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Comment

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Source: *The American Economic Review*, Vol. 103, No. 5 (AUGUST 2013), pp. 2021-2040

Published by: American Economic Association

Stable URL: <https://www.jstor.org/stable/42920638>

Accessed: 22-12-2019 16:27 UTC

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Intergenerational Occupational Mobility in Great Britain and the United States Since 1850: Comment[†]

By MICHAEL HOUT AND AVERY M. GUEST*

In “Intergenerational Occupational Mobility in Britain and the United States Since 1850,” Jason Long and Joseph P. Ferrie (2013) introduce valuable data on men’s intergenerational occupational mobility in the United States and Britain for men employed in 1880 or 1881 and compare patterns with those for the same countries for men employed in the early 1970s.

Long and Ferrie advance three major substantive conclusions:

- (i) Occupational mobility was greater in the United States than in Britain in the 1880s. This result is consistent, as they note, with contemporary and current images of an expanding, open America and a rigid, class-conscious Victorian England. Their study is the first to address this issue with such broadly representative data.
- (ii) The United States became increasingly stratified over the ensuing 90 years, decreasing social mobility. This contradicts previous research that concluded that the strength of the intergenerational correlation in the United States either remained constant (Hauser et al. 1975; Guest, Landale, and McCann 1989) or fluctuated without a consistent trend upward or downward (Grusky and Fukumoto 1989) at least until the 1960s. Other research indicated a significant decline in American stratification from 1962 to 1985 (Featherman and Hauser 1978; Hout 1984, 1988; DiPrete and Grusky 1990).
- (iii) Britain and the United States were similarly stratified in the 1970s. This accords with previous research that used the same original data sources but a broader age range, encompassing all men 25-64 years old (Kerckhoff, Campbell, and Winfield-Laird 1985; Yamaguchi 1987; Erikson and Goldthorpe 1992; Xie 1992; Goodman and Hout 1998).

Long and Ferrie make no direct comparisons between the British mobility patterns in 1881 and 1972.

We are motivated to comment by our reanalyses of the published version of Long and Ferrie’s dataset and some other tables that differ in some particulars.

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[†] Go to <http://dx.doi.org/10.1257/aer.103.5.2021> to visit the article page for additional materials and author disclosure statement(s).

We conclude that exchange mobility was more similar across time and place than they suggest; what differences there were between the United States and Britain in 1880–1881 and between 1880 and 1973 in the United States were quite specific. There are two noteworthy differences in specific aspects of stratification across the four samples that deserve to be mentioned: (i) In 1880 American men from nonfarm origins faced a lower barrier to entering farming than did American men with nonfarm origins in 1973 or British men from nonfarm origins in either 1881 or 1972; (ii) British men from the highest and lowest ranks were significantly more likely to persist in their father's class in 1881 than were American men at that time or either British or American men in the early 1970s. This exceptional persistence resulted in a higher intergenerational correlation for young men in Britain in 1881 than in the other three combinations of place and time. These specific features of the data elude the statistical approach Long and Ferrie took but appear as significant nonlinearities in our regression-like approach to the data.

We also point out that overall mobility depends as much on how similar or different fathers' and sons' occupational distributions are as on the lack of correlation between father's and son's occupational status. Long and Ferrie focus almost exclusively on that correlation and miss the contribution of occupational change and differentiation to mobility chances as they differ over time and between nations. We develop this point in the next section. It is important because total mobility in the United States was much greater in the twentieth century than it had been in the nineteenth century. Treating the intergenerational correlation as the only metric of interest leads to misleading conclusions, in particular, about US mobility in the twentieth century.

I. Vocabulary, Models, and Data

Individuals become socially mobile either because they escape the constraints of their social background or because young people face an occupational structure that differs from what their parents encountered. At least since the 1880s, American men were fortunate to have the advantage of accessing both channels of mobility, according to sociological and historical research (e.g., Guest, Landale, and McCann 1989; Fischer and Hout 2006). A significant correlation of roughly 0.3 or 0.4 between father's and son's occupational status kept nonfarm workers closer to their social backgrounds than a mobility pattern with more equal opportunity would have, but that magnitude was, nonetheless, consistent with substantial mobility (Blau and Duncan 1967; Featherman and Hauser 1978). At the same time, economic and social factors fostered an expansion of professional and managerial occupations and a relative contraction of unskilled ones. This too fostered mobility, mostly upward (Hout 1988).

Long and Ferrie, like many sociologists and economists, focus on the intergenerational correlation and downplay how essential for mobility changes in the occupational distribution can be. The correlation across generations is important, of course; it informs theories of genetic heritability, human capital, and the consequences of discrimination because these theories take as given the opportunities at a given time and propose hypotheses about who gets better or worse outcomes given those opportunities. Correlations, slopes, odds ratios, and composites of odds ratios like

the measure Long and Ferrie use appropriately measure movement within a hypothetically fixed opportunity structure.

Mobility researchers refer to this mobility due to the imperfect correlation across generations by names such as “relative,” “circulation,” and “exchange” mobility. We will use the term “exchange” in the rest of this paper because it emphasizes one of the most salient features of this kind of mobility—its symmetry. In the hypothetical society in which the son’s occupational distribution is the same as the father’s, if there is any mobility, then every upward move is balanced by a downward move. On net, exchange mobility is neither upward nor downward across the generations; the upwardly mobile worker changes places with some downwardly mobile worker (Sobel, Hout, and Duncan 1985).

A comprehensive view of mobility complements a correlational measure with one that quantifies the intergenerational differences in the occupational structure. Known as “structural mobility,” this kind of mobility that affects all origins more or less proportionately is the source of upward and downward mobility in a labor market. The different occupational distributions that fathers and sons encounter allows the sons to move up and down at different rates. All empirical tables—including all the ones presented by Long and Ferrie—exhibit different distributions for fathers and sons, and most—also including all the ones presented by Long and Ferrie—exhibit more upward than downward mobility.

A useful measure of structural mobility must be as free of influence from the correlation as the correlation is from the distributions of occupations. Sobel, Hout, and Duncan (1985) propose such a measure, and we adopt their specification here because it is commensurate with both our approach to measuring exchange mobility and that taken by Long and Ferrie.

Mobility is the substantive focus in popular discussion and the social science literature, and rightly so, but *immobility* is quantitatively quite important in most mobility tables. In the American and British mobility tables presented by Long and Ferrie and reanalyzed here, roughly half the men worked in an occupation that fell into the same occupational category as their father’s occupation. Were we to have access to mobility tables with more occupational categories, some additional short-distance mobility might be revealed. But even in a table with over 100 categories, the observed counts in the cells $i = j$ exceed the expected counts under models that ignore it (e.g., Weeden and Grusky 2005). This feature of empirical data is usually modeled through dummy variables applied to the cells that classify father and son the same (see below).

Sociologists have translated the distinction between exchange and structural mobility into statistical models they usually express as multiplicative models for counts in a table (see Goodman 1979; Hout 1983; Sobel, Hout, and Duncan 1985). But each multiplicative model has an equivalent expression as a system of multinomial logit regression equations in which the parameters pertaining to structural mobility appear as intercepts and exchange mobility is proportional to the slopes (Goodman 1981; Hout 1983, 1988). As the socioeconomic differences among occupations differ very little over time or between places (Treiman 1977; Hauser 1982; Hauser and Warren 1997; Hout and DiPrete 2006; Hauser 2010), differences in slopes for data from different times and places reflect differences in the intergenerational association or correlation.

Specifically, equation (1) shows an illustrative model for the counts (F) in a mobility table that classifies persons by their origin, their destination, and any conditioning variables. In the present context of father-to-son occupational mobility by country and time period, origin is father's occupation (i), destination is own current occupation (j), and the conditioning variables are country (k) and time period (t). The model is

$$(1) \quad F_{ijkt} = \mu \lambda_{1ikt} \lambda_{2jkt} \theta_{kt}^{X_i X_j} \delta_{ikt}^{D_{ij}}$$

for $i = 1, \dots, I; j = 1, \dots, J; k = 1, \dots, K; t = 1, \dots, T$; X_i is a score for father's occupational category i ; X_j is the corresponding score for son's occupational category j ; and D_{ij} is a dummy variable = 1 if $i = j$ and 0 otherwise. Because of the one-for-one correspondence between rows and columns, we impose the constraint that the father's and son's scores are the same, i.e., $X_i = X_j$ for $i = j$, but separate row and column scores can be identified in the general form of the model (Goodman 1979). The λ s can be identified by norming them to sum to zero or setting $\lambda_{1i''kt} = 0$ and $\lambda_{2i''kt} = 0$ for some baseline category $i'' = j''$; we use the latter here. The μ term norms the counts to the actual sample size, the λ s norm the row and column totals in each table to equal the observed totals, and θ measures the overall association between father's and son's occupations in each country and time period scaled according to the time- and place-invariant scores X_i and X_j . The δ s measure the net tendency toward occupational persistence; as equation (2) shows, they amount to nonlinearities in the logit regressions. With θ_{kt} in the model, we can identify only $(I - 2)$ scores (Goodman 1979), so we set the score for the least prestigious, lowest paid category to zero and the score for the most prestigious, highest paid category to one. We expect the estimated scores to be between zero and one but do not constrain them to be.

Models for counts become substantially more familiar when we express them as multinomial logit regression models (see Goodman 1981):

$$(2) \quad \ln\left(\frac{F_{ijkt}}{F_{ij'kt}}\right) = \ln(\lambda_{2jkt}/\lambda_{2j'kt}) + \ln\theta_{kt}(X_j - X_{j'})X_i + \ln\delta_{jkt} D_{ij} - \ln\delta_{j'kt} D_{ij'} \\ = \beta_{0(jj')kt}^* + \beta_{1(jj')kt}^* X_i + \beta_{2kt}^* D_{ij} + \beta_{3kt}^* D_{ij'}$$

where $j \neq j'$, $\beta_{0(jj')kt}^* = \ln(\lambda_{2jkt}/\lambda_{2j'kt})$, $\beta_{1(jj')kt}^* = \ln\theta_{kt}(X_j - X_{j'})$, $\beta_{2kt}^* = \ln\delta_{jkt}$, and $\beta_{3kt}^* = -\ln\delta_{j'kt}$. Many logit regressions of this form could be formed from the j, j' pairs, but only $I - 1$ are identified—a familiar result in the application of multinomial logistic regression (e.g., Long 1997). It is conventional to form the $I - 1$ independent and identified regressions by choosing one category as the reference category and taking each other category, in turn, as the numerator of the logit. We follow that convention and take the least prestigious, lowest paid to be the baseline of the four identified logit regressions. That allows us to interpret each logit as the odds on a “better” job and to interpret the intercepts in terms of “upward” and “downward” structural mobility, depending on their sign (Hout and Hauser 1992).

Coupling these constraints with the constraint that $X_{j'} = 0$, we simplify the notation substantially:

$$\begin{aligned} \ln\left(\frac{F_{ijkt}}{F_{ij'kt}}\right) &= \ln \lambda_{2jkt} + (\ln \theta_{kt} X_j) X_i + \ln \delta_{jkt} D_{ij} - \ln \delta_{j'kt} D_{ij'} \\ &= \beta_{0jkt}^* + \beta_{1jkt}^* X_i + \beta_{2kt}^* D_{ij} + \beta_{3kt}^* D_{ij'}, \end{aligned}$$

where j' is the baseline column category, $\lambda_{2j'kt} = 1$, $X_{j'} = 0$, $\beta_{0jkt}^* = \ln \lambda_{2jkt}$, $\beta_{1jkt}^* = \ln \theta_{kt} X_j$, and β_{2kt}^* and β_{3kt}^* are defined as before.

The slope parameters β_{1jkt}^* , β_{2jkt}^* , and β_{3jkt}^* measure exchange mobility. As θ and δ approach one from above $\ln \beta_{1kt}^*$, β_{2jkt}^* , and β_{3jkt}^* approach zero, correlation between father's and son's occupation approaches zero, and the model implies increasing exchange mobility. Exchange mobility also increases as $X_j - X_{j'}$ approaches zero; close occupational scores are a smaller barrier to mobility than more distant occupational scores are.

The regression-based approach has six advantages over the analytic approach Long and Ferrie took. First, as we have emphasized, the regression-based approach has parameters for both structural and exchange mobility; the alternative used by Long and Ferrie has no measure of structural mobility. To see how structural mobility disappears from their calculations, note that the odds ratios that form the basis of their measure of mobility are differences between logits for different origin categories:

$$\begin{aligned} (3) \quad \ln \theta_{(ii')(jj')kt} &= \ln\left(\frac{F_{ijkt} F_{i'j'kt}}{F_{ij'kt} F_{i'jkt}}\right) \\ &= \ln \theta_{kt} (X_j - X_{j'}) (X_i - X_{i'}) + (\ln \delta_{ikt} - \ln \delta_{i'kt}) \\ &\quad \times (D_{ij} - D_{ij'} - D_{i'j} + D_{i'j'}) \\ &= \beta_{1(jj')kt}^* (X_i - X_{i'}) + \Delta_{(ii')(jj')kt}, \end{aligned}$$

where $i \neq i'$, $j \neq j'$, $\Delta_{(ii')(jj')kt} = (\ln \delta_{ikt} - \ln \delta_{i'kt}) (D_{ij} - D_{ij'} - D_{i'j} + D_{i'j'})$. The traces of structural mobility ($\lambda_{2(jj')kt}$) disappear from the difference-in-differences that make up the log-odds ratio calculation.

Second, the regression-based approach is flexible enough to allow us to model general patterns that pertain to both times and places and see departures from those patterns. Long and Ferrie are limited to pairwise comparisons varying time but not place or place but not time. We will exploit this flexibility in our analysis below.

Third, the regression-based approach allows us to consider the relative socioeconomic distances among occupations and model the expectation that moves between similar occupations will be more common than between dissimilar ones. Mobility between unskilled manual and upper nonmanual occupations will presumably be far less frequent than mobility between unskilled and skilled manual occupations or between upper and lower nonmanual occupations. The scores that are so prominent in equations (1) and (2) capture this feature, but it is hidden amid the melange of factors that contribute altogether to their index of exchange mobility ($d(P, Q)$).

Fourth, our maximum likelihood estimates appropriately weight the strength of the evidence in deriving the two kinds of exchange mobility parameters—the θ s and δ s; $d(P, Q)$ gives equal weight to log-odds ratios based on many and few cases, giving random fluctuations substantial leverage over the estimate of the key quantity of interest.

Fifth, multinomial regression models like equation (2) readily lend themselves to expansion as observations of other factors—gender, race, region, education—become available; it is not clear how to expand Long and Ferrie’s analysis beyond pairwise comparisons.

Finally, the regression-based approach is familiar. Readers and users do not need to recast how they think about the data. The effects of growth and redistribution between generations show up in the intercepts of the regression-like model; the inequalities among sons from different backgrounds show up as the slopes of the multinomial logit regressions (scaled by the differences between scores for pairs of occupational categories so that the slope is steepest for the most different occupations).

All the data we use come from tabulations originally made by Long and Ferrie reflecting the mobility of samples of young men matched to their fathers roughly 20 years earlier. Online Appendix Table A3-1 in Long and Ferrie (2013) contains information about young men’s current occupations and the sons’ retrospective reports of their fathers’ occupations. The US data were collected in 1973 and asked about the father’s occupation “when you were about 16 years old” (Featherman and Hauser 1978, p. 502); the British data were collected in 1972 and asked about the father’s occupation when the son was 14 years old (Goldthorpe 1980). Online Appendix Table A3-2 in Long and Ferrie (2013) contained US data from the 1860 and 1880 censuses that matched men who were in their thirties in the 1880 census with their fathers in the 1860 census. The fourth table, from the British censuses of 1861 and 1881, makes similar matches of sons from the 1881 census to their fathers in the 1861 census; not in their article, this table was kindly supplied to us by Long and Ferrie. We refer to them by the country and the date the son’s occupation was measured (1880 and 1973 for the United States, 1881 and 1972 for Britain). There are several other tables in their paper, but these four suffice for our purposes.

We associate the occupational categories with the following index numbers (i and j): 1 – farmer, 2 – unskilled manual, 3 – skilled manual, 4 – clerical and sales, and 5 – professional and managerial (see Long and Ferrie for discussion of how they constructed the occupational categories).

We identify the λ s by taking the ones that refer to unskilled manual occupations as our baseline, i.e., $\ln \lambda_{12kt} = \ln \lambda_{22kt} = 0$ for all combinations (k, t). Similarly, $X_2 = 0$. We also apply the constraint $X_5 = 1$ to identify the other scores $X_1, X_3,$ and X_4 . We expect the order $\hat{X}_1 \leq \hat{X}_2 \leq \hat{X}_4$ but do not constrain the estimation algorithm to yield that result.

II. Comparisons without Models

We begin with scatterplots of the observed logits for son’s current occupation, $\ln(f_{ij}/f_{ij'})$ (where i refers to father’s occupation, j refers to son’s occupation, and j' refers to the baseline category of son’s occupation, i.e., unskilled manual occupations

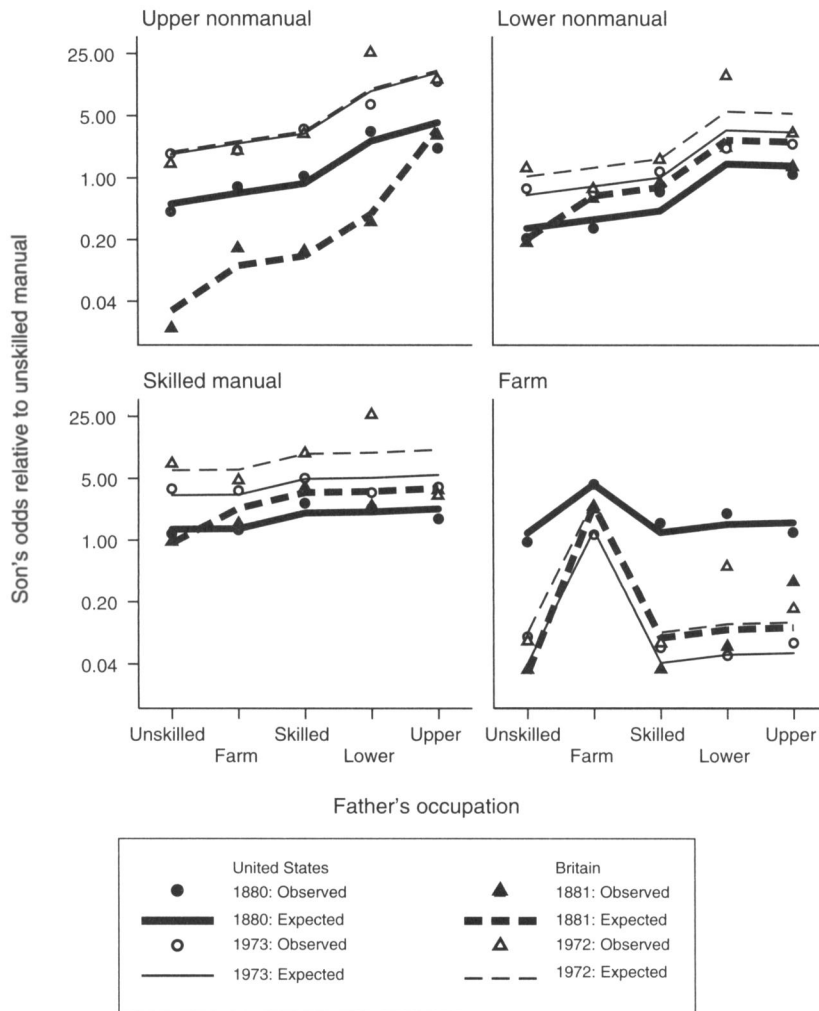


FIGURE 1. OBSERVED AND EXPECTED ODDS FOR SON'S OCCUPATIONS WITH A BASELINE OF UNSKILLED MANUAL OCCUPATIONS BY FATHER'S OCCUPATION, NATION, AND YEAR

Notes: Odds shown on log scale. Expected odds refer to the preferred model (see Table 1).

$j = 2$), arrayed on the y-axis and the categories of father's occupation on the x-axis. Unskilled manual occupations provide an unambiguously low-status category for reference and in that way yield logits that are easier to interpret than others might be. The panels of Figure 1 vary the son's occupation being compared to that baseline. We note that some of the odds are based on few cases and, consequentially, quite imprecisely measured.¹ The figure also displays lines connecting odds expected

¹ Although the aggregated size of the four samples is almost 8,200, many cells of the mobility tables have fewer than ten cases in them. Given the strong association between father's and son's occupation, it would take a much larger overall sample to reduce sampling error in the smallest cells sufficiently to estimate these logits precisely. The prevalence of small counts in some cells thus poses some problems in interpreting the observed odds in Figure 1. For example, the three most discrepant points in the figure refer to British men of lower nonmanual origin in 1972. There are only two of those men who were working in unskilled manual occupations in 1972; thus the

under our preferred model for the data; this model is explained in the next section. We include its expected odds in this figure to save the space a second figure would require. It is an added benefit that the lines help guide the reader's eye through the swarms of observed data points.

The order of father's occupational categories along the x-axis of each panel in Figure 1 follows the socioeconomic status of nonfarm occupations (Treiman 1977; Hauser and Warren 1997). People tend to see farm occupations as good or excellent jobs to have, but farmers average lower income and education than unskilled manual workers, so their position, especially relative to unskilled manual occupations, is more ambiguous than that of the nonfarm occupations. In the nineteenth century American farmers were central to the economy and very heterogeneous. The devastation of Southern farms during the Civil War further complicates the task of figuring out their socioeconomic position. Ultimately the data will decide the order among farm, skilled manual, and lower nonmanual occupations, relative to the anchoring assumptions $X_2 = 0$ and $X_5 = 1$. For now we merely follow convention and rank farmers between skilled and unskilled manual workers.

The four combinations of nation and time period are distinguished with symbols and line styles inside each panel. The legend explains our scheme. We discuss exchange mobility—the father-son slopes—for the manual and nonmanual occupations first, then we discuss farming, then structural mobility, and, finally, occupational persistence.

Sons' odds on achieving jobs in the top category—upper nonmanual—generally increase as the status of nonfarm fathers' occupations increased (see top left panel of Figure 1). The two exceptions to the general pattern are based on few cases and fall within the confidence interval of the line showing expected odds that rises monotonically with father's status. The patterns for both American samples and the British 1972 sample are quite similar in the clear correlation they show between father's status and the odds a son will achieve a top position. Even clearer is the greater intergenerational correlation in the British 1881 sample; the odds on an upper nonmanual occupation were one-in-30 (0.034) for the sons of unskilled fathers in Britain 1881 and almost 100 times greater (3.00) for the sons of upper manual fathers that year.

The odds on lower nonmanual and skilled manual occupations also rose with rising father's status in each country and time period (upper right and lower left panels of Figure 1). The pattern is clearer for the somewhat higher status lower nonmanual occupations than for the skilled manual ones.

Turning to the odds of farmers' sons achieving nonfarm occupations, we see a sharp contrast between the nineteenth and twentieth centuries but not much difference between the United States and Britain. In the early 1970s, farmers' sons had nonfarm occupational destinations that closely resembled those of unskilled workers' sons. Around 1880, farmers' sons had nonfarm occupational destinations that closely resembled those of skilled workers' sons.

Very few sons entered farming unless their fathers worked on a farm, except in the United States in 1880 (lower right panel of Figure 1). The odds of a farm occupation relative to an unskilled manual one for men whose fathers were not farmers were

denominator for all three odds is 2; had there been three instead, the odds would all be much more nearly in line with expectation.

between one-in-20 and one-in-five for British men in both years and American men in 1973. For American men in 1880, the odds were much higher—slightly above one-to-one. In neither country and neither century did father's status correlate much with farm outcomes for men who had nonfarm origins.

Farm persistence was the single strongest aspect of the father-to-son correlation in all four tables. The odds of a son being a farmer were 2.5-to-one in Britain in both time periods, compared to 0.05 or 0.10 for nonfarm origin British men. For American men in 1973 the difference was between one-to-one odds for farmers' sons and 0.10 for other men's sons. This aspect of the father-to-son correlation was substantially weaker for American men in 1880. The odds on going into farming instead of lower manual occupations were five-to-one for nineteenth-century American farmers' sons and 1.1-to-one for other men's sons. Guest, Landale, and McCann (1989) argued that the odds of entering farming were relatively high for nineteenth-century American men because farms were close to cities and towns. Preserving meat, dairy products, fruits, and vegetables was difficult; they had to be produced near population centers. Thus, it seems proximity to urban centers, not inexpensive land on the remote frontier, made switching in and out of farming relatively easy. Long and Ferrie make reference to Turner's famous "frontier hypothesis" that stated that American opportunity derived from the inexpensive land in the West. Guest (2005) presented strong evidence against that thesis, showing, among other evidence, that structural mobility was higher in New England than west of the Mississippi over the period 1880–1900; exchange mobility differed little across regions.

It is a puzzle why technological limits did not facilitate mobility on and off farms in Britain, too. Britain had no unsettled frontier land, and British law governing land tenure was different. This largest difference between the American and British data remains a puzzle for future research.

In the modeling exercise below we will reduce all this complexity to a general regression pattern that applies to all combinations of time and place plus three differences. Those three differences are: (i) British men from upper nonmanual origins were significantly more likely to follow their fathers into the top occupations in 1881 than in 1972 and than American men from top origins in 1880 and 1973. (ii) British men from unskilled manual origins were significantly more likely to follow their fathers into an unskilled occupation in 1881 than in 1972 and than American men from unskilled origins in 1880 and 1973. (iii) American men from nonfarm origins were significantly more likely to enter farming in 1880 than in 1973 and more likely to do that than British men from nonfarm origins in either 1881 or 1972.

The exchange mobility reflected in the father-son slopes are only part of the total mobility picture. Structural mobility, indicated by the magnitudes of the odds in Figure 1, is at least as important for the prevalence of mobility. In the early 1970s men in both the United States and Britain were more likely to work in upper nonmanual occupations than in unskilled manual occupations, regardless of their father's occupation (as indicated by odds greater than 1.0 for all five categories of father's occupation). The odds increased as father's status increased, as we said above, but the economic growth and occupational redistribution of the 1950–1974 period strongly favored upward mobility in both countries. Structural mobility also

favored skilled over unskilled manual occupations, even in the 1880s; all men's odds of skilled versus unskilled manual work were greater than 1.0. The complement, except in the United States in 1880, was farming. The odds of working in farming were closer to 0.1 than 1.0 in Britain in both time periods and in the United States in 1973. Given the low status of unskilled manual work and the low pay and education of farmers, this redistribution from unskilled manual work and farming to nonmanual employment, especially in the professional and managerial occupations of the upper nonmanual stratum, was a significant spur to upward mobility in the third quarter of the twentieth century.

Long and Ferrie conclude that mobility in the United States in 1880 was the distinctive mobility pattern among these four cases, characterized by low relative inequality in comparison to Britain in 1881 and to the United States in 1973. By implication, they seem to suggest that it also had low relative inequality compared to Britain in the 1970s as well. However, aside from the relative prevalence of farming (an aspect of structural mobility, outside the purview of their measure) and weaker farm inheritance than in the other datasets, Figure 1 indicates that the United States did not have a very distinctive system of occupational inequality in 1880. For non-farm occupations, exchange mobility in 1880 America was about what it was in both Britain and America in the early 1970s. American men did have uncommonly easy access to farming in the nineteenth century, but it is not clear if that was an advantage or disadvantage. The quality of land available and the opportunity that farming it presented was more highly variable then than now. For some families farming was a path to opportunity and independence; for others it was synonymous with rural poverty and subsistence (Fischer 2010). For African Americans, farming was more often tenancy and sharecropping than independence. All we can say from these data is that the boundary between farming and the rest of the labor market was more fluid in nineteenth-century America than it was then in Britain or than it became by the 1970s.

Part of the case Long and Ferrie make for thinking of the 1880 American data as distinct is the pairwise comparison of 1880 American and 1881 British odds ratios. In the context of all four mobility tables, though, it becomes clear that it is the father-son slopes in the 1881 British sample that stand out more. The father-son slopes appear steeper for them in all four panels, most clearly in the odds on an upper nonmanual son's occupation. In the analysis below, it turns out that two distinctions capture the differences; British men from the top and bottom occupations persisted in their father's position in 1881 more than British men from those origins in 1972 or than American men from those origins in either 1880 or 1973.

We now turn to statistical models to parameterize and test these ideas.

III. Models of Exchange Mobility

The modeling strategy for mobility tables first appeared as a kind of analysis of variance for counts (Goodman 1968). Thus the convention developed that modeling starts with independence and proceeds from simple to complex as association terms of interest are added. We follow that convention here even though we could, in fact, proceed directly from our exploratory analysis of Figure 1 to what we eventually label Model 3d.

TABLE 1—ASSOCIATION MODELS DEFINED AS CONSTRAINTS ON θ AND δ PARAMETERS IN EQUATION 1

Model	Name	Constraints on:	
		$\ln \theta_{ijk_t}$	$\ln \delta_{ikt}$
M0	Perfect mobility	0	0
M1	Constant association	$\ln \theta^*$	$\ln \delta_i^*$
M2a	US 1880 farm persistence	$\ln \theta^*$	$\ln \delta_i^*$ if $i \neq 5$ $\delta_{512} = \delta_{521} = \delta_{522}$
M2b	British 1881 unskilled persistence	$\ln \theta^*$	$\ln \delta_i^*$ if $i \neq 4$ $\delta_{411} = \delta_{412} = \delta_{422}$
M2c	British 1881 upper persistence	$\ln \theta^*$	$\ln \delta_i^*$ if $i \neq 1$ $\delta_{111} = \delta_{112} = \delta_{122}$
M2d	All three persistence terms	$\ln \theta^*$	$\ln \delta_i^*$ if $i = 2$ or 3 $\delta_{111} = \delta_{112} = \delta_{122}$ $\delta_{411} = \delta_{412} = \delta_{422}$ $\delta_{512} = \delta_{521} = \delta_{522}$
M3	Uniform differences	$\psi_{ij} \phi_{kt}$	not in the model

Notes: See text for equation 1 and definitions of parameters θ_{kt} and δ_{ikt} . Unless otherwise noted, constraints on $\ln \theta_{ijk_t}$ apply for all (i, j, k, t) ; constraints on $\ln \delta_{ikt}$ apply for all (i, k, t) .

Table 1 shows seven models that we fit to the four mobility tables treated as a four-way classification of father's occupation by son's occupation by country by time. We fit a null model, a model of constant association, four models that contain specific changes suggested by examining Figure 1, and a model that represents our attempt to translate Long and Ferrie's approach into a model of this type. Model M0 is conditional independence, obtained by constraining all $\ln \theta_{kt}$ and $\ln \delta_{ikt}$ terms to zero; in this context it is known as "perfect mobility" because, hypothetically under this model, a son's occupation is uncorrelated with his father's occupation. Model M1 adds the association parameters but constrains them $\ln \theta_{kt} = \ln \theta^*$ and $\ln \delta_{ikt} = \ln \delta_i^*$ so they do not vary by country or time (k, t) ; M1 is called "constant association" because of those constraints. Models M2a-M2c separately add each of the three country- and time-specific terms that our exploratory analysis of Figure 1 suggested: below-average persistence in farming among American men in 1880 and above-average persistence in unskilled manual and upper nonmanual occupations among British men in 1881. Model 2d adds all three of these terms at once. Model 3 is our attempt to translate Long and Ferrie's approach into a model we could compare with the others. We discuss it after discussing the results of fitting models M0-M2d.

To guard against simultaneous inference bias and overfitting, we use a combination of classical and Bayesian methods to compare models (Goodman 1969; Raftery 1995). The key statistics for the classical approach are the likelihood ratio chi-square (L_m^2) and Pearson chi-square (X_m^2) for each model m . For the Bayesian comparisons we use Raftery's approximation, $Bic_m = L_m^2 - df_m \ln N$, where df_m is the degrees of freedom under model m and N is sample size. In this context Bic is the -2 times the difference between the log of the posterior probability of model m and the log of the posterior probability of the "saturated" model that reproduces all the counts exactly. The preferred model by this criterion is the one with the Bic furthest below

TABLE 2—GOODNESS-OF-FIT STATISTICS FOR ASSOCIATION MODELS DEFINED IN TABLE 1 APPLIED TO MOBILITY DATA FOR MEN IN THE UNITED STATES AND BRITAIN CIRCA 1880 AND CIRCA 1970 ($N = 8,197$)

m	Model name	L^2	X^2	df	Bic	Δ
M0	Perfect mobility	1,459.3	1,968.8	64	882.6	15.7
M1	Constant association	247.0	254.2	55	-248.6	5.5
M2a	US 1880 farm persistence	137.4	141.0	54	-349.2	4.1
M2b	British 1881 unskilled persistence	212.5	216.5	54	-274.1	4.7
M2c	British 1881 upper persistence	233.7	234.4	54	-252.9	5.5
M2d	All three persistence terms	96.7	95.2	52	-371.9	3.3
M3	Uniform differences	76.4	75.8	45	-331.0	2.9

Notes: L^2 is the likelihood-ratio chi-square statistic; X^2 is the Pearson chi-square statistic; df is the degrees of freedom under the model, Bic is the Bayesian information coefficient, and Δ is the index of dissimilarity between observed and predicted counts. See Table 1 for definitions of the models.

zero; if none are below zero, then the saturated model is preferred. The percentage of all observations that are misclassified by each model— $\Delta = \frac{1}{2} \sum_{i,j} |f_{ij} - F_{ij}|/N$ —is also of some interest as a descriptive fit metric. All of these calculations for each model are shown in Table 2.

The test statistics for the “perfect mobility” model lead us to reject it and move on to more interesting models of how fathers’ and sons’ occupations are correlated. Researchers often view the L_0^2 value for this model to be a useful metric for the association to be explained by the analysis. By that metric, we could say that model m “explains” $100 \times (1 - L_m^2/L_0^2)$ percent of the baseline association (Hout 1983).

The constant association model (M1) captures the general pattern of association between father’s and son’s occupations in the four mobility tables. These four tables turn out to have very much in common; 83 percent ($1 - L_1^2/L_0^2$) of the total association stems from the common pattern captured by constant θ s and δ s. Using seven more parameters to account for all 16 degrees of freedom in the common pattern—what is called a “full-interaction” model—reduces L^2 further to 214.5, implying that the common association is 85 percent of the total.² The literature contains dozens of results of this sort; most of the association in market economies, at least, is very similar across space and time (Featherman, Jones, and Hauser 1975; Erikson and Goldthorpe 1992; Hout and DiPrete 2006).

The rest of our modeling effort is directed toward finding the country and time period differences that account for the 17 percent of the association that is not captured by the main parameters. Our exploratory analysis of Figure 1 led us to hypothesize three deviations from constant association: (i) more nonfarm to farm mobility (i.e., less farm persistence) in the United States in 1880, (ii) more upper nonmanual persistence in Britain in 1881, and (iii) more unskilled manual persistence in Britain in 1881.³

The next four rows in Table 2 (Models 2a, 2b, 2c, and 2d) show the consequences of adding the hypothesized persistence terms one at a time and all together. The

²The “full-interaction” version of the common mobility model is: $F_{ijk} = \mu \lambda_{1ik} \lambda_{2jk} \theta_{ij}$. We make no further use of this model because, although the improvement of fit is statistically significant by classical criteria (a χ^2 test of 32.5 with 7 degrees of freedom is significant at the 0.05 level), the Bic value of -218 for this model is not competitive with the alternatives in Table 2.

³The third one is harder to see in Figure 1 but quite clear when we shift the baseline to skilled manual occupations (not shown).

combined effect is dramatic; L^2 reduced from 247.0 for Model 1 to 96.7 for Model 2d with the expenditure of only three degrees of freedom. The *Bic* statistic declines impressively from -248.6 to -371.9 . Together these classical and Bayesian statistics lead us to prefer M2d over the others in Tables 1 and 2.

Our regression-based approach accommodates a more fine-grained analysis of the four mobility tables than is possible with the simple summary measures of overall difference that Long and Ferrie use. It is also possible to approximate the model implicit in their approach by using model M3 mentioned above, known as the model of “uniform differences” (Xie 1992; Erikson and Goldthorpe 1992):

$$(4) \quad \ln \theta_{ijkt} = \psi_{ij} \phi_{kt},$$

where the log-odds ratio for father’s occupation i and son’s occupation j relative to the baseline occupational category ($i' = j' = 2$ in this analysis) in country k and time t is the product of a common log-odds ratio $\ln \theta_{ij}^*$ for each country-time combination and coefficient that varies by country and time but not occupation (ϕ_{kt}) for $i = 1, 3, 4, 5, j = 1, 3, 4, 5, k = 1, 2$, and $t = 1, 2$.⁴ This model captures the essence of Long and Ferrie’s reliance on $d(P, Q)$ and similar summary measures that average over all the odds ratios in a mobility table by (i) placing no restrictions on the pattern of odds ratios across rows and columns, while (ii) reducing between-table comparisons to a single number. From Long and Ferrie’s discussion of cross-national differences and changes in them, we infer that $\phi_{11} < \phi_{12}$ and $\phi_{12} \approx \phi_{22}$ would be an outcome consistent with their thinking about their results. Fitting the uniform differences model (M3) subject to an identifying constraint on equation (4) of $\phi_{12} = 1$ (which makes the American pattern in 1973 the basis for comparison), we obtain $\hat{\phi}_{11} = 0.59$, $\hat{\phi}_{21} = 1.70$, and $\hat{\phi}_{22} = 1.37$. The estimated $\hat{\phi}_{11} = 0.59$ is consistent with the $d(P, Q)$ results and, thus, equivalent to Long and Ferrie’s focus on the openness of 1880 America—the association between father’s and son’s occupation was only 59 percent as strong in 1880 as in 1973. The other two $\hat{\phi}$ s point to differences that we have focused on but do not feature as prominently in their discussion. In short, uniform differences captures the main feature of their concept—summarizing differences between tables in a single contrast—and substance—the 1880 American data stand out.

Having found a statistical model that is consistent with their view of these data, we can make a formal comparison between uniform differences (M3) and our preferred model (M2d). M3 has a smaller residual than M2d, that is, $L_3^2 < L_{2d}^2$, but that is achieved by fitting seven more parameters. *Bic* assesses the strength of the models relative to the degrees of freedom used. As an approximation of the log of the odds of a saturated model (one with no degrees of freedom that perfectly reproduces every count in every table) to the model in question (m), *Bic* returns large negative numbers for strong models; as $Bic_{2d} < Bic_3$ the evidence for choosing M2d over M3 is very strong.⁵

⁴The full model is: $F_{ijkt} = \mu \lambda_{1ikt} \lambda_{2jkt} \exp(\psi_{ij} \phi_{kt})$.

⁵Raftery (1995) proposed these rules of thumb for characterizing the evidence for one model over another based on the difference between *Bics* for two models: rounding off to integer differences, a difference of between 0 and -2 is “weak” evidence, a difference of between -2 and -6 is “positive” evidence, a difference of between -6 and -10

TABLE 3—MAXIMUM LIKELIHOOD ESTIMATES OF SELECT PARAMETERS FROM MODEL M2D

Occupation	Score	Diagonal	Diagonal interactions	
			United States 1880	Britain 1881
Upper nonmanual	1.000 —	0.240 (0.323)	—	1.728 (0.448)
Lower nonmanual	0.879 —	0.260 (0.243)	—	—
Skilled manual	0.324 —	0.327 (0.066)	—	—
Unskilled manual	0.000 —	−0.110 (0.162)	—	0.895 (0.170)
Farm	0.195 —	3.495 (0.216)	−2.186 (0.232)	
<i>Overall</i> $\hat{\theta}$	1.979			

Note: Standard errors in parentheses; scores do not have standard errors.

Our preferred model (M2d) contains several parameters of interest; we report them in Table 3. The identifying restriction we use for M2d constrains the scores for the top and presumed bottom of the occupational hierarchy to be 1 and 0, respectively, and estimates scores for the other three categories relative to those anchors.⁶ The scores rank the nonfarm occupations in the expected order with lower nonmanual and skilled manual between the top and bottom and in the right order relative to each other. Given the prominence of terms like “middle class” and “working class” as well as “white collar” and “blue collar” jobs in popular discussions, it is interesting to note that the largest distance between adjacent scores is the differences between the score of 0.879 for lower nonmanual occupations and 0.324 for skilled manual occupations; that is, the difference between the lower nonmanual occupation’s score and the higher manual occupation’s score is greater than the difference between upper and lower nonmanual occupations’ scores and between skilled and unskilled manual occupations’ scores. In short, these scores make substantive sense.

We were quite uncertain where farming would score before fitting the model; it turns out to be between the skilled and unskilled manual workers. With δ_1 in the model, this score is mainly supported by the destinations of men who do not follow their fathers into farming. The result $\hat{X}_1 = 0.195$ implies that farmers’ sons’ nonfarm destinations are slightly better than the destinations of unskilled workers’ sons and not quite as good as the destinations of skilled workers’ sons.

Persistence in skilled manual occupations is an important part of the intergenerational correlation in both countries and both centuries, as indicated by the significant

is “strong” evidence, and a difference of beyond -10 is “very strong” evidence in favor of the preferred model. In our case, the difference of -41 qualifies as “very strong.”

⁶Because we use an algorithm that fits the scores, then fixes them to estimate the coefficients, and iterates between scores and coefficients until convergence (Goodman 1979), we do not have standard errors for the \hat{X} s or for $\hat{\theta}$.

estimate $\hat{\delta}_3 = 0.327$. Persistence in upper nonmanual and unskilled manual occupations was significant in Britain in 1881. Otherwise persistence in nonfarm occupations does not exceed that implied by the scores for nonfarm occupations. Persistence in farming was very substantial, net of structural mobility, and, commensurate with that observation, the barrier nonfarm men faced was huge in three of four cases. In the United States in 1880, persistence in farm was much lower (but still present), and men from nonfarm origins faced a lower barrier ($\hat{\delta}_{511} = 3.495 - 2.186 = 1.309$).

In summary, the tests of the various models in Table 1 show that the two 1970s samples show no noteworthy difference in relative inequality, a pattern that has been validated generally over a broader range of age groups by other studies (Kerckhoff, Campbell, and Winfield-Laird 1985; Erikson and Goldthorpe 1992). Goodman and Hout's (1998) more exacting tests revealed some differences that we cannot discern here. We cannot say without further analysis whether mobility patterns in Britain and the United States in the 1970s differed at higher ages (in the Goodman and Hout analysis but absent here) or from the larger counts (and therefore greater statistical power) in the tables they analyzed.

The nineteenth-century samples provide new data and the most interesting results. The British 1881 sample had unusually high persistence in the top and bottom occupational categories. The US 1880 sample had unusually high flow of men from nonfarm origins into farming. These telling differences—captured parsimoniously in our models by a single parameter each—are the sum total of the differences in exchange mobility among the four cases. The constraints faced by mobile sons were remarkably similar across the four samples.

The picture of change and cross-national difference in mobility patterns that emerges from our reanalysis differs from Long and Ferrie's in substance, specificity, and parsimony. Our approach—crafting a multinomial logistic regression model that derived scores for the occupational categories from the observed mobility patterns—allows us to be more specific about the cleavages that result in a correlation between father's and son's occupations than broad summary measures allow researchers to be. Our modeling strategy identifies several cleavages that extend and alter the inferences Long and Ferrie draw.

Our methods have all the standard benefits of regression techniques. Because we pool all the observations in one dataset, we have an overall sample that is large enough to separate underlying patterns from sampling variation. We think our results come closer to correctly ranking inequality of opportunity in these four tables than their measures do. We retain some uncertainty, of course, as the debate turns on three-way interaction effects—differences in differences of log-odds—that may require more than 8,197 cases to estimate precisely. But the available evidence strongly favors our pointed differences over a model of global differences (equation (4)).

Several of the odds ratios at the foundation of Long and Ferrie's calculations are based on few cases and sample-by-sample comparisons. Cells with few cases—five of the 100 cells have exactly one person in them and 20 cells have six or fewer cases—contribute substantial uncertainty to many of the odds ratios that sum to $d(P, Q)$ and similar measures. These small cells have far less leverage in the multinomial regression analysis we use, and the estimates that depend heavily on small counts have proportionately higher standard errors, reflecting the relative uncertainty of different estimates.

IV. Total and Structural Mobility

Mobility is more than lack of correlation between father's and son's occupations. The variation in upward mobility reflects the variation in structural mobility—the sum of factors that differentiate the distribution of father's and son's occupations—across samples. Economic growth is obviously key, although other factors such as differential fertility and child survivorship by occupation can also contribute.

For a variety of reasons, most academic studies of social mobility, including Long and Ferrie's analysis, have emphasized exchange mobility and ignored or given less attention to structural mobility. Perhaps this is a reflection of the more complex (and perhaps more interesting) techniques that must be used to analyze exchange versus structural mobility. Suffice it to say that the actual experience of social mobility reflects both structural and exchange mobility. We are not saying that exchange mobility estimates are biased—if they are based on odds ratios, they are not biased—just incomplete. A full accounting of substantive difference among times and places needs to acknowledge the presence and importance of structural mobility.

In regard to structural mobility, the patterns in these data are quite clear and robust to different statistical techniques. Upward mobility exceeds downward mobility in all four cases.⁷ Relative mobility is symmetrical (Sobel, Hout, and Duncan 1985). More workers move up than down when economic conditions improve the odds on employment in a better occupation independent of origins. American men were far more upwardly mobile in the 1970s than in 1880 and than British men in either 1881 or 1972. British men in the 1970s were more upwardly mobile than the men in either country in the 1880s.

Upward mobility was generally high across in each place and time as a consequence of the expansion of professional and managerial employment and the corresponding decline of farming and unskilled work. Changes in the occupational structure from generation to generation were present in the nineteenth century but accelerated in the twentieth century. The changes were especially dramatic in the third quarter of the twentieth century in the United States as the postindustrial postwar economy emerged. At the risk of overgeneralizing, we believe these results are consistent with two major epochs of economic growth in the United States. The post-Civil War period involved the transition from an agricultural to a manufacturing economy, where many new skilled manual jobs were being created. There was also an important growth in nonmanual work, but especially in its bureaucratic aspects such as clerical and sales positions. The twentieth century continued some of these trends but especially saw the creation of managerial, medical, legal, and research jobs requiring advanced levels of educational training at the same time that machines reduced the demand for unskilled labor (e.g., Fischer and Hout 2006; Goldin and Katz 2008).

To quantify upward and downward mobility we must rank occupational categories. Many rankings are reasonable, but one straightforward approach would be to follow the ranking suggested by the scores estimated under model 2d. Those scores identify a relatively larger gap between nonmanual and other occupations and place

⁷This inference can rest on the estimated scores from our model or from efforts to score the desirability, goodness, and prestige of occupations in the nineteenth and twentieth centuries (Treiman 1977; Hauser 1982).

TABLE 4—UPWARD AND DOWNWARD MOBILITY RATES, CLASSIFIED AS FAR OR NEAR, BY COUNTRY AND TIME PERIOD (percent)

Direction	Distance	1880–1881		1972–1973	
		Britain	United States	Britain	United States
Upward	Far	12	15	23	28
	Near	16	16	15	19
Immobile		53	48	48	37
Downward	Near	10	16	6	8
	Far	9	5	7	8
Total		100	100	100	100
Observations		1,455	2,632	1,123	2,987

Note: Percentages rounded independently so sums might differ slightly from 100.

upper and lower nonmanual occupations, on the one hand, and the manual and farming occupations, on the other hand, relatively closer together. With that information in hand, we define five mobility categories: (i) Upward, far is mobility from a manual or farm origin to a nonmanual destination, (ii) Upward, near is mobility from unskilled to farming or skilled, from farming to skilled, or from lower to upper nonmanual, (iii) Immobile is being in the same occupational category as father, (iv) Downward, near is mobility from farm or skilled to unskilled, from skilled to farm, or from upper to lower nonmanual, and (v) Downward, far is mobility from a nonmanual origin to a manual or farm destination.

Britain in 1881 was most unequal, exhibiting the least upward mobility, most immobility, and second most downward mobility among the four cases. This is hardly surprising given its lowest rank in exchange mobility. But exchange mobility is not definitive, as we see when looking to the United States at that time. Highest in exchange mobility (thanks to the relatively weak barrier to entering farming), the United States in 1880 nonetheless had the second-lowest upward mobility and highest downward mobility among the four place-time combinations. Britain in 1972 had more upward mobility than the United States had in 1880, and the United States in 1973 had by far the most structural mobility because of the combined decline of farming and expansion of upper nonmanual opportunities. Britain and the United States had virtually identical exchange mobility in the 1970s, and both had expansion at the top, but the American workers had the quantitative advantage of greater growth in professional and managerial occupations.

More statistically sophisticated methods of estimating structural mobility are available. Sobel, Hout, and Duncan (1985) advocate an approach that is akin to focusing on the intercepts in the logit regressions that correspond to equation (2). Applying their approach and graphing the results (Figure 2) we see very quickly the large quantitative differences in structural mobility over time and place. The standard deviation of the logarithms of the structural mobility multipliers, marked as “SD” in the figure, is a useful summary measure for each table. The SD values range from 0.64 for 1881 Britain to 1.61 for 1973 United States. Farming was already a rare occupation among British fathers around 1860. American workers in the 1880s

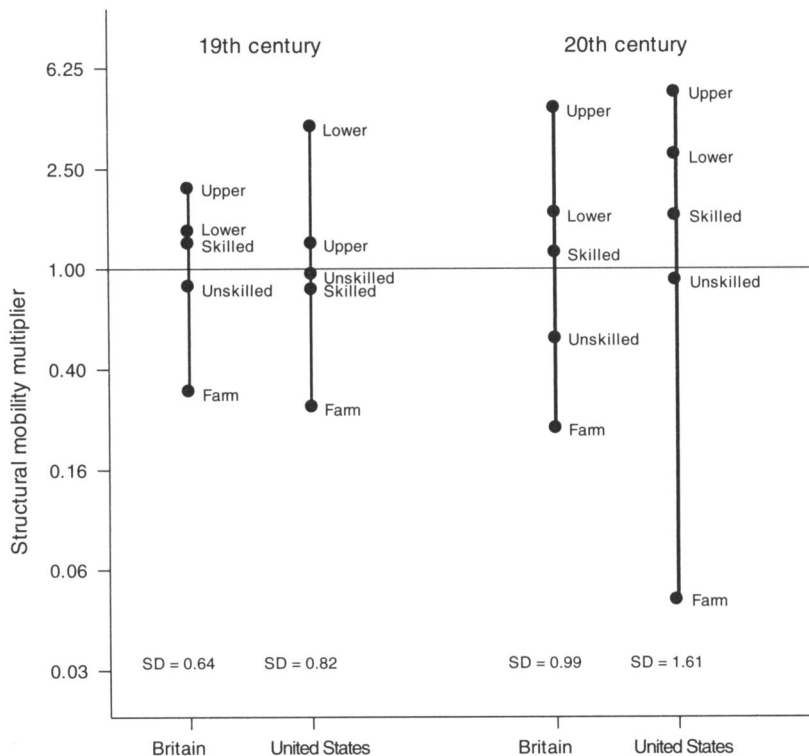


FIGURE 2. STRUCTURAL MOBILITY MULTIPLIERS FROM MODEL 2D, BY COUNTRY AND TIME PERIOD

Notes: Multipliers shown on log scale. Occupational categories are “upper” = upper nonmanual, “lower” = lower nonmanual, “skilled” = skilled manual, “unskilled” = unskilled manual, and “farm” = farm.

got a stronger push from structural mobility than their British counterparts; lower nonmanual employment got the strongest push (in the other three cases the top category had the strongest positive structural mobility). In both countries the twentieth-century emergence of postindustrial managerial and professional employment soared, redistributing men of all origins upward in the occupational structure during the 1970s. The decline of farming contributed to the exceptional structural mobility of the United States in 1973.

V. Conclusions

We clarify and highlight aspects of the data presented by Long and Ferrie by taking a more conventional approach to modeling the data. We specify a multinomial regression model for young men’s occupations as a log-linear function of their fathers’ occupations. In doing so we parse total mobility into exchange mobility (reflected in the slopes of the regression model) and structural mobility (reflected in the intercepts of the regressions). Long and Ferrie’s approach attends to exchange mobility in a gross way and hides structural mobility patterns completely. Our regression

approach reveals that differences in exchange mobility among places and times can be summarized in three very specific differences. In the 1880s American farms were far more open to men from nonfarm backgrounds than American farms were in the twentieth century or British farms in either time period; British men from the highest and lowest status origins were far more likely to follow their fathers into those top and bottom positions in the 1880s, making exchange mobility in late nineteenth-century Britain distinctly unequal. Structural mobility in twentieth-century America raised more men above their origins than either structural mobility or exchange mobility allowed in late nineteenth-century America or Britain in either century.

We owe a great debt to Long and Ferrie for collecting this impressive and valuable nineteenth-century data and hope to see further analysis of occupational and labor force outcomes for these men. A first expansion, in our opinion, should be coverage beyond the early career mobility discussed here. The status of a first job was quite formative and influential in the twentieth century (Featherman and Hauser 1978; Goldthorpe 1980), but nineteenth-century American and British capitalism was far less orderly and organized. The similarities we see for young men may or may not generalize to their older contemporaries.

To date, most of the analyses of occupational mobility patterns have focused on differences across samples at one time period. Increasingly, historical datasets on related issues are becoming available, especially as manuscripts from older censuses become electronically transcribed. We await the exciting research opportunities new data provide.

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