sociological science

# The Effects of Social Mobility

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**Abstract:** The question of how social mobility affects outcomes, such as political preferences, well-being, and fertility, has long been of interest to sociologists. But finding answers to this question has been plagued by, on the one hand, the non-identifiability of "mobility effects" as they are usually conceived in this literature, and, on the other, the fact that these "effects" are, in reality, partial associations which may or may not represent causal relationships. We advance a different approach, drawing on a causal framework that sees the destination categories as treatments whose effects may be heterogeneous across origin categories. Our view is that most substantive hypotheses have in mind a hypothetical within-person comparison, rather than a between-person comparison. This approach is not subject to many of the problematic issues that have beset earlier attempts to formulate a model of mobility effects, and it places the study of such effects on a more reliably causal footing. We show how our approach relates to previous attempts to model mobility effects and explain how it differs both conceptually and empirically. We illustrate our approach using political preference data from the United Kingdom.

**Keywords:** mobility effects; social mobility; causality; redistributive preferences

**Replication Package:** A replication package for this article, called Mobility Effects, has been posted on OSF: https://osf.io/c34ta/.

WHAT are the consequences for individuals of being intergenerationally mobile? This is a perennial question in sociology and other social sciences, and studies have focused on a range of effects, including fertility, political preferences, and psychological well-being. Yet, an underlying problem has persisted: how should the effects of mobility be defined and estimated? Several approaches have been used in applied work, and we discuss the most important of these below, but none, in our view, is satisfactory. Accordingly, we develop an approach to the study of the effects of intergenerational mobility which draws on a causal framework that sees the destination categories as treatments whose effects may be heterogeneous across origin categories. We argue that this is appropriate because, whereas current approaches are based on between-person comparisons, most substantive hypotheses, such as Sorokin's dissociative hypothesis or the arguments for why social mobility should affect fertility or political preferences, are implicitly within-person comparisons: how mobility changes a person's outcome compared with what it would have been had they, hypothetically, remained in their origin class. Because of this reformulation our approach is not subject to many of the problematic issues that have beset earlier efforts to develop a model of mobility effects. We illustrate our approach using political preference data from the United Kingdom.

To avoid confusion in what follows, we make a distinction between two uses of the word "identification": statistical identification and the identification of effects in a causal model. The issue of statistical identification (*s-identification*) arises when,

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for a set of parameters of interest, the number of linearly independent quantities that can be derived from them is less than the number of parameters. Thus, the quantities that can be estimated depend on constraints on these parameters. Causal identification (*c-identification*) means that, given the data and a set of assumptions, it can be shown that an association between two variables arises because one is a cause of the other. This requires a careful definition of the causal effect in which one is interested. In the words, of Zang, Sobel and Luo (2023, p.7) 'we cannot start with a model and deem various coefficients effects, as in previous work.'

Social mobility effects refer to impacts on an outcome arising from movements between an origin state (e.g. social class) and a destination state. Our estimand is the effect of destination among those moving to that destination, conditional on their origin. We discuss conditions for identification of this effect and methods for estimating it, and how our effect estimate relates to the parameters of the traditional statistical approaches. Zang, Sobel and Luo (2023) discuss the same estimand though, to our knowledge, no previous studies have estimated it. [1]

In the next section of the article we briefly discuss the history of sociologists' interest in the consequences and effects of mobility and the problems of identifying mobility effects and how these are manifest in the commonly used approaches. We then introduce our causal approach and explain how it relates to previous ones. This is followed by estimations using data simulated from a structural model in which we incorporate both causal effects and selection into mobility, comparing three estimators. The next section is an application of our approach, compared with the conventional models, to estimating the impact of intergenerational occupational mobility on preferences concerning redistribution. For this we use data from the UK Household Longitudinal Study (*Understanding Society*). Our estimates suggest that upward mobility causes preferences more favourable to redistribution whereas downward mobility does the opposite. A short section concludes.

## Mobility Effects and Mobility Consequences

### Research on Mobility Effects

An interest in the consequences of social mobility goes back at least to the middle of the 19th century. This interest was motivated less by any direct concern for the individuals who experienced mobility and more by the consequences for society as a whole. In this article we distinguish between the *effects* of mobility at the individual or micro-level, and the *consequences* of mobility at the macro- or societal level. It was the latter that 19th century writers cared about. The best known of these was Marx, who argued that individual advance from the working class inhibited the development of that class as a collective actor. Upward social mobility changed people's interests and the macro-level consequence was the absence of class conflict. Marx and others took the US as the exemplar; unlike European societies with "a developed formation of classes", in the US, "the position of the wage labourer is for a very large share of the American people but a probational stage which they are sure to leave" (quoted in Goldthorpe 1980: 5).

The argument recurs among 20th century writers, with Sorokin (1959), among others, noting that social mobility undermines the revolutionary potential of the working class. Unlike Marx, however, he regarded this as a good thing, and later writers, especially in the US, agreed: social mobility was both necessary to legitimate liberal democratic societies and efficient in that it helped to avoid a wastage of talent. Nevertheless, many of the same authors paid attention to the micro-level, recognising that social mobility, upward as well as downward, could have negative effects on the individuals and families who experienced it.[2] Sorokin (1959) advanced the dissociative hypothesis that mobility, by removing individuals from their social origin, could have negative effects on well-being. Lenski (1954) believed that status inconsistency could derive from mobility and that this would impose psychological costs. Lipset and Bendix (1967) advanced similar ideas. But because these authors were mainly concerned with the societal level, they focused heavily on the societal consequences of these negative individual effects, in Lipset's (1963) case, for example, for the growth of extreme right-wing groups.

Much research, however, has addressed the individual effects of social mobility on a range of outcomes, with less concern for aggregate, societal consequences. Following Sorokin and Lenski, mobility's role in shaping well-being and other subjective states (such as life satisfaction), has been extensively tested (Ellis and Lane 1967; Houle 2011; Houle and Martin 2011; Daenekindt 2017; Hadjar and Samuel 2015; Marshall and Firth 1999; Tiikkajaet al. 2013; Chan 2018). Related to this are analyses of the effects of mobility on participation, for example in voluntary organizations (Vorwaller 1970; Mirande 1973). Other work addresses the effects of mobility on physical health and mortality (Blane, Harding and Rosato 2002) and on fertility (Kasarda and Billy 1985 is an early review; Sobel 1985; Dalla Zuanna 2007). Finally, a good deal of work has examined mobility effects on political attitudes and preferences (Breen 2001; Clifford and Heath 1993; De Graaf, Nieuwbeerta and Heath 1995; Weakleim 1992).[3]

## Conventional Approaches to Mobility 'Effects': The SAM and the DMM

Throughout, however, a problem has cast a shadow over studies of the individual effects of mobility. It dates back to Duncan's 1966 methodological paper on social mobility in which he argued that:

> one is not entitled to discuss "effects" of mobility ... until he has established that the apparent effect cannot be due merely to a simple combination of effects of the variables used to define mobility (Duncan 1966: 91)

Duncan adopted an analysis of variance (ANOVA) framework to study mobility effects and his approach later became known as the 'square additive model' or SAM. This can be written:

$$Y_{ijk} = \mu + \alpha_j + \beta_k + \gamma_{jk} + \varepsilon_{ijk} \quad (1)$$

**Table 1:** Square additive model with main and interaction effects (r=3).

| Origins↓/Destinations→ | Low | Middle | High |
|---|---|---|---|
| Low | $\mu+\alpha_L+\beta_L+\gamma_{LL}$ | $\mu+\alpha_L+\beta_M+\gamma_{LM}$ | $\mu+\alpha_L+\beta_H+\gamma_{LH}$ |
| Middle | $\mu+\alpha_M+\beta_L+\gamma_{ML}$ | $\mu+\alpha_M+\beta_M+\gamma_{MM}$ | $\mu+\alpha_M+\beta_H+\gamma_{MH}$ |
| High | $\mu+\alpha_H+\beta_L+\gamma_{HL}$ | $\mu+\alpha_H+\beta_M+\gamma_{HM}$ | $\mu+\alpha_H+\beta_H+\gamma_{HH}$ |

Where $i$ indexes individual observations, $j$ (=1,...,r) indexes origin and $k$ (=1,...,r) destination, $\mu$ is a 'reference mean' of the outcome measure $Y$, against which the effects can be measured, $\alpha_j$ is an origin effect on the outcome and $\beta_k$ is the destination effect; $\varepsilon_{ijk}$ is a residual error term and $\gamma_{jk}$ are interaction 'effects'. The main effects are statistically identified via constraints such as $\sum_{j=1}^{r}\alpha_j = 0$ , $\sum_{k=1}^{r}\beta_k = 0$ .[4] These constraints define the main origin and destination effects in terms of differences from the grand mean across all cells (to which $\mu$ refers in this case). Alternative constraints would be to set $\alpha_1 = \beta_1 = 0$; then the main effects would be defined relative to the mean of the cell for origin=1 and destination=1, to which $\mu$ would refer in this case. By the nature of the ANOVA framework, the SAM entails between-person comparisons.

Duncan analyzed British data on social mobility and fertility from Berent (1952) and concluded that "mobility produces no differences in fertility that cannot be fully accounted for by the additive mechanism implied by the model" (Duncan 1966: 93). In other words, the SAM without interaction parameters (the 'baseline SAM') fitted the data. The difficulties arise when this is not the case and interaction terms are included in the SAM to represent the effects of mobility over and above the main effects of origins and destinations.

The baseline SAM fits $1+2(r-1)$ parameters, leaving $1+r(r-2)$ degrees of freedom to fit the $r^2$ possible mobility/immobility effects. In the more general SAM model, we need $2r-1$ additional identification constraints. The model is illustrated in Table 1 using the example of $r = 3$ , the categories being labelled "Low", "Middle", and "High" (L, M, H). Here there are nine possible $\gamma_{ij}$ parameters, but we can identify no more than four of them. This is the statistical identification problem: there are more "mobility parameters" than can be estimated, and so arbitrary constraints must be imposed (often called 'coding schemes'). For example, instead of $\sum_{j=1}^{r}\alpha_j = 0 \; and \; \sum_{k=1}^{r}\beta_k = 0,$ we might impose the following constraints: $\alpha_L = \beta_L = \gamma_{LM} = \gamma_{ML} = \gamma_{LH} = \gamma_{HL} = \gamma_{LL} = 0$ (so called 'dummy variable coding'). Then we can identify $\gamma_{MH}$, $\gamma_{MM}$, $\gamma_{HM}$ and $\gamma_{HH}$ along with the constant (now the L,L cell of the matrix of cell means) and the four remaining main effect parameters.[5]

Sobel's (1981) diagonal mobility model, DMM, fits a baseline model:

$$Y_{ijk} = p\theta_j + (1-p)\theta_k + u_{ijk} \tag{2}$$

Here $p$ is a weight $(0 \leq p \leq 1)$, the $\theta_j$ are the effects of origins and $\theta_k$ of destinations, and $u_{ijk}$ is a residual error term. The origin and destination main effects are homogeneous: that is, the $\theta$ parameter for the r$^{\text{th}}$ category has the same

**Table 2:** Diagonal reference model with main effects only (r=3).

| Origins↓/Destinations→ | Low | Middle | High |
|---|---|---|---|
| Low | $\theta_L$ | $p\theta_L + (1-p)\theta_M$ | $p\theta_L + (1-p)\theta_H$ |
| Middle | $p\theta_M + (1-p)\theta_L$ | $\theta_M$ | $p\theta_M + (1-p)\theta_H$ |
| High | $p\theta_H + (1-p)\theta_L$ | $p\theta_H + (1-p)\theta_M$ | $\theta_H$ |

value in origins and destinations. The weighting parameter $p$ is chosen so that under the assumed statistical model in (2) the observed data is most probable (maximum likelihood estimation). The model fits $1 + r$ parameters, leaving $r(r-1) - 1$ degrees of freedom to model the $r(r-1)$ possible mobility effects. Table 2 shows the parameterization of the model in the three by three case. The weights $p$ can be origin or destination specific (e.g. Weakleim 1992). Zang, Sobel and Luo (2023) discuss many applications and extensions to the DMM model.

In the SAM, it is assumed that the effects of origins and destinations are linear, in the sense that the partial effect of each origin category on $Y$ does not differ depending on the destination category. The DMM assumes that the effects for the categorical origin and destination variables are homogeneous and the baseline DMM expresses outcomes as a weighted average of origin and destination effects. In both cases, mobility effects are usually added to the baseline model (for example, using a single dummy variable distinguishing upward from downward moves) and the best fitting model would be chosen via a criterion such as the Akaike Information Criterion, AIC, or the Bayesian Information Criterion, BIC. Thus, mobility effects are defined net of origin and destination effects. But neither the SAM nor the DMM has sufficient degrees of freedom to fit separate parameters to all the possible mobility effects; the researcher must specify a model in which some are constrained, typically to be zero, or to be equal to linear combinations of other effects.

Despite their widespread use of the term "effects", studies of mobility effects using the SAM or DMM estimate partial associations rather than plausibly causal effects because neither can be c-identified. The mobility effects literature posits the following stochastic relationship:

$$Y = f(O, D, M) \tag{3}$$

where $Y$ is an outcome, $O$ and $D$ are categorical origin and destination variables, having the same $r$ categories, and $M$ is mobility. However, there is also a deterministic relationship:

$$M = D - O \tag{4}$$

because mobility, $M$, is defined as the difference between $D$ and $O$. To estimate mobility effects, net of the effects of origins and destinations (as in the ANOVA-based approaches like the SAM), we would need to be able to vary (or imagine varying),$Y$ with respect to $M$, holding $O$ and $D$ constant, but this represents a state of affairs that cannot exist in the real world because of (4) (see Wie and Xie 2022). This is similar to the situation encountered in the attempt to identify age, period and cohort effects, except that, in the case considered here, the variables, origin and destination, have a clear temporal order (something we exploit in our approach).

## A Causal Approach to Mobility Effects

In this article we propose a different approach to the study of mobility effects which, unlike the SAM and DMM, does not seek to separate mobility effects from the effects of origins and destinations. Whereas the SAM and the DMM are concerned with the effects of relative mobility (mobility net of origins and destinations) we estimate the effects of absolute mobility. For many questions – such as whether promoting greater social mobility would improve health or reduce fertility or change voting behaviour – it is likely to be absolute mobility that matters and the distinction between main and interaction effects would be unimportant. For example, if we return to the classical focus on the societal consequences of mobility, absolute mobility seems more relevant. Marx and others, although not possessing the concepts of relative and absolute mobility, were surely thinking of the consequences of absolute mobility effects, not of mobility effects net of origins and destinations, in shaping individuals' interests. Likewise, consider the effect of geographic mobility on earnings. Suppose that there are three types of areas: rural, small town and city, and we want to characterise the effect on earnings of migration from a rural area to a city. Suppose also that the person earned the mean level in the rural area and earned the mean level in the urban area after the move. According to the 'relative mobility effect' definition, there would be no effect of migration on their earnings. But clearly it was rural-urban migration which produced the increase in their earnings, and so it would be misleading to say that migration had no effect on earnings. Similarly, Sorokin's (1959) dissociative hypothesis strongly suggests an effect of absolute mobility—we are trying to compare the mobile person with their hypothetical self if they had remained in their origin class, not with other people in their destination class who did not move there or moved from a different origin.

Our approach is based explicitly on seeking to estimate causal effects, which by their nature are 'within-person' comparisons, albeit hypothetical ones, rather than, as in previous work, between-person comparisons. Rather than thinking of the outcome, $Y$, as a function of additive origin, destination, and mobility effects, we focus on the causal effect on $Y$ of being in one destination category rather than another, conditional on origin. Our thought experiment asks: how would the outcome among people from origin $j$ who entered destination $k$ have been different if those people had, counterfactually, entered destination $k'$ instead? The estimands are therefore the conditional causal effects of destinations at a given origin. Our approach replaces "mobility effects" with heterogeneous (over origins) effects of destinations. We emphasise, therefore, that we are not providing another "solution" to the s-identification problems which beset ANOVA-based approaches that try to distinguish mobility effects from the effects of origins and destinations.

Write the potential outcome for respondents $i$ for each destination $D$ as $Y_i(D)$; this means that each individual is considered to have a set of potential outcomes, one for each destination they might have entered, though we only observe their outcome in the destination they did, in fact, enter (Neyman et al. 1935). We make two initial assumptions: (A1) positivity (everyone has a non-zero chance of entering every destination); and (A2) the stable unit treatment value assumption (SUTVA). SUTVA is the assumption that each unit's potential outcomes are unaffected by the mechanism used to assign treatments and by the treatments assigned to other units. These are standard assumptions in the causal inference literature. Our goal is to estimate conditional Average Treatment effects on the Treated (ATT) as follows: among those starting in origin $j$ the average effect of moving to destination $k$ rather than $k^{'}$ among those who did move to $k$ is defined as

$$\begin{aligned} ATT_{jkk'} &= E\left(Y_i(k) - Y_i(k^{'})|O = j,\ D = k\right) \\ &= E\left(Y(D = k|O = j,\ D = k)\right) - E\left(Y(D = k^{'}\middle|O = j,\ D = k\right)) \end{aligned} \tag{5}$$

The observed quantity $E(Y|O = j,\ D = k)$ is a consistent estimator of the first potential outcome in (5), and so the problem of estimating the conditional ATT involves finding an estimate of the counterfactual potential outcome $E(Y(D = k^{'}|O = j,\ D = k))$ among those with origin $j$ and destination $k$; in other words, what the outcome, for people originating in origin $j$, would have been if they had moved to destination $k'$, rather than to destination $k$.[6] Notice that we have avoided having to consider the consequences of varying $M$ while keeping $O$ and $D$ fixed; we keep $O$ fixed and consider the effects of varying $D$.

Because we are interested in mobility, an interesting special case of (5) is when $k^{'} = j$ which we write as:

$$\begin{aligned} ATT_{jkj} &= E\left(Y_i(k) - Y_i(j)|O = j,\ D = k\right) \\ &= E\left(Y(D = k|O = j,\ D = k)\right) - E\left(Y(D = j|O = j,\ D = k)\right) \end{aligned} \tag{6}$$

That is, for those mobile from origin $j$ to destination $k$, we compare their potential outcomes given their observed mobility with their potential outcomes if, counterfactually, they had been immobile.[7]

To estimate causal effects we require a third assumption: (A3) unconfoundedness. If people from a given origin were randomly assigned to their destinations, (A3) would hold and potential outcomes would be independent of destination, conditional on origin. In the absence of randomization we need to consider whether, given our data and assumptions A1 and A2, we can reasonably assume that A3 holds.

In sociology the most common approach is to invoke the conditional independence assumption, namely that, conditioning on a set of observed variables, $X$, destinations are as good as randomly assigned. In terms of potential outcomes, $Y(D) \perp D|O,\ X$: that is, the potential outcomes are independent of actual destination, conditional on origins and covariates, $X$. The plausibility of this assumption depends on what, and how extensive, the set $X$ is. But, given this assumption, numerous methods could then be used to estimate the causal effects. In other circumstances, the availability of natural experiments might make the unconfoundedness assumption more plausible, even if only for a subset of cases ("compliers"), but unverifiable assumptions would still be required. The important point, however, is that the definition of the causal estimands we propose is invariant to the specific estimator employed: for mobility from $j$ to $k$ compared with immobility at $j$ they are always $E\left(Y(D = k|O = j,\ D = k)\right) - E\left(Y(D = j|O = j,\ D = k)\right)$. Unlike the traditional approaches, ours is s-identified and, conditional on assumptions A1 to A3 holding, it is also c-identified.

## Relationship Between Our Model and the SAM

Assume, for the sake of transparency, but without loss of generality, that people in each origin are randomly assigned to their destinations and we estimate our causal mobility effects via regression.[8] Returning to the $r = 3$ example above with categories Low (L), Middle (M) and High (H), and focusing on cases originating in origin L, we have:

$$E(y_{Lk}|\ j = L) = \varphi_{L0} + \varphi_{LM} I(k = M) + \ \varphi_{LH} I(k = H) \tag{7a}$$

Here $I(k = .)$ is a dummy variable denoting destination category (k = L, M, or H) and $\widehat{\varphi}_{LM}$ and $\widehat{\varphi}_{LH}$ estimate the effects of mobility from low origins to middle and high destinations, respectively. In this case, $\varphi_{LM}$ is the average effect on Y of being in destination M rather than L for those who moved to M.

Similar equations apply to origins in $M$ and $H$:

$$E(y_{Mk}|\ j = M) = \varphi_{M0} + \varphi_{ML} I(k = L) + \ \varphi_{MH} I(k = H) \tag{7b}$$

$$E(y_{Hk}|\ j = H) = \varphi_{H0} + \varphi_{HL} I(k = L) + \ \varphi_{HM} I(k = M) \tag{7c}$$

If we now consider the SAM, we can rewrite (7), using the notation in equation (1), as

$$E(y_{Lk}|\ j = L) = (\mu + \alpha_L + \beta_L + \gamma_{LL}) + (\beta_M - \beta_L + \gamma_{LM} - \gamma_{LL}) I(k = M) + \ (\beta_H - \beta_L + \gamma_{LH} - \gamma_{LL}) I(k = H) \tag{8a}$$

$$E\left(y_{Mj}|j = M\right) \ = \ (\mu + \alpha_M + \beta_M + \gamma_{MM}) + (\beta_L - \beta_M + \gamma_{ML} - \gamma_{MM})\, I(k \ = \ L) + (\beta_H - \beta_M + \gamma_{MH} - \gamma_{MM})\, I(k = H) \tag{8b}$$

$$E(y_{Hj}|j \ = \ H) \ = \ (\mu + \alpha_H + \beta_H + \gamma_{HH}) + (\beta_L - \ \beta_H + \gamma_{HL} - \gamma_{HH})\, I(k \ = \ L) + (\beta_M - \beta_H + \gamma_{HM} - \gamma_{HH})\, I(k = M) \tag{8c}$$

Comparing (7) with (8) shows that each origin regression does not directly recover separate estimates of the SAM's main and interaction effects, but for our purposes this is not necessary or even desirable, and we show below that using all three regressions together we can identify all of the SAM parameters if necessary constraints are placed on the $\gamma_{jk}$. The SAM's main effects plus interactions formulation comes from thinking in terms of a statistical model (analysis of variance) but our approach, based on the potential outcomes framework, asks a different question: what is the effect, given origin, on the outcome $Y$, of moving to one destination rather another for those moving to that destination?

The terms $\gamma_{jk} - \gamma_{jj}$ are what Luo (2022) calls 'mobility effects' in her 'mobility contrast model.' The equations above show that our treatment effects are equal to these plus $\beta_k - \ \beta_j$, the difference in the SAM main effects between the destination and origin. Inclusion of the latter in the ATT can be defended on theoretical grounds in terms of the parameters of the SAM model. An outcome, such as fertility, can be viewed as a result of socialisation as a child in the parental home, captured by $\alpha_j$ the main effect of origin $j$, and of socialisation as an adult $\beta_k$, the main effect for destination $k$. Social mobility, relative to parents' status, affects socialisation as an adult, and so $\beta_k - \beta_j$ should be part of the treatment effect of mobility. Our treatment effects are invariant to the choice of coding scheme (i.e. the parameter constraints imposed by dummy variable coding or "effect" coding). To see this note that $\gamma_{jk} - \gamma_{jj} = \mu_{jk} - \mu_{jj} + \beta_k - \beta_j$, where the difference $\mu_{jk} - \mu_{jj}$ is the difference in cell means, which is always identified. The coding scheme affects the estimate of $\beta_k - \beta_j$, but not $\mu_{jk} - \mu_{jj}$. The expected value of our estimate of our causal effect when assignment of origins and destinations is random is $\beta_k - \beta_j + \gamma_{jk} - \gamma_{jj} = \mu_{jk} - \mu_{jj}$.

We can identify the SAM parameters from the three regressions in (7). This is easiest to see if we use dummy variable coding by setting one group as the reference. In particular, let $\alpha_L = \beta_L = \gamma_{LM} = \gamma_{ML} = \gamma_{LH} = \gamma_{HL} = \gamma_{LL} = 0$ . We then have six regression coefficients and three constants to identify the nine parameters of the SAM model; in particular,

$\mu = \varphi_{L0}$, $\beta_M = \varphi_{LM}$ and $\beta_H = \varphi_{LH}$,
$\gamma_{MM} = -\varphi_{ML} - \varphi_{LM}$, $\quad \gamma_{HH} = -\varphi_{HL} - \varphi_{LH}$
$\gamma_{HM} = \varphi_{MH} - \varphi_{LM} - \varphi_{HL}$, $\gamma_{MH} = \varphi_{MH} - \varphi_{LH} - \varphi_{ML}$
$\alpha_M = \varphi_{M0} - \varphi_{L0} + \varphi_{ML}$,
and $\alpha_H = \varphi_{H0} - \varphi_{L0} + \varphi_{HL}$.

This is not surprising because analysis of variance, based on differences in cell means, is used to estimate the parameters of the SAM model, and cell mean differences are also represented by regression coefficients and constants in our three regressions, equations (7a) through (7c). But we could also use estimators of the $\varphi$ parameters derived from methods other than ordinary least squares regression, which address selection into mobility, such as propensity score weighting or instrumental variables, and then 'back out' the SAM's main origin and destination effects and the identified interaction effects by using the estimated $\varphi$ parameters.

We can also estimate the parameters of the baseline model (in which all the $\gamma_{jk}$ parameters are set to zero) by estimating $\varphi_{jk}$ from the three regressions, equation 7, subject to some cross-equation parameter restrictions: $\varphi_{LM} = -\varphi_{ML}$, $\varphi_{LH} = -\varphi_{HL}$ and $\varphi_{MH} = -\varphi_{HM}$.[9] Because we can also fit a model without them, these cross-equation restrictions can be tested. For example, using the data analyzed later in this article, we cannot reject the three restrictions, and so the effects estimates would be consistent with the baseline SAM model. This is in line with what we found when estimating the SAM model with constraints on the $\gamma_{jk}$.

So, if one is interested in the SAM parameters and there are restrictions such that some $\gamma_{jk} = 0$ and some $\gamma_{jk} \neq 0$, the SAM parameters can be identified, so that nothing is lost relative to conventional approaches by focusing on treatment effects of destination, and this approach may allow us to address possible selection into mobility while also giving us the option of using different estimators.

## Estimation of Causal Effects with Simulated Data

It is instructive to illustrate our approach using a simple structural model in which we know the effects of mobility. For some outcome variable $Y$ and two origins and destinations (0 and 1),

$$Y|(O=0) = \xi_0 + \delta_0 I(D=1) + u_0 \quad (9a)$$
$$Y|(O=1) = \xi_1 + \delta_1 I(D=0) + u_1 \quad (9b)$$

Here we have an equation for each origin, and *I(D=k)* is, once again, a dummy variable for destination. $\delta_0$ is the effect of moving to destination 1 from origin 0 and $\delta_1$ is the effect of moving from origin 1 to destination 0. The $u_j$ (*j*=0,1) are unobserved random variables. Origin class is randomly assigned in the model, so the classes are of the same expected size.[10]

Mobility from origins to destinations depends on latent variables, $M_0^*$ and $M_1^*$, which in turn are functions of an observed random variable, $Z$, as follows:

$M_0^*|(O=0) = \psi_0 Z + e_0$, and $D=1$ if $M_0^*>0$, $D=0$ otherwise
$M_1^*|(O=1) = \psi_1 Z + e_1$ and $D=0$ if $M_1^*>0$, $D=1$ otherwise

The $\psi$ parameters relate $Z$ to the latent variables and $e_0$ and $e_1$ are random variables capturing unobserved influences on mobility. $Z$ is assumed to be distributed as standard Normal, and $u_j$ and $e_j$ $(j=0,1)$ are joint standard Normal. Throughout the simulations we assume the following: the $u$ and $e$ variables have zero means, as does $Z$; $E(e_0,e_1)=0$, and $E(u_0,u_1)=0$. We denote the correlation between the corresponding error terms: $E\left(u_j,e_j\right)=\rho_{jj}$ for $j=0,1$. The structural parameters are $\xi_j, \delta_j,\ \psi_j$, and $\rho_{jj},\ j$=0,1. The primary aim is to estimate $\delta_0$ and $\delta_1$; that is the effects of mobility relative to immobility, conditional on origin.

For example, $Y$ could represent family size. Women from origin class 0 with a preference for fewer children (lower $u_0$) might be more likely to move upward (higher $e_0$) so that $\rho_{00}<0$. In that case, for instance, $E(Y|O=0,\ D=1)$ may be lower than $E(Y|O=0, D=0)$ even if there is no mobility effect $(\delta_0=0)$. The model with pure selection below illustrates this scenario.

All the simulations use a sample size of 10,000. Our first simulation makes the following assumptions:

$\xi_0=3,\ \xi_1=2.5, \delta_0=-1, \delta_1=-0.5,\ \psi_j=0.5,\ j=0,1,\ \rho_{11}=0.1, \rho_{00}=-0.1.$

In this case there are both mobility effects, captured by the $\delta$ parameters, and selection, via the $\rho$ parameters. The positive $\rho_{11}$ means that those who are more likely to be downwardly mobile from origin 1 are likely to have a higher value of the outcome whereas the negative $\rho_{00}$ means that those more likely to be upwardly mobile from origin 0 are likely to have a lower value of $Y$. Table 3 shows, in the first two rows of each cell, the population expected value of $Y$ and the sample mean in the simulated data, respectively.

Fitting the baseline SAM model to the sample outcomes (*r*=2 in the example and $\alpha_0=-\alpha_1$, $\beta_0=-\beta_1$) returns estimates of $\alpha_0$ = 0.11 (SE=0.01) and $\beta_0$ = 0.20 (SE=0.01), and the estimate of $\mu$ is 2.36 (SE=0.01). The sample predictions from this model are reported in the third row of each cell in Table 3. As we might expect when there are true mobility effects (i.e. non-zero $\delta_0$ and $\delta_1$), the sample predictions from the baseline SAM model are very different from E($Y$) in each cell, and the differences between the SAM prediction and sample means in the off-diagonal cells

**Table 3:** E(Y) by intergenerational mobility.*

| Origins↓/Destinations→ | | 0 | 1 |
|---|---|---|---|
| 0 | E(Y) | 3.00 | 2.00 |
| | Sample mean | 3.05 | 1.90 |
| | SAM prediction | 2.67 | 2.27 |
| 1 | E(Y) | 2.00 | 2.50 |
| | Sample mean | 2.08 | 2.43 |
| | SAM prediction | 2.45 | 2.05 |

N=10,000
*$\xi_0 = 3,\ \xi_1 = 2.5, \delta_0 = -1,\ and\ \delta_1 = -0.5, \psi_j = 0.5,\ j = 0, 1.\ \rho_{11} = 0.1\ \ and\ \rho_{00} = -0.1.$

suggest that mobility reduces $Y$. But we cannot distinguish this from selection into mobility when using the SAM approach.

In our approach we can estimate the causal parameters $\delta_0$ and $\delta_1$ directly. Panel A of Table 4 shows three sets of estimates for $\delta_0$ and $\delta_1$: Ordinary Least Squares (OLS), inverse propensity score weighting (IPW) using only $Z$ to predict the propensity score, and instrumental variables (2 stage least squares, 2SLS) using $Z$ as the instrument. Because $\rho_{jj} \neq 0$ in the simulated data we would expect that only this last estimator would be consistent. Not only is our approach a more direct way to measure the effect of intergenerational mobility than modelling using the SAM or DMM models, but it readily allows for different estimators of the effect. The OLS estimate of $\delta_0$ ( $\delta_1$) is biased upward (downward) in size, and the 2SLS point estimates are close to the true values of $\delta_0$ and $\delta_1$, although their confidence intervals are wide. The IPW estimates which only use $Z$ in the propensity score exhibit a similar bias to OLS. When $\rho_{jj} = 0$ in generating the sample (that is, no selection), all estimates are close to their true values and the OLS estimator is more efficient (results not shown).

**Table 4:** Alternative estimates of $\delta_0$ *and* $\delta_1$ (standard errors in parentheses).*

| | OLS | IPW | 2SLS |
|---|---|---|---|
| A. Causal effects and selection | | | |
| $\delta_0$ | −1.15 | −1.16 | −1.01 |
| | (0.03) | (0.03) | (0.08) |
| $\delta_1$ | −0.35 | −0.33 | −0.48 |
| | (0.03) | (0.03) | (0.08) |
| B. Pure selection | | | |
| $\delta_0$ | −0.15 | −0.16 | −0.02 |
| | (0.03) | (0.03) | (0.08) |
| $\delta_1$ | 0.15 | 0.17 | 0.02 |
| | (0.03) | (0.03) | (0.08) |

*section A: $\delta_0 = -1,\ \ \delta_1 = -0.5,\ \psi_j = 0.5\ ,\ \rho_{11} = 0.1\ \ and\ \rho_{00} = -0.1.$
*section B: $\delta_0 = 0,\ \ \delta_1 = 0,\ \psi_j = 0.5,\ \rho_{11} = 0.1\ \ and\ \rho_{00} = -0.1.$

**Table 5:** E(Y) by intergenerational mobility.*

| Origins↓/Destinations→ | | 0 | 1 |
|---|---|---|---|
| 0 | E(Y) | 3.00 | 3.00 |
| | Sample mean | 3.05 | 2.90 |
| | SAM prediction | 3.05 | 2.90 |
| 1 | E(Y) | 2.50 | 2.50 |
| | Sample mean | 2.58 | 2.43 |
| | SAM prediction | 2.58 | 2.43 |

* $\xi_0 = 3,\ \xi_1 = 2.5, \delta_0 = 0,$ and $\delta_1 = 0$, $\rho_{11} = 0.1$ and $\rho_{00} = -0.1$.

Next, we consider what happens when mobility has no causal impact (i.e. $\delta_0 = 0$ and $\delta_1 = 0$), but there is a non-zero correlation between u and e as assumed above ($\rho_{11} = 0.1$ *and* $\rho_{00} = -0.1$) capturing selection into mobility. The SAM estimates are $\alpha_0$ = 0.23 (SE=0.01) and $\beta_0$ = 0.08 (SE=0.01), and the estimate of $\mu$ is 2.74 (SE=0.01). Table 5 shows that the SAM estimates reproduce the sample mean, but are biased estimates of E($Y$) in each cell. The differences in predicted means between the diagonal and off-diagonal cell in each row in Table 5 only reflect selection, not true differences in E($Y$). Panel B of Table 4 shows that, in this case, and as expected, OLS and IPW (using only $Z$) are biased (i.e. significantly different from zero), but 2SLS performs relatively well in producing estimates close to zero.

It is worth noting that, in this two by two case, only one interaction term can be identified. If we use effect coding in the SAM then $\gamma_{11} = \gamma_{22} = -\gamma_{12} = -\gamma_{21}$, and there is then only one "mobility effect" defined by $\gamma_{jk} - \gamma_{jj}$ which is the same for upward and downward mobility ($-2\gamma_{11}$). In the simulated data with causal effects and selection summarised in Table 3 it is equal to -0.75. With data simulated by a model with pure selection in which $\rho_{11} = \rho_{00} = -0.1$ it is -0.14.[11]

## Example: the Impact of Intergenerational Occupational Mobility on Redistributive Preferences.

In our empirical analysis we are interested in how mobility affects preferences relating to redistribution. The data are from waves 11 and 12 of *Understanding Society*. *Understanding Society* (the UK Household Longitudinal Study) is a longitudinal survey of the members of approximately 40,000 households in the United Kingdom. Households recruited at the first round of data collection (2009-11) were visited each year to collect information on changes to their household and individual circumstances. Annual interviews were conducted face-to-face in respondents' homes. All members of the households selected at the first wave and their descendants, who become full members of the panel when they reach age 16, constitute the core sample who are followed wherever they move within the UK. All others who join their households in subsequent waves do not become part of the core sample but they are interviewed as long as they live with at least one core sample member. Thus, the sample is refreshed with younger members annually. *Understanding Society* is designed to be representative of the UK population at each wave, repre-

**Table 6:** Occupational mobility by occupational groups.

| | Offspring→ | | | Total | Col.% |
|---|---|---|---|---|---|
| Father↓ | High | Middle | Low | | |
| High | 1,349 | 879 | 704 | 2,932 | 30.58 |
| Row % | 46.0 | 30.0 | 24.0 | 100 | |
| Middle | 637 | 533 | 440 | 1,610 | 16.79 |
| Row% | 39.6 | 33.1 | 27.3 | 100 | |
| Low | 1,381 | 1,424 | 2,240 | 5,045 | 52.62 |
| Row % | 27.4 | 28.2 | 44.4 | 100 | |
| Total | 3,367 | 2,836 | 3,384 | 9,587 | 100 |
| | 35.1 | 29.6 | 35.3 | 100 | |

senting all ages and all educational and social backgrounds (for more details see Understanding Society 2021a, 2021b).

The outcome variable, $Y$, is 'tax and expenditure preferences' measured on a scale of 1 ('cut taxes and spend much less') through 10 ('raise taxes and spend much more'): thus a higher value indicates a preference for taxing and spending more (i.e. more redistribution). Fathers' and their children's occupations were originally coded to 3-digits using the UK Office for National Statistics 2010 Standard Occupational Classification coding. We have grouped them into three: higher occupations (codes 100 to 299), middle (codes 300-499), and lower (codes 500 and above). Higher occupations comprise managers, directors and professionals, middle includes other skilled white collar workers, and lower is made up of manual workers and semi-skilled or unskilled white collar workers. Both waves 11 and 12 are used in the estimations that follow, allowing for correlation of the two observations for each individual in calculating the standard errors (i.e. clustering on the personal identifier).

Figure 1 shows the distribution of tax and expenditure preferences by a person's occupational group. In all three groups, most variation occurs at values of five and higher. The bottom occupational group exhibits a stronger concentration at 5, and has a smaller percentage at all higher values, than the other two groups. The top and middle occupational groups have a similar distribution, with the top group slightly favouring more redistribution through taxes and spending.

Table 6 shows occupational mobility between father and offspring using the three-group coding. The patterns are very similar for men and women.

We estimate the baseline SAM and DMM models ($\gamma_{jk} = 0$) including three additional covariates: gender, age and age-squared. The SAM parameter estimates (effect coding) are:

$\widehat{\alpha_L} = -0.204\ (SE = 0.027)$, $\widehat{\alpha_M} = 0.035\ (SE = 0.035)$ , $\widehat{\alpha_H} = 0.169\ (SE = 0.030)$, $\widehat{\beta_L} = -0.215 (SE = 0.028)$, $\widehat{\beta_M} = 0.056\ (SE = 0.028)$, $\widehat{\beta_H} = 0.158\ (SE = 0.028)$

The DMM estimates are:

$\widehat{\theta_L} = -0.420\ (SE = 0.027)$,$\widehat{\theta_M} = 0.096\ (SE = 0.043)$ , $\widehat{\theta_H} = 0.324\ (SE = 0.038)$, $\widehat{\rho} = 0.495\ (0.047)$

On either Akaike or Bayesian information criteria, the baseline DMM model (with roughly equal weights for origin and destination parameters) performs better than the main effects baseline SAM model. In neither model does the addition of interaction effects in terms of whether mobility is upward or downwards or Luo's (2022) mobility contrasts ($\gamma_{jk} - \gamma_{jj}$) have any significant impact: these parameter estimates do not exceed their standard errors in either model.

We now consider our estimates of the conditional average effects of treatment on the treated. Two estimates for each mobility effect are shown in Table 7: OLS and IPW. We could not find a convincing instrumental variable for mobility with these data, a common occurrence. The estimate of the probability of mobility of each type and of immobility is derived from a multinomial logit model to predict destination, conditional on origin, from which we obtain estimates of the probability that the destination is $k$, $P_{jk}$, $k$=1,2,3. Thus, the estimate of the propensity score for movement from origin $j$ to destination $k$ is $\widehat{p}_{jk}\left(X_i\right) = \frac{\widehat{P}_{jk}}{\widehat{P}_{jk}+\widehat{P}_{jj}}|X_i,\ j \neq k$. Here $X_i$ contains (a) father's education (6 categories, including one for missing information[12]); (b) whether the person was born in 1957 or later and so affected by the increase in the minimum school leaving age from 15 to 16 in 1972: (c) whether the person was born in the UK; (d) whether they were living with both parents at age 16; (e) whether their mother worked at age 14; (f) ethnic group (9 categories); (g) age and age-squared and (h) whether a female. All these variables are determined in childhood or earlier.

Upward mobility from the low occupation group is found to be more likely among persons (a) whose fathers have higher education; (b) born in the UK; (c) living with both parents at age 16; (d) had a mother in employment at age 14; and (e) from particular ethnic groups compared to white British (e.g. Indian or Caribbean). Downward mobility from the high group was more likely among those (a) with less educated fathers; (b) born outside the UK; (c) not living with both parents at age 16; (d) had a mother not in employment at age 14; and (e) from particular ethnic groups compared to white British (e.g. Pakistani or Bangladeshi). Mobility in either direction from the middle occupational group is not influenced by father's education, but downward mobility was more likely for the foreign born and for those whose mothers were not employed when they themselves were aged 14, and less likely if their mother was deceased at age 14. Of course, one can never be sure if this set of covariates assures satisfaction of the Conditional Independence Assumption, but they do have plausible impacts on the propensity scores.

Both estimators indicate that upward mobility from the low group has a positive effect on preferences favouring redistribution (Panel A of Table 7). There is a negative effect of downward mobility from the high group to the low group irrespective of estimator (Panel B). In both cases, in comparison with the IPW estimates, the OLS estimates over-state the size of the impact of mobility on redistributive preferences, by more than one standard error for mobility from a high to low occupation. The effect of upward mobility from the middle occupational group is positive but not precisely estimated. Downward mobility from the middle group has a negative effect on redistributive preferences.

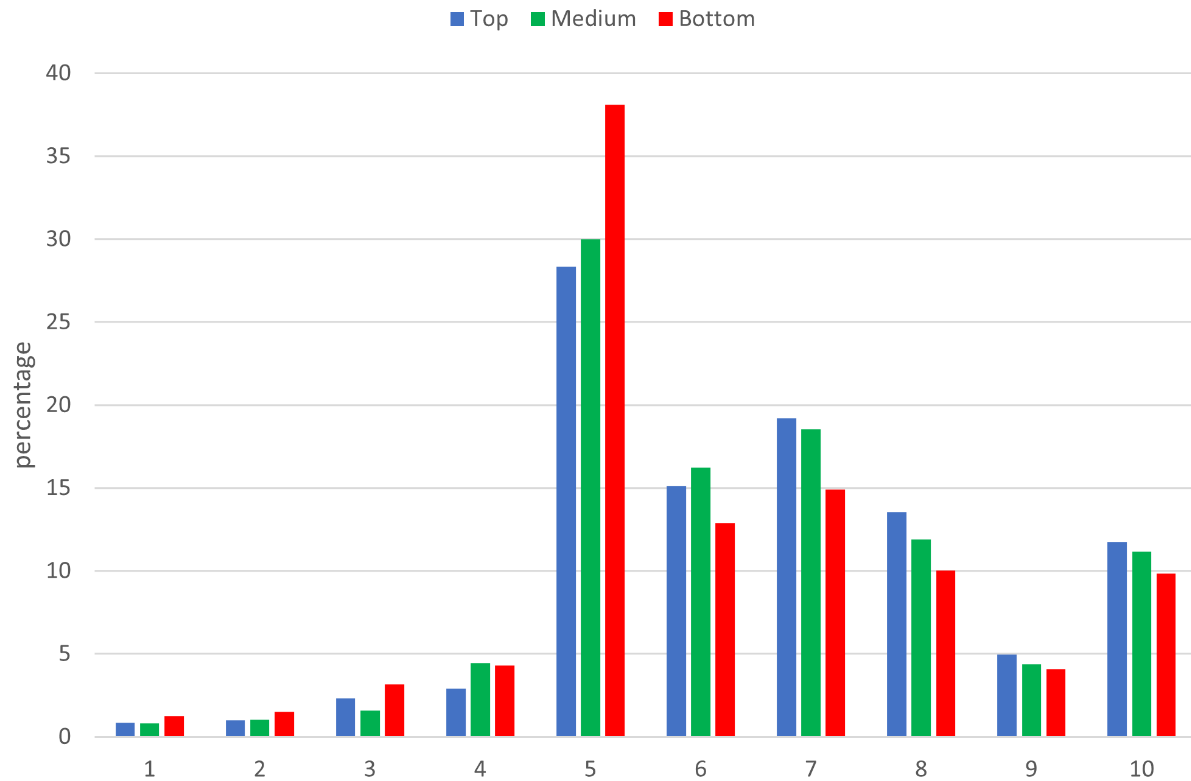


**Figure 1:** Distribution of tax/spending preferences by occupational group.

Because we could only control for measured confounders through IPW, it is important to check how much unmeasured confounding would be required to overturn the conclusions based on these IPW estimates. Ding and Vanderweele (2016) developed a measure called the 'E-value' which 'is the minimum strength of association, on the risk ratio scale, that an unmeasured confounder would need to have with both the treatment and outcome, conditional on the measured covariates, to fully explain away a specific treatment–outcome association.' (Ding and Vanderweele 2016: 2). With a continuous outcome like the one we have here they propose an approximation of the 'relative risk ratio' (RR), which equals exp(0.91*standardised effect size), where the 'standardised effect size' is the regression coefficient in Table 7 divided by the standard deviation of the outcome variable in the sample.

For example, for upward mobility from the low to high group, RR=1.17 (95 percent CI:1.08, 1.28). The corresponding E-value $= RR + \sqrt{RR(RR-1)}$ is 1.62 in this example, which is interpreted as follows: the observed risk ratio of 1.17 could be explained away by an unmeasured confounder that was associated with both the treatment and the outcome by a risk ratio of 1.62-fold each, above and beyond the measured confounders, but weaker confounding could not do so. Similarly, the lower confidence limit could be moved to include the null of zero by an unmeasured confounder that was associated with both the treatment and the outcome by a risk

**Table 7:** Estimates of mobility effects.

| | OLS | IPW | RR & E-values (IPW) |
|---|---|---|---|
| A. Mobility from Low Group | | | |
| Low to High | 0.36 | 0.34 | RR=1.17 [1.08, 1.28] |
| | (0.07) | (0.08) | E-value (pt. est.)=1.62 |
| | | | E-value (CI)=1.39 |
| Low to Middle | 0.30 | 0.24 | RR=1.12 [1.04, 1.21] |
| | (0.07) | (0.08) | E-value (pt. est.)=1.48 |
| | | | E-value (CI)=1.23 |
| B. Mobility from High Group | | | |
| High to Low | −0.40 | −0.24 | RR=0.89 [0.80,0.99] |
| | (0.10) | (0.11) | E-value (pt. est.)=1.49 |
| | | | E-value (CI)=1.11 |
| High to Middle | −0.14 | −0.06 | RR=0.97 [0.88,1.07] |
| | (0.09) | (0.10) | E-value (pt. est.)=1.19 |
| | | | E-value (CI)=1.00 |
| C. | | | |
| Middle to High | 0.09 | 0.15 | RR=1.07 [0.94, 1.23] |
| | (0.13) | (0.14) | E-value (pt. est.)=1.36 |
| | | | E-value (CI)=1.00 |
| Middle to Low | −0.24 | −0.20 | RR=0.91 [0.78, 1.06] |
| | (0.14) | (0.17) | E-value (pt. est.)=1.43 |
| | | | E-value (CI)=1.00 |

ratio of 1.39-fold each. The RR and E-values associated with the IPW estimates are shown for all mobility types in the third column of Table 7.

It appears that, with the possible exception of upward mobility from the low group and downward mobility from the high group to the low group, the claims for causality are not particularly strong with our estimates; put differently, they are not very robust to unmeasured confounders. This is especially true for mobility in either direction from the middle occupations and downward mobility from the high to middle group.

Overall, there is some evidence that upward mobility causes preferences more favourable to redistribution whereas downward mobility does the opposite. We would not have drawn these inferences from estimation of the SAM or DMM models and, as noted above, none of Luo's (2022) 'mobility contrasts' ($\gamma_{jk} - \gamma_{jj}$) are statistically significant, suggesting virtually no 'mobility effects'.[13] As we have shown, when the ATT is written in terms of the parameters of the SAM model, the causal effect of moving from low to high is $\beta_H - \beta_L + \gamma_{LH} - \gamma_{LL}$, not just $\gamma_{LH} - \gamma_{LL}$. Taking the baseline SAM parameter estimates above, $\widehat{\beta_H} - \widehat{\beta_L}$=0.158+0.215=0.373, which is close to our OLS causal effect estimate of the effect of mobility from low to high occupations of 0.36, and slightly larger than the IPW estimate of 0.34; $\widehat{\beta_M} - \widehat{\beta_L}$ =0.056+0.215=0.271, which is slightly larger than the IPW estimate of 0.24, but less than the OLS estimate of low to medium occupational mobility of 0.30.

**Table 8:** Estimates of mobility consequences (IPW estimates, standard errors in parentheses).

| | | Mobility | | |
|---|---|---|---|---|
| Origin | Down | | Up | Aggregate |
| Low | | | 0.077<br>(0.014) | |
| Middle* | | -0.005<br>0.011 | | |
| High | -0.037<br>(0.011) | | | |
| Sum | | | | 0.034<br>(0.040) |

*Net weighted positive effect of upward mobility and negative effect of downward mobility

## From Effects to Consequences

Returning to the classical interest in the societal consequences of individual mobility we can ask whether mobility in the UK leads to a shift towards more support for redistribution in the population as a whole. We adopt a simple approach to answering this question, based on comparing the observed level of support for redistribution with the counterfactual level had there been no intergenerational mobility. We can write this as

$$E(Y) - \sum_j E(Y_{jj})p_j \tag{10}$$

This is the observed average level of support for redistribution minus the weighted sum of the average levels of support in the immobile cells of the mobility table. The weights, $p_j$, are the proportions of the population in each of the origin categories. In terms of the parameters of our model (10) can be written $\sum_{j \neq k} \varphi_{jk} p_{jk}$, having the advantage that we can insert parameter estimates from whatever procedure we used to estimate equations 7. This assumes that the aggregate outcome is a simple sum of individual effects: this assumption may be less plausible in other contexts.

To calculate the $p_{jk}$ we use the wave 11 sample of Understanding Society because its weights are designed to create a representative cross-section of the population. The results shown in Table 8 use estimates from the IPW model reported in Table 7. Because we have individual data, we can compute the standard errors of the aggregate estimate.

The net aggregate consequence of mobility favours more redistribution, but its magnitude is very small: 0.034 compared with the observed mean of 6.4 and standard deviation of 1.94. Although the aggregate consequences of upward mobility from the bottom and downward mobility from the top are quite precisely estimated, the sum of the mobility effects is not.[14]

## Conclusions

The effects for individuals of being intergenerationally mobile is an important issue in sociology and related disciplines. There are theoretically grounded reasons why we should expect mobility to affect outcomes like well-being, fertility, and political views, but the models commonly used in studies of mobility effects are neither statistically nor causally identified. We have introduced a new approach that focusses on the question of how the outcome among people from origin $j$ who entered destination $k$ would have been different if those people had, counterfactually, remained in origin $j$ instead. This leads to a well-defined estimand which is statistically identified and causally identified conditional on the data we have and a set of assumptions.

We are focusing on the effects of absolute mobility, whereas the interaction parameters in the SAM or the DMM try to capture relative mobility. But these relative mobility effects, based on the estimated interaction effects of a statistical model, depend on the particular constraints applied to the model's parameters. For instance, although Luo (2022) might appear to estimate the full set of interaction (relative mobility) effects, that is because of the 'zero-sum' constraints imposed on them. These in turn constrain the estimated "mobility effects" in a non-transparent and non-intuitive way (see Appendix A in the online supplement).

The SAM and, especially, the DMM have long been the default model for the analysis of mobility effects and this may have prevented adequate consideration of whether the effects in question are better thought of as due to absolute, rather than relative, mobility. Our view is that most substantive hypotheses, such as Sorokin's dissociative hypothesis, have in mind a within-person comparison: how mobility changed the outcome for a person compared with their remaining in their origin class. The fact that destination influences their outcome when they move is part of the effect of mobility compared with remaining at their origin.

We have illustrated our approach with simulated data for which we know the true effects of mobility compared with immobility and the degree and nature of selection into mobility. This analysis showed that the conventional approach can estimate non-zero mobility effects (from the interaction terms) even when there are none because of the influence of selection on the distribution of outcomes by origin and destination. Furthermore, it is not possible to address selection in the conventional framework. In our approach we can do so under certain conditions using estimators such as inverse propensity score weighting or instrumental variables. Also, using any of these estimators of destination effects we can 'back out' main effects of origins and destinations and the identified interaction effects by using the estimates for all origins together.

Finally, we have used data on individual preferences relating to redistribution (through taxation and government spending) along with information about father's and respondent's occupation from the UK Household Longitudinal Study to estimate effects of destination. This analysis concludes that upward mobility appears to cause preferences more favourable to redistribution whereas downward mobility from high to low occupations does the opposite. These results are robust as long as unmeasured confounding is small to moderate. Estimation of "mobility effects" from the conventional SAM model suggests, in contrast, that there are no mobility effects. This is because, viewed through the lens of the SAM parameterization, our approach includes the difference in SAM destination effects in the effect of mobility. In our view, this is correct on theoretical grounds because redistributive preferences can be viewed as a result of socialisation as a child in their parents' home (origin effect) and of socialisation as an adult (destination effect). Social mobility relative to parents' status affects socialisation as an adult, and so the difference in SAM destination effects should be part of the causal effect of mobility.

One important issue we have not addressed here is the possibility of reverse selection: individual attitudes to redistribution affecting individual social mobility. Piketty (1995) presents a theoretical model in which this is the case, but it implies that those who favour redistribution are less (more) likely to be upwardly (downwardly) mobile. But this is the opposite of what we have found: preferences for redistribution are stronger among those who are upwardly mobile. We thus have no grounds for thinking that reverse causality is an issue for our findings but it is something that might need to be addressed in other applications.

# Notes

1 We were made aware of Zang et al.'s article by a reader of an early draft of our article.

2 A notable early example is Durkheim (1951).

3 There is also a literature on the consequences of intragenerational mobility (a recent example is Präg, Fritsch and Richards 2022), though we do not address it here.

4 We can add further variables, $X$, to both the SAM and the diagonal mobility model (DMM), but, in the interests of clarity, we omit them from our exposition.

5 Luo (2022) presents a new parameterisation of 'mobility effects' based on the SAM. We discuss Luo's model in Appendix A in the online supplement and show that it is not s-identified.

6 The naïve estimator $E\left(Y\middle|O=j,\ D=k^{'}\right)$ of $E\left(Y(D=k^{'}\middle|O=j,\ D=k\right)$ will not yield unbiased estimates of the conditional ATT unless potential outcomes are independent of destination category conditional on origin category: $Y(D)\perp D|O$

7 Using $ATT_{jkk'}$ in equation (5) we can calculate the sample ATT of being in destination $k$ relative to $k'$ across all origins as $\sum_j ATT_{jkk'}\pi_j$ where $\pi_j$ is the proportion of cases in each origin category. The standard error of this can be easily approximated using the delta method. It also allows us to test the null hypothesis that the conditional ATTs are homogeneous.

8 In Appendix B in the online supplement we develop the material in this section for the case in which we assume conditional independence of the potential outcomes given covariates, $X$.

9 In this case there are 5 free $\varphi$ parameter estimates and 5 SAM parameters to estimate.

10 Notice that in 9a the omitted destination category is different from that in 9b.

11 In the pure selection simulated data summarised in Table 5 the estimate of $\gamma_{11}=0$ because opposite correlations for selection in the two mobility processes cancel each other out.

12 In a small number of cases in which the mother's education was known, but not the father's, we used the mother's education rather than assign the missing category.

13 If we focus on 'longer distance' mobility from Low to High or High to Low and include appropriate interaction parameters in the SAM model ($\gamma_{LL}$, $\gamma_{LH}$, $\gamma_{HL}$ and $\gamma_{HH}$) there is only one mobility contrast for movements in either direction ($\gamma_{LH} - \gamma_{LL} = \gamma_{HL} - \gamma_{HH} = -2\gamma_{LL}$); its estimate (SE) is -0.034 (0.056).

14 OLS estimates with no covariates produce a similar aggregate effect of 0.035 (0.036).

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