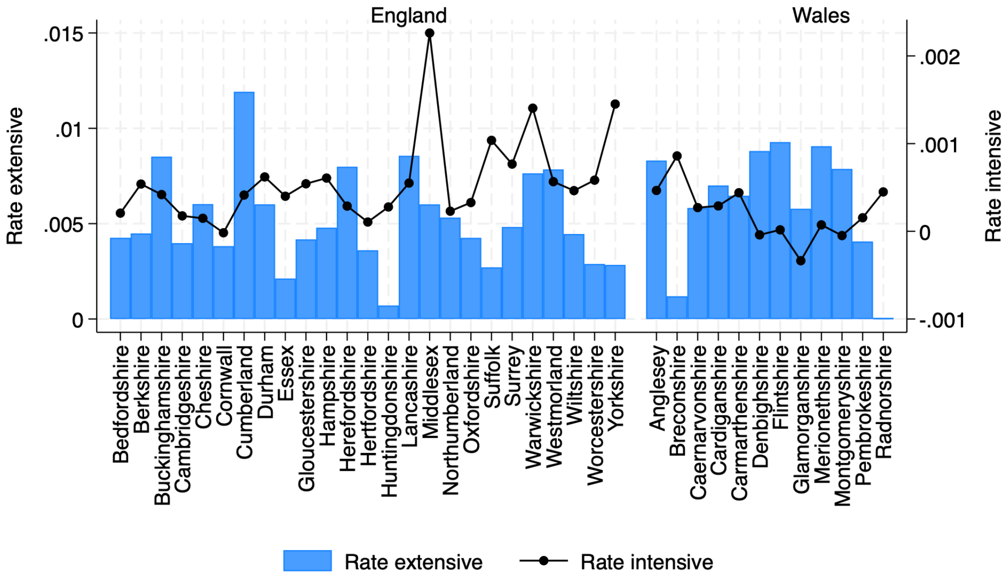


Figure A14: Average yearly rates of extensive and intensive change in Specialisation by county
Note: the figure reports average yearly rates of change in extensive and intensive division of labour by county, computed by regressing the natural log of the variable against decade. Only counties with at least five decades are included. Sources: see text.

B Apprenticeship Datasets

We employ two datasets drawn from historical records of apprenticeship training in Britain for our analysis. In the paper and appendices, these are identified as apprentice fathers and apprentice masters, respectively. The number of observations in each of the datasets per decade and the number of counties in observation is given in Table A2 and Table A3 .

The first dataset, apprentice fathers, consists of 348,740 observations, dated between 1580 and 1799, taken from urban and guild records that survive for London, Boston, Bristol, Durham, Gloucester, Leicester, Lincoln, Liverpool, Norwich, Oxford and Shrewsbury. It is an unbalanced panel that is dominated by London, which provides 88% of the observations due to its dominance of training in this period (Wallis, 2025). Some indication of the scale of the sample is given by the right-hand column of Table A2 which reports the share of English male teenagers who appear in the dataset. At the peak, over one in twenty teenagers were becoming apprentices in one of these cities, mainly London.

The occupations of apprentices' fathers, along with their location, were recorded when their indentures were registered with the urban authorities, as the father was usually serving as one of the counterparties to the contract, and so needed to be clearly identified. Some fathers were reported with a status indicator, such as gentleman, or an indicator that they were a guild member, and we exclude these. Occupations that could be categorised using the PST system were reported for 92% of registered indentures in the years studied. Most of the apprentices whose fathers are not included in our analysis are omitted because there was no occupation registered. Only 0.3% of father occupations were not coded.

The second dataset of apprentice masters consists of 354,102 observations from geolocated records from the 18th century (1710-1799) with the job titles of individuals who took apprentices in this period (Van der Beek, 2013; Minns and Wallis, 2012). This dataset derives from tax records, as apprenticeship fees, or 'premiums', were subject to a Stamp Tax of 2.5%. Not all apprentices paid fees to their masters, and some fees were exempt, if funded by charity or the poor law. The dataset thus represents the more desirable and prosperous occupations of the period.

The Stamp Tax records cover all of mainland Britain, including Scotland, unlike any of our other datasets. They also captured a larger share of young people, as masters taking apprentices in villages and small towns were also recorded. Almost one in ten teenagers appear in these records at their peak. On an annual basis, the rate is higher at times, as some sections of the original sources are now lost, especially before 1750. In an economy in which around 40% of workers were in agriculture, this dataset contains a substantial share of workers in other sectors of the economy.

As with the probate data we use in our main analysis, these two datasets also tended to over-represent the wealthy and the old. However, they are not necessarily as biased towards those with capital. Moreover, while agricultural occupations are obviously very little represented in the master's dataset, both apprenticeship datasets are arguably more socially inclusive than the probate dataset, with several youths receiving training in prosaic manual trades such as blacksmithing and shoemaking that required little or no fee (Minns and Wallis, 2013).

Age is also less of an issue here. In particular, we observe apprentices' masters at a point when many would be much closer to the median age of the workforce than the individuals whose probate records we study. Masters frequently began taking apprentices within five years of finishing their own training, putting them in their late twenties. Training careers varied greatly in length, but we would expect some over-representation of longer-lasting and successful individuals who trained a larger share of apprentices, introducing some age bias.

The geographical and temporal coverage is significantly different between the two apprentice datasets, and for this reason we do not seek to combine them. Notably, the size of apprentice fathers dataset declines after the 1680s, reflecting a gradual increase in the availability of local training and the growth of manufacturing outside incorporated boroughs (Wallis, 2025), with the result that fewer and fewer youths travelled afar. On the plus side, the apprentice masters dataset allows us to gain insights also into the division of labour in Scotland, which is not covered by the other two datasets.

For the apprentice father dataset we filter duplicate entries based on the father's name, surname, location and occupation so that each father appears once at most in each decade. Otherwise, our data would be biased towards families with the resources that would allow them to place more sons into an apprenticeship.

For the apprentice masters dataset we include all entries, as training was very unevenly spread between masters. We use the data as an indicator of the size of flows into occupations over this period, something it is well suited to by its nature.

Decade	England		Wales		England
	Obs.	Counties	Obs.	Counties	% Teenagers
1580	4,092	40	228	13	1.1
1590	6,990	40	317	13	1.8
1600	11,722	41	519	13	2.9
1610	17,833	42	834	13	4.4
1620	17,030	41	586	13	3.8
1630	21,325	41	768	13	4.7
1640	20,901	41	551	13	4.5
1650	26,500	42	721	13	5.5
1660	21,965	42	372	13	4.5
1670	23,077	42	421	13	5.5
1680	23,805	42	329	13	5.7
1690	22,096	41	284	13	5.2
1700	19,751	41	233	13	4.2
1710	18,619	40	245	13	3.8
1720	14,714	40	172	13	2.9
1730	12,575	42	157	12	2.6
1740	10,362	41	92	13	2.3
1750	10,357	40	126	13	1.8
1760	10,938	41	121	12	2.0
1770	9,237	40	71	12	1.5
1780	8,662	40	68	11	1.3
1790	8,906	41	68	12	1.2
Total	341,457		7,283		5.7

Table A2: Apprentice Fathers Dataset, 1580-1799

Source: see text and Wallis (2025); the number of male teenagers is estimated by taking the share of 15-24 year olds within the population, dividing it by two to restrict this to males, and then by ten to isolate a single cohort entering training, using the figures in Wrigley *et al.* (1997), tab. A9.1, pp. 614-5, p. 134. No equivalent calculation can be made for Wales.

Decade	England		Scotland		Wales		Total	England
	Obs.	Counties	Obs.	Counties	Obs.	Counties	Obs.	% Teenagers
1710	42,930	40	1,325	8	209	12	44,464	8.7
1720	19,488	40	462	6	125	10	20,075	3.9
1740	22,478	40	787	8	267	12	23,532	5.0
1750	35,777	40	1,015	7	725	12	37,517	6.4
1760	50,256	40	1,204	9	1,189	12	52,649	9.0
1770	51,215	40	988	9	1,670	12	53,873	8.4
1780	56,991	40	869	11	1,632	12	59,492	8.7
1790	59,341	40	660	11	2,505	12	62,506	7.9
Total	338,476		7,310		8,322		354,108	

Table A3: Apprentice Masters Dataset, 1711-1799
Source: see text and Wallis (2025); male teenagers are estimated by taking the share of 15-24 year olds within the population, dividing it by two to restrict this to males, and then by ten to isolate a single cohort entering training, using the figures in Wrigley *et al.* (1997), tab. A9.1, pp. 614-5, p. 134.

C Estimating Market Potential

The gravity model holds that trade is determined by two variables: it is positively related to GDP and negatively related to trade costs (Head and Mayer, 2014). This insight is embodied in measures of *market potential*, a concept which can be traced back to Harris' (1954) analysis of the determinants of industrial location and has since become part of the standard tool-kit of economic geography.

Formally, market potential in county i and decade t is defined as:

$$\text{Market potential}_{it} = \sum_{j=1}^{51} \frac{\text{GDP}_{jt}}{\text{Trade cost}_{ij,t}} \tag{6}$$

where the subscript j also refers to counties.

Computing market potential requires estimates of counties' GDP and of trade costs between (as well as within) counties. Broadberry *et al.* (2015)'s national GDP figures detect continuous growth during our centuries, mainly determined by population growth in the 16$^{\text{th}}$ century, GDP per capita growth in the 17$^{\text{th}}$ century and a combination of both in the 18$^{\text{th}}$ century. We distribute national GDP estimates across counties relying on Geary and Stark (2015)'s method. Our trade costs rely on linear interpolation of Alvarez-Palau *et al.* (2025)'s least cost pathway transport costs between counties' main towns in 1680 and 1830 and are extrapolated backwards to the 1520s with the trend in wheat price gaps between London and provincial England. As we detect a long-term fall in trade costs, they too contributed to increasing market potential. We discuss the construction of both in detail below.

Market potential is an established concept in economic geography, used in several applications over the years (e.g. Crafts, 2005; Head and Mayer, 2011; Missiaia, 2016; Basile and Ciccarelli, 2018; Maurer and Rauch, 2023). Some researchers have opted for the slightly different concept of *Market access* (e.g. Redding and Venables, 2004; Donaldson and Hornbeck, 2016; Alvarez-Palau *et al.*, 2025). Market access differs from market potential in two respects: it allows the absolute value of the trade elasticity with respect to trade costs to be greater than one and posits an inverse relationship between market access in competing places (Donaldson and Hornbeck, 2016). The equation thus becomes:

$$\text{Market access}_{it} = \sum_{j=1}^{51} \frac{\text{GDP}_{jt}}{(\text{Trade cost}_{ij,t})^{\theta} \cdot (\text{Market access}_{jt})^{\frac{1+\theta}{\theta}}} \tag{7}$$

where θ is equal to minus the trade elasticity and $(\text{Market access}_{j,t})^{\frac{1+\theta}{\theta}}$ captures competition between counties.

Market access has the advantage of being micro-founded in a general equilibrium trade model, but in our baseline estimation we decided to stick to the older concept of market potential on two grounds.

Firstly, available evidence indicates that in our context the absolute value of the trade elasticity was indeed close to one. Estimating directly the trade elasticity in our setting would require data on trade flows between counties which are not available. A viable alternative is employed by Alvarez-Palau *et al.* (2025) in a setting very similar to ours, market access between cities in England between 1680 and 1830: they perform a grid search for (absolute) values of the trade elasticity over a plausible range (1 to 8) and pick the one that maximises the log-likelihood function in a regression of (log of) urban population on (log of) market access, where the latter is computed with a simplified equation, neglecting competition between places. The results of their exercise turn out to be very interesting: the log likelihood function is maximised with an absolute trade elasticity of 2, with 1 coming a very close second. Such values are much lower than those estimated between larger units in later times, like present-day nation states or 19th-century US or Indian states: for instance, in late 19th/early 20th century India, estimates of minus the trade elasticity between states range from -9.60 to 29.21, with a mean value of 7.80, depending on the commodity (Donaldson, 2018, 921). In our setting, the regression specification analogous to that run by Alvarez-Palau *et al.*, 2025 is a fixed-effects panel of (log of) counties' GDP on (log of) market access. In Figure A15 we show that both for the log likelihood function and the (easier to interpret) R-squared, the fit of the model progressively and significantly deteriorates with absolute values of the trade elasticity greater than 1.

The second reason to stick to market potential rather than market access as our baseline is that we are wary of imposing too much structure on the estimation. In their baseline empirical strategy, Donaldson and Hornbeck (2016) opt for a simple equation, which like our Equation 4

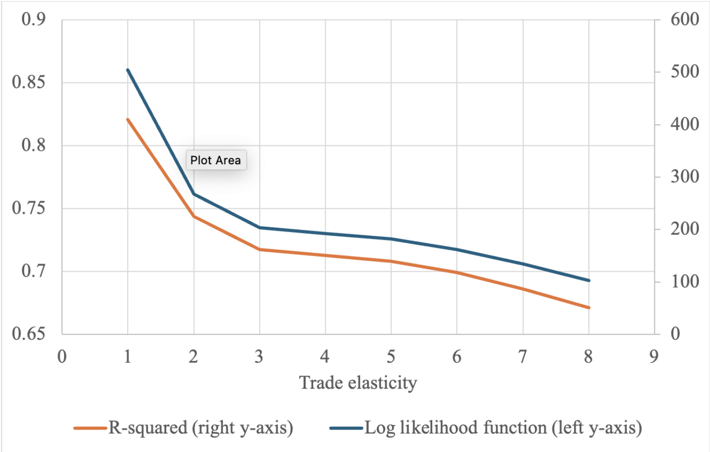


Figure A15: Fit of the GDP-Market Access regression with a range of trade elasticities.
Notes: the regression equation is $\ln(\text{GDP}_{it}) = \alpha_i + \beta \ln(\text{Market Access}_{it}) + \varepsilon_{it}$, where i refers to counties and t to decades. Market access is defined as $\text{Market Access}_{it} = \sum_{j=1}^{51} \frac{\text{GDP}_{jt}}{(\text{Trade Costs}_{ij})^{-\theta}}$, where j also indexes counties and θ is the trade elasticity. The reported R^2 is the within R^2 from the fixed-effects regression. Sources: see Section 3, Appendix B and Wallis *et al.*, 2018, (Appendix 1).

neglects the term capturing competition between counties, so as not to be excessively reliant on the predictions of the theoretical model. This issue is particularly salient in our setting: unlike them, we also consider the county's own market; while, logically, this market should be treated differently from other counties' markets when it comes to competition, Donaldson and Hornbeck's (2016) model offers no guidance on how to deal with this issue. What is more, we confirm another of the points made by Donaldson and Hornbeck (2016): the results are bound to be insensitive to the choice of market development measure, given that estimates with and without the term capturing competition between counties are highly correlated, with a correlation coefficient of 89%, rising to 92% after taking logs.[20] For the sake of robustness, however, we also present the results using market access, including the term capturing competition between counties (and, again, setting the trade elasticity equal to -1), in place of market potential.

[20] Like Alvarez-Palau *et al.* (2025), we compute market access by solving a system of 51 non-linear equations with a matlab code using the command fsolve. The solutions cannot be constrained to be positive and 3 values out of 1,326 (0.2% of the observations) were returned as negative. These values are not considered in the correlations between logs and are linearly interpolated (before taking the logs) to run the regressions presented in the main text.

C.1 County GDP Estimates

Geary and Stark's (2015) estimates of British counties' GDPs only start in 1861. However, using their approach we can reconstruct series for earlier decades by combining available data on national GDP and output per worker by sector with counties' occupational structures and agricultural wages. We find huge variations in GDP, reflecting both differences in counties' size and economic growth: GDP ranged from 16 million 2011 international dollars in the small Welsh county island of Anglesey in the 1550s to 3,699 million dollars in Yorkshire, by far the largest county in the sample as we treat it as a combined unit, in the 1760s; Yorkshire was also the county with the most rapid average yearly rate of growth, at 0.82% (vs. a sample mean of 0.50% and a minimum of 0.24% in Westmorland).[21]

We update Wallis *et al.*'s (2018) estimates of the counties' occupational structures adjusted for uneven coverage. We extrapolate counties' trends in decades not covered by the probate dataset with trends in neighbouring counties, distinguishing between trends in southern England, northern England and Wales. We rely on Broadberry *et al.*'s (2015) outputs per worker by sector, linearly interpolated between benchmark years, to convert employment shares into indices of value added per worker (normalised to 100% for the whole country), assuming that the English figures applied also to Wales before 1700 and that the British figures applied to both England and Wales thereafter.

We are also able to adjust our indices for differences in labour productivity across counties in agriculture (but not in the other two sectors or over time), relying on agricultural wages in English counties in the 1760s from Hunt (1986, 965) (as used by Kelly *et al.*, 2023) and predicting agricultural wages in the Welsh counties with the age of the dominant rock type (from Asch, 2005), with a log-log OLS regression. In fact, as stressed by Kelly *et al.* (2023), within England, agricultural wages and the age of the dominant rock type were strongly correlated (with a coefficient of -0.72). The adjusted indices of value added per worker are multiplied by national series of GDP per capita in England/Britain from 1700 from Broadberry *et al.* (2015) (decadal means, converted in 2011 international dollars by Maddison Project, 2023 edition) and then by counties' populations to obtain the final estimates.

Our sources of county populations are the same as those used in Wallis *et al.* (2018). However,

[21] Computed by regressing the natural log of GDP against decade.

we also exploit English county populations in 1377 from Broadberry *et al.* (2015), so that our estimates for English counties in the sixteenth century are based on linear interpolations, rather than extrapolations from national figures. As our source of county populations in Wales starts in the 1540s, for the 1520s and 1530s, we rely on the estimate by Powell and Cook (1977, 197) for Wales in 1500, linearly interpolate the national population between 1500 and 1540, and extrapolate county trends with the resulting national trend.

C.2 Trade Costs

To estimate trade costs between counties we rely on two sources: Alvarez-Palau *et al.* (2025) and Federico *et al.* (2021). Alvarez-Palau *et al.* (2025) estimated least cost pathways' transport costs between cities in 1680 and 1830, which consider changes in the real price of transport and developments of the road and canal networks. We allocate one city to each county (the county town or the largest city) and linearly interpolate between 1680 and 1830.

No analogous estimates exist for the preceding period and thus we have to assume one common trend across counties. Although the assumption is strong, transport infrastructural developments were concentrated in the eighteenth century. Thus before 1680, it is reasonable to assume that persistent geographical features were the main determinants of cross-sectional differences in transport costs across counties.

To estimate trends in trade costs before 1680 we rely on (the absolute value of) wheat price differences between London and eighteen other English cities for which prices are available in our period (from the replication file of Federico *et al.*, 2021), deflated with the London wheat price: under the relatively undemanding assumption that there was ongoing trade between London and these cities, our real price differences can be interpreted as estimates of 'iceberg' costs of trading wheat between them.[22] As the panel of wheat prices is unbalanced we rely on a fixed-effects regression to fit a trend. The English cities in our sample are on average 167 km away from

[22] Price differences are expected to be equal to trade costs between two trading cities and lower than them otherwise, as else there would be opportunities to profit from trade (Federico, 2012). Since London acted as a wheat distribution centre within early modern England, not only importing increasingly large quantities but also re-exporting significant shares of them (Kerridge, 1988), the assumption of on-going trade with London is less demanding than between the other pairs of cities. Our focus on London thus ensures that it is reasonable to expect our price differences to closely approximate trade costs.

London.[23]

To chain the estimates from our two sources, we express least cost pathway's transport costs in 1680 as a proportion of London's wheat price to obtain 'iceberg' costs.[24] We then adjust these iceberg costs to consider that wheat tended to be much more expensive than most other commodities traded in early modern England, particularly coal, so that wheat iceberg trade costs were lower than for a representative commodity. To do so, we multiply our wheat iceberg costs by the ratio between wheat price and the weighted average price of traded commodities used to deflate transport costs in 1680 by Alvarez-Palau *et al.* (2025, Table C3): 3.38. These levels are then combined with the national trend in wheat iceberg costs (relative to the London price) until 1680 shown in Figure A16 (indexed to be equal to 1 in the 1680s) to obtain county- and time-varying estimates of iceberg costs.

While studies of changes in transport connectivity typically neglect the own market potential of the unit of observation, such as a city or county, in our setting—similarly to when market potential explains economic growth—changes in the county's own GDP can be expected to be a significant factor in accounting for uneven growth in specialisation. We thus include own market potential in the computations. As with the GDP of other counties, we need to divide own GDP by trade costs.

Following Redding and Venables (2004, 62) (see also Missiaia, 2016, Equation 2), internal iceberg costs within each county i in decade t are computed by treating the county as if it were a circle with average distances equal to two-thirds of its radius and assuming that costs increased with distance in line with the average of the time, i.e., using the equation:

$$\text{Internal Iceberg Cost}_{it} = \frac{2}{3}\sqrt{\frac{\text{Area}_i}{\pi}} \cdot \left(\frac{1}{50} \sum_{j=1}^{50} \frac{\text{Iceberg Cost}_{ij,t}}{\text{Distance}_{ij}} \right) \tag{8}$$

where, similarly to Equation 6, the subscript j refers to other counties.[25]

The final step to compute trade cost is to add 1 to the iceberg costs, as customary in applications of gravity trade models (cf. e.g. Donaldson and Hornbeck, 2016, 822; Alvarez-Palau *et al.*, 2025,

[23] 163 km if we weight the average by the number of observations.

[24] Different scholars use different deflators; we opt for London prices because they can be used both for the 1680 level and the trend.

[25] Historic counties' areas are from Wikipedia – List of counties of England by area in 1831 (consulted on 3/10/2024).

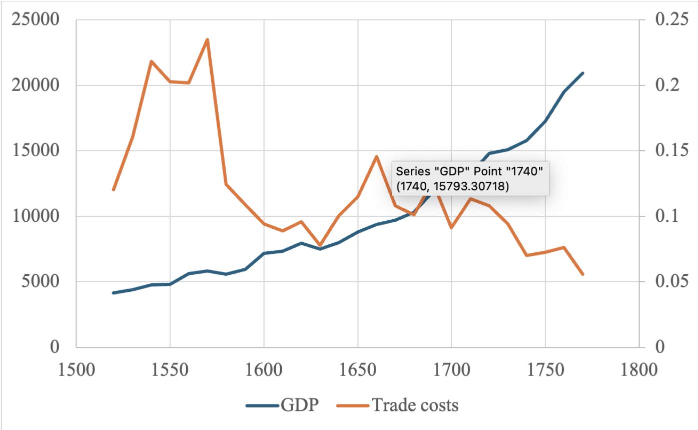


Figure A16: GDP (left y-axis) and 'iceberg' wheat trade costs with London (right y-axis) 1520s-1770s.
Notes: GDP figures are decadal means based on yearly figures. England's GDP pc after 1700 is equal to Britain's GDP pc times 1.043, as in 1700. Trade costs are computed from an unbalanced fixed effects panel of 1,980 wheat price percentage differences between London and 18 other English cities (average distance 167 km), using the natural log of the absolute value of the yearly price difference divided by London's price as the dependent variable and decadal dummies as the sole explanatory variables. It can be interpreted as the real trade cost of wheat between London and an average English city. Sources: GDP: GDP pc is Broadberry et al (2015) as included in the Maddison dataset (2023 edition) (available at https://www.rug.nl/ggdc/historicaldevelopment/maddison/releases/maddison-project-database-2023 consulted on 26/04/2024); population is from A Millennium of Macroeconomic Data for the UK (sheet A2; available at: https://www.bankofengland.co.uk/statistics/research-datasets consulted on 1/6/2023); wheat prices: Federico et al. (2021: on-line database).

12). Our trade costs are thus greater than 1; they can be interpreted as markups, indicating how much larger prices at destination are compared to prices at origin. As expected, trading between counties was usually much more expensive than trading between them: our mean trade costs are 1.23 and 4.90, respectively. The latter value is in line with estimates of 7.63 for trade between English cities in 1680 made by Alvarez-Palau *et al.* (2025, 13), particularly if one considers that we deflate with London prices rather than prices in producing counties, which are lower and thus imply higher trade costs.

Wheat price gaps (Figure A16) detect an initial rise of iceberg costs during the turbulent early decades of the English Reformation, from 12% of the London price in the 1520s up to a maximum of 23% in the 1570s. This rise was followed by a sharp fall from the 1580s, after the implementation of the Elizabethan religious settlement. By 1600–09, the fitted iceberg cost had become as low as 9%.[26]

[26] Looking at price ratios since the 13th century confirms that by the beginning of the 17th century price

The central part of the 17^{th} century was characterised by marked political instability, culminating in the English Civil War of 1642–1651. Trade costs started rising in the 1640s and remained higher than 10% until the end of the century. A subsequent substantial decline, to a minimum of 6% in the 1770s, is as expected: during the 18^{th} century, density of the inland transport network significantly increased thanks to the construction of new canals and roads (Alvarez-Palau *et al.*, 2025).

We find marked variations in trade costs over space as well as time: trade costs between counties ranged from only 1.03 for shipping goods to the mainland from the Welsh island of Anglesey, which was just off the coast of Caernarvonshire, in the 1770s to as much as 22.60 for trading between the English and Welsh landlocked counties of Northamptonshire and Radnorshire in the 1570s; those within counties went from as little as 1.04 in the tiny county of Rutland in the 1770s to over twice as much (2.11) in Yorkshire in the 1570s.

Figure A17 shows our estimates of counties' market potential in four benchmark decades. To facilitate interpretation, we normalise market potential to take a value between 1 and 100, with 100 equivalent to Middlesex in the 1770s.

While widespread, growth was uneven, with two gradients: market potential growth in western and land-locked counties tended to be lower than in eastern and coastal counties. These differences can be traced to uneven economic growth (the east vs. west gradient) and uneven transport connectivity (the land-locked vs. coastal gradient). As a results, while differences were relatively modest to begin with in the 1520s, when market potential's range was between 5% (in the land-locked Welsh county of Radnorshire) to just over 25% (in Suffolk, on the eastern coast near London), they became substantial by the 1770s, when the range was between 44% and 99% (with Radnorshire at the bottom and Sussex, also on the coast near London, at the top). Market potential was comparatively high near London, with a mean value in Middlesex of 47% as compared to 38% in the rest of England and Wales.[27]

ratios had become significantly lower than any time in the previous centuries. These results are not presented here for reasons of space but are available upon request.

[27] This difference is somewhat less marked than for urban market access in 1680 (Alvarez-Palau *et al.*, 2025, Figure 4), as, presumably, it is tempered by factoring in the rural population

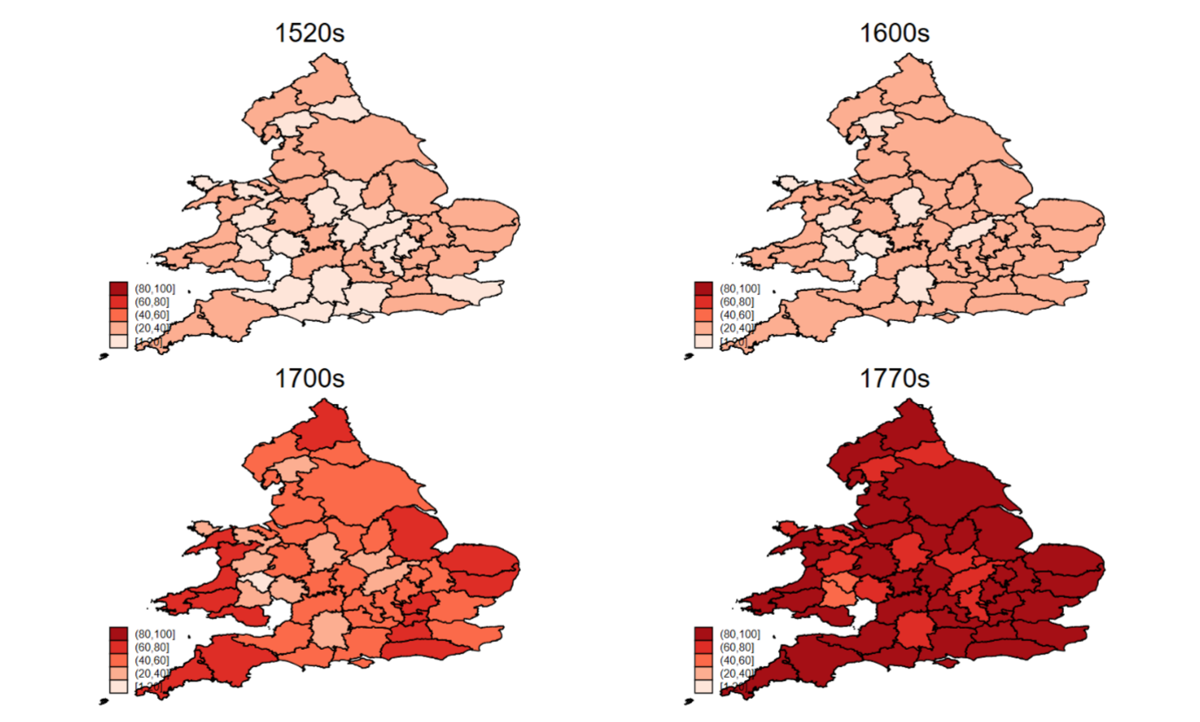


Figure A17: Counties' market potential in four benchmark decades.
Notes: counties' market potential computed with Equation 4. For ease of interpretation, the values have been normalised between 1 (=Radnorshire in the 1560s) to 100 (=Middlesex in the 1770s). Monmouthshire is not included due to a lack population data. The same scale is used for all four maps, with the distribution split into quintiles. sources: see the text

D Other explanatory variables

This appendix provides further information on the sources used in our analysis of the drivers of specialisation and the correlation coefficients between them:

D.1 International Trade

A national series on the value of exports (including Wales from 1697) at constant 2013 £ covering our decades is available in the Bank of England's Millennium's database (sheet A35). Trends in trade over time are shown in Figure A18. Variations in the counties' exposure to international trade can be systematically observed through the value of imports in the eighteenth century, thanks to Spike Sweeting's on-going work on customs' incomes collected by Musgrave and held in the British Library.[28] For instance, in the 1720s, 26 out of the 51 counties in our sample were involved in

[28] We gratefully acknowledge Spike Sweeting's permission to use the data.

international trade (i.e. they had least one port), but the lion's share of customs' income, 79%, was received by Middlesex; the next county was Gloucestershire – encompassing the port city of Bristol - with 8%; five counties, all in England, received between 1% and 3% of customs' income and all the others accounted for less than 1% each; in the last six spots were the Welsh counties, each accounting for less than 0.3%.

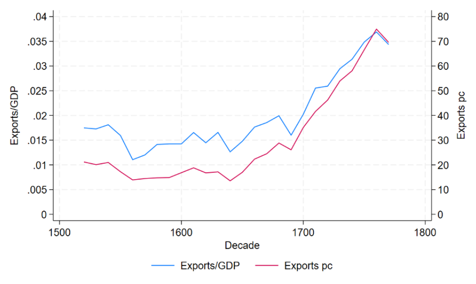


Figure A18: England's openness: exports relative to GDP and per capita
Note: values of exports and GDP used to compute openness are at 2013 market prices; exports also include re-exports; exports from 1697 also include exports from Wales. Sources: Millennium (sheets A21 and A35).

To estimate shares of international trade by county/decade we rely on direct observations on shares of customs' income for the eighteenth century and the mean shares in 1710, 1720 and 1730 for the preceding period. Combining these shares (largely based on imports) to give us county-level involvement in trade with the national series of trade exports allows us to construct an estimate of exports by county, which are then normalised by the size of each county's population.

D.2 Agricultural Share

Estimates of the share of the male labour force employed in agriculture for the sixteenth to eighteenth century have been recently produced by Keibek (2017) and Wallis *et al.* (2018), both using overlapping data drawn from probate and different correction methods. We use an updated version of Wallis *et al.*'s (2018) estimates of the counties' occupational structures adjusted for uneven coverage. England's share of workers employed in agriculture decreased significantly over the seventeenth century, unlike Wales'.

D.3 Urbanisation

We take the size of the urban population as the number of individuals living in places with at least 5,000 inhabitants, as is standard in much recent work. Our source of urban population is Buringh (2021)'s on-line database (available at https://ssh.datastations.nl/dataset.xhtml?persistentId=doi:10.17026/dans-xzy-u62q, consulted on 15/02/2024). The data are available at 50-year benchmarks and we linearly interpolate between them. The urban population of England grew at a nearly constant yearly rate of growth of 0.97%. This is average rate of growth, computed by regressing the natural log of the urban population against year; its 95% confidence interval is very narrow, between 0.96% and 0.98%.

D.4 Correlation between explanatory variables

In table A4 we present the correlation coefficients between the set of variables we use in Section 7 to examine the determinants of specialisation.

Table A4: Correlation coefficients between explanatory variables

	MP	**FMP**	**MA**	**Trade**	**Ag**	**Urban**	**Wills**	**Occs.**
Market potential	1.000							
‘Foreign’ Market potential	0.999	1.000						
Market access	0.885	0.878	1.000					
International trade	0.271	0.245	0.295	1.000				
Agricultural share	-0.355	-0.321	-0.348	-0.557	1.000			
Urban population	0.213	0.176	0.254	0.605	-0.618	1.000		
Share of wills	-0.342	-0.336	-0.232	-0.158	0.231	-0.153	1.000	
Share of occupations	0.500	0.493	0.306	0.107	-0.182	0.206	-0.186	1.000

Notes: The correlation coefficients refer to the variables used in the regression analysis, i.e. after taking logs and, in some cases, adding one (see Table 2 for details).
MP = Market potential, **MA** = Market access, **FMP** = ’Foreign’ Market potential, **Trade** = International trade, **Ag** = Agricultural share, **Urban** = Urban population, **Wills** = Share of wills, **Occs.** = Share of occupations. Sources: see Table 2.

E From Smithian Growth to the Industrial Revolution

To estimate the predictive power of Smithian specialisation on the location of industry during the Industrial Revolution in Section 8, we run the following regression:

$$\ln(y_i) = \alpha + \beta_1 \ln(Specialisation_{it}) + \sum_k \beta_k ln(X_{ki}) + \varepsilon_i \tag{9}$$

Where the subscripts i and t refer to counties and decades, respectively. Following Kelly *et al.* (2023), we use a semi-parametric spatial regression with a thin-plate spline in longitude and latitude, which is robust to spatial autocorrelation. We run separate regressions for all decades for which we have data on Specialisation (defined here by the number of jobs, our general measure) from the apprentice masters database (1710s, 1720s, 1740s, 1750s, 1760s, 1770s, 1780s and 1790s). The dependent variable y is the employment share of textiles among males aged 20–29 in 1851 (from Schurer and Higgs 2024) or the share of males aged 20+ employed in industry in 1831 (plus 1) (from Marshall 1833). Both variables are in percentages.

We control for agricultural wages in the 1760s, market potential in the 1750s (see Appendix C for the sources of both variables) and distance from the nearest carbon strata (which, unlike the nearest coal-field, is exogenous). For carbon strata, we use data collated by the German Federal Institute for Geosciences and Natural Resources (BGR) for a project that mapped the European geological landscape: the 1:5 Million International Geological Map of Europe and Adjacent Areas (Asch, 2005). This was a pan-European project that involved a high level of collaboration across several national geological offices; the result was a high-resolution GIS map containing a number of geological features including age and rock type. To create a proximity to carbon variable, we used QGIS to calculate the shortest distance from the edge of each county's polygon (at 1831 borders) to the edge of the nearest carboniferous strata.

The main results are plotted in the text in Figure 9. We report the full regression results here. Table A5 reports the regression with Textile Employment in 1851 as the dependent variable. Table A6 reports the regression with Industrial Employment in 1831 as the dependent variable.

Table A5: Determinants of Textile Employment in 1851: Smithian Specialisation

	1710s	1720s	1740s	1750s	1760s	1770s	1780s	1790s
Specialisation	0.327	0.370	0.354	0.642	0.580	0.811	0.875	0.914
	(0.235)	(0.206)	(0.235)	(0.286)	(0.287)	(0.303)	(0.291)	(0.316)
Wage 1760s	-2.743	-3.340	-3.963	-4.430	-4.586	-4.338	-4.402	-4.515
	(3.170)	(2.421)	(2.336)	(2.284)	(2.320)	(2.230)	(2.192)	(2.209)
Mkt Potential 1750s	1.766	0.652	0.761	0.785	0.823	0.727	0.727	0.741
	(0.996)	(0.457)	(0.446)	(0.433)	(0.437)	(0.425)	(0.417)	(0.419)
Distance from carbon	-0.589	-0.513	-0.378	-0.293	-0.299	-0.250	-0.251	-0.275
	(0.318)	(0.260)	(0.240)	(0.232)	(0.240)	(0.226)	(0.217)	(0.216)
N	51	49	51	51	51	51	51	51
R^2 Adj.	0.546	0.353	0.312	0.347	0.334	0.372	0.393	0.386
AIC	151.1	155.1	162.5	159.8	160.8	157.8	156.1	156.7
$s(\text{lat}, \text{lon})$	0.278	0.225	0.200	0.159	0.194	0.176	0.156	0.104

Notes: The dependent variable is the employment share of textiles among males aged 20–29 in 1851 (in percent). The unit of observation is the county. We rely on semiparametric regressions with a thin-plate spline in longitude and latitude to address spatial auto-correlation: $s(\text{lon}, \text{lat})$ is the approximate significance of a thin-plate spline term. All dependent and explanatory variables are logged, so coefficients refer to elasticities. A value of one was added to industrial employment before log transformation to include Huntingdonshire, where the census recorded zero. Each coefficient is from a separate regression with the baseline of Smithian specialisation (jobs in the given decade) as the main explanatory variable.

Table A6: Determinants of Industrial Employment in 1831: Smithian Specialisation

	1710s	1720s	1740s	1750s	1760s	1770s	1780s	1790s
Specialisation	0.069	0.109	0.161	0.433	0.407	0.624	0.676	0.721
	(0.146)	(0.156)	(0.183)	(0.196)	(0.197)	(0.207)	(0.197)	(0.205)
Wage 1760s	-0.652	-0.492	-0.904	-2.051	-2.078	-2.178	-2.299	-2.319
	(1.953)	(1.928)	(1.929)	(1.698)	(1.757)	(1.619)	(1.586)	(1.567)
Mkt Potential 1750s	0.669	0.434	0.523	0.153	0.313	-0.066	-0.057	-0.010
	(0.604)	(0.620)	(0.623)	(0.563)	(0.564)	(0.552)	(0.534)	(0.522)
Distance from carbon	-0.507	-0.632	-0.478	-0.427	-0.412	-0.366	-0.373	-0.385
	(0.193)	(0.215)	(0.192)	(0.162)	(0.168)	(0.156)	(0.147)	(0.145)
N	51	49	51	51	51	51	51	51
R^2 Adj.	0.547	0.349	0.306	0.344	0.331	0.371	0.392	0.385
AIC	151.1	155.4	163.0	160.0	161.0	157.9	156.2	156.8
$s(\text{lat}, \text{lon})$	0.242	0.218	0.182	0.160	0.194	0.176	0.157	0.104

Notes: The dependent variable is the share of males aged 20+ employed in industry in 1831 (in percent). The unit of observation is the county. We rely on semiparametric regressions with a thin-plate spline in longitude and latitude to address spatial auto-correlation: $s(\text{lon}, \text{lat})$ is the approximate significance of the spline term. All dependent and explanatory variables are logged so that the coefficients refer to elasticities. A value of one was added to industrial employment before log transformation to include Huntingdonshire, where the census recorded zero. Each coefficient is from a separate regression, using Smithian specialisation (jobs in a specific decade) as the main explanatory variable.

F Using HISCO as an alternative coding system

Our main analysis relies on PST, an occupational coding system developed for English historical data. To provide a check on our results and test our method holds using a different occupational coding scheme, we repeated our analysis with the job titles encoded into HISCO (the Historical International Standard Classification of Occupations). The recoding was carried out using Dahl *et al.* (2024) OccCANINE machine learning model.

HISCO is a historical occupational coding scheme developed by Marco van Leeuwen, Ineke Maas and Andrew Miles with the aim of allowing comparable international analyses of social mobility. Their starting point was the International Labour Organisation's 1968 ISCO codes and HISCO retains the underlying structure of this system, with each occupation assigned to a position within a three-tier hierarchy of major, minor and unit groups. The groups are defined by economic sector, or field of work (Van Leeuwen *et al.*, 2004). In addition, the group added separate codes for status (eg: master, apprentice, aristocrat) and relationships (wife, child).

Given that we are using HISCO to validate our method, it is worth noting that while PST was generated by a group seeking to study structural change, HISCO was developed by a group researching a question, social mobility, that is significantly further from our area of interest here. Importantly, the underlying principles of the two systems are nonetheless the same, in their focus on organising occupations into economically coherent categories.

In this Section, we report the results of recoding into HISCO and then repeat our analysis using the full HISCO code as our indicator of an occupational group. The main difference is that HISCO produces fewer fine classifications of occupations: once coded, we have 362 different categories in our dataset, as compared to 606 PST occupation codes.[29]

The recoding exercise was successful. The method generates a probability score and indicates occupations that cannot be identified. Using the cleaned job titles (N = 4,098 strings) we obtain the probabilities for matches presented in Table A7, allowing us to define a reasonable match threshold. Note this table treats all occupations equally. Most individuals are identified with one of a small

[29] Dahl et al.'s (2024) HISCO encoding model produces a probability score for each assignment of a job title. 91 per cent of our observations match with a probability of at least 95%. We restrict our analysis to observations that meet this threshold, giving us 517,032 observations. The HISCO algorithm also produces second and third codes for some job titles. Only 2% of our observations were assigned a second code, and only 0.06% were assigned a third occupation. We therefore exclude these from discussion.

group of well-coded occupations.

Table A7: Probabilities of Matches Between Job Titles and HISCO Codes

Outcome	**# Job Titles**	**Share (%)**	**Cumulative (%)**
Not coded	167	4.08	4.08
Not occupation	21	0.51	4.59
Prob <25%	52	1.27	5.86
Prob 25–50%	516	12.59	18.45
Prob 50–75%	873	21.30	39.75
Prob 75–95%	1,135	27.70	67.45
Prob >95%	1,334	32.55	100.00
Total	**4,098**	**100.00**	

Notes: Probability score obtained after matching job titles and HISCO codes with Dahl et al.'s (2024) algorithm.
Sources: See Section 3, Appendix B, and Wallis et al. (2018: Appendix 1).

Most job titles match appropriately. If we look at the 30 most common job titles in our dataset (Table A8), nearly all of them are identified with a probability score of c. 99%. The most notable mis-codings are 'husbandman' which recodes as 'labourer' (999999), and 'butcher' which recodes as 'metal moulder'. 'Widow' is also strikingly miscoded as 'messenger', but is excluded from analysis as we focus on male occupations. In our main analysis, we omit status titles, such as 'gentleman', and we apply that restriction here.

Table A8: The 30 most common job titles, recoded into HISCO

Job Title	PST code	HISCO1	Prob. score (%)	HISCO1 Occupation Description	Freq.	Share (%)
YEOMAN	1,1,1,2	61115	97.92	Small Subsistence Farmer (Husbandman)	200,464	31.02
HUSBANDMAN	1,1,1,3	99910	98.23	Labourer	78,858	12.20
GENTLEMAN	5,65,0,1	-1	99.45	Missing, no title	68,417	10.59
MARINER	5,1,3,1	98135	99.98	Seaman, Able or Ordinary	23,102	3.57
LABOURER	90,0,0,30	99910	99.98	Labourer	16,560	2.56
TAILOR	2,10,1,1	79100	99.98	Tailor, Specialisation Unknown	11,061	1.71
CARPENTER	2,80,4,1	95410	99.99	Carpenter, General	10,503	1.63
CLERK	5,30,1,40	30000	99.29	Clerical or Related Worker, Specialisation Unknown	9,034	1.40
BLACKSMITH	2,60,0,2	83110	99.91	Blacksmith, General	8,461	1.31
WEAVER	2,20,0,2	75400	99.96	Weaver, Specialisation Unknown	8,121	1.26
VICTUALLER	5,10,3,1	51050	99.30	Working Proprietor (Bar and Snack Bar)	8,097	1.25
FARMER	1,1,1,1	61110	99.97	General Farmer	8,010	1.24
BUTCHER	2,1,4,1	72500	83.36	Metal Moulder or Coremaker, Specialisation Unknown	7,428	1.15
CLOTHIER	2,20,3,6	41030	99.68	Working Proprietor (Retail Trade)	6,539	1.01
INNHOLDER	5,10,1,2	51020	95.56	Working Proprietor (Hotel and Restaurant)	5,672	0.88
CORDWAINER	2,15,1,1	80110	99.66	Shoemaker, General	5,135	0.79
BAKER	2,1,2,1	77610	99.98	Baker, General	4,664	0.72
MALTSTER	2,1,1,2	77810	99.89	Brewer, General	4,506	0.70
TANNER	2,30,1,1	76145	99.97	Tanner	4,482	0.69
MERCHANT	3,0,0,3	41025	99.97	Working Proprietor (Wholesale or Retail Trade)	4,329	0.67

Sources: See Section 3, Appendix B, and Wallis et al. (2018: Appendix 1).

We focus here on replicating the main national results in the paper. In Figure A26 we compare counts of HISCO and PST categories as unadjusted measures of extensive specialisation. The trends in both series are similar in both England and Wales, although the levels are different, because of the lower degree of subdivision of occupations within HISCO.

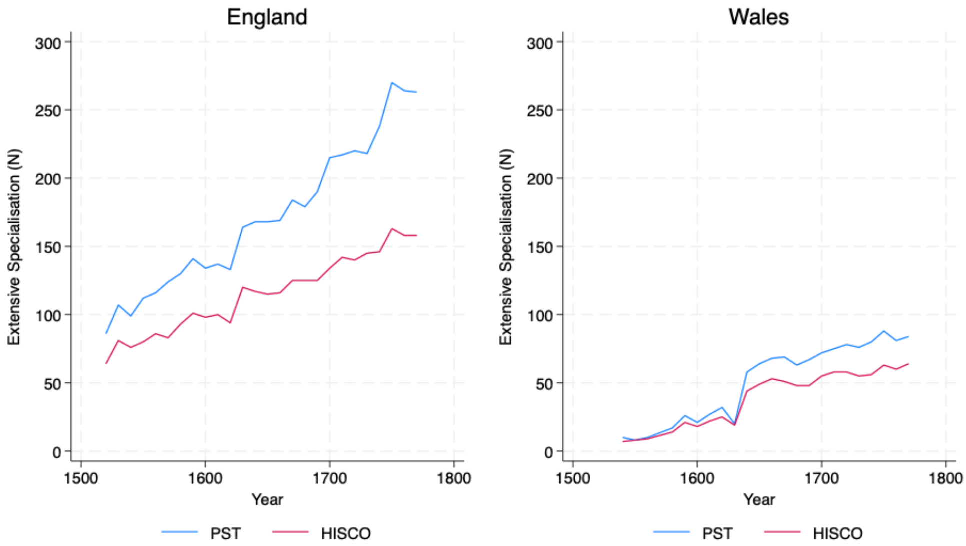


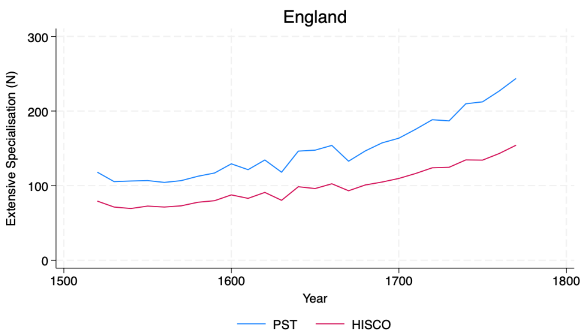
Figure A19: Specialisation by country, 1520-1780.
Note: 'PST' refers to the number of PST level-1 occupational categories per decade; ' HISCO' refers to the number of HISCO level-1 occupational categories per decade. Sources: see Section 3, Appendix B and Wallis et al. (2018: Appendix 1).

We then repeat the process described in the Appendix A to adjust for compositional effects. In Figure B2 we report the adjusted estimates using PST and HISCO. Again, the trends are the same, while the levels differ.

Finally, we repeat our analysis of the determinants of specialisation. We report the results using HISCO besides the results presented in the main paper using the PST coding. As Table A9 shows, the coefficients are similar in size and significance across all three main models whichever occupational coding scheme we use.

In summary, our approach and results do not change if we use an alternative approach to coding.

(a) England



(b) Wales

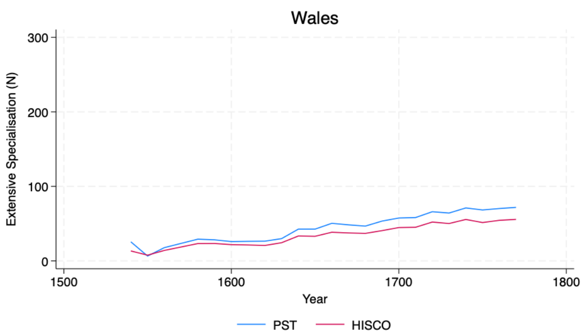


Figure A20: Specialisation in an average county adjusted for partial coverage, 1520-1780
Note: The figures are adjusted for the share of the male population not included in the dataset using the same approach as for occupational counts (see Appendix A and the text for details).

Table A9: The determinants of Smithian specialisation: panel regression results

Estimator	**OLS**		**OLS**		**IV**	
Logged variable	PST	HISCO	PST	HISCO	PST	HISCO
Market potential	0.409***	0.387***			0.405***	0.384***
	(0.0542)	(0.0468)			(0.0539)	(0.0466)
Market access			0.932***	0.883***		
			(0.138)	(0.119)		
International trade	0.0414	0.0411	0.0419	0.0415	0.0424	0.0418
	(0.0323)	(0.0344)	(0.0355)	(0.0360)	(0.0322)	(0.0344)
Agricultural share	-0.220*	-0.180*	-0.301**	-0.256**	-0.224**	-0.183*
	(0.111)	(0.0944)	(0.116)	(0.100)	(0.112)	(0.0947)
Urban population	0.00188	-0.00224	0.00145	-0.00267	0.00202	-0.00214
	(0.0203)	(0.0190)	(0.0218)	(0.0204)	(0.0204)	(0.0191)
Share of wills	0.387***	0.343***	0.385***	0.341***	0.386***	0.342***
	(0.0449)	(0.0396)	(0.0454)	(0.0401)	(0.0449)	(0.0395)
Share of occupations	0.487***	0.462***	0.539***	0.511***	0.489***	0.464***
	(0.0486)	(0.0450)	(0.0480)	(0.0449)	(0.0487)	(0.0452)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	663	663	663	663	663	663

Notes: Standard errors or t-statistics in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

G Alternative Data on Occupations from Apprenticeship

In this appendix, we replicate our main results using our additional datasets drawn from apprenticeship records. The two datasets are chronologically and spatially distinct, and we treat them separately here as a result.[30]

The apprentice fathers dataset – even more markedly than the probate dataset – indicates that specialisation progressed in England – where number of job titles went from 162 in the 1580s to 541 in the 1790s - much more than in Wales – where the same figures went from a minimum of 19 in the 1580s to a maximum of 52 in the 1690s, with lower figures in the 18th century (Figure A21). In England, too, the trend flattened in the eighteenth century. However, as mentioned in Section B, the dataset becomes increasingly less representative in this period, with the opening of alternative local opportunities for apprentice training.

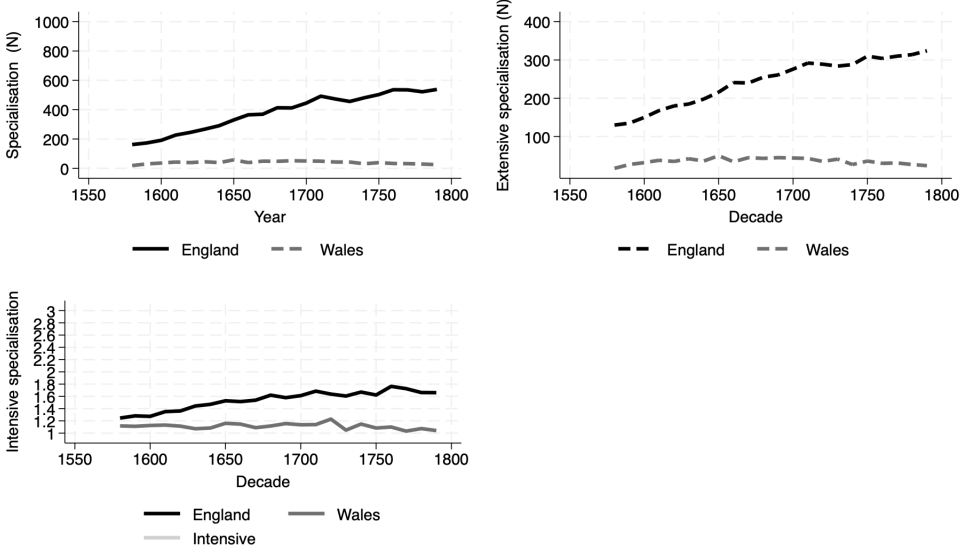


Figure A21: Specialisation by country, apprentice fathers dataset, 1580-1799.
Note: Sources: see Appendix B and (Wallis *et al.*, 2018).

Notably, this eighteenth century tendency towards stagnation or even decline is not confirmed by the apprentice masters dataset, for which the number of job titles markedly increased between the 1710s and the 1790s both in England, from 666 to 932, and Wales, from 42 to 103 (Figure A22).

[30] National trends are not adjusted for compositional effects, but addressing this issue with a fixed effects panel regression, like we did for the trends based on the probate dataset, hardly affects the interpretation (adjusted trends are not presented here of reasons of space but are available upon request).

The apprentice fathers dataset nevertheless detects stagnation in Scotland, at a level closer to the low Welsh level than to the high English level: in Scotland, the number of job titles went from 88 in the 1710s to 82 in the 1780s and 67 in the 1790s (Figure A22).

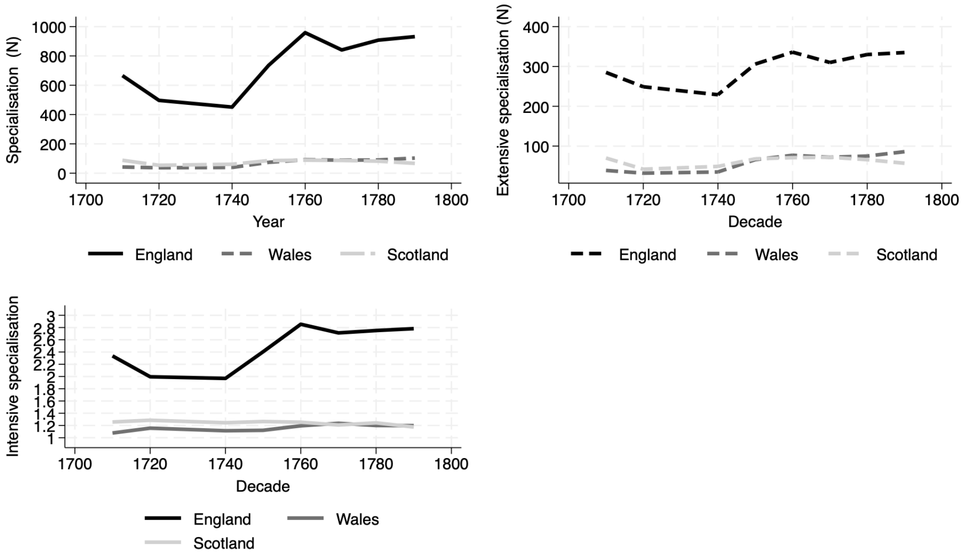


Figure A22: Specialisation by country, apprentice masters dataset, 1710s-1790s.
Note: Sources: see Appendix B and (Wallis *et al.*, 2018).

Both apprenticeship datasets also highlight that number of job titles increased significantly more in Middlesex than in any other county. Moreover, it was only in Middlesex that a large gap between number of job titles and PST occupation categories opened, indicating that for the apprenticeship datasets, too, intensive change was concentrated in London.

The patterns of development within the sectors, sub-sectors and regions of the British economy we observe in the probate data are corroborated by trends in the apprenticeship datasets. Thus, both apprenticeship datasets confirm a clear and widening hierarchy in the extent of specialisation between sectors, with manufacturing on top, services a not so distant second, and agriculture clearly at the bottom (though agriculture is obviously only very little represented in the masters dataset) (Figures A23, A24).

During the eighteenth century, number of job titles in mechanical occupations grew significantly more rapidly than those in textile manufacturing for the apprenticeship datasets, too.

Like the probate dataset, the apprentice masters dataset detects comparatively rapid intensive

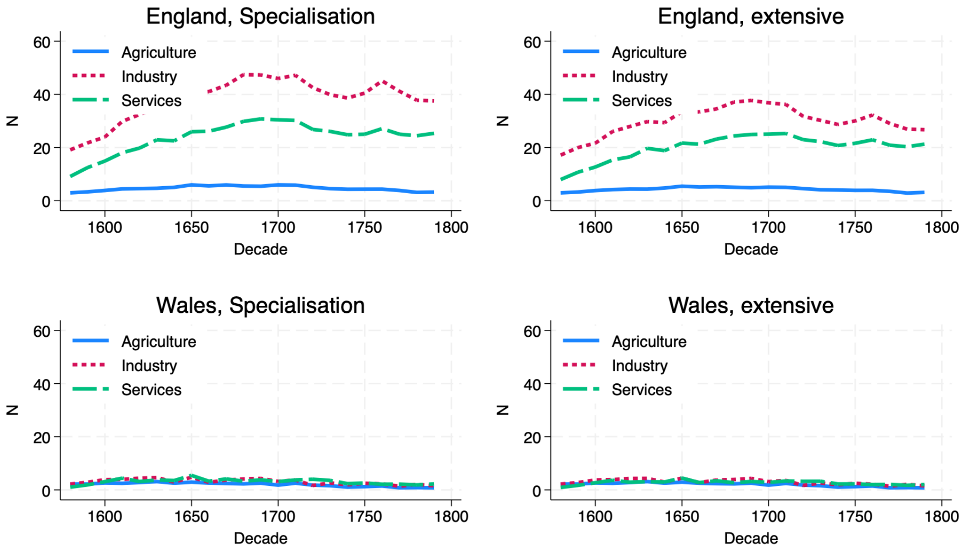


Figure A23: Sectoral trends in an average county, apprentice fathers dataset, 1580-1799
Note: Sources: see Appendix B and (Wallis *et al.*, 2018).

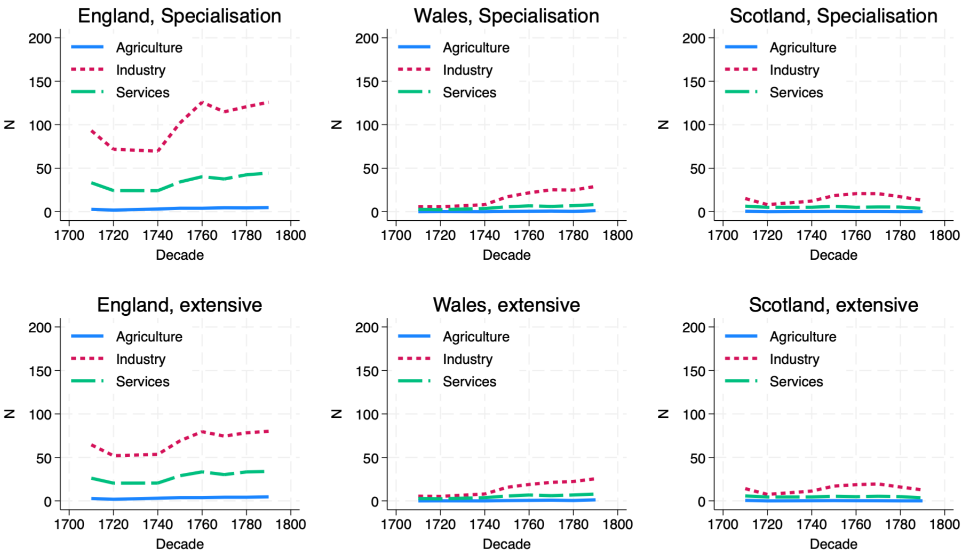
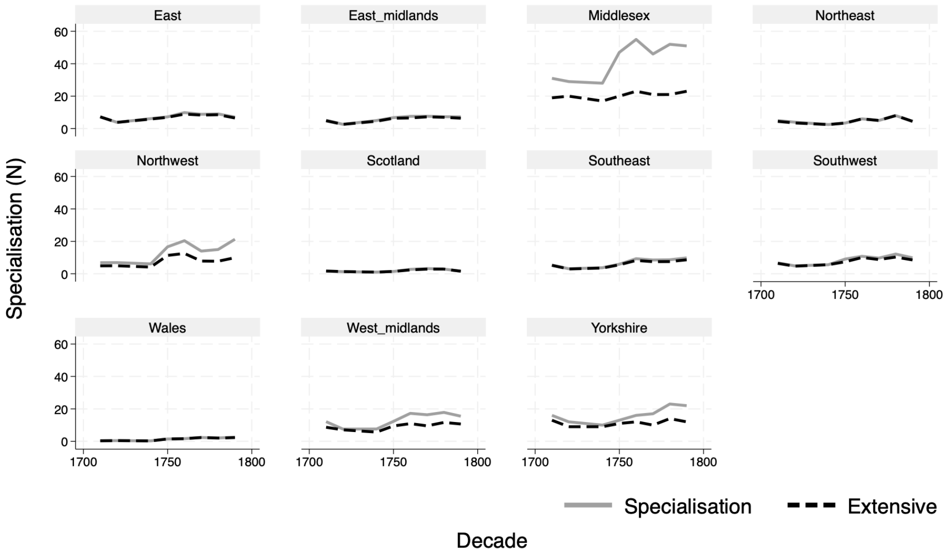


Figure A24: Sectoral trends in an average county, apprentice masters dataset, 1710-1799.
Note: Sources: see Appendix B and (Wallis *et al.*, 2018).

growth in specialisation within textile manufacturing in the northwest during the 18th century and highlights similar dynamics also in another northern region, Yorkshire (not covered in that century by the probate dataset) (Figure A25).

While the apprentice masters dataset depicts more marked intensive growth in specialisation within mechanical manufacturing in the northern regions (northwest, west Midlands and Yorkshire) than the probate dataset, in this sub-sector progress happened in the second half of the 18th century (Figure 24(a)), i.e. during the early decades of the industrial revolution, rather than before it. Moreover, the apprenticeship masters datasets also re-asserts that, both from the perspective of mechanical manufacturing and, to a lesser extent, that of textile manufacturing, Middlesex stood out for its particularly rapid and significant intensive changes in specialisation since c. 1650 (Figure A25).

(a) Mechanical Occupations



(b) Textile Manufacturing

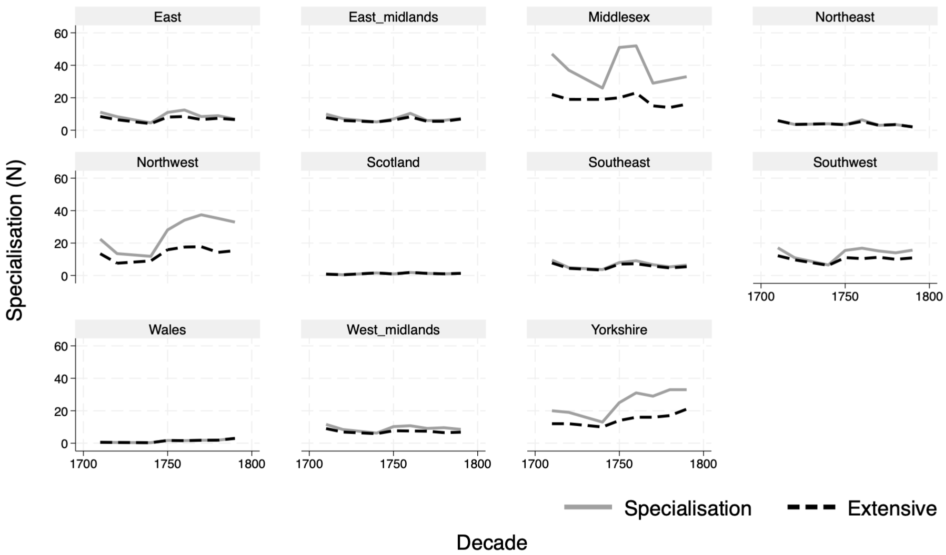


Figure A25: Specialisation in mechanical and textile manufacturing by region, apprentice masters 1710-1799
Note: Mechanical manufacturing includes all occupations under PST codes 2/52, 2/62 and 2/65; textile manufacturing includes all occupations under PST code 2/20. see Appendix B and (Wallis *et al.*, 2018).

H Alternative Measures of Occupational Distance

We present three alternative approaches to measuring specialisation in this appendix to test the robustness of our main results. We also present results using measures of the share of new jobs in the economy, which is a related indicator of development visible through occupational change.

H.1 Dixit-Stiglitz Variety Index of the Division of Labour

Following Ades and Glaeser (1999), we compute the Dixit-Stiglitz variety index of the division of labour with the following equation for county i, job j, and decade t:

$$\text{Dixit-Stiglitz Index}_{it} = \left[\sum_j \sqrt{\frac{\text{Employment}_{ijt}}{\text{Aggregate Employment}_{it}}}\right]^2$$

The figures are adjusted for the share of the male population not included in the dataset using the same approach as for occupational counts (see Equations 1 to 3 in the text for details).

The results are reported in Figure C1 and present no significant difference to our main strategy.

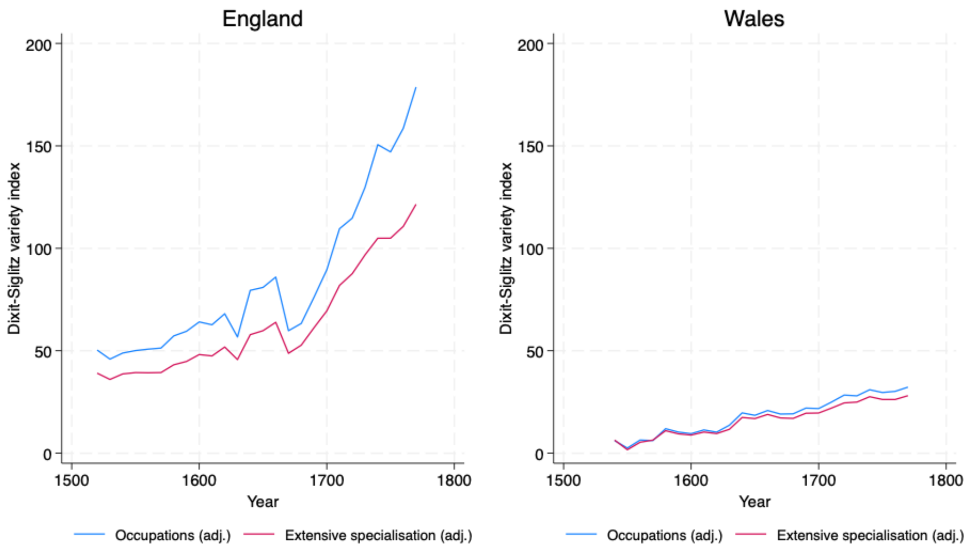


Figure A26: Dixit-Stiglitz variety index of the division of labour in an average county (adjusted for partial coverage), 1520-1780.
Note: The line 'Occupations' refers to the index computed assuming that each job title defines a distinct job; the line 'Extensive specialisation' refers to the index computed assuming that each PST occupation category defines a job. Sources: see Section 3 and Wallis *et al.*, 2018 (Appendix 1).

H.2 Probability that different workers have different occupations

As an alternative indicator of specialisation, we consider the probability that three random workers had different occupations. This is estimated at the level of PST occupational category, not job title.

The estimates are adjusted for the share of the male population not included in the dataset using the same approach as for occupational counts (see Appendix A for details), but a slightly different specification: given that the dependent variable is fractional, to estimate the effects on probabilities of share of deaths covered by wills and share of wills with an occupation we use Papke and Wooldridge (1996)'s model.

The results in figure A27 largely mirror the trends in our main specification.

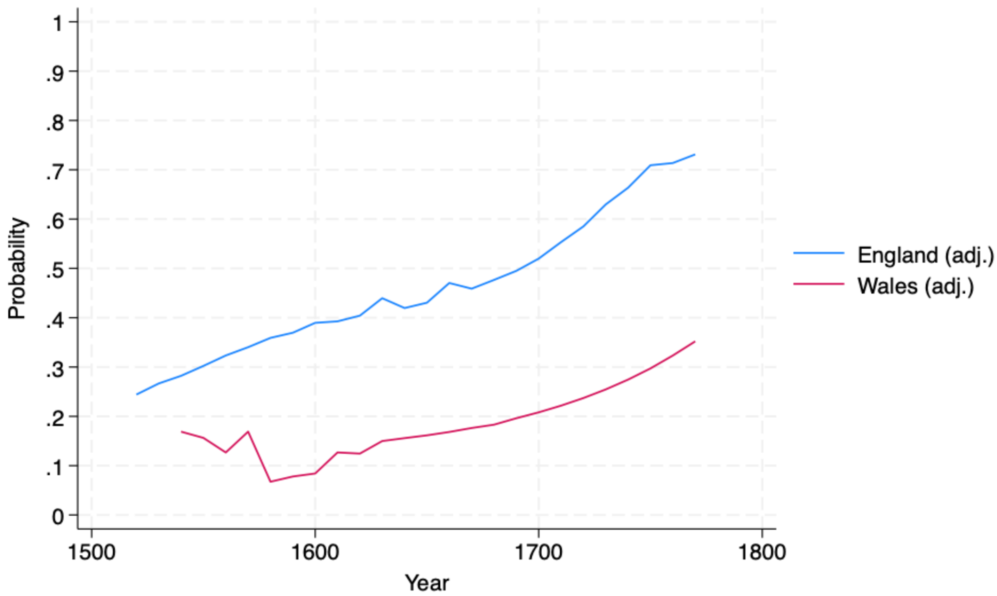


Figure A27: Probability that three different workers have three different occupations in an average county, 1520-1780.
Note: Estimates are adjusted for partial coverage. Sources: see Section 3

H.3 Occupational distance between two workers

As a further indicator of diversification, we consider occupational distance. We estimate occupational distance between two workers on a scale from 0, for two workers with the same PST occupation, to 4 for two workers with different PST sectors, groups, sections and occupations. The estimates are adjusted for the share of the male population not included in the dataset using the same approach as for occupational counts (see Appendix A for details).

Figure A28 shows that for England from the start of the sixteenth century to the early eighteenth century there is a constantly rising occupational distance, while in Wales the distance seems effectively trendless.

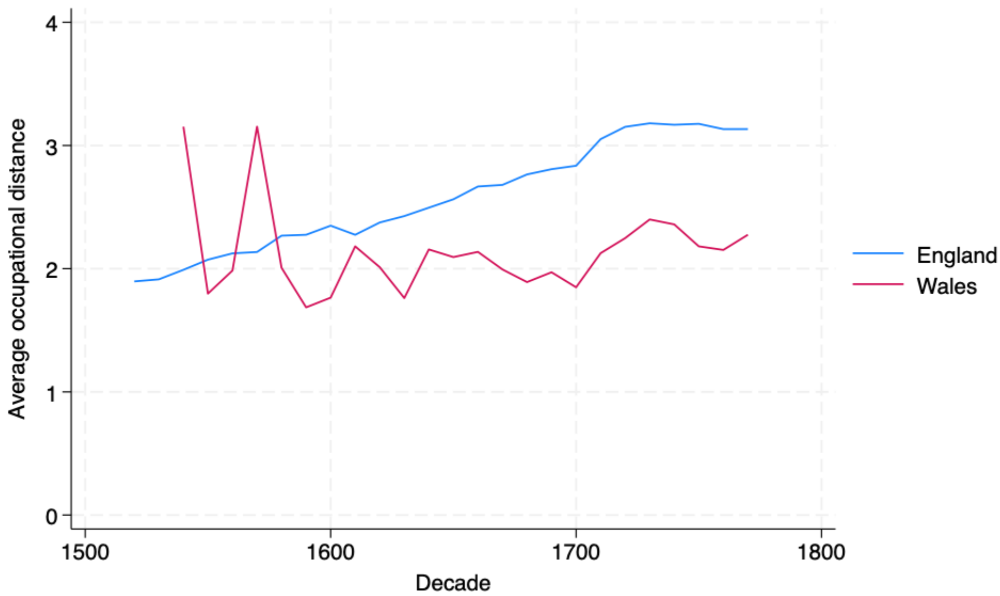


Figure A28: Mean occupational distance between two workers in an average county, 1520-1780.
Note: Estimates are adjusted for partial coverage. Sources: see Section 3

H.4 Share of New Jobs

As a further way to test the validity of our method, we look at what shares of the workforce became employed in occupations not mentioned by our sources in the previous decade.

The shares of new jobs (job titles or occupation categories absent in Britain in the previous decades) and workers with new jobs confirm that Middlesex was particularly dynamic as shown by Figure A29.

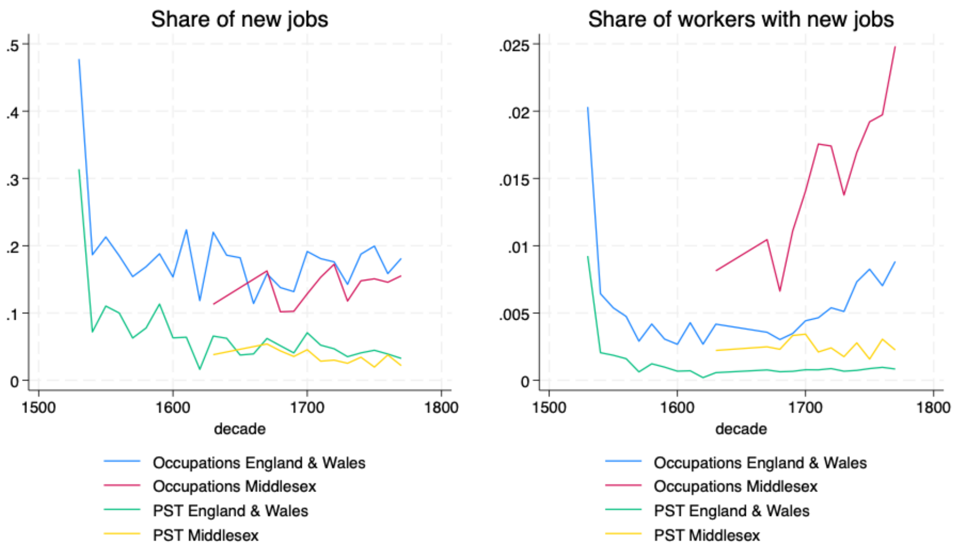


Figure A29: Shares of new jobs and workers with new jobs, 1520-1780.
Note: new jobs are defined as occupations absent in the dataset in the previous decades. ‘Occupations’ refers to all job titles, while ‘PST’ refers to PST occupation categories. Sources: see Section 3

I Determinants of Specialisation: Alternative specifications

As further robustness checks, we explore two alternative specifications. First, in Table A10, we implement a stricter definition of the instrument by excluding not only the county itself but also all the neighbouring counties when constructing the 'foreign' market potential used in the IV analysis. This addresses concerns about potential spillovers and ensures that the instrument is more plausibly exogenous. The results remain stable and consistent with our main findings, reinforcing the conclusion that the size of the domestic market was the primary driver of Smithian specialisation.

Second, in Table A11, we add time fixed effects and county-by-time fixed effects to our baseline specification. In particular, time fixed effects are defined over half-century intervals (e.g. 1550–1590, 1600–1640, 1650-1690, etc.) to allow for broader structural shifts while preserving sufficient variation for estimation. This demanding specification absorbs any nationwide shocks and flexible county-specific time trends, offering a stringent test of our identification. Despite the reduction in identifying variation, the coefficients on market potential remain positive and statistically significant for both extensive and intensive specialisation, further confirming the robustness of our core result.

Table A10: The determinants of Smithian specialisation: panel regression results with different Foreign MP

Estimator	OLS			OLS			IV (Foreign MP)		
	Occ.	**Ext. Spec.**	**Int. Spec.**	**Occ.**	**Ext. Spec.**	**Int. Spec.**	**Occ.**	**Ext. Spec.**	**Int. Spec.**
Market potential	0.462***	0.418***	0.044***				0.450***	0.406***	0.044***
	(0.066)	(0.056)	(0.015)				(0.065)	(0.055)	(0.015)
Market access				1.049***	0.948***	0.101***			
				(0.156)	(0.140)	(0.033)			
International trade	0.029	0.033	-0.004	0.030	0.034	-0.004	0.031	0.036	-0.004
	(0.035)	(0.033)	(0.008)	(0.038)	(0.036)	(0.008)	(0.035)	(0.033)	(0.008)
Agricultural share	-0.287*	-0.275**	-0.012	-0.380**	-0.359***	-0.020	-0.297**	-0.285**	-0.012
	(0.147)	(0.121)	(0.036)	(0.151)	(0.126)	(0.035)	(0.148)	(0.122)	(0.036)
Urban population	0.020	0.003	0.017***	0.019	0.002	0.017***	0.020	0.003	0.017***
	(0.021)	(0.021)	(0.005)	(0.024)	(0.023)	(0.005)	(0.022)	(0.021)	(0.005)
Share of wills	0.495***	0.444***	0.051***	0.492***	0.441***	0.051***	0.492***	0.443***	0.051***
	(0.042)	(0.045)	(0.007)	(0.043)	(0.045)	(0.007)	(0.042)	(0.045)	(0.007)
Share of occupations	0.566***	0.534***	0.032**	0.626***	0.589***	0.037***	0.574***	0.541***	0.032**
	(0.054)	(0.051)	(0.014)	(0.049)	(0.049)	(0.012)	(0.053)	(0.051)	(0.014)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared (within)	0.850	0.831	0.414	0.846	0.828	0.410	0.850	0.831	0.414
R-squared (within) first stage							0.999	0.999	0.999
F-statistic first stage							66272	66272	66272
Observations	663	663	663	663	663	663	663	663	663

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels respectively. Standard errors clustered by county are in parentheses. All variables are in logs, and 1 was added to zero-valued variables before logging. In IV estimates, Market potential is instrumented with foreign Market potential (excluding the neighbouring county's markets and the county's own market) .

Table A11: The determinants of Smithian specialisation: panel regression results with different Fixed Effects

Estimator	OLS			OLS			IV (Foreign MP)		
	Occ.	**Ext. Spec.**	**Int. Spec.**	**Occ.**	**Ext. Spec.**	**Int. Spec.**	**Occ.**	**Ext. Spec.**	**Int. Spec.**
Market potential	0.160***	0.125**	0.0345**				0.157***	0.122**	0.0347**
	(0.0536)	(0.0479)	(0.0151)				(0.0531)	(0.0475)	(0.0150)
Market access				0.506***	0.406***	0.100***			
				(0.106)	(0.102)	(0.0355)			
International trade	-0.0159	-0.00261	-0.0133*	-0.0207	-0.00667	-0.0141*	-0.0157	-0.00240	-0.0133*
	(0.0366)	(0.0338)	(0.00757)	(0.0369)	(0.0343)	(0.00732)	(0.0366)	(0.0338)	(0.00758)
Agricultural share	-0.592***	-0.545***	-0.0471	-0.598***	-0.549***	-0.0491	-0.593***	-0.546***	-0.0471
	(0.174)	(0.149)	(0.0300)	(0.169)	(0.144)	(0.0297)	(0.174)	(0.149)	(0.0299)
Urban population	0.0916***	0.0839***	0.00773*	0.0897***	0.0824***	0.00733	0.0916***	0.0838***	0.00773*
	(0.0271)	(0.0258)	(0.00450)	(0.0284)	(0.0270)	(0.00445)	(0.0271)	(0.0258)	(0.00450)
Share of wills	0.490***	0.447***	0.0431***	0.503***	0.457***	0.0453***	0.490***	0.446***	0.0431***
	(0.0376)	(0.0367)	(0.00625)	(0.0378)	(0.0370)	(0.00643)	(0.0376)	(0.0367)	(0.00625)
Share of occupations	0.607***	0.560***	0.0474***	0.612***	0.563***	0.0488***	0.608***	0.561***	0.0474***
	(0.0461)	(0.0428)	(0.0137)	(0.0435)	(0.0409)	(0.0130)	(0.0461)	(0.0428)	(0.0137)
County Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County $\times$ Time Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared (within)	0.922	0.918	0.621	0.923	0.919	0.625	0.922	0.831	0.414
Observations	663	663	663	663	663	663	663	663	663

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels respectively. Standard errors clustered by county are in parentheses. All variables are in logs, and 1 was added to zero-valued variables before logging. In IV estimates, Market potential is instrumented with foreign Market potential (excluding the county's own market) .