Appendix (For Online Publication Only)

Social Mobility in Sweden before the Welfare State

Contents

A Linking Procedure

In this section, we provide a more detailed description of the procedure used to link individuals between the 1880 and 1910 censuses. In the 1880 census, we observe children residing in their childhood households. We identify their fathers (occupation) through co-residence in the same household and/or relationship pointers in cases where a child's father resides in a different household. The 1880 census sample is restricted to male children aged 16 or below, which results in a baseline sample of 849,996 boys. We then want to link these individuals forward to the 1910 census where we can observe their occupational attainment when they are in their 30s and 40s.

To link individuals from the 1880 to the 1910 census, we first designate a set of index variables that have to match exactly for two records to be considered potential matches: sex, birth year and parish of birth.[24] We find a potential match with identical sex, birth year, and parish of birth in the 1910 census for 848,949 individuals out of the 849,996 boys in our baseline sample from the 1880 census.

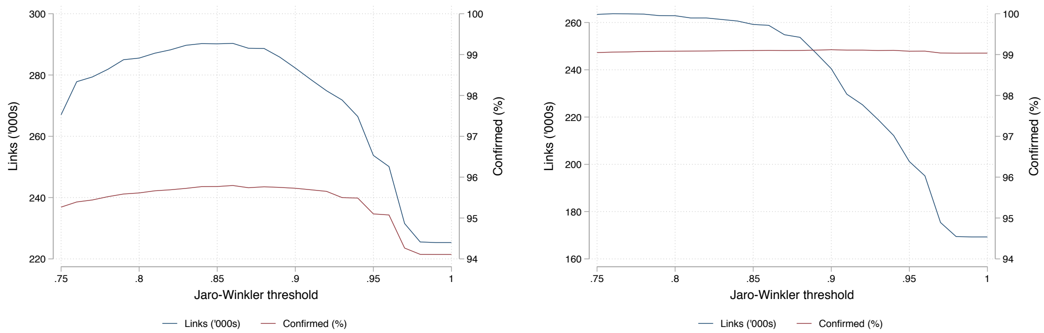
The next, and most critical, step in the linking process involves separating true links from false among all these potential matches. To identify which of these potential matches is the same individual, we rely on first and last names as recorded in the censuses. However, names are in some cases recorded with a certain degree of imprecision in the digitized censuses, due to transcription errors or differences in spelling. We thus need to allow for the fact that the name of the same individual may not be identical in the 1880 and 1910 census. To reduce the influence of minor differences in spelling or transcription errors, we first standardize names by removing nobility prefixes, patronymic suffixes and all non-alphabetic characters. To allow for the fact that even standardized names may differ between censuses for the same individual, we then use the Jaro-Winkler (JW) algorithm (Winkler, 1990) to estimate the similarity of first and last names recorded for potential matches. The JW algorithm assigns a similarity score between 0 (no similarity) and 1 (identical) by comparing characters and transpositions in text strings.[25]

When choosing a threshold for the JW similarity score there exists a tradeoff between the resulting sample size and the quality of matches. By prioritizing a high number of matches by lowering the required similarity between names, the risk of introducing false positives increase. This, in turn, might create a false impression of high social mobility (Bailey et al., 2020). A low match rate due to a overly restrictive similarity threshold, on the other hand, reduces the number of false positives but results in a smaller sample that might be an unrepresentative subset of the full population.[26] We thus need to find an optimal threshold for the JW similarity score that maximises the number of linked individuals, while maintaining a low rate of false

[24]In Table E.7 we summarize the characteristics and variables used for linking in comparable samples. Although the precision by which variables are recorded differ, the basic approach is similar across the samples in terms of indexation and comparisons of names.

[25]The JW algorithm adjusts for when strings have the same initial characters and accounts for the fact that irregularities are more common in longer strings than in shorter.

[26]Recently developed tools to address this challenge include machine learning techniques based on manually linked training data (Bailey et al., 2020; Feigenbaum, 2016) and fully automated processes which seeks to identify optimal thresholds that separate true links from false (Abramitzky et al., 2019; Dribe et al., 2019).



(A) Links based on one first name

(B) Links based on two first names

Figure A.1: Evaluation of Jaro-Winkler tresholds

Notes: These figures display the number of links and the share of links that are confirmed for different Jaro-Winkler thresholds using one and two first names respectively.

positives.

To identify an optimal JW threshold, we use secondary characteristics not used for the original match to evaluate the quality of links at different threshold levels for the JW similarity score. Here a link is classified as "true" if there is a unique candidate in the 1910 census whose similarity score exceeds the chosen JW threshold for both the first and last name. If there is no such candidate, or more than one, no link is made. To assess the quality of the links, we evaluate the share of matches that we can confirm using information on additional first ("middle") names that are not used to generate the original link. We consider a link as confirmed if middle name initials match.

Figure A.1 displays the number of resulting links and the share of confirmed links at different JW thresholds. For links made using one first name, the share confirmed as true based on the second first name initials (95.8%), as well as the number of resulting links, is maximized at a JW score of 0.85 (Figure A.1A). For individuals that can be linked on the basis of two first names, the share of confirmed links based on third first name initials is consistently higher across all JW thresholds and relatively stable around 99% (Figure A.1B). The number of links, however, start to decrease substantially beyond a JW threshold of 0.85. Thus, in order to maximize the number of links that can be confirmed as true, while minimizing the number of false positives, we set the JW threshold to 0.85.

Using this threshold for the JW similarity score, we identify unique links for 310,183 out of the 848,949 sons observed in the 1880 census with at least one potential match (with identical sex, birth year, and place of birth) in the 1910 census. In order to get to our analytical sample we only include sons whose father's age was between 30–60 in 1880 (272,153). Because of sons or fathers with missing or indistinct occupational titles which cannot be assigned into one of the four occupational groups, a further 31,212 observations are excluded. This leaves us with a sample of 240,941 father–son pairs that constitutes the baseline sample used in the main analysis.

B Modern Samples

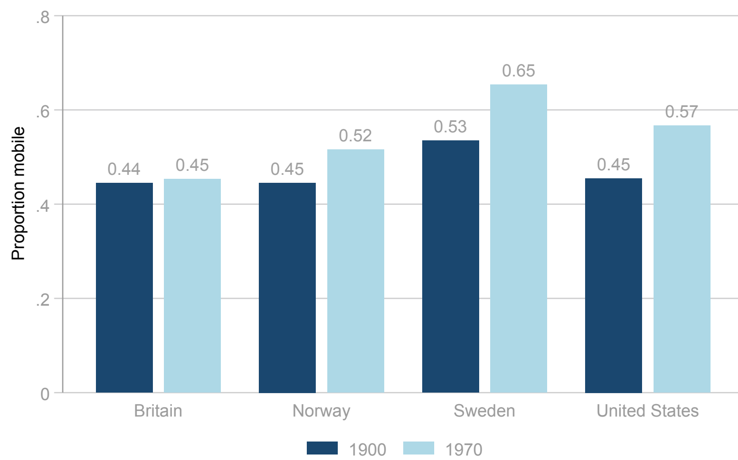
In this section, we provide further detail on our analysis comparing historical estimates of Swedish mobility to mobility rates in Britain, Norway, Sweden, and the United States among cohorts that came of age during the rise of welfare states in the latter half of the 20th century.

To measure mobility in the post-World War II period, we mainly rely on retrospective survey data where respondents were asked to report the occupation that their father held when they grew up. In particular, we use the 1976–1990 rounds of the Swedish Study of Living Conditions (ULF), carried out annually by Statistics Sweden (Vogel et al., 1988), and restrict the sample to native-born sons aged 30–60 at the time they were surveyed. These data were made available to us by Jan O. Jonsson (Breen & Jonsson, 2020). The underlying mobility matrix is presented in Table E.5 and the class scheme used for conversion in Table E.3. We make use of similar samples for our comparison countries. We use estimates for British sons born between 1935 and 1941 surveyed in the 1972 Oxford Mobility Study and US sons born between 1934 an 1940 in the 1973 Occupational Changes in a Generation Study, both reported by Long & Ferrie (2013a). Finally, the mobility table for post-World War II Norway comes from the 1910–1960 linked father–son sample analyzed by Modalsli (2017).[27]

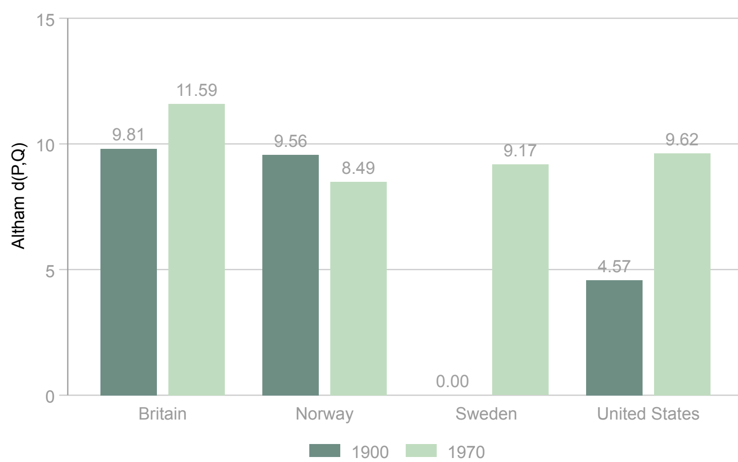
Figure 2 in the main text reports estimated Altham $d(\mathbf{P}, \mathbf{I})$ statistics for Sweden and the other three countries for which historical and modern data exist. This figure shows that, with the exception of the 19th-century United States, historical Sweden exhibited a smaller departure from the case of full mobility than any of the other samples. In each sample, the χ^2 statistic indicates that we can reject (at the 1% level) the null hypothesis that row-column associations in the mobility table is the same as would have been observed in the case of full mobility. Figure B.1A further shows that Sweden historically also displayed high levels of absolute mobility compared to countries in the post-World War II era.

To directly examine the extent to which Sweden's historical mobility pattern departs from that of other countries, we present additional estimates of Altham $d(\mathbf{P}, \mathbf{Q})$ statistics in Figure B.1B. Interestingly, the Altham $d(\mathbf{P}, \mathbf{Q})$ statistics show that Sweden's pattern of mobility lies much closer to that observed in the 19th-century United States than to any other country or period. At the same time, Sweden's historical mobility pattern deviates significantly from that observed in the late-20th century samples; based on the χ^2 statistics, we can reject at the 1% level that mobility patterns in historical Sweden are identical to that in any of the other samples. Taken together with the estimated Altham $d(\mathbf{P}, \mathbf{I})$ statistics, these estimates show that Sweden at the turn of the 20th century displayed significantly higher rates of relative mobility than Britain, Norway, and the United States did in the post-World War II era.

[27] The census and survey data are subject to distinct sources of bias, but as these are both downward in magnitude, they are likely to counterbalance each other. Error in the probabilistic matching may introduce attenuation bias in the census data that is absent in survey data. Conversely, retrospective survey data contain recall errors which, if random, will lead to attenuation bias that is absent in the census data. Bielby et al. (1977) evaluate misreporting of occupations in the 1973 Occupational Changes in a Generation data and find that errors are strictly random. Research also shows that for the analysis of occupational transition matrices, the resulting bias is small (Breen & Jonsson, 1997). Although the Norwegian data point is earlier than those of other countries, Modalsli (2017) shows that mobility remained at a comparable level throughout the 20th century.



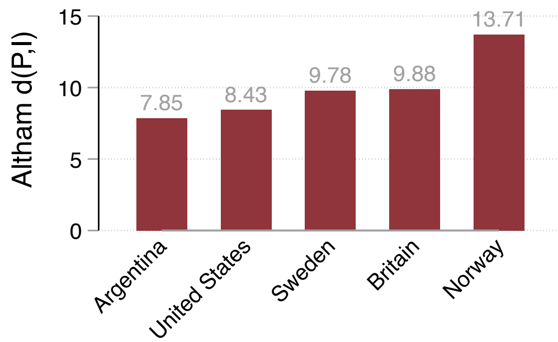
(A) Absolute mobility



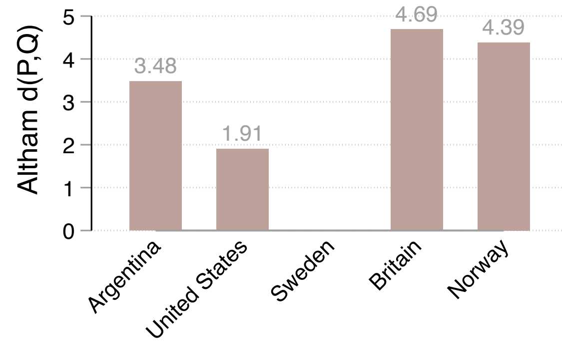
(B) Relative mobility (vs historical Sweden)

Figure B.1: Mobility in historical and modern samples

Notes: Panel A displays estimates of absolute mobility, or the share of sons that are observed in a different occupational group than their father. Panel B displays Altham $d(\mathbf{P}, \mathbf{Q})$ statistics that measure the distance between each country-period mobility table and the historical Swedish mobility table.



(A) Relative mobility (vs independence)



(B) Relative mobility (vs Sweden)

Figure C.1: Mobility in the Old and New World: excluding farmers

Notes: Panels A and B display Altham $d(\mathbf{P}, \mathbf{I})$ and $d(\mathbf{P}, \mathbf{Q})$ statistics respectively when excluding farmers from the underlying samples.

C Robustness and Additional Estimates

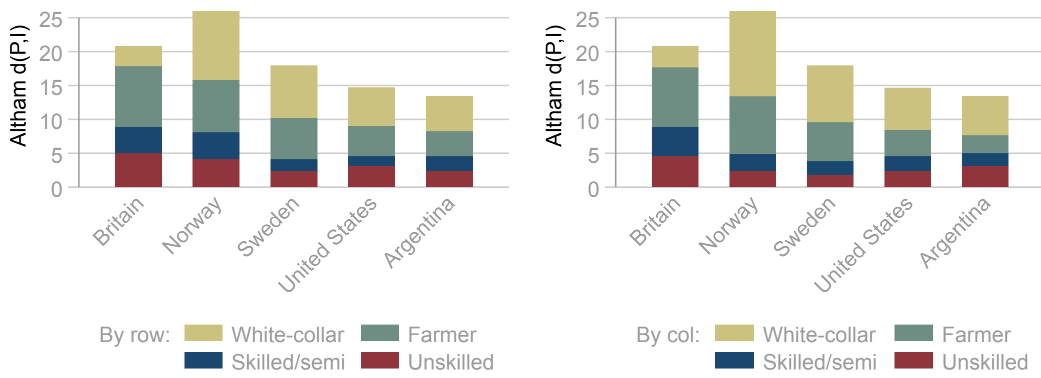
C.1 The Role of Farmers

A key concern in historical mobility research is that the differential depletion of the farming class may explain a substantial part of cross-country differences and long-run trends in mobility (Long & Ferrie, 2013b; Xie & Killewald, 2013; Song et al., 2020).[28] While no meaningful estimate of 19th-century mobility can exclude farmers, it is important to establish whether mobility differences are driven solely by this group. To investigate this issue, we estimate Altham $d(\mathbf{P}, \mathbf{I})$ and $d(\mathbf{P}, \mathbf{Q})$ statistics excluding all farmer cells from the underlying mobility table in Figure C.1. This reduces the mobility differences between countries and puts Sweden and Britain at a comparable level, but otherwise keeps the ranking of countries intact. Interestingly, Figure C.1B reveals that the pattern of mobility in Sweden remains closest to that found in the US, even with farmers excluded.

C.2 Contribution of Individual Origins/Destinations

A useful property of the Altham statistic is that it can be broken down into contributions per cell. Doing so tells us which combinations of fathers' and sons' occupational group

[28]Indeed, a relative ease of transitioning into farming is emphasized by both Long & Ferrie (2013a) and Pérez (2019) as an avenue for occupational mobility in both Argentina and the United States due to the existence of a vast internal frontier. Here Sweden resembles the New World in some respects: as new farms were established due to the clearing of large swaths of land in northern Sweden, the rural proletariat could advance into the farmer group by securing their own piece of land (Myrdal & Morell, 2011). However, high rates of mobility in the Americas extended beyond frontier areas and remained elevated several decades after the "closure" of the frontier (Long & Ferrie, 2013a). Similarly, areas in Sweden that saw extensive land clearing in the North exhibit relatively lower rates of mobility (see Figure 4A below).



(A) Contribution by row (father)

(B) Contribution by column (son)

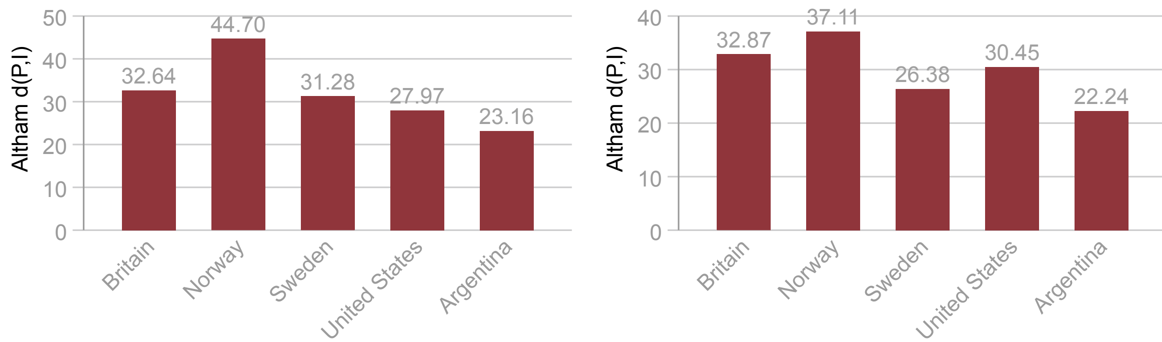
Figure C.2: Decomposing mobility rates across countries

Notes: Panel A displays the contribution of each occupational group by row to the Altham $d(\mathbf{P}, \mathbf{I})$. Panel B presents the contribution of each occupational group by column to the estimated $d(\mathbf{P}, \mathbf{I})$ statistic.

are most overrepresented relative to independence. We present disaggregations of $d(\mathbf{P}, \mathbf{I})$ by row and column in Figure C.2, using the method described by Bouchet-Valat (2019). The row-wise decomposition shows us which groups of fathers' occupations contribute the most to the deviation from independence, while the column-wise decomposition shows us which groups of sons' occupations do so. Because dependencies are strongest in the main diagonal of the mobility table, reflecting sons who stay immobile, the results look similar regardless of whether we disaggregate by father's or son's occupation. The lion's share of persistence in Sweden is accounted for by the white-collar and farming sector, whereas the boundary between skilled and unskilled labor is more permeable. This pattern is replicated in the United States and Argentina, which helps explain the similarities between Sweden and the New World. By contrast, the skilled/unskilled distinction matters more in Britain. In Norway, entry into the white-collar elite is extremely restricted and this accounts for a large part of the difference between Norway and Sweden.

C.3 More Detailed Occupational Classifications

Could the high rate of mobility in Sweden be an artefact of a relatively coarse categorization of occupations that fails to distinguish immobility at the extremes of the distribution? In Figure C.3 we introduce two alternative, more fine-grained occupational codings following Long & Ferrie (2013a) and Pérez (2019). We first split the "white collar" category into a higher group, comprising managers and higher professionals (HISCLASS groups 1–3), and a lower, composed of lower professionals and clerical and sales personnel (HISCLASS groups 4–5). Using this categorization leads to a higher Altham statistic for all countries, but less so in Britain than elsewhere. Nevertheless, the relative ranking of countries is preserved. Next, we split the low-skilled group into farm (HISCLASS groups 10 & 12) and non-farm workers



(A) Low vs high white-collar

(B) Farm labor vs other unskilled

Figure C.3: Relative mobility with five occupational categories

Notes: Panel A displays Altham $d(\mathbf{P}, \mathbf{I})$ statistics when separating "low" and "high" white-collar occupations. Panel B reports Altham $d(\mathbf{P}, \mathbf{I})$ statistics when distinguishing "farm laborers" and other unskilled occupations.

(HISCLASS groups 9 & 11). The latter recoding reverses the ranking between Sweden and the United States, such that the only country more mobile than Sweden is Argentina.

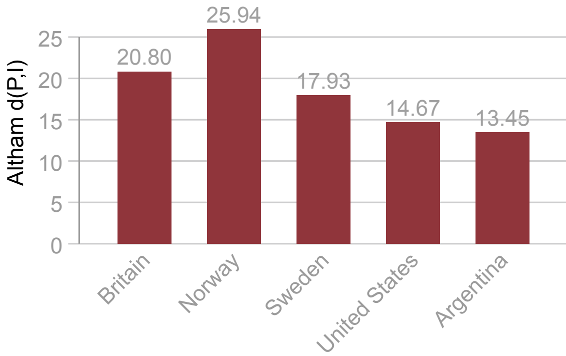
C.4 Alternative Estimators of Relative Mobility

The Altham $d(\mathbf{P}, \mathbf{I})$ statistic comes with several potential drawbacks. The first issue is variability due to small cell counts. The standard approach using the Altham statistic assigns equal importance to each odds-ratio contrast. This may be undesirable for at least two reasons. First, cells with few father–son pairs have a larger sampling error, which leads to a risk of mistaking sampling variability for substantive variation. Based on a Bayesian framework, Zhou (2015) presents a shrinkage estimator that we apply to the Altham $d(\mathbf{P}, \mathbf{I})$ statistic presented in Figure C.4C. Second, it might be desirable to assign lesser importance to groups that make up a small part of the population.[29] In Figure C.4E, we also present Altham statistics where each pairwise comparison $p_{ij}p_{i'j'}/p_{ij'}p_{i'j}$ is weighted by the marginal proportions of the corresponding rows and columns.

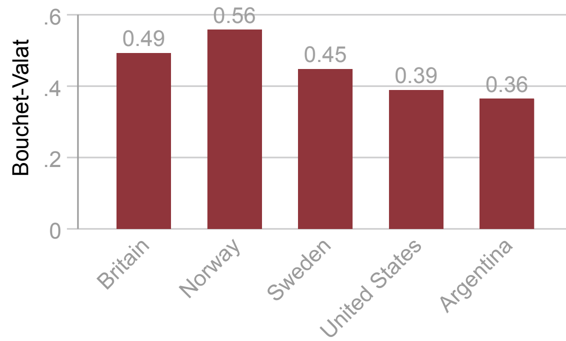
Another shortcoming of the Altham statistic is that it lacks an upper bound, and that it increases (weakly) with the number of dimensions in a table. A transformation has been proposed by Bouchet-Valat (2019) which is bounded in the $[0, 1]$ range and that behaves similarly to a correlation. If we let $\sum \log \theta_{ij,i'j'}$ denote the log-odds ratios from the full set of pairwise comparisons:

$$\sum \log \theta_{ij,i'j'} = \sum_{i=1}^{r} \sum_{j=1}^{s} \sum_{i'=1}^{r} \sum_{j'=1}^{s} \left[\log \left(\frac{p_{ij}p_{i'j'}}{p_{ij'}p_{i'j}} \right) \right].$$

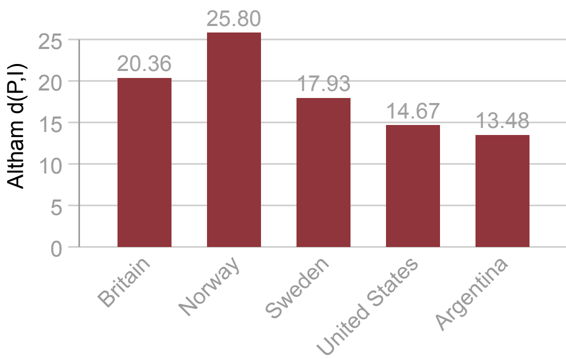
[29]If farmers, for example, account for a small share of the population their contribution to estimated persistence should not remain constant (Xie & Killewald, 2013).



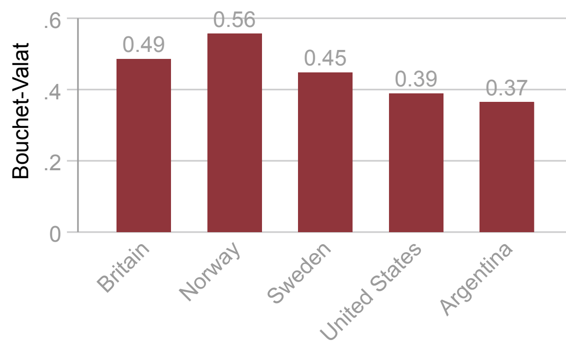
(A) Altham d(P,I)



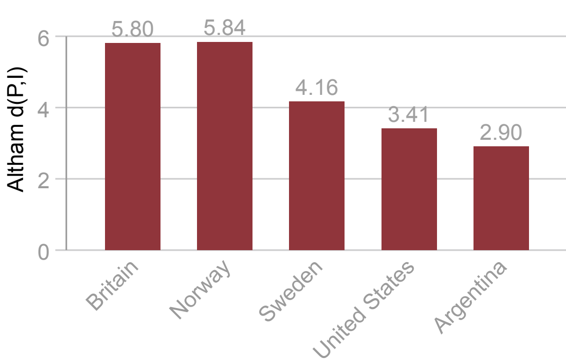
(B) Bouchet-Valat statistic



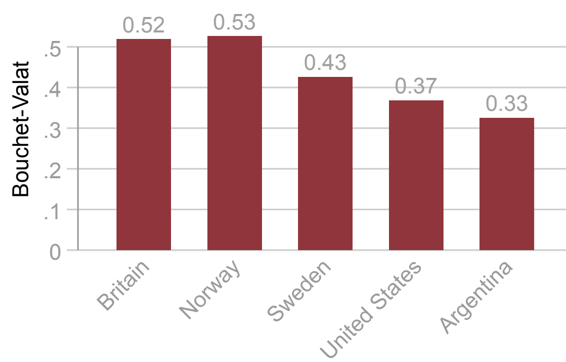
(C) Altham d(P,I), with shrinkage



(D) Bouchet-Valat, with shrinkage



(E) Altham d(P,I), margin-weighted



(F) Bouchet-Valat, margin-weighted

Figure C.4: Alternative measures of relative mobility

Notes: The left column (panels A, C, and E) displays Altham $d(\mathbf{P}, \mathbf{I})$ statistics. The right column (panels B, D, and F) present Bouchet-Valat statistics. In panels A and B we make no adjustment for cell sizes; panels C and D are estimated with Bayesian shrinkage for small cells; panels E and F are estimated with weights proportional to table margins.

then the Bouchet-Valat statistic[30] is defined as:

$$BV = \sqrt{1 + 1 \Big/ \left(\frac{1}{(rs)^2} \sum \log \theta_{ij,i'j'} \right)^2} - 1 \Big/ \left(\frac{1}{(rs)^2} \sum \log \theta_{ij,i'j'} \right).$$

As the notation suggest, the Bouchet-Valat statistic is closely related to the Altham $d(\mathbf{P}, \mathbf{I})$ statistic. Specifically, the two are related through the equation $d(\mathbf{P}, \mathbf{I}) = 2rs \frac{BV}{1-BV^2}$. In Figure C.4B we present results using the Bouchet-Valat statistic with uniform weights, in Figure C.4D the Bouchet-Valat statistic with Bayesian shrinkage for small cells, and in Figure C.4F the Bouchet-Valat statistic with cell contributions weighted by the table margins. Across all these measures of association, our main result remains robust. The main difference from our baseline results is that Britain appear less mobile once odds ratios are weighted by margin sizes. This is mainly a result of the disproportionately high mobility out of farming, which is smaller in Britain than any of the other countries.

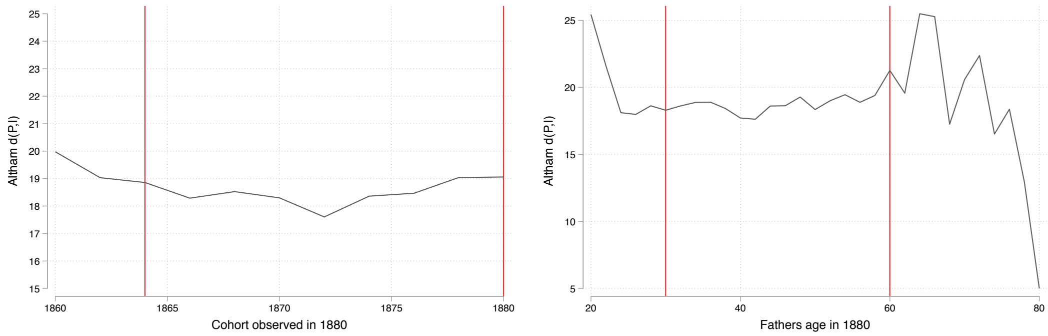
C.5 Life-cycle Bias

One challenge in measuring mobility between generations is that occupational attainment differs over the life cycle. Ideally, we want to measure the attainment of fathers and sons when they have reached occupational "maturity", which motivates the age restrictions of the sample to fathers (aged 30–60) and sons (30–46) in our main analysis. As a more flexible way to examine how life-cycle bias may affect our estimates, we re-estimate the Altham $d(\mathbf{P}, \mathbf{I})$ statistic for each cohort of sons born between 1850 and 1880 in Figure C.5A. Mobility stabilizes among sons born in the late 1850s and remains stable throughout the window used in our baseline sample (i.e., sons aged 16 or below in 1880). We perform a similar robustness exercise restricting the sample by fathers' age, showing that Altham $d(\mathbf{P}, \mathbf{I})$ statistics stabilize in the age range used in our baseline sample (i.e., fathers aged 30–60) in Figure C.5B. Together, these estimates demonstrate that life-cycle bias is not a major concern for the cohorts that we study.

C.6 Selection into the Linked Sample

Another concern is that the linked individuals in our Swedish sample differ from the underlying population, which could lead to biased estimates of mobility. Above, we showed that individuals with, for example, more unusual first names are slightly more likely to be successfully linked across censuses. To examine whether such selection affects our estimates, we re-estimate our baseline Altham $d(\mathbf{P}, \mathbf{I})$ statistic after reweighting the linked data. First, we estimate individual-level regressions of the probability of a successful link on observable

[30] These estimations were carried out using the `logmult` package for the R statistical computing environment. Bouchet-Valat (2019) refers to BV as $\tau^{\dagger}$ or the normalized intrinsic association coefficient with uniform weighting. We use the author's name in analogy with the Altham statistic.



(A) Sons cohort

(B) Fathers age in 1880

Figure C.5: Altham $d(\mathbf{P}, \mathbf{I})$ statistics with different age spans for sons and fathers

Notes: Panel A displays Altham $d(\mathbf{P}, \mathbf{I})$ statistics estimated for each cohort of sons in our main sample. Panel B displays Altham $d(\mathbf{P}, \mathbf{I})$ statistics when restricting the sample by fathers' age in 1880 in 5-year bins. Two vertical red lines denote the age restrictions we impose in our baseline sample in both panels.

childhood characteristics.[31] Second, we use the inverse of the predicted probability of being included in the linked sample to reweight all father–son pairs in the original mobility table. The reweighted Altham $d(\mathbf{P}, \mathbf{I})$ statistic is 18.05, which is very close to our baseline estimate of 17.93. Thus, our results are unlikely to be driven by selection into the linked sample based on observable childhood characteristics.

C.7 Alternative Linking Procedures

A potential source of bias to mobility estimates are: (1) differences in the quality of the underlying data and (2) linking methodology. To ensure that this does not drive our results, we create supplementary samples using alternative linking methodologies. A key difference between in particular the U.S. and Swedish censuses is the detail by which place of birth and accuracy by which birth years are recorded. Place of birth is recorded at the state level, while birth years are commonly misreported in the U.S. censuses. Thus, links may be less precise than for the Swedish censuses, where place of birth is recorded at the parish level and age heaping is non-existent (see Figure D.2).

To examine whether such underlying data differences could affect the estimated mobility levels in Sweden relative to the other countries in our sample, we create alternative links that mimic the level of detail available in other censuses. First, we replicate our linking approach identifying the place of birth of individuals based on 24 counties, rather than 2,500 parishes. Second, we allow up to a 5-year difference in birth years, rather than requiring an exact match. The Altham $d(\mathbf{P}, \mathbf{I})$ statistics for the sample created by matching on county of birth and allowing birth years to differ are 18.81 and 19.02 respectively.

[31]More specifically, we regress an indicator for being included in the matched sample on fixed effects for the childhood household's county of residence, the son's age and birthplace, as well as the father's birthplace and occupation.

In order to ensure that the specific linking algorithm is not the cause of mobility differences, we use the methods employed by Pérez (2019) and Abramitzky et al. (2019) to create alternative linked samples. Both methods are similar to our approach, but use slightly different cutoffs for the JW scores and allow for misreporting and age heaping by considering candidates within age bands (see Table E.7).[32] The samples produced using the linking approach of Pérez (2019) and Abramitzky et al. (2019) results in Altham $d(\mathbf{P}, \mathbf{I})$ statistics of 18.81 and 18.38 respectively. [33]

Although it is clear that linking algorithms and underlying data differences do affect the resulting samples and mobility levels, the alternative estimates are close to our baseline Altham $d(\mathbf{P}, \mathbf{I})$ statistic of 17.93 and well within the variation displayed across the other four countries when considering alternative linked samples (see Figure C.6). Importantly, when considering alternative samples, the ranking of countries in terms of relative mobility is maintained. Consequently, differences in linking procedure and data quality is unlikely to account for our main findings.

C.8 Additional Linked Datasets

Another concern is that mobility in Sweden and the other four countries in our sample is measured over different time intervals, due to the years when censuses were conducted in different countries. Here we show that the mobility gradient is similar when we expand our sample to include additional mobility estimates for the 19th and 20th century. Although these datasets are all generated in a broadly similar way, they differ in terms of census years, linking procedures, and sample restrictions, which allows us to examine whether such discrepancies are likely to affect our cross-country comparisons. In Figure C.6, we display our historical estimates for Sweden compared with a range of alternative estimates for Britain (Long & Ferrie, 2013a), Norway (Modalsli, 2017), and the United States (Long & Ferrie, 2013a; Feigenbaum, 2018; Ward, 2020a). Reassuringly, alternative estimates of mobility are similar to those used in our main analysis and the ranking of countries remains identical.

C.9 Missing Occupations

A common problem in historical census data is missing occupational information. In our linked sample, about 5.5% of sons do not report an occupational title which can be assigned to

[32]When implementing the alternative linking methods we use sex and birth parish as index variables. Pérez (2019) uses the JW scores and age differences (which may not exceed 5 year) to predict matching scores. We set the upper and lower thresholds for the matching scores to 0.7 (the absolute score which a match has to exceed) and 0.3 (the margin by which a match has to exceed the second best match). In order for a match to be classified as true by Abramitzky et al. (2019) method, JW scores must exceed 0.9, age differences must not exceed 5 years and there must not be a competing match within a 2 year age band.

[33]We also create a sample which only includes the links which all methods agree on by considering the intersection of samples created using Pérez (2019) and Abramitzky et al. (2019) and our preferred method. This sample of jointly made links have an Altham $d(\mathbf{P}, \mathbf{I})$ statistic of 18.81. The full transition matrices for these alternative samples are presented in Tables E.8, E.9, E.10, E.11 and E.12. It should be noted from these transition matrices that the alternative samples are all less representative of the underlying population when compared to our main sample.

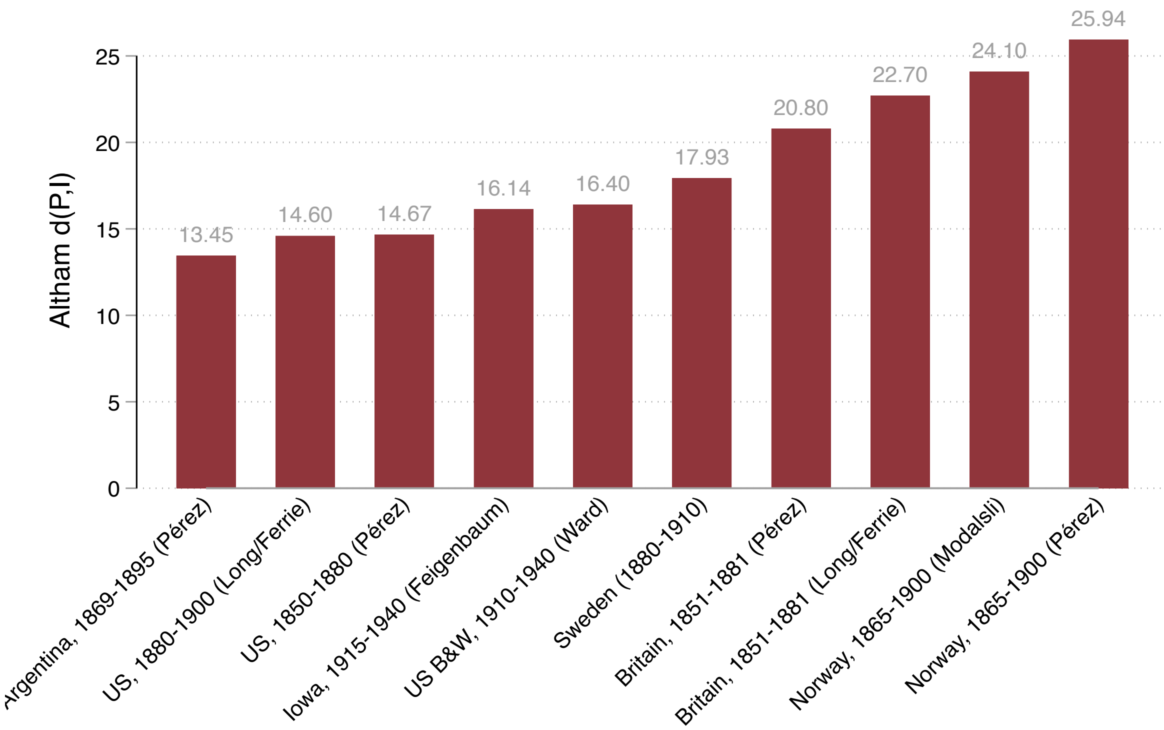


Figure C.6: Mobility in the Old and New World: additional samples

Notes: This figure displays Altham $d(\mathbf{P}, \mathbf{I})$ statistics that capture the distance from the case of full mobility where a larger statistic corresponds to less mobility. Data are drawn from Long & Ferrie (2013a), Pérez (2019), Ward (2020a), Feigenbaum (2018), and Modalsli (2017).

one of the four occupational groups. If this group is less mobile, it may bias our estimates. To bound any potential upward bias in mobility due to missing occupations, we re-estimate the Altham $d(\mathbf{P}, \mathbf{I})$ statistic under the extreme assumption that all sons with missing occupational information are perfectly immobile (i.e., that they hold the same occupation as their father). The estimated $d(\mathbf{P}, \mathbf{I})$ statistic is 19.30, naturally somewhat larger than our baseline estimate of 17.93. However, even this lower level of relative mobility is higher than our estimates for Britain (20.80) and Norway (25.94). Consequently, even assuming that sons with missing occupational information are completely immobile in Sweden *and* that British and Norwegian census data do not suffer from the same problem, Sweden still appears more mobile. Thus, missing occupational information is unlikely to explain our main finding of high levels of mobility in Sweden.

C.10 Emigration

About a quarter of the Swedish population emigrated to the United States prior to World War I. This could skew our remaining sample toward higher mobility, if emigration was driven by poor economic prospects in the circumstances that emigrants chose to leave (Abramitzky et al., 2012). Constructing a counterfactual mobility estimate absent emigration requires two inputs. First, we need to identify individuals in the 1880 census that emigrated before 1910. To do this, we link the 1880 census to emigrant records available from church books and passenger lists. Second, we need to approximate emigrants' occupational attainment had they stayed in Sweden. We impute their occupations using information on the occupations that their non-emigrant brothers had attained in 1910.[34] We estimate the counterfactual Swedish mobility rates by adding all identified emigrants based on their imputed occupations to our baseline mobility table, which results in marginally more mobility: the resulting Altham $d(\mathbf{P}, \mathbf{I})$ statistic is 17.6 as opposed to 17.9 in the baseline estimate.

Swedish emigration to the New World peaked in the 1880s and 1890s, which are the cohorts whose social mobility we are interested in. Self-selection into emigration means that emigrants likely differ from stayers both with regard to their social background and occupational attainment in adulthood. Moreover, the fact that almost a quarter of Swedish population emigrated in itself makes overseas migration a potential source of bias: it would lead us to overestimate mobility if emigrants were less mobile, or underestimate mobility if emigrants were more mobile.

To examine the extent to which emigration may bias our estimates of Swedish mobility, we construct a counterfactual mobility table which includes sons that emigrated between 1880–1910. For this we need to know: (1) the number of emigrants in the relevant cohorts; and (2) what their occupational attainment would have been had they stayed behind in Sweden.

First we calculate the number of emigrants in our studied cohorts by subtracting all dece-

[34]This procedure eliminates the influence of migrant self-selection that is constant across households where brothers grew up, for example, due to financial constraints or unobserved ability that is shared between brothers. It does not eliminate within-household selection. Within households, it is likely that emigrants were selected on traits that predisposed them toward higher mobility, which means that the actual counterfactual mobility rate may be even higher than we estimate.

dents between 1881 and 1910 and those enumerated in Sweden in 1910 from the initial number enumerated in 1880.[35] In order to identify sons lost to emigration in our cohorts, we link the 1880 census records to EMIBAS (Swedish Emigrant Institute and Federation of Swedish Genealogical Societies, 2005), an emigrant register containing the majority of all Swedish emigrants between 1880–1910, allowing us to identify sons that are "missing" in 1910 due to emigration.[36]

Because the occupations of sons that emigrated are not observed, we need to construct a proxy for their occupational attainment had they stayed in Sweden. We leverage the fact that in many cases emigrants had brothers who stayed behind, which can be used as a proxy for the occupations that emigrants would have attained.[37] Under the assumption that inherently more mobile brothers were more prone to emigrate, the occupational attainment of their stayer brothers is likely a conservative estimate of emigrants' attainment had they stayed in Sweden. In that case, our counterfactual estimate would underestimate the level of mobility.

Using information on the number of emigrants and our proxy for their occupational attainment, we proceed to construct the counterfactual mobility table that includes emigrants. To do this, we add the predicted occupational transitions for emigrants to the baseline mobility table, which includes sons that resided in Sweden in 1910. We impute occupational transitions for emigrants using the attainment of non-emigrant brothers, which we scale to the actual number of emigrants between 1880–1910 to also include emigrants without brothers enumerated in the 1910 census.

We then use this counterfactual mobility table to estimate the Altham $d(\mathbf{P}, \mathbf{I})$ statistic separately for stayers (i.e., our baseline estimate), emigrants ($\mathbf{E}$), and stayers and emigrants combined ($\mathbf{S}$):[38]

$$d(\mathbf{P}, \mathbf{I}) = 17.9 \quad d(\mathbf{E}, \mathbf{I}) = 15.7 \quad d(\mathbf{S}, \mathbf{I}) = 17.6$$

The counterfactual mobility of emigrants $d(\mathbf{E}, \mathbf{I})$ indicates that they were more mobile than stayers. Yet, when accounting for emigration in $d(\mathbf{S}, \mathbf{I})$, estimated social mobility increases only slightly, despite the large number of emigrants. Thus, compositional effects due to emigration is unlikely to be an important explanation for the high social mobility in Sweden at the time.

[35]Of the 849,996 sons observed in 1880, 543,155 were enumerated again in 1910. The loss of 128,750 sons is attributable to mortality between the two censuses, leaving 178,091 sons whose loss we can attribute to emigration, meaning that 21 per cent of all sons observed in 1880 emigrated during the following 30 years. We collect information about the number of decedents from the Swedish Death Index (Federation of Swedish Genealogical Societies, 2018).

[36]Since emigration registers contain the same identifying information as the censuses, we apply the same linking method as for the main sample, described in Appendix A. We are able to locate a large number of emigrants by linking individuals in the 1880 census to emigrant lists. In total we identify 101,508 emigrants who meet the same linking restrictions that we imposed on our main analytical sample. The social background of these emigrants confirm the notion that emigration was more common among sons with lower skilled and unskilled fathers.

[37]Of the identified emigrants, 20,381 are observed with at least one brother in 1880 who in turn is linked to 1910 with their own occupational title. When multiple brothers are identified, we favor the brother closest in age.

[38]We present the full occupational transition matrix for emigrants' brothers in Table C.1.

Table C.1: Occupational transitions for fathers and emigrant's brothers, 1880–1910

	Brother's occupation				
Father's occupation	White-collar	Farmer	Skilled/semi-skilled	Unskilled	Total
	%	%	%	%	%
White-collar	48	12	26	13	100
Farmer	9	48	23	20	100
Skilled/semi-skilled	15	11	55	19	100
Unskilled	11	16	40	33	100
Total	13	32	33	22	100
N	2,687	6,588	6,663	4,443	20,381

Notes: This table displays occupational transitions for emigrants' brothers relative to their fathers. Each column corresponds to the occupational group of brothers observed in the 1910 census. Each row corresponds to the occupation of fathers observed in the 1880 census.

D Additional Figures

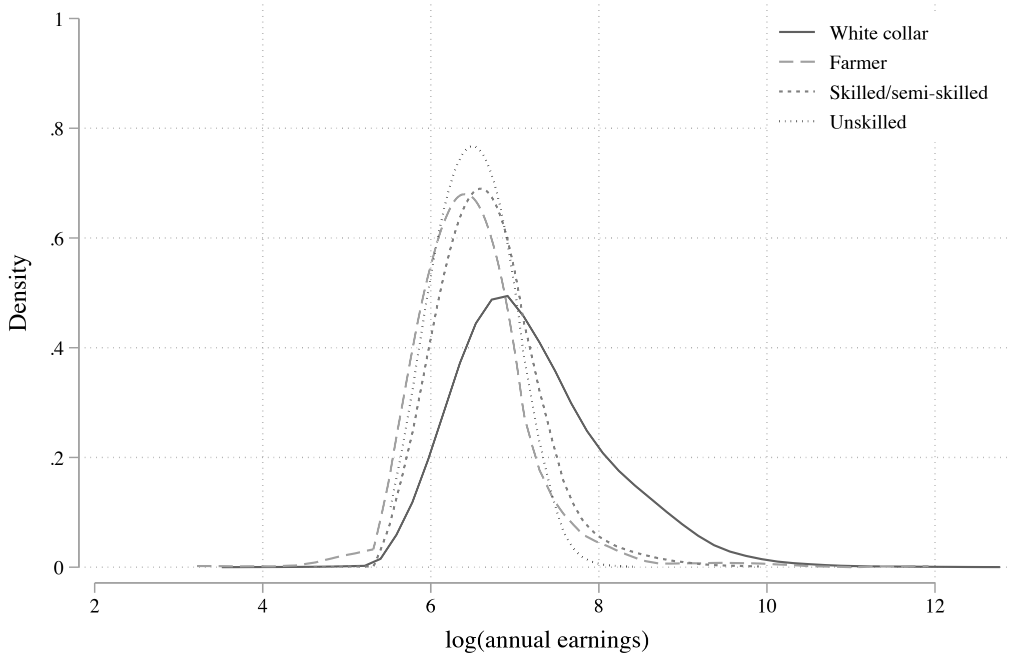


Figure D.1: Distribution of log(Annual Earnings) in Sweden, 1900

Notes: This figure shows the distribution of male log(annual earnings) in Sweden in 1900 among the stratified sample of approximately 15 000 taxpayers collected by Bengtsson et al. (2021).

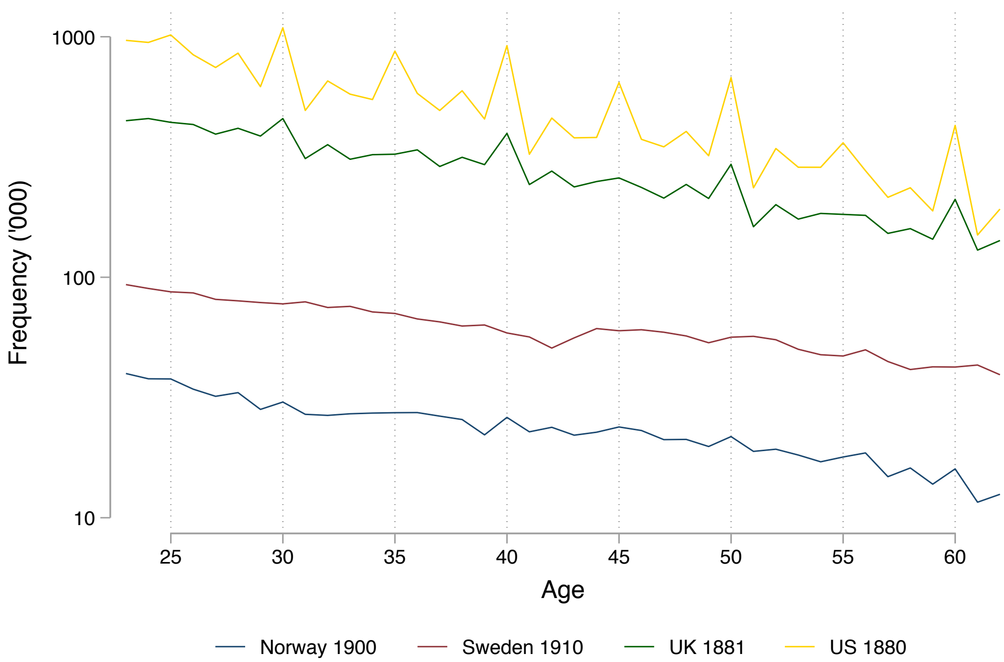
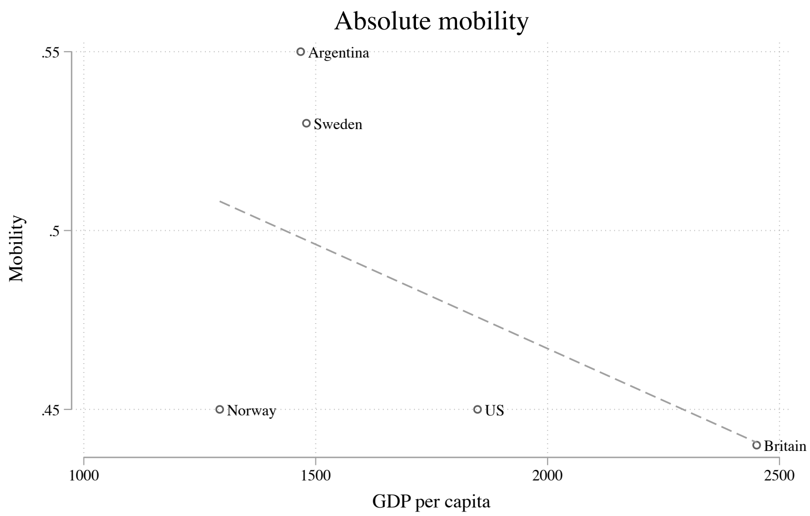
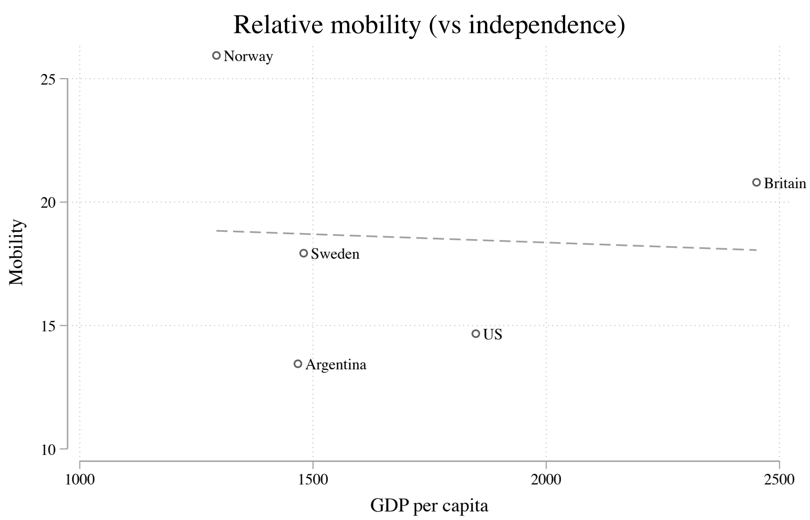


FIGURE D.2: DISTRIBUTIONS OF REPORTED AGES IN THE SWEDISH, NORWEGIAN, UK AND US CENSUSES

Notes: The figure shows the distribution of ages in the Swedish 1910, Norwegian 1900, UK 1881 and US 1880 censuses. The distributions and the corresponding Whipple's indices (Sweden 1910, 100.2; Norway 1900, 105.4; UK 1881, 114.8; US 1881, 144.5) suggests that reported ages are significantly more accurate in the Swedish census.



(A) ABSOLUTE MOBILITY: CROSS-COUNTRY



(B) ABSOLUTE MOBILITY: MUNICIPALITIES

FIGURE D.3: CROSS-COUNTRY CORRELATION BETWEEN GDP PER CAPITA LEVELS AND MOBILITY

Notes: This figure shows the cross-country correlation between absolute and relative mobility and GDP per capita levels. GDP per capita levels are measured in the first census year used to compute mobility rates. GDP per capita figures from Bolt et al. (2018).

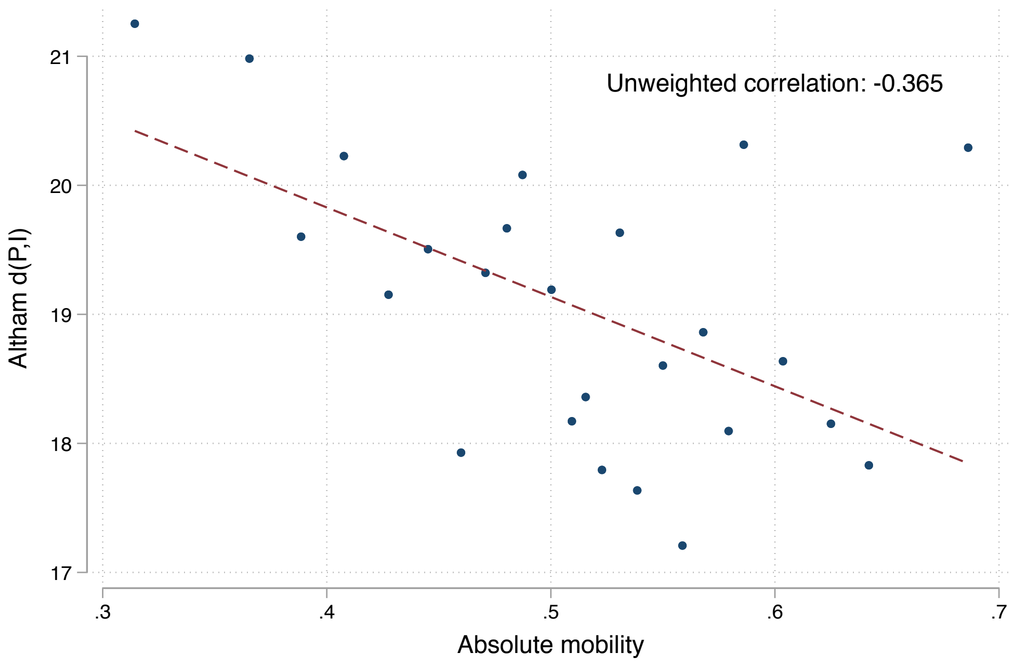
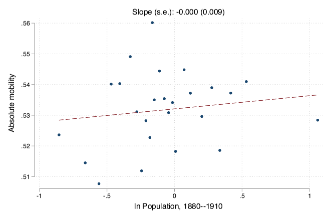
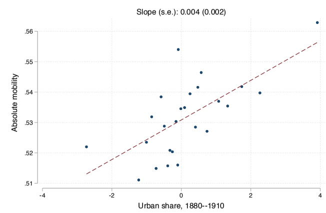


Figure D.4: Absolute and relative mobility across municipalities, 1880–1910.

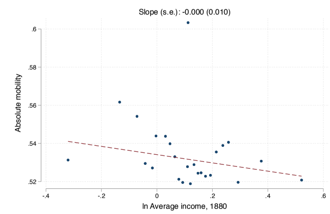
Notes: This figure displays the non-parametric relationship between relative mobility measured by the Altham $d(\mathbf{P}, \mathbf{I})$ statistic and absolute mobility (the share of sons transitioning into another occupation than that held by their father) across 282 municipalities. Sons are allocated to the municipality where they resided in childhood (i.e., in 1880). We group all municipalities into 25 equal-sized bins based on municipalities' absolute mobility rate where dots denote the mean level of relative mobility in each bin. Also shown is a best-fit line estimated from the underlying (ungrouped) data.



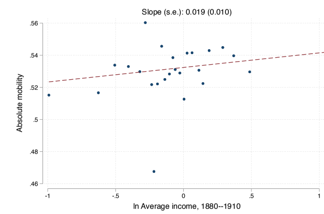
(A) Population growth, 1880–1910



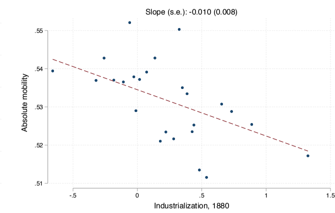
(B) Urbanization, 1880–1910



(C) Avg income, 1880

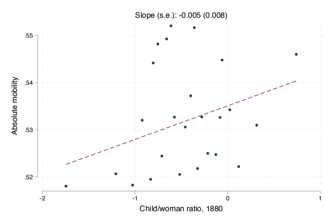


(D) Income growth, 1880–1910

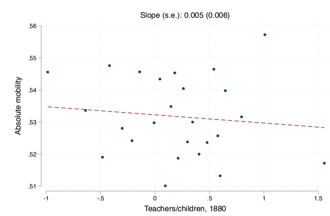


(E) Industrialization, 1880

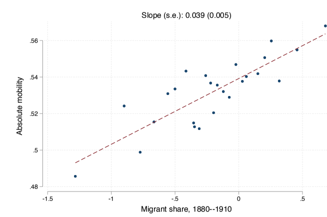
(F) Industrialization, 1880–1910



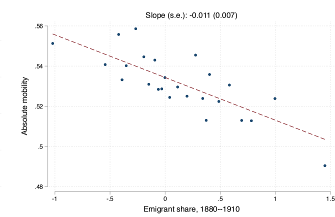
(G) Child/woman ratio, 1880



(H) Teacher/child ratio, 1880



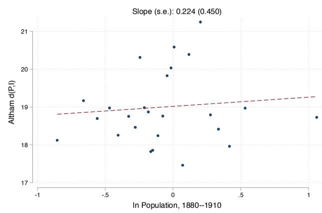
(I) Migrant share, 1880–1910



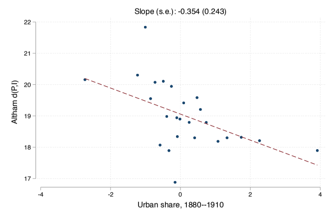
(J) Emigrant share, 1880–1910

Figure D.5: Correlates of municipality-level absolute mobility, 1880–1910

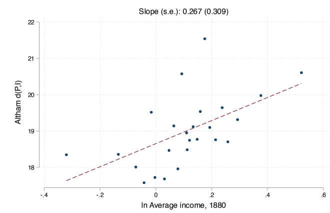
Notes: This figure displays the non-parametric relationship between absolute mobility (the share of sons transitioning into a different occupational group than that held by their father) and the main covariates in Table 2. All covariates are standardized to have mean 0 and a SD of 1. We residualize all variabels using the baseline set of municipality controls in Table 2 and weight all observations by municipal populations in 1880. When estimating absolute mobility rates, we allocate sons to the municipality where they resided in childhood (i.e., in 1880). To construct each figure, we group all municipalities into 25 equal-sized bins based on each respective covariate where dots denote the mean level of absolute mobility in each bin. Also shown is a best-fit line estimated from the underlying (ungrouped) data.



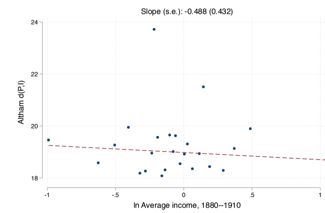
(A) Population growth, 1880–1910



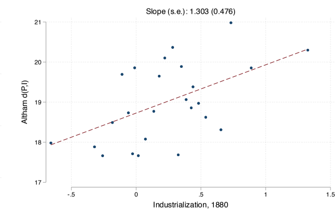
(B) Urbanization, 1880–1910



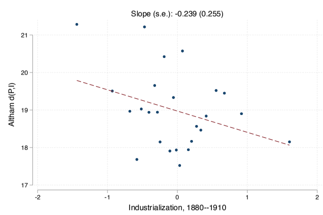
(C) Avg income, 1880



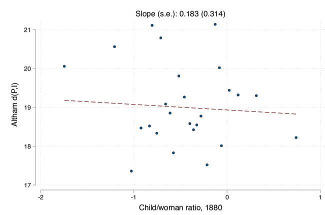
(D) Income growth, 1880–1910



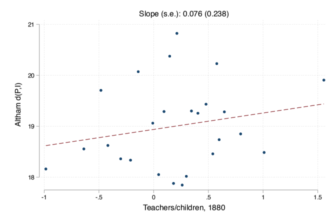
(E) Industrialization, 1880



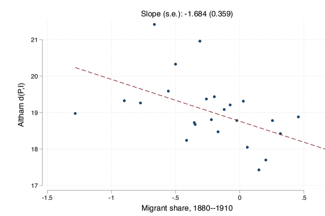
(F) Industrialization, 1880–1910



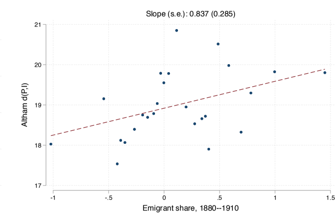
(G) Child/woman ratio, 1880



(H) Teacher/child ratio, 1880



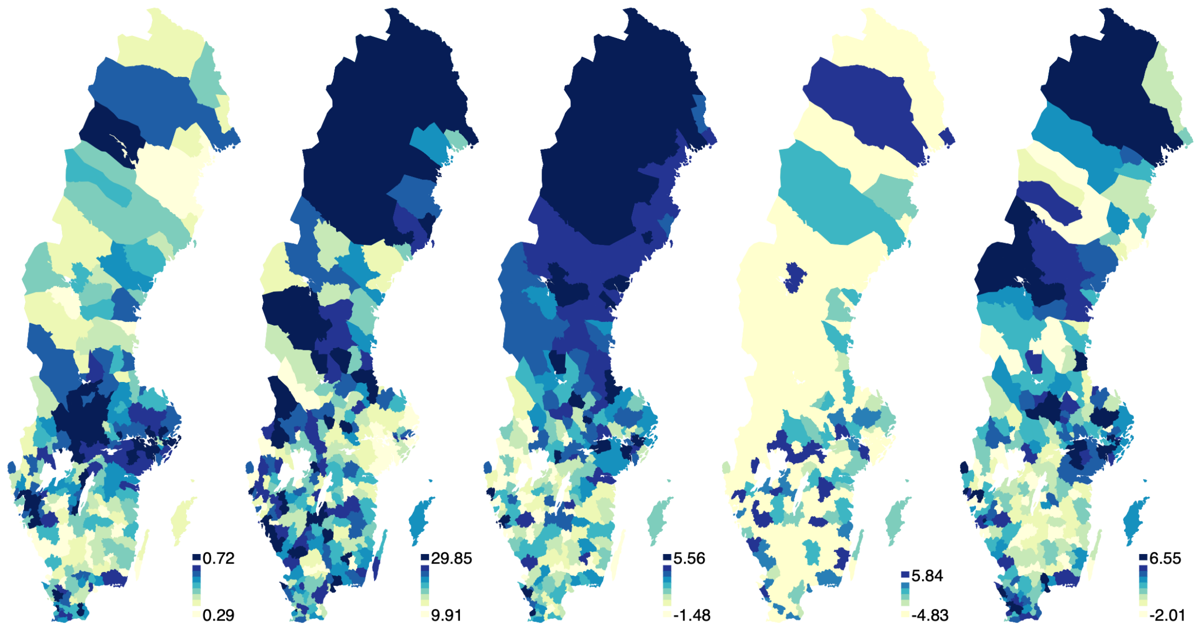
(I) Migrant share, 1880–1910



(J) Emigrant share, 1880–1910

Figure D.6: Correlates of municipality-level relative mobility, 1880–1910

Notes: This figure displays the non-parametric relationship between relative mobility (Altham $d(\mathbf{P}, \mathbf{I})$ statistics) and the main covariates in Table 2. All covariates are standardized to have mean 0 and a SD of 1. We residualize all variabels using the baseline set of municipality controls in Table 2 and weight all observations by municipal populations in 1880. When estimating relative mobility rates, we allocate sons to the municipality where they resided in childhood (i.e., in 1880). To construct each figure, we group all municipalities into 25 equal-sized bins based on each respective covariate where dots denote the mean level of absolute mobility in each bin. Also shown is a best-fit line estimated from the underlying (ungrouped) data.



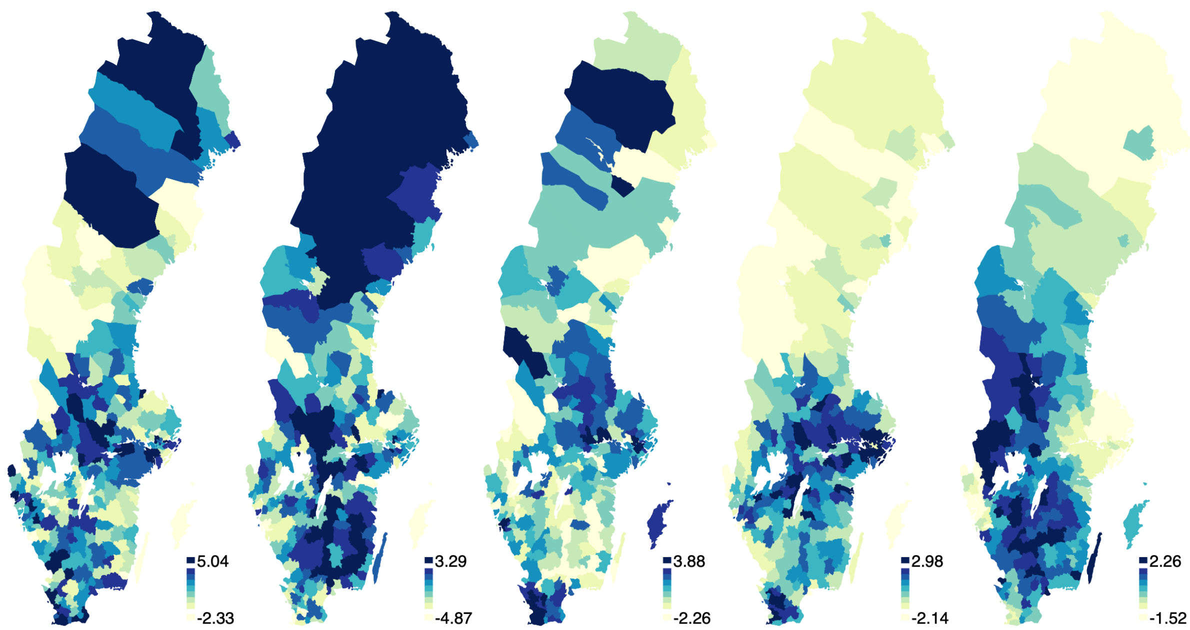
(A) Absolute mobility

(B) Altham $d(\mathbf{P}, \mathbf{I})$

(C) Population growth

(D) Urbanization

(E) Income growth



(F) Industrialization

(G) Child/woman ratio

(H) Teachers

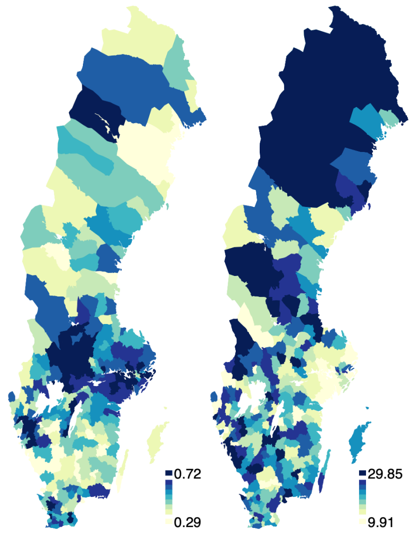
(I) Migration

(J) Emigration

Figure D.7: Geography of opportunity and correlates of intergenerational mobility

Notes: Maps display the distribution of absolute and relative mobility and other characterstics across 282 municipalities. Each variable is divided into 9 equal-sized bins where darker blue shades correspond to higher values.

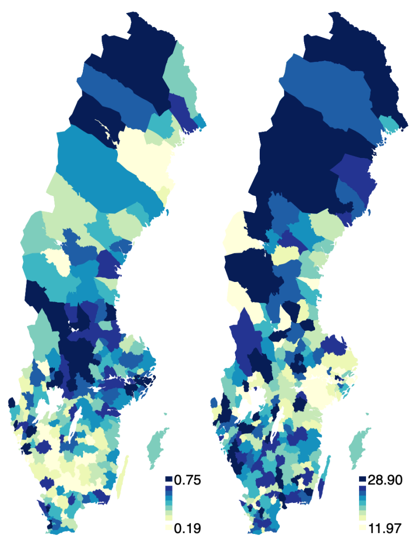
Mobility by municipality of residence in childhood (1880)



(A) Absolute mobility

(B) Altham $d(\mathbf{P}, \mathbf{I})$

Mobility by municipality of residence in adulthood (1910)



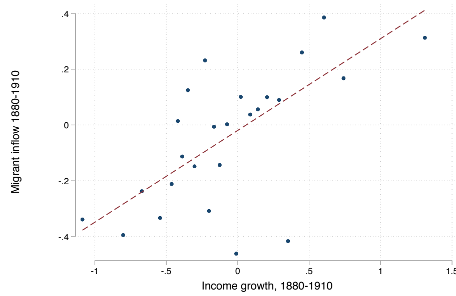
(C) Absolute mobility

(D) Altham $d(\mathbf{P}, \mathbf{I})$

Figure D.8: Mobility by municipality of residence in childhood and adulthood

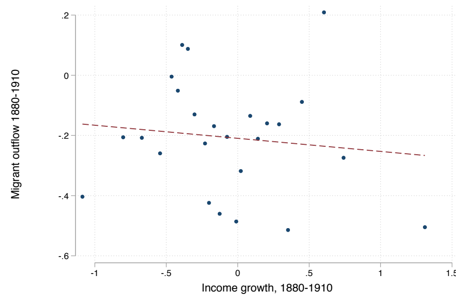
Notes: Panels A and C displays municipality-level measures of absolute mobility, or the fraction of sons that are observed in a different occupational group than their father. Panels B and D displays municipality-level Altham $d(\mathbf{P}, \mathbf{I})$ statistics that capture the distance from the case of full mobility where a larger statistic corresponds to less mobility. Son's geographical location is defined based on their municipality of residence in childhood/adulthood in the 1880/1910 census respectively in the upper and lower panel.

(A) Migrant inflow

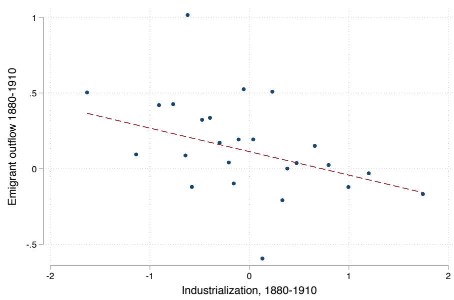


(B) Migrant inflow

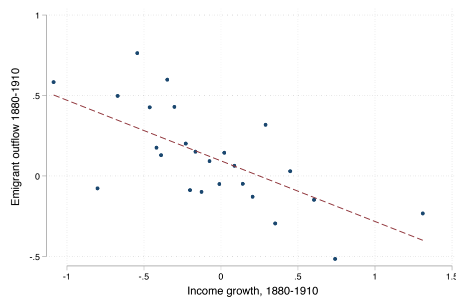
(C) Migrant outflow



(D) Migrant outflow



(E) Emigrant outflow



(F) Emigrant outflow

Figure D.9: Migrant flows and local growth across municipalities

Notes: This figure displays the non-parametric relationship between migration flows and industrialization or changes in average incomes between 1880–1910 respectively. In panels A and B we calculate migrant inflows by assigning sons in our linked sample to their municipality of residence in 1910 and calculate the share that did not reside in that municipality in 1880. In panels C and D we calculate migrant outflows by assigning sons in our linked sample to their municipality of residence in 1880 and calculate the share of sons that left that municipality by 1910. In panels E and F we define emigrant outflows by assigning sons in our linked sample to their municipality of residence in 1880 and calculate the share of sons that emigrate between 1880–1910. Both proxies for industrialization and growth are standardized to have mean 0 and and a SD of 1. We residualize all variables using the baseline set of municipality controls in Table 2 and weight all observations by municipal populations in 1880. To construct each figure, we then group all municipalities into 25 equal-sized bins based on either the rate of industrialization or income growth where dots denote the mean migrant flow in each bin. Also shown is a best-fit line estimated from the underlying (ungrouped) data.

E Additional Tables

Table E.1: Sample characteristics

	1880			1910		
	All (1)	Linked (2)	Diff (2)-(1) (3)	All (4)	Linked (5)	Diff (5)-(4) (6)
Age	8	7.9	-0.099	37.4	37.4	0.000
Father's age	43.3	43.4	0.100	.	.	.
Urban	0.12	0.11	-0.010	0.26	0.24	-0.020
County migrant	0.06	0.04	-0.020	0.28	0.27	-0.009
Parish migrant	0.21	0.17	-0.039	0.64	0.63	-0.009
Father's occ						
White collar	0.08	0.08	0.000	.	.	.
Farmer	0.50	0.50	0.000	.	.	.
Skilled/semi-skilled	0.18	0.18	0.000	.	.	.
Unskilled	0.24	0.24	0.000	.	.	.
Son's occ						
White collar	.	.	.	0.15	0.14	-0.010
Farmer	.	.	.	0.25	0.28	0.030
Skilled/semi-skilled	.	.	.	0.34	0.33	-0.009
Unskilled	.	.	.	0.26	0.26	0.000
Observations	575,831	235,008		498,500	293,264	

Notes: This table reports descriptives for linked sons compared to the full population after applying the sample restrictions set out in the main text. Columns (1) and (2) reports descriptives for individuals in the 1880 census. Columns (4) and (5) similarly compares linked individuals when they are observed as adults in the 1910 census, after applying the same sample restrictions to the underlying census data.

Table E.2: Probability of matching by father's occupation, father's and son's age, and son's name

	(1)	(2)	(3)	(4)
Father's occupation:				
White collar	0.045***	0.044***	0.023***	0.019***
	(0.004)	(0.004)	(0.004)	(0.004)
Farmer	0.019***	0.019***	0.031***	0.027***
	(0.003)	(0.003)	(0.003)	(0.003)
Skilled/semi-skilled	0.011***	0.012***	-0.003	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Unskilled	0.023***	0.024***	0.026***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Ages:				
Age		-0.003***	-0.002***	-0.002***
		(0.000)	(0.000)	(0.000)
Father's age		0.001***	0.002***	-0.002***
		(0.000)	(0.000)	(0.000)
Name characteristics:				
First name length			0.002***	0.004***
			(0.000)	(0.000)
Last name length			0.001***	0.002***
			(0.000)	(0.000)
First name commonness			-0.074**	-0.083***
			(0.000)	(0.002)
Last name commonness			-0.009***	-0.008***
			(0.000)	(0.000)
County of birth FE	No	No	No	Yes
Observations	613,137	613,137	613,137	613,137
McFadden's R2:	0.000	0.001	0.007	0.024

Notes: This table displays marginal effects from probit models with a indicator variable for a successful match as the outcome. Name commonness is measured as the percentage of individuals holding the same name in the 1880 census. Marginal effects calculated holding all other variables at the mean of the sample. Standard errors clustered at the household level are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.3: Occupational classification schemes

Panel A. HISCLASS and the Abbreviated Class Scheme

HISCLASS		**Abbreviated**
Number	*Title*	*Title*
1	Higher managers	White-collar
2	Higher professionals	
3	Lower managers	
4	Lower professionals, clerical and sales personnel	
5	Lower clerical and sales personnel	
6	Foremen	Skilled/semi-skilled
7	Medium-skilled workers	
8	Farmers and fishermen	Farmers
9	Low-skilled workers	Unskilled
10	Low-skilled farm workers	
11	Unskilled workers	
12	Unskilled farm workers	

Panel B. Erikson–Goldthorpe and the Abbreviated Class Scheme

Erikson–Goldthorpe		**Abbreviated**
Number	*Title*	*Title*
I	Large proprietors, higher professionals, and managers	White-collar
II	Lower professionals and managers	
IIIa	Routine nonmanual workers, higher grade	
IIIb	Routine nonmanual workers, lower grade	
IVa	Small proprietors, with employees	Skilled/semi-skilled
IVb	Small proprietors, without employees	
V	Lower grade technicians and manual supervisors	
VI	Skilled manual workers	
IVc	Self-employed farmers, with employees	Farmers
IVd	Self-employed farmers, without employees	
VIIa	Unskilled manual workers	Unskilled
VIIb	Agricultural laborers	

Table E.4: Occupational transition matrix: frequencies

	Son's occupation				
Father's occupation	White-collar	Farmer	Skilled/semi-skilled	Unskilled	Total
	No.	No.	No.	No.	No.
White-collar	10,896	1,738	4,129	2,442	19,205
Farmer	11,080	55,090	26,429	25,185	117,784
Skilled/semi-skilled	6,927	4,172	23,256	9,408	43,763
Unskilled	5,889	8,209	23,285	22,806	60,189
Total	34,792	69,209	77,099	59,841	240,941

Notes: This table displays frequencies of occupational transitions for father–son pairs across the four HISCLASS groups used in the main analysis. Each column corresponds to the occupational group of sons observed in the 1910 census. Each row corresponds to the occupation of fathers observed in the 1880 census.

Table E.5: Occupational transition matrix: modern Sweden

Panel A. Frequencies

	Son's occupation				
Father's occupation	1	2	3	4	Total
	No.	No.	No.	No.	No.
1	974	6	243	119	1342
2	574	227	520	429	1750
3	1112	16	904	428	2460
4	918	17	823	655	2413
Total	3578	266	2490	1631	7965
N	3,578	266	2,490	1,631	7,965

Panel B. Row percentages

	Son's occupation				
Father's occupation	1	2	3	4	Total
	%	%	%	%	%
1	73	0	18	9	100
2	33	13	30	25	100
3	45	1	37	17	100
4	38	1	34	27	100
Total	45	3	31	20	100
N	3,578	266	2,490	1,631	7,965

Notes: This table displays occupational transitions for father–son pairs in the modern Swedish sample. Each row corresponds to the occupational group of sons born 1915–1930 and interviewed in the 1976–1990 Swedish Study of Living Conditions (ULF), carried out annually by Statistics Sweden (Vogel et al., 1988). Each row corresponds to the occupation that the respondent reports as their father's main occupation when they grew up (until age 16). See Table E.3 for a description of the modern EGP schema and the coding of the four groups.

Table E.6: Absolute mobility, standard errors

	(1) Absolute Mobility	(2) Margin-adjusted
Sweden	(ref.)	(ref.)
Britain	-0.090***	-0.076***
	(0.010)	(0.010)
Norway	-0.090***	-0.049***
	(0.004)	(0.004)
United States	-0.080***	0.031***
	(0.002)	(0.002)
Argentina	0.012**	0.054***
	(0.005)	(0.005)
Constant	0.535***	0.535***
	(0.001)	(0.001)
Observations	452,489	452,425

Notes: This table shows the uncertainty and significance associated with estimates of absolute mobility in other countries relative to Sweden (compare Figure 1A and 1B). Column 1 reports estimates of absolute mobility, or the share of sons that are observed in a different occupational group than their father, with Sweden as the reference group. Column 2 reports similar measures of absolute mobility adjusted to the occupational distribution in Sweden. Linear probability model estimated with OLS, robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.7: Summary of linked samples characteristics

		t				t+1				Linkage rate		Index variables			
	Country/region (1)	Age restriction (2)	Year (3)	Sample size (4)	Observations (5)	Year (6)	Sample (7)	Observations (8)	Links (9)	Prospective (10)	Retrospective (11)	Birth place (12)	Birth year (13)	Initials (14)	Name comparison algorithm (15)
	Sweden	≤ 16	1880	100%	849,996	1910	100%	543,155	310,183	36.5%	57.1%	Parish	Exact	None	Jaro-Winkler
Perez (2017)	Argentina	≤ 16	1869	95%	208,432	1895	100%	-	24,615	11.8%	-	Province	$\pm$ 5 years	First and last name	Jaro-Winkler
	United States	≤ 16	1850	100%	-	1880	100%	-	-	-	-	State	$\pm$ 5 years	First and last name	Jaro-Winkler
	Norway	≤ 16	1865	100%	-	1900	100%	-	-	-	-	Municipality	$\pm$ 5 years	First and last name	Jaro-Winkler
	Britain	≤ 16	1851	2%	-	1881	100%	-	-	-	-	Parish	$\pm$ 5 years	First and last name	Jaro-Winkler
Modalsli (2017)	Norway	≤ 16	1865	100%	-	1900	100%	160,352	-	-	37%	Municipality	$\pm$ 5 years	None	Levenshtein
Ferrie and Long (2013a)	United States	≤ 25	1850	1%	43,438	1880	100%	-	9,497	21.9%	-	State	$\pm$ 3 years	None	SOUNDEX/SPEDSIS
	England and Wales	≤ 25	1851	2%	69,785	1881	100%	-	14,191	20.3%	-	Parish	$\pm$ 5 years	None	SOUNDEX/SPEDSIS
Ward (2020)	United States	≤ 14	1910	100%	-	1940	100%	-	394,864	4.6%	-	State	$\pm$ 2 years	First and last name	Jaro-Winkler
Feigenbaum (2018)	Iowa	3-17	1915	1.8-5.5%	7,580	1940	100%	-	-	59%	-	State	$\pm$ 3 years	None	Jaro-Winkler

Notes: This table summarizes variables used for linking across historical census data together with number of observations and linkage rates.

Table E.8: Occupational transitions for fathers and sons, 1880–1910 (Supplementary linked sample 1)

	Son's occupation				
Father's occupation	White-collar	Farmer	Skilled/semi-skilled	Unskilled	Total
	%	%	%	%	%
White-collar	62	7	20	11	100
Farmer	11	46	22	21	100
Skilled/semi-skilled	19	8	53	20	100
Unskilled	11	12	40	37	100
Total	19	24	33	23	100
N	25,190	31,167	43,100	30,233	129,690

Notes: This table displays occupational transitions for sons relative to their fathers. Each column corresponds to the occupational group of sons observed in the 1910 census. Each row corresponds to the occupation of fathers observed in the 1880 census. The sample was created using our preferred method of linking using county of birth in place of parish of birth.

Table E.9: Occupational transitions for fathers and sons, 1880–1910 (Supplementary linked sample 2)

	Son's occupation				
Father's occupation	White-collar	Farmer	Skilled/semi-skilled	Unskilled	Total
	%	%	%	%	%
White-collar	66	6	19	9	100
Farmer	14	43	22	21	100
Skilled/semi-skilled	22	7	53	19	100
Unskilled	13	11	41	36	100
Total	25	20	34	21	100
N	16,554	13,351	22,383	14,289	66,577

Notes: This table displays occupational transitions for sons relative to their fathers. Each column corresponds to the occupational group of sons observed in the 1910 census. Each row corresponds to the occupation of fathers observed in the 1880 census. The sample was created using our preferred method of linking using county of birth in place of parish of birth and allowing for birth years to differ by up to 5 years.

TABLE E.10: OCCUPATIONAL TRANSITIONS FOR FATHERS AND SONS, 1880–1910 (SUPPLEMENTARY LINKED SAMPLE 3)

	Son's occupation				
Father's occupation	White-collar	Farmer	Skilled/semi-skilled	Unskilled	Total
	%	%	%	%	%
White-collar	64	7	19	10	100
Farmer	12	45	22	21	100
Skilled/semi-skilled	18	8	54	20	100
Unskilled	10	13	39	38	100
Total	19	25	32	23	100
N	13,893	17,819	23,109	16,791	71,612

Notes: This table displays occupational transitions for sons relative to their fathers. Each column corresponds to the occupational group of sons observed in the 1910 census. Each row corresponds to the occupation of fathers observed in the 1880 census. The sample was created using Pérez (2019) methodology.

TABLE E.11: OCCUPATIONAL TRANSITIONS FOR FATHERS AND SONS, 1880–1910 (SUPPLEMENTARY LINKED SAMPLE 4)

	Son's occupation				
Father's occupation	White-collar	Farmer	Skilled/semi-skilled	Unskilled	Total
	%	%	%	%	%
White-collar	61	8	20	11	100
Farmer	11	45	23	21	100
Skilled/semi-skilled	17	9	53	20	100
Unskilled	10	13	38	38	100
Total	18	26	32	24	100
N	19,292	28,734	35,275	26,129	109,430

Notes: This table displays occupational transitions for sons relative to their fathers. Each column corresponds to the occupational group of sons observed in the 1910 census. Each row corresponds to the occupation of fathers observed in the 1880 census. The sample was created using Abramitzky et al. (2019) methodology.

TABLE E.12: OCCUPATIONAL TRANSITIONS FOR FATHERS AND SONS, 1880–1910 (SUPPLEMENTARY LINKED SAMPLE 5)

	Son's occupation				
Father's occupation	White-collar	Farmer	Skilled/semi-skilled	Unskilled	Total
	%	%	%	%	%
White-collar	64	7	19	10	100
Farmer	12	45	22	21	100
Skilled/semi-skilled	18	8	54	20	100
Unskilled	10	13	39	38	100
Total	19	25	32	23	100
N	13,798	17,699	22,959	16,671	71,127

Notes: This table displays occupational transitions for sons relative to their fathers. Each column corresponds to the occupational group of sons observed in the 1910 census. Each row corresponds to the occupation of fathers observed in the 1880 census. The sample was created by using the intersection of links made using our preferred method and links made using Pérez (2019) and Abramitzky et al. (2019) methodologies.

Table E.13: Upward mobility across municipalities, 1880–1910

Dependent variable:	Upward mobility			
	(1)	(2)	(3)	(4)
Δ ln Population, 1880–1910	0.007			0.012
	(0.010)			(0.015)
Δ Urban share, 1880–1910	0.004			0.004
	(0.003)			(0.003)
ln Average income, 1880		-0.004		-0.003
		(0.010)		(0.010)
Δ ln Average income, 1880–1910		0.002		-0.011
		(0.009)		(0.010)
Industrialization, 1880			0.038***	0.056***
			(0.009)	(0.011)
Δ Industrialization, 1880–1910			0.025***	0.028***
			(0.008)	(0.009)
Child/woman ratio, 1880				0.008
				(0.008)
Teachers/children, 1880				-0.005
				(0.008)
Migrant share, 1880–1910				0.039**
				(0.016)
Emigrant share, 1880–1910				-0.004
				(0.008)
Municipality controls	Yes	Yes	Yes	Yes
Observations	282	282	282	282
R-squared	0.12	0.12	0.19	0.25
Mean dep. var.	0.63	0.63	0.63	0.63

Notes: Municipality-level OLS regressions. When estimating upward mobility rates, we allocate sons to the municipality where they resided in childhood (i.e., in 1880). All right-hand-side variables are standardized to have mean 0 and and a SD of 1. Municipality controls include ln population, occupational shares (white-collar, farmers, skilled/semi-skilled, and unskilled), and the share living in urban areas, all measured in 1880. Robust standard errors clustered at the county level are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.14: Absolute and relative mobility across municipalities, 1880–1910: alternative measures of local migration

Dependent variable:	Absolute mobility			Altham $d(\mathbf{P}, \mathbf{I})$		
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant share, 1880–1910	0.039***			-1.684***		
	(0.005)			(0.359)		
Share born in diff muni (1880 census)		0.014			-1.500***	
		(0.009)			(0.522)	
Share born in diff muni (1910 census)			0.027***			-1.985***
			(0.009)			(0.491)
Municipality controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	282	282	282	282	282	282
R-squared	0.33	0.15	0.19	0.17	0.11	0.15
Mean dep. var.	0.53	0.53	0.53	19.00	19.00	19.00

Notes: Municipality-level OLS regressions. Alternative measures of local migration are all standardized to a have mean 0 and a standard deviation of 1. Municipality controls include ln population, occupational shares (white-collar, farmers, skilled/semi-skilled, and unskilled), and the share living in urban areas, all measured in 1880. Robust standard errors clustered at the county level are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE E.15: GEOGRAPHIC AND OCCUPATIONAL MOBILITY, 1880–1910: INDIVIDUAL-LEVEL ESTIMATES ACROSS DIFFERENT GEOGRAPHIES

Dependent variable:	Absolute mobility (=1)		
	(1)	(2)	(3)
Municipality migrant (=1)	0.151***		
	(0.006)		
County migrant (=1)		0.135***	
		(0.007)	
Parish migrant (=1)			0.167***
			(0.006)
Son's age	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Observations	117926	117926	117926
Mean dep. var.	0.54	0.54	0.54

Notes: Individual-level OLS regressions. Sample restricted to households with at least two (linked) sons. Robust standard errors clustered at the 1880 household level are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.16: Geographic and occupational mobility, 1880–1910: individual-level estimates by father's occupational group

Dependent variable:	Absolute mobility (=1)			
Father's occupational group:	White-collar	Farmer	Skilled	Unskilled
	(1)	(2)	(3)	(4)
Municipality migrant (=1)	-0.068***	0.295***	-0.034**	0.073***
	(0.019)	(0.008)	(0.014)	(0.012)
Son's age	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Observations	9846	57897	21631	28552
Mean dep. var.	0.43	0.56	0.46	0.62

Notes: Individual-level OLS regressions. Sample restricted to households with at least two (linked) sons. Robust standard errors clustered at the 1880 household level are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.17: Geographic and occupational mobility, 1880–1910: individual-level estimates by different migrant origins

Dependent variable:	Absolute mobility (=1)							
	Δ ln Population		Δ Urban share		Δ ln Average Income		Δ Share in manufacturing	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Migrant (=1)	0.120***	0.182***	0.126***	0.174***	0.134***	0.168***	0.136***	0.167***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Son's age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61544	56382	56088	61838	61403	56523	59486	58440
Mean dep. var.	0.54	0.54	0.54	0.54	0.55	0.53	0.55	0.53

Notes: Individual-level OLS regressions. Sample restricted to households with at least two (linked) sons. Each pair of columns reports estimates separately for individuals residing in municipalities above/below the median municipality in terms of growth in population, urbanization, income, and employment share in manufacturing. Robust standard errors clustered at the 1880 household level are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.