The Mobility Effects Hypothesis: Past, Present, and Future*

Emma Zang
Departments of Sociology and Biostatistics
Yale University

Michael E. Sobel
Department of Statistics
Columbia University

Liying Luo
Department of Sociology and Criminology
Pennsylvania State University

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* Send correspondence to Emma Zang, Departments of Sociology and Biostatistics, Yale University, New Haven, CT 06520 (Email: emma.zang@yale.edu).

Abstract

We discuss hypotheses researchers have put forth to explain how outcomes of socially mobile and immobile individuals might differ and/or how mobility experiences are related to outcomes of interest. Next, we examine the methodological literature on this topic, culminating in the development of the diagonal mobility model (DMM, also called the diagonal reference model in some studies), the primary tool of use since the 1980's (Sobel 1981). We then discuss some of the many applications of the DMM. Although the model was proposed to examine the effects of social mobility on outcomes of interest, the estimated relationships between mobility and outcomes that researchers have called mobility effects are more appropriately regarded as partial associations. When mobility is not associated with outcomes, as is often found in empirical work, the DMM provides a parsimonious quantitative description of the empirical regularity that on average, the responses of mobile individuals tend to lie between those of immobile individuals in the associated origin and destination states. Therefore we briefly develop several generalizations of the current DMM that future researchers should also find useful. Finally, we propose new estimands of mobility effects, based on the explicit notion that a unit effect of mobility is a comparison of an individual with herself under two conditions, one in which she is mobile, the other in which she is immobile, and we discuss some of the challenges in identifying such effects.

1 Introduction

Vertical social mobility, the upward or downward movement across ordered social strata, has been intensively studied by social and behavioral scientists. The sociological literature (e.g., Blau and Duncan 1967; Jarvis and Song 2017; Song et al. 2020; Sobel et al. 1998), and more recently work by economists (e.g., Long and Ferrie 2013; Chetty et al. 2014), has paid considerable attention to trends and patterns of mobility, and their implications for the economy and society. A second strand of literature has focused on the role of social organizations, policies, and local infrastructure in promoting upward mobility. (e.g. Michelman et al. 2022; Costa-Fernández et al. 2020; O'Brien and Robertson 2018).

A third strand, spanning a number of disciplines, is concerned with individual-level consequences of social mobility. Psychologists have compared means of psychological outcomes between intra-generationally mobile and immobile individuals (e.g. Ashford 1990; Marin et al. 2008). Public health researchers have used a variety of statistical methods to study the consequences of inter- and intra-generational mobility for health outcomes and behaviors (e.g., self-rated health, obesity), operationalizing mobility primarily through measures of educational attainment, income, and/or occupation. Given the diversity of mobility measures, outcomes, and methods used in the literature, it is not surprising that findings are mixed (e.g., Bridger and Daly 2020; Hart et al. 1998). A handful of studies by economists and political scientists have also looked at the effect of social mobility perceptions on political attitudes using structural econometric models or randomized experiments (Piketty 1995; Fehr et al. 2020; Acemoglu et al. 2018; Benabou and Ok 2001).

The focus of this paper is the large sociological literature, dating back at least to Sorokin (1927, 1959), on the consequences of social mobility (e.g., mental health, fertility, etc.). Two overarching and opposed ideas have dominated this literature (Mirande 1973). The socialization hypothesis asserts that mobile individuals exhibit behaviors and attitudes between those prevailing in their origin and destination states. The dissociative hypothesis asserts that mobility, either upward or downward, is stressful, resulting in social isolation and abnormal behavior (Durkheim 1951; Sorokin 1927).[1]

More recent work has proposed hypotheses about the effects of mobility on mental health. For instance, the "falling from grace" hypothesis asserts that only downward mobility, which lowers an individual's socioeconomic status, harms mental health (Katherine 1999; Houle and Martin 2011). The complementary "rising from rags hypothesis" suggests that upward mobility improves mental health, as the material and psychological benefits outweigh the costs of adapting to a new social class (Gugushvili et al. 2019). Other work has examined heterogeneous responses to social mobility. For example, Zang and de Graaf (2016) highlight the importance of selection into social mobility groups and the role of social comparison in shaping mental health: while upward mobility can worsen mental health for a group of highly motivated individuals who compare themselves to individuals with higher social status ("frustrated achievers"), downward mobility might not worsen mental health among individuals who are more satisfied with their lives ("satisfied losers").

Our paper is organized as follows. In section two, we review the methodological work that has guided much of the empirical research, paying particular attention to the diagonal mobility model (DMM, also called the diagonal reference model) (Sobel 1981). Section three discusses some of the many applications of these models. In many instances, researchers did not find a relationship between mobility and outcomes. In this case, which supports the socialization hypothesis, the DMM provides a parsimonious

[1]Status inconsistency theory has a similar flavor: it posits that persons with consistent statuses, e.g., high education and high income, behave differently than individuals with inconsistent statuses, e.g., high education and low income (Lenski 1954, 1956).

quantitative description of the empirical regularity that on average, the responses of mobile individuals tend to lie between those of immobile individuals in the associated origin and destination states. Therefore we briefly develop several generalizations of the current DMM that future researchers should also find useful. Thus, section four briefly sketches several generalizations of the current DMM that future researchers should also find useful. Although the DMM was proposed to examine the "effect" of social mobility on outcomes of interest, the associations researchers using the model have called effects would not be deemed such following the modern statistical literature on causal inference, in which the idea is that an inference about causation should sustain a counterfactual conditional statement, e.g., had John, who was mobile from state A to state B, not been mobile, his outcome would have been different. In line with this idea, section five reconceptualizes the mobility effects hypothesis, introducing several casual estimands and briefly discussing some practical challenges to their identification. Section six concludes.

While previous work did not distinguish between associations of mobility with outcomes and effects of mobility on outcomes, it seems likely that earlier scholars, (e.g., Sorokin 1959), meant that social mobility predicted (was associated with) poor mental health, as the idea that the causal relationship sustained a counterfactual conditional was not prevalent in the social sciences until later. Rather than attempting to rewrite the historical record, second-guessing earlier work, and providing new nomenclature to distinguish between possibly different versions of the "mobility effects hypothesis", it should be understood that in sections two through four, the work we discuss is best understood as modeling the association between mobility and outcomes, not effects of mobility on outcomes: to highlight this, the word "effect" appears in quotes.

Further, while we believe it is important to clarify that previous work using the DMM does not estimate the effects of mobility and to reformulate the mobility effects hypothesis, several caveats are in order. First, researchers need to think carefully about their research question and ask whether they are actually interested in estimating effects or attempting to predict or describe differences between mobile and immobile individuals. For many questions, describing patterns and associations between variables is more relevant than making causal inferences about mobility effects. As an example, drug overdose mortality in the US has increased over the past few decades, first among non-Hispanic Whites, later among non-Hispanic Blacks and Hispanics (Case and Deaton 2015; Hoopsick et al. 2021; Zang et al. 2018). Some researchers argued that diminished economic opportunities for working-class Americans, as indicated by relatively low rates of upward mobility, may have contributed to this trend (Venkataramani et al. 2016). Dennison (2018b) applied the DMM to examine the relationship between intergenerational mobility and drug use, finding that individuals who experienced downward mobility had higher rates of drug use than immobile individuals, providing some evidence for the hypothesis. Identifying specific groups of individuals at risk of drug overdose mortality is useful to policymakers: it allows them to design and deliver specially tailored treatment programs to those most likely to benefit. In contrast, even if downward mobility were found to affect overdose mortality, this has no policy implications, as it is not feasible to intervene directly on individual mobility experiences or implement a large-scale social intervention to decrease the risk of downward mobility.

2 The Diagonal Mobility Model: Historical Context and Current State

Early investigations of the "effects" of social mobility compared average outcomes of mobile and immobile individuals. Duncan (1966) argued this comparison is flawed: "one is not entitled to discuss 'effects' of mobility (or other status discrepancy measures) 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". This framing of the issue has dominated methodological and substantive work in sociology ever since. Duncan (1966) considered the relationship between intergenerational occupational mobility and fertility, using a categorical measure of occupational status, proposing an additive analysis of the variance model to represent this baseline:

$$E(Y_\ell \mid O_\ell = o, D_\ell = d) = \mu_{od} = \mu + \alpha_o + \beta_d, \tag{1}$$

where Y_ℓ is the response of individual $\ell \in \{1, ..., n\}$; $O_\ell \in \{1, ..., I\}$ and $D_\ell \in \{1, ..., I\}$ denote ℓ's origin and destination categories, respectively; the parameters μ, α_o and β_d are, respectively, the intercept, the row (origin) "effect", and the column (destination) "effect". To identify these parameters, Duncan used the weighted 0 sum constraints $\sum_{o=1}^{I} n_{o+}\alpha_o = \sum_{d=1}^{I} n_{+d}\beta_d = 0$, where n_{o+} and n_{+d} are, respectively, the number of respondents with origin o and the number of respondents with destination d.

Duncan (1966) observed that the fertility of movers tends to be "intermediate between that prevailing in their origin and that prevailing in their destination status". When the measures of occupational origins and destinations are ordered categorical, it is possible to speak of the direction of mobility, also long or short distance mobility when this is equated with the number of "steps" between origin and destination categories. With the exception of long distance movers, Duncan found that the model (1) adequately describes the data. To deal with deviations from the additive model, he included interactions for long distance upward mobility and long distance downward mobility. Similarly, Luo (2022) proposed an alternative "mobility contrast model", quantifying "mobility effects" by selected combinations of origin-destination interactions.

Duncan's formulation has been criticized because the parameters of the baseline additive model already include in some sense a linear mobility "effect" $\lambda : \alpha_o + \beta_d + \lambda(d - o) = (\alpha_o - \lambda o) + (\beta_d + \lambda d) = \alpha_o^* + \beta_d^*$. Equivalently, the number of steps $D_\ell - O_\ell$ respondent ℓ moved is a linear combination of the origin and destination ranks, which means that origins, destinations, and the number of steps are co-linear. Further, the interpretation of model parameters depends on the coding scheme used to identify the main effect parameters and the interactions, and it seems difficult to specify a substantive rationale for using a particular parameterization.[2]

In lieu of Duncan's baseline additive model, Hope (1971) proposed the "halfway model" with identical origin and destination parameters:

$$\mu_{od} = \mu + h_o + h_d. \tag{2}$$

A little arithmetic gives $\mu_{oo} = \mu + 2h_o$, $\mu_{od} = \mu_{do} = .5(\mu_{oo} + \mu_{dd})$. Subsequently, Hope (1975) proposed the "diamond additive" regression model, in which origins and destinations are treated as interval variables:

$$E(Y_\ell \mid O_\ell = o, D_\ell = d) = \beta_1(o + d) + \beta_2(d - o). \tag{3}$$

Hope argued that $o+d$ represented an overall status and that differences between statuses $d - o$ represented status inconsistency. Status inconsistency "effects" could thus be studied by regressing outcomes on both sets of variables.

In the context of social mobility, Hope argued that persons who are immobile (or stayers) constitute the appropriate baseline against which to measure "mobility effects", and he also advocated using the diamond model to study these. In this model, the ordered categorical origin and destination variables are combined by addition and subtraction to form two variables, each treated as metrical. Sobel (1981) showed how the model could be extended to the case where both the overall status variable and the status inconsistency variable are treated as categorical:

$$\mu_{od} = \mu + \alpha_{o+d} + \beta_{d-o} \tag{4}$$

[2] A similar problem plagues the age-period-cohort literature (Yang and Land 2016; Luo and Hodges 2022; Land et al. 2016; Fu et al. 2021).

He then pointed out that when $O + D > 2$ and even, stayers in category $(O + D)/2$ are combined with movers from O to D, implying the α_{o+d} parameters do not represent solely the experience of immobile individuals, therefore do not represent the baseline in Hope's proposal. For example, in a 3-by-3 mobility table, α_4 mixes persons who moved between categories 1 and 3 with persons who originate in category 2 and stay in 2. There is no reason to believe that movers between categories 1 and 3 are similar to stayers in category 2 with respect to the outcome.

To represent Duncan's framing of the problem and Hope's argument for using stayers as a baseline, Sobel (1981) proposed the diagonal mobility model (DMM), in which the baseline outcomes of movers from origin category o to destination category d is a weighted average of the outcomes of stayers in categories o and d, with either a common weight for all respondents or origin (or destination) specific weights, for example:

$$\mu_{od} = \pi_o \nu_o + (1 - \pi_o)\nu_d, \qquad 0 \leq \pi_o \leq 1, \tag{5}$$

where π_o is a row (origin) specific weight, $\nu_o = \mu_{oo}$ (as is evident by putting μ_{oo} on the left side of (5)), and $\nu_d = \mu_{dd}$. Under the baseline diagonal model (5), μ_{od} lies on the line segment connecting μ_{oo} and μ_{dd}, precisely representing Duncan's observation that the responses of movers are "intermediate" between those of stayers in o and d. Further, if $\pi_o = .5$ for all o, (2) and (5) generate the same values of μ_{od}, i.e., although not parametrically nested under the diagonal model, the halfway model is a special case of the diagonal model. "Mobility effects" were then equated with deviations from the baseline, represented by parameters of additional terms reflecting the movement of respondents between categories, e.g., the number of steps up or down, long distance vs. short term moves, etc.

Sobel (1981, 1985) viewed the diagonal means μ_{oo} and μ_{dd}, the average outcomes of stayers in o and d, as typical values that movers from o to d used as a reference (not necessarily consciously). He also pointed out (as have others since) that when the proportion of stayers in a status is small, this interpretation may be unwarranted. In this case, the model may not represent the actual process by which origins and destinations combine to produce outcomes.

The DMM was subsequently extended in several directions: for simplicity, we describe several extensions of the baseline DMM without mobility "effects". Weakleim (1992) allowed the weight parameters to depend on both origins and destinations and he modeled a binary left/right voting outcome using a logistic diagonal model:

$$g(\mu_{od}) = logit(\mu_{od}) = \pi_{od}\nu_o + (1 - \pi_{od})\nu_d, \qquad 0 \leq \pi_{od} \leq 1. \tag{6}$$

Sobel (1985) allowed the diagonal means to depend on covariates $\mathbf{X}_\ell = (X_{\ell 1}, ..., X_{\ell k})'$:

$$\nu_o(\mathbf{x}_\ell) = \alpha_o + \boldsymbol{\beta}_o'\mathbf{x}_\ell \tag{7}$$

and Sobel et al. (2004) modeled an ordered categorical class identification using a nonlinear proportional odds model, with weights also depending on covariates:

$$\pi(\mathbf{x}_\ell) = \frac{\exp(\gamma_0 + \boldsymbol{\gamma}'\mathbf{x}_\ell)}{1 + \exp(\gamma_0 + \boldsymbol{\gamma}'\mathbf{x}_\ell)}. \tag{8}$$

While these weights do not depend on origin or destination status, it is trivial to allow this by interacting covariates with status categories. Temporal information on mobility, for example, the relative amount of time in origin and destination statuses, if available, could be included as a covariate.

For a metrical outcome, Sobel (1981, 1985) used nonlinear least squares to estimate the model parameters. Clifford and Heath (1993) used the EM algorithm to estimate the diagonal model with a constant weight π and no covariates. More generally, for response variables in the exponential dispersion family and link functions g, a diagonal model of the form

$$g(\mu_{od}(\mathbf{x}_\ell)) = \pi_{od}(\mathbf{x}_\ell)\nu_o(\mathbf{x}_\ell) + (1 - \pi_{od}(\mathbf{x}_\ell))\nu_d(\mathbf{x}_\ell), \tag{9}$$

with $\mu_{oo}(\mathbf{x}_\ell) = g^{-1}(\nu_o(\mathbf{x}_\ell))$, can be estimated using maximum likelihood, yielding consistent and asymptotically normal estimates of model parameters. For count data and binary outcome data, where overdispersion is often present, quasi-likelihood or other alternatives, e.g., negative binomial regression for counts, can be employed. For further details on the estimation theory for these models, see Agresti (2013). For software for fitting nonlinear generalized linear models see Kaiser (2018) and Turner and Firth (2022): both programs constrain the weights to lie in (0,1) by using the parameterization in (8). For a complimentary and more extended review of the mobility effects hypothesis prior to 1993, see Hendrickx et al. (1993) and for additional comments on the DMM see Cox (1990).

We have considered the DMM without mobility "effects". It is straightforward to add to these models, e.g. (9), variables measuring the discrepancy between origins and destinations. But whereas the responses $g(\mu_{od}(\mathbf{x}_\ell))$ in (9) are a convex combination of $\nu_o(\mathbf{x}_\ell)$ and $\nu_d(\mathbf{x}_\ell)$, the DMM with mobility "effects" no longer implies $\min(\nu_o(\mathbf{x}_\ell), \nu_d(\mathbf{x}_\ell)) < g(\mu_{od}(\mathbf{x}_\ell)) < \max(\nu_o(\mathbf{x}_\ell), \nu_d(\mathbf{x}_\ell))$: nevertheless, researchers using the DMM with mobility "effects" have typically found that average responses of movers are between those of stayers in the origin and destination states.

3 Empirical Applications of the DMM

Many studies examining the "effect" of inter- and/or intra-generational social mobility using the DMM have focused on health-related outcomes, including self-rated health (Monden and de Graaf 2013; Zang and Bardo 2019), mortality, obesity, physiological stress, and functional somatic symptoms (Billingsley et al. 2018; van der Waal et al.

2017; Claussen et al. 2005; Jonsson et al. 2017; Präg and Richards 2019), mental health, e.g., depression and other mental disorders, psychological distress, self-acceptance (Meng et al. 2020; Gugushvili et al. 2019; Houle and Martin 2011), subjective well-being (Kwon 2022; Schuck and Steiber 2018; Zhao et al. 2017), and health behaviors such as smoking, drug use, and mammogram screenings (Gugushvili et al. 2020; Yang 2020; Dennison 2018a; Missinne et al. 2015). However, the findings are mixed. Using five waves of data from 2002 to 2010 from the European Values Study, Kaiser and Trinh (2021), applying the DMM, found that upward mobility was associated with increased life satisfaction, while downward mobility was associated with decreased life satisfaction. But Dhoore et al. (2019) did not find a statistically significant relationship between intergenerational class mobility and life satisfaction using only the 2008 wave. Studies examining physical health also report mixed findings. While many studies found that intragenerational downward mobility was associated with higher overall mortality rates (Billingsley et al. 2018; Billingsley 2012), Billingsley (2019) found that downward mobility was not associated with mortality.

The DMM has also been used to study political attitudes (Tolsma et al. 2009; De Graaf et al. 1995; Daenekindt et al. 2018; Breen 2001; Jaime-Castillo and Marqués-Perales 2019) and behaviors (Clifford and Heath 1993; Weakleim 1992; Nieuwbeerta et al. 2000; Fan and Yan 2019; De Graaf and Ultee 1990). For example, Daenekindt et al. (2018) found that intergenerational downward educational mobility was associated with political distrust in the Netherlands.

A more recent literature on aesthetic interests (Coulangeon 2015; Daenekindt and Roose 2013b), cultural practices (Daenekindt and Roose 2013a), cultural consumption (Chan and Turner 2017; De Graaf 1991), cultural dissonance (Daenekindt and Roose 2014), and subjective social status (Engzell and Ichou 2020) has emerged. For example, Engzell and Ichou (2020) studied the association between inter-country educational mobility of immigrants in Europe and self-perceived financial and social status at destination. To operationalize educational mobility, they measured the relative educational standing of the immigrants with respect to others in their country of origin, and with respect to others in their destination country. They found that downward mobility (i.e., higher relative standing in the country of origin than in the destination country) was associated with worse self-perceived social and financial status.

Finally, several studies have examined family-related outcomes such as fertility (Liang et al. 2014), child-rearing values (Sieben 2017) and family relationships (Kulis 1987). For example, Liang et al. (2014) find that rural to urban migration (typically considered upward mobility in the Chinese context) was associated with decreased fertility, whereas urban to rural migration was associated with increased fertility in China.

The DMM has also been used to examine the relative salience of different statuses or the weight of different individuals contributing to a decision, For example, Eeckhaut (2017) found that male and female educational attainments were of about equal importance for predicting the contraceptive use decisions of couples. Other examples include Sorenson (1989), who studied the relationship between the husband's education, the wife's education and fertility, Van Berkel and de Graaf (1995), who studied cultural behavior, and Andersson (2018), who studied the inconsistency between respondents' perceived social status at large versus their perceived social status among neighbors and friends.

4 Some Extensions

Duncan and subsequent researchers found that outcomes of movers tend to be between those of stayers in the respective origin and destination statuses. The baseline DMM attempts to represent the socialization process and offers a precise representation of this empirical regularity. Researchers have found this useful, especially in typical applications where mobility "effects" are not found. Thus, we briefly sketch a few potentially useful extensions of the DMM.

4.1 Multiple and Continuous Statuses

The relationship between income and/or educational mobility and outcomes such as health and well-being has been of interest in recent work. In some instances, investigators may wish to treat origin and destination statuses as categorical or ordered categorical (e.g., education coded as less than high school, high school, some college, bachelors or more, or income coded into selected quantiles), as in section two. In others, an investigator might prefer to treat these as continuous (e.g., the natural logarithm of income, education coded in single years of schooling). The DMM can be extended to handle continuous origin and destination variables, as well as multiple statuses (e.g., both income and education).

Let $\mathbf{O}_\ell$ and $\mathbf{D}_\ell$ denote, respectively, vectors of origin and destination statuses, and define

$$\mu_{\mathbf{od}}(\mathbf{x}_\ell) = E(Y_\ell \mid \mathbf{O}_\ell = \mathbf{o}, \mathbf{D}_\ell = \mathbf{d}, \mathbf{X}_\ell = \mathbf{x}_\ell), \tag{10}$$

$$g(\mu_{\mathbf{od}}(\mathbf{x}_\ell)) = \pi_{\mathbf{od}}(\mathbf{x}_\ell)\nu_{\mathbf{o}}(\mathbf{x}_\ell) + (1 - \pi_{\mathbf{od}}(\mathbf{x}_\ell))\nu_{\mathbf{d}}(\mathbf{x}_\ell). \tag{11}$$

As in (9), when g is the identity link $\nu_{\mathbf{o}}(\mathbf{x}_\ell) = \mu_{\mathbf{oo}}(\mathbf{x}_\ell)$, $\nu_{\mathbf{d}}(\mathbf{x}_\ell) = \mu_{\mathbf{dd}}(\mathbf{x}_\ell)$, and $\pi_{\mathbf{od}}(\mathbf{x}_\ell) \in (0, 1)$ is the scalar weight, which can depend on a vector of origin and destination statuses, with continuous, categorical and/or mixed components.

4.2 Longitudinal Data

In the past few decades, longitudinal data that include information on individuals' social statuses at more than two time points and/or repeated measures of outcomes have become increasingly available, e.g., the Panel Study of Income Dynamics, the National Longitudinal Study of Youth cohorts, the National Longitudinal Study of Adolescent to Adult Health. We propose two extensions of the DMM for longitudinal studies.

4.2.1 Case 1: Origins and Destinations Precede Responses

The relationships between origin, destination, and mobility with outcomes may change over the course of an individual's life (Ferraro et al. 2009; Billingsley et al. 2018). The cumulative inequality hypothesis (Ferraro et al. 2009) suggests that adverse social and economic conditions experienced in earlier life accumulate to shape later life health. In contrast, the "aging as leveler" hypothesis suggests that conditions experienced in earlier life diminish in importance as individuals accrue more resources as they age. Thus, it would be of interest to model the relative importance of economic conditions in earlier life and adulthood on outcomes of interest.

We extend the DMM to allow for time varying covariates $\vec{\mathbf{X}}_{\ell t} = (\mathbf{X}_{\ell 1}, ..., \mathbf{X}_{\ell t})$ and responses $\vec{Y}_{\ell t} = (Y_{\ell 1}, ..., Y_{\ell t})$, where $\mathbf{X}_{\ell t}$ and $\mathbf{Y}_{\ell t}$ denote the response and covariate vector, respectively, at time $t \in \{1, ..., T\}$. It is assumed that the vectors indexing origins and destinations $\mathbf{O}_\ell$ and $\mathbf{D}_\ell$ are measured prior to $t = 1$. This extension allows the relative salience of origins and destinations ($\pi_{\mathbf{od}t}$ and $(1-\pi_{\mathbf{od}t})$) to vary over time. The responses may depend on the prior covariates and response history. Let

$$\mu_{\mathbf{od}t}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t}) = E(Y_{\ell t} \mid \mathbf{O}_\ell = \mathbf{o}, \mathbf{D}_\ell = \mathbf{d}, \vec{Y}_{t-1} = \vec{y}_{t-1}, \vec{\mathbf{X}}_{\ell t} = \vec{\mathbf{x}}_{\ell t}, \mathbf{U}_{\ell t} = \mathbf{u}_{\ell t}), \quad (12)$$

where $\mathbf{U}_{\ell t}$ denotes a vector of fixed and/or random effects, and let

$$g(\mu_{\mathbf{od}t}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t})) = \pi_{\mathbf{od}t}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t})\nu_{\mathbf{o}}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t})$$
$$+(1 - \pi_{\mathbf{od}t}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t}))\nu_{\mathbf{d}}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t}). \quad (13)$$

As an example, for a binary response, one might consider a nonlinear logistic normal diagonal model with discrete origins O and destinations D:

$$logit(\mu_{odt}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t})) = \frac{\exp(\gamma_{0t} + \boldsymbol{\gamma}_t'\mathbf{x}_{\ell t})}{1 + \exp(\gamma_{0t} + \boldsymbol{\gamma}_t'\mathbf{x}_{\ell t})}(\alpha_{ot} + \boldsymbol{\beta}_{ot}'\mathbf{x}_{\ell t} + u_\ell + v_t)$$
$$+(1 - \frac{\exp(\gamma_{0t} + \boldsymbol{\gamma}_t'\mathbf{x}_{\ell t})}{1 + \exp(\gamma_{0t} + \boldsymbol{\gamma}_t'\mathbf{x}_{\ell t})})(\alpha_{dt} + \boldsymbol{\beta}_{dt}'\mathbf{x}_{\ell t} + u_\ell + v_t), \quad (14)$$

where the weights are parameterized as in (8), U_ℓ, $\ell \in \{1, ..., n\}$, are independent normally distributed random variables with mean 0 and variance σ_u^2 and V_t, $t \in \{1, ..., T\}$, are independent normally distributed random variables with mean 0 and variance σ_v^2. If $O = D = o$, (14) reduces to $\alpha_{ot} + \boldsymbol{\beta}_{ot}'\mathbf{x}_{\ell t} + u_\ell + v_t$, hence

$$\mu_{oot}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t}) = \frac{\exp(\alpha_{ot} + \boldsymbol{\beta}_{ot}'\mathbf{x}_{\ell t} + u_\ell + v_t)}{1 + \exp(\alpha_{ot} + \boldsymbol{\beta}_{ot}'\mathbf{x}_{\ell t} + u_\ell + v_t)}. \quad (15)$$

To illustrate, suppose the responses are repeated binary measures of disability, starting at age 60 ($t = 1$). Suppose also that origins and destinations are measured on an ordered categorical scale at ages 18 and 59, respectively, and covariates such as marital status and income are measured repeatedly starting from age 60. The origin weights $(\pi_{\mathbf{od}t}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t}))$ and destination weight $(1 - \pi_{\mathbf{od}t}(\vec{y}_{t-1}, \vec{\mathbf{x}}_{\ell t}, \mathbf{u}_{\ell t}))$ depend on age. If the salience of social origins increases (decreases) as individuals age, this offers support for the cumulative inequality hypothesis ("aging as leveler" hypothesis).

4.2.2 Case 2: Additional Statuses

Intergenerational and intragenerational mobility often involve multiple changes of status, e.g., father's status, son's status in first job, subsequent status in current job. The critical period theory posits that the timing of exposures plays an important role in accounting for individuals' later-life health (Kuh et al. 2004). The relationship between multigenerational social mobility and outcomes of grandchildren is another example where a sequence of more than two statuses is of interest (Song 2021, 2016). Extending the DMM to handle such cases allows us to study the relative salience of statuses at more than two time points.

Here we consider the case of a univariate response Y_ℓ, measured after time T. Let $\mathbf{S}_{\ell t}$ denotes the status of respondent ℓ at time $t \in \{1, ..., T\}$, $\vec{\mathbf{S}}_{\ell T} = (\mathbf{S}_{\ell 1}, ..., \mathbf{S}_{\ell T})$. As an example of how the two state diagonal model can be extended, suppose

$$g(\mu_{\vec{\mathbf{s}}_T}(\vec{\mathbf{x}}_{\ell T})) = \sum_{t=1}^{T} \pi_{\vec{\mathbf{s}}_T}(t, \vec{\mathbf{x}}_{\ell T}) \nu_{s_t}(\vec{\mathbf{x}}_{\ell t}), \tag{16}$$

where $\mu_{\vec{\mathbf{s}}_T}(\vec{\mathbf{x}}_{\ell T}) = E(Y_\ell \mid \vec{\mathbf{X}}_{\ell T} = \vec{\mathbf{x}}_{\ell T}, \vec{\mathbf{S}}_{\ell T} = \vec{\mathbf{s}}_T)$, $0 < \pi_{\vec{\mathbf{s}}_T}(t, \vec{\mathbf{x}}_{\ell T}) < 1$, $t = 1, .., T$, and $\sum_{t=1}^{T} \pi_{\vec{\mathbf{s}}_T}(t, \vec{\mathbf{x}}_{\ell T}) = 1$. For many potential applications, (16) is more general than required. For the special case where g is the identity link, with $\mathbf{X}_{\ell t} = \mathbf{X}_\ell$ for all t, and discrete statuses S_t at time t taking values $s_t \in \{1, ..., I\}$, (16) reduces to:

$$\mu_{\vec{s}_T}(\mathbf{x}_\ell) = \sum_{t=1}^{T} \pi_{\vec{s}_T}(t, \mathbf{x}_\ell) \nu_{s_t}(\mathbf{x}_\ell). \tag{17}$$

When $S_t = s$ for all t, $\nu_{s_t}(\mathbf{x}_\ell) = E(Y_\ell \mid S_1 = ... = S_T = s, \mathbf{X}_\ell = \mathbf{x}_\ell)$, and when $T = 2$, this reduces to (9).

To illustrate, suppose social status is measured at birth, in childhood (e.g., age 12), in adolescence (e.g., age 17), and in emerging adulthood (e.g., age 25), and the response is a measure of health at age 40. For each point in time there is a corresponding weight

$(\pi_{\vec{\mathbf{s}}_T}(t, \vec{\mathbf{x}}_{\ell t}))$. The comparison of these weights is of interest to life course researchers, also of potential policy importance: for example, if the weight at birth is greatest, this suggests focusing on policies and interventions targeting infants and their mothers. To ensure the weights lie in the unit interval (0,1) and add to 1, the parameterization in (8) is easily generalized.

5 Mobility Effects: A Reformulation

5.1 Associations and Effects

To this point, we have considered parametric and semi-parametric models describing the association between outcomes and mobility, comparing respondents with different mobility profiles, e.g., the mental health status of mobile vs. immobile individuals. In the statistical literature on causal inference, an effect is conceptualized as a within subject comparison, as vs. a between subject comparison, as above. We now consider comparisons of respondents with themselves under alternative states, here one in which they are mobile vs. another in which they are immobile. Comparisons of this nature are challenging because respondents are only observed under one of the conditions in the comparison, necessitating the use of between subject comparisons to make these within subject comparisons, as above. Nevertheless, comparisons between different respondents can be used to acquire knowledge of population effects (commonly called, with some redundancy " average causal effects") under some additional conditions. To understand these conditions, we cannot start with a model and deem various coefficients as effects, as in previous work: it is necessary to start by defining the effects of interest, after which we can ask whether it is possible to identify and estimate these. Often data that are adequate for studying the association between outcomes and mobility will not be adequate for studying the effects of mobility.

In this section, we briefly sketch a few estimands an investigator might wish to consider and discuss the identification of these. Our treatment is meant to be illustrative, not definitive. But first, an important caveat: we are not suggesting that previous research is devoid of interest or merit. In many instances, past and present, an investigator who thinks carefully about his research question may discover that he was or is more interested in comparing differences between mobile and immobile respondents than in asking, for example, how respondents who were mobile might have behaved had they not been mobile.

An obvious strategy for studying mobility "effects", prominent before Duncan moved the goalpost, compared the mean outcome μ_{od} of movers from categorical origin status $O = o$ to categorical destination status $D = d$ with the mean outcome μ_{oo} of stayers in origin o or the mean outcome μ_{dd} of stayers in d, e.g., $\mu_{od} - \mu_{oo}$. In essence, Duncan decomposed this as follows:

$$\mu_{od} - \mu_{oo} = (\mu_{od} - \mu^*_{od}) + (\mu^*_{od} - \mu_{oo}), \tag{18}$$

where μ^*_{od} is the mean outcome of movers from o to d in the absence of mobility "effects". The first term of this decomposition is the residue Duncan and subsequent researchers have equated with mobility "effects". The second term is the average difference between the movers from o to d and the stayers in o in the absence of a "mobility effect". The components of (18) are not unique, depending on the manner in which the baseline average response in the absence of mobility effect μ^*_{od} is operationalized.

We see two problems with Duncan's formulation. First, as noted above, to speak of mobility effects, respondents ℓ should be compared with themselves under alternative conditions. Second, it seems more reasonable than otherwise to say that for respondents ℓ who move from o to d and have the same value of the outcome they would have had had they remained in status o, the effect of mobility is 0.

5.2 Some Estimands of Potential Interest

We now reconceptualize the mobility effects hypothesis using the potential outcomes notation from the statistical literature on causal inference (see Imbens and Rubin (2015) for a nice introduction). There are any number of questions that might be asked, and the potential outcomes we define will depend on these questions. For example, we might define potential outcomes $Y_\ell(o, d)$ to represent the response of respondent ℓ were she (possibly counterfactually) to have originated in origin o and moved to destination d. These could then be used to ask what would happen if respondents originated in status o and moved to status d as versus originated in o and remained there. But it is not immediately clear why it would be of interest to ask how respondents would behave or fare if they were to move to destination d from an origin o that differs from their actual origin status. Instead, one might prefer to ask how respondents with actual origin $O = o$ would behave were they to move, possibly counterfactually, to destination d vs. destination d^*, e.g., 1) among respondents with origin $O = o$, what is the effect of moving to destination d vs. remaining in $d^* = O = o$, 2) among respondents with origin $O = o$ and destination $D = d$, what is the effect of moving from o to d?

To address such questions, potential outcomes $Y_\ell(d)$ are defined to represent the response ℓ would have were her destination status d: note only the one value $Y_\ell \equiv Y_\ell(D)$ associated with the actual destination to which ℓ moved is observed. Several assumptions, revisited later, are implicitly made using this notation: 1) there are not multiple versions of the treatment, and 2) the response of unit ℓ depends only on her "assignment" and not the "assignments" of other respondents, i.e., there is no "interference" between units. Whether or not these assumptions are reasonable will depend on the population studied and the response variable under consideration.

To begin, we define the unit effect on respondent ℓ of moving to destination d vs. d^*,

$Y_\ell(d) - Y_\ell(d^*)$ The unit effects are then used to define population estimands, e.g.:

$$E(Y_\ell(d) - Y_\ell(d^*)), \tag{19}$$

$$E(Y_\ell(d) - Y_\ell(d^*) \mid O_\ell = o), \tag{20}$$

$$E(Y_\ell(d) - Y_\ell(d^*) \mid D_\ell = d), \tag{21}$$

$$E(Y_\ell(d) - Y_\ell(d^*) \mid D_\ell = d, O_\ell = o). \tag{22}$$

Equation (19) is the average effect of moving to d vs. d^* in the population $\mathcal{P}$ from which ℓ is drawn. The estimand is overly broad. For example, suppose the origin and destination statuses are categorical, with labels $1, ..., 5$, and $d = 1$, $d^* = 3$: for further concreteness, suppose origin status is the respondent's father's education (1 = post-baccalaureate degree, 2 = bachelor's degree, 3 = some college, 4 = high school diploma, 5 = less than high school diploma), destination status is respondent's education, coded identically, and the outcome is a continuous measure of mental health. Then (19) is a weighted average of the effect of obtaining a post-baccalaureate degree versus only some college for respondents in each origin status. For respondents with origin status 1 ($o = 1$), this is the effect of remaining at the highest educational level versus obtaining an educational level between high school and college completion, whereas for respondents originating at the lowest educational level, it is the effect of obtaining a post-baccalaureate degree versus some college: while it seems clear one might want to ask about the effect of staying in status 1 versus moving down to status 3 for respondents who originate in status 1, it is not so clear why one would want to know the effect of moving to status 1 versus status 3 for respondents originating in status 5. Further, even were (19) of interest, most likely its component effects would be of even greater interest, as we expect these to be unequal.

The more refined estimands (20) - (22) answer various questions of possible interest:

1. Equation (20) is the average effect of moving to destination d vs. destination d^* for the sub-population of individuals who originate in status $O = o$: these effects are the components of the global effect (19). If $d^* = o$, this is the effect of moving to destination d vs. remaining in origin o for respondents with origin o; with $d = 1$ and $d^* = 3$, as above, this is the effect of obtaining a post-baccalaureate degree vs. attending (but not finishing) college for respondents who attended but did not finish college.

2. Equation (21) is the average effect of moving to destination d vs. destination d^* for the sub-population of individuals who actually move to destination $D = d$. It is a version of the "effect of treatment on the treated", the average effect of treatment (here destination status d) in the sub-population of individuals who actually take treatment (move to d) (Rubin 1977; Belson 1956): with d and d^* as before, this is the effect of obtaining a post-baccalaureate degree vs attending but not finishing college for those who actually obtain a post-baccalaureate degree.

3. Equation (22) is the average effect of moving to destination d vs. destination d^* for the sub-population of individuals who originate in status $O = o$ and move to destination $D = d$. With $d = 1$ and $d^* = 3$, this is the effect of obtaining a post-baccalaureate degree vs. some college for respondents who originate in o and obtain a post-baccalaureate degree. In the special case where also $0 = o = d^*$, this is the average effect of mobility from origin o to destination d in the sub-population of individuals who actually made this transition (hereafter $\text{EMM}(o, d)$)): in our example, this is the effect of obtaining a post-baccalaureate degree versus attending but not finishing college on mental health among respondents who actually obtained a post-baccalaureate degree and whose fathers attended but did not finish college. The "effect of mobility on the mobile" from o to d $\text{EMM}(o, d)$, also

a version of the effect of treatment on the treated, compares the actual mobility experiences of movers from o to d with the counterfactual experience they would have had if they remained in origin o. This estimand is also a conditional (on origin and destination status) version of the "effect of treatment on the treated".

The estimands (20)-(22) compare outcomes among specific destination pairs in different sub-populations of respondents. Of these, we believe the estimand (22), especially the special case EMM(o, d), which asks what is the effect of mobility from o to d for respondents who actually made this transition, will generally be of greater interest than the effect of mobility from o to d for all respondents who originate in status $O = o$, regardless of their actual destination, or all respondents who move to d, regardless of origin status.

The estimands above are destination-specific. Traditionally, mobility researchers have been interested in more global comparisons, e.g., the effect of upward mobility vs. immobility, long distance mobility vs. short distance mobility). While the estimands above do not address such comparisons, they can be used as building blocks to define such effects. We consider the case where origins and destinations are measured on a categorical scale: extension to the continuous case is straightforward.

Let Ω_D denote the set of all possible destinations, and let α_ℓ denote a subset of Ω_D specific to respondent ℓ, for example, for respondents who are upwardly mobile, $\alpha_\ell = \{d : d < O_\ell\}$, following the convention that higher ranked statuses are associated with smaller integers. Define $Y_\ell(\alpha_\ell) = \sum_{d \in \alpha_\ell} Y_\ell(d) 1_{\alpha_\ell}(d)$. Let δ_ℓ denote another subset of Ω_D, where $\alpha_\ell \bigcap \delta_\ell = \emptyset$. Unit effects are then defined as comparisons $Y_\ell(\alpha_\ell) - Y_\ell(\delta_\ell)$. Population estimands are then defined as averages of these, e.g.:

$$E(Y_\ell(\alpha_\ell) - Y_\ell(\delta_\ell) \mid \mathbf{X}_\ell = \mathbf{x}) = E(Y_\ell(\alpha_\ell) \mid \mathbf{X}_\ell = \mathbf{x}) - E(Y_\ell(\delta_\ell) \mid \mathbf{X}_\ell = \mathbf{x}), \qquad (23)$$

where $\mathbf{X}_\ell$ is a vector of covariates. The two components of (23) are weighted averages of destination specific expectations:

$$E(Y_\ell(\alpha_\ell) \mid \mathbf{X}_\ell = \mathbf{x}) = \sum_{d \in \alpha_\ell} E(Y_\ell(d) \mid \mathbf{X}_\ell = \mathbf{x}) \Pr(d \mid \alpha_\ell, \mathbf{x}), \tag{24}$$

with probabilities "allocated" to destinations within α_ℓ, $0 < \Pr(d \mid \alpha_\ell, \mathbf{x}) < 1$ for all d and $\mathbf{x}$, $\sum_{d \in \alpha_\ell} \Pr(d \mid \alpha_\ell, \mathbf{x}) = 1$ for all $\mathbf{x}$.

As an example, consider the effect of downward mobility from origin $O_\ell = o$. Here $\alpha_\ell = \{d : d > O_\ell = o\}$, δ_ℓ is a singleton set, $\mathbf{X}_\ell = (O_\ell)$, and (23) reduces to:

$$\sum_{d > o} E(Y_\ell(d) \mid \mathbf{O}_\ell = o) \Pr(d \mid O_\ell = o) - E(Y_\ell(o) \mid O_\ell = o). \tag{25}$$

Here a natural choice for the "allocated" probabilities $\Pr(d \mid o)$ are the population probabilities of moving to each category $d > o$.

5.3 Identification

Without further assumptions, the estimands above are not identified because $Y_\ell(d)$ is only observed when $D_\ell = d$. Thus, for example, $E(Y_\ell(d) \mid O_\ell = o, D_\ell = d)$ is identified, as it is the conditional expectation among respondents who originated in status $O_\ell = o$ and transitioned to destination $D_\ell = d$, but $E(Y_\ell(d) \mid O_\ell = o) = \sum_{d^*} E(Y_\ell(d) \mid O_\ell = o, D_\ell = d^*) \Pr(D_\ell = d^* \mid O_\ell = o)$ is not, as we only observe $\mathrm{E}(Y_\ell(d) \mid O_\ell = o, D_\ell = d^*)$ when $d^* = d$. However, if destinations were chosen at random,

$$\{Y_\ell(d)\}_{d \in \Omega_D} \perp\!\!\!\perp D_\ell \tag{26}$$

(where $\perp\!\!\!\perp$ denotes statistical independence), as in a randomized experiment, $E(Y_\ell(d) \mid O_\ell) = E(Y_\ell(d) \mid O_\ell = o, D_\ell = d)$ is identified for every destination D. But destinations are not chosen at random, and for almost any outcome of substantive interest, it would be unreasonable to assume (26) holds. The usual identification strategy in observational studies is to specify other covariates $\mathbf{C}_\ell$, temporally prior to D_ℓ, such that

$$\{Y_\ell(d)\}_{d \in \Omega_D} \perp\!\!\!\perp D_\ell \mid \mathbf{C}_\ell, \quad 0 < \Pr(D = d \mid \mathbf{C}_\ell) < 1, \tag{27}$$

and $\sum_d \Pr(D = d \mid \mathbf{C}_\ell) = 1$, hence

$$E(Y_\ell(d) \mid \mathbf{C}_\ell = \mathbf{c}, D_\ell = d) = E(Y_\ell(d) \mid \mathbf{C}_\ell = \mathbf{c}), \tag{28}$$

where $\mathbf{C}_\ell$ may include the social origin variable, in which case $\mathbf{C}_\ell = (\mathbf{C}_{\ell 1}, O_\ell)$.

As an example, consider the estimand $\text{EMM}(o, d)$, with components $\text{E}(Y_\ell(d) \mid O_\ell = o, D_\ell = d)$ and $\text{E}(Y_\ell(o) \mid O_\ell = o, D_\ell = d)$. The first component is the expected value $\text{E}(Y_\ell \mid O_\ell = o, D_\ell = d)$ for movers from o to d. Repeated application of (27) gives

$$\begin{aligned} E(Y_\ell \mid O_\ell = o, D_\ell = o, \mathbf{C}_{\ell 1} = \mathbf{c}_1) = E(Y_\ell(o) \mid O_\ell = o, D_\ell = o, \mathbf{C}_{\ell 1} = \mathbf{c}_1) = \\ E(Y_\ell(o) \mid O_\ell = o, \mathbf{C}_{\ell 1} = \mathbf{c}_1) = E(Y_\ell \mid O_\ell = o, D_\ell = d, \mathbf{C}_{\ell 1} = \mathbf{c}_1), \end{aligned} \tag{29}$$

$$\begin{aligned} E(Y_\ell(o) \mid O_\ell = o, D_\ell = d) &= EE(Y_\ell(o) \mid O_\ell = o, D_\ell = d, \mathbf{C}_{\ell 1} = \mathbf{c}_1) \\ &= AE(Y_\ell \mid O_\ell = o, D_\ell = o, \mathbf{C}_{\ell 1} = \mathbf{c}_1) \end{aligned} \tag{30}$$

where the notation A is used to indicate that the observed conditional expectation $E(Y_\ell \mid O_\ell = o, D_\ell = o, \mathbf{C}_{\ell 1} = \mathbf{c}_1)$ is averaged over the distribution of $C_{\ell 1}$ given $O_\ell = o, D_\ell = d$, not the distribution of $C_{\ell 1}$ given $O_\ell = o, D_\ell = o$.

When assumption (27) holds, the estimands considered herein can be estimated using a variety of procedures, such as propensity score weighting and matching, linear regressions, doubly robust methods, targeted maximum likelihood, Bayesian additive regression trees, and selected machine learning algorithms (e.g., random forests).

While assumption (27) is straightforward, putting forth a convincing set of covariates $\mathbf{C}_\ell$ may be challenging in many instances: for a respondent with origin status O_ℓ, (27) implies her potential outcomes in destination d do not depend on actual destination status given her covariates and origin status. For example, the health status of a respondent with blue collar origins who moves, possibly counterfactually, to a professional occupation, does not depend on her actual destination status, e.g., professional or agricultural laborer, given the covariates C_ℓ.

When assumption (27) is untenable, this is typically due to unobserved variables U_ℓ that affect both the destination to which a respondent moves and her outcomes. Thus, (27) holds if these variables $\mathbf{U}_\ell$ are added to the conditioning set. There are several ways social scientists and statisticians have attempted to deal with this situation. First, a sensitivity analysis may be conducted (e.g., Rosenbaum 2002; Ding and VanderWeele 2016). Second, there is a literature on bounding effects, going back at least to Robins (1989). As an example, consider the estimand $\mathrm{EMM}(o, d)$. Here, the term $E(Y_\ell(d) \mid D_\ell = d, O_\ell = o)$ is identified, but the term $E(Y_\ell(d^*) \mid D_\ell = d, O_\ell = o)$ is not. However, if outcomes are bounded, i.e., $m \leq Y_\ell(d^*) \leq M$, it is easy to bound $\mathrm{EMM}(o, d)$; in practice, however, such bounds are often too wide to be useful. Third, social scientists have used "fixed effects" models in conjunction with regression models for longitudinal data to take into account temporally invariant variables $\mathbf{U}_\ell$. One might try to use this approach in conjunction with the extended DMM proposed in section 4.2.1. However, associations between mobility and outcomes will not warrant an interpretation as effects unless very unrealistic identification conditions are met (Sobel 2012). Fixed effects models for clustered data have also been widely used. As an example of how one might apply such models in the mobility context, siblings will have the same origin status, but their destination statuses may differ and one might want to estimate the effect of moving from origin $O = o$ to destination $D = d$ on an outcome of interest, e.g., attitudes toward immigrants. Even with a large set of measured confounders, the common unmeasured familial environment is likely to be a confounder. However, the usual applications of these models make the often untenable assumption of no interference (sometimes called no spillover or no indirect effects) between units and identical treatment effects among units (Petersen and Lange 2020). Joensen and Nielsen (2018) also discuss this and use a fixed effect model for siblings, in conjunction with instrumental variables, to identify treatment effects in the presence of interference.

Several approaches that do not make use of (27) include regression discontinuity (RD) designs, and instrumental variables (IV): we take up the latter in the subsequent section on mediation. In RD designs, individuals are observed on either side of a threshold that determines treatment assignment. Under suitable conditions, units "close" to the threshold are deemed to be comparable, and this serves as a source of identification. In a sharp RD design, where units to the left (right) of the threshold do not receive (do receive) treatment, the effect of assignment on the response can be identified, and in a fuzzy RD design, where there are some units to the left (right) of the threshold that receive (do not receive) treatment, the effect of the treatment can also be identified. The main limitation of these designs is that such effects are only locally identified. For further work and examples see the classic paper by Hahn et al. (2001), also Lee and Lemieux (2010) and Cattaneo and Titiunik (2021).

5.4 Some Additional Challenges

We briefly point out several directions and issues that merit the attention of future researchers, the consideration of which will facilitate the development of more interesting and credible analyses of mobility when the effects of mobility are of interest.

5.4.1 Mediation

While researchers have proposed various mediators on the pathway(s) between mobility and outcomes that might account for mobility effects (should these exist), for example stress, they have devoted little effort to measuring and incorporating such variables into analyses of mobility, rendering it impossible to empirically assess the role, if any, of these hypothesized mechanisms. In future work, we hope this is addressed. That said, the challenges are formidable, as the identification conditions that are typically invoked in mediation analyses are often unreasonable. Thus, we briefly mention some estimands discussed in the statistical literature on mediation that investigators might wish to consider, and we offer some comments about the identification of these. Readers who are not familiar with this literature might wish to consult Holland (1988), who first considered mediation within the potential outcomes framework, Wang and Sobel (2013), who consider controlled direct effects and the pure direct and indirect effects (often called natural direct and indirect effects) defined and considered by Robins and Greenland (1992), and especially the book length treatment by VanderWeele (2015).

Let $M_\ell \equiv M_\ell(D_\ell)$, taking values $m \in \Omega_m$, denote ℓ's value on the mediator, and let $M_\ell(d)$ denote the value when ℓ moves, possibly counterfactually, to destination d. Using the potential outcomes $M_\ell(d)$ and $Y_\ell(d)$, the effect of mobility on the mediator and the effect of mobility on the outcome can be examined using the estimands previously defined. The manner in which mediation is typically conceptualized also postulates potential outcomes $Y_\ell(d, m)$, the value of ℓ's response were she to have moved to destination d and to have, possibly counterfactually, value m of the mediator. Controlled direct effects compare potential outcomes $Y_\ell(d, m)$ with $Y_\ell(d^*, m)$ or $Y_\ell(d, m^*)$, e.g., $Y_\ell(d, m) - Y_\ell(d^*, m)$, the controlled direct effect of moving to d vs. d^* for ℓ were she, possibly counterfactually, to have value m on the mediator. As before, averaging over subgroups defined by mobility status leads to controlled direct effects conditional on subgroup membership.

The identification conditions for estimating controlled direct effects are more stringent than those previously considered: in addition to the identification condition in (27) applied to $M_\ell(d)$, it is assumed

$$Y_\ell(d,m) \perp\!\!\!\perp M_\ell \mid D_\ell = d, \mathbf{C}_\ell = c_\ell. \tag{31}$$

It is also common to consider indirect effects of mobility that operate through the mediator. To estimate pure direct and indirect effects in linear structural equation models (sometimes called ”natural direct effects” and “natural indirect effects”), no additional identification conditions need to be put forth. But linear models are often unreasonable, and the so-called “cross-world assumption” that is made to identify these effects more generally precludes post-treatment confounding by variables affected by treatment, i.e., there cannot be variables subsequent to respondent’s destination that are affected by the destination which affect both the mediator and the outcomes. If the time interval between destinations and outcomes is sufficiently small, this might be plausible, but otherwise, it is not, i.e., in general, these effects will not be identified from the observed data. Thus, we do not consider them further. However, it is important to note that even with post-treatment confounding, it is possible to estimate controlled direct effects using marginal structural models and to consider randomized interventional analogues of indirect effects. In addition, one should note that if mobility does not affect the mediator (say stress as per the disassociative hypothesis) in the first place, then a mobility effect, if any, is not due to the mediator examined; however, if mobility does affect the mediator, it does not imply that this mediator mediates as it may not affect the outcome. Finally, although we have only considered the case of a single mediator, it is possible to consider several mediators: here matters become considerably more difficult quickly. For further treatment of these and other issues in mediation, see VanderWeele (2015). See also Robins (2003) for a clear exposition of the conditions needed to identify various causal effects using directed acyclic graphical models and note that Robins (1986)’s finest fully randomized causally interpreted structured tree graph

(FRCISTG) model does not make the cross-world assumption made in the special case of the non-parametric structural equation model later proposed by Pearl.

Finally, we briefly mention the principal stratification framework (Frangakis and Rubin 2002), which can be viewed as providing an alternative approach to mediation. For simplicity, we take up the case in Angrist et al. (1996), who considered the case of a randomized treatment assignment variable Z, and a binary intermediate outcome D whose effect on a response Y it is desired to estimate. The effect of Z on D may vary across individuals but Z may not directly affect Y (the exclusion restriction). Under suitable additional conditions, Angrist et al. (1996) shows that the instrumental variable (IV) estimand identifies the average effect of D on Y in a sub-population (or principal stratum) of "compliers", i.e., persons who take treatment if offered and who do not take treatment if it is not offered. In mobility research, this framework might be useful when it is not possible to intervene on mobility (the usual case), but it is possible to intervene on prior variables that influence mobility. As an example, Barnard et al. (2003) studied the effects of school choice on reading and math scores in New York City, where a randomized experiment in which approximately 20,000 low-income families applied for 1300 scholarships for children to attend private schools. Approximately one-quarter of the awards were not used (the \$1400 scholarship did not cover the cost of tuition) and a little less than 10% of the applicants who did not receive an award attended private school anyhow. They found small positive effects on the intent to treat (ITT) estimand, the effect of offering a voucher, and somewhat larger effects (Causal Average Complier Effect) of attending a private school among the subgroup of compliers. Although this is not a study of social mobility, it is easy to imagine a randomized study of the effect of mobility from a low-status background to a high-status destination on income using a college scholarship as a treatment (instrument). However, it is important to note that the compliers are a latent sub-population, and complier effects may not be generalizable to a larger population of interest. For some further work on principal stratification and IV's, see Ding and Lu (2017) and Baiocchi et al. (2014).

5.4.2 Multiple Versions of "Treatment"

Previously, we considered average effects of downward mobility by averaging over mobility effects that might vary among the particular categories to which a downwardly mobile respondent could move. More generally, when "treatments" are heterogeneous, additional considerations concerning identification and definition of estimands arise (VanderWeele and Hernan 2013). This suggests choosing destination categories that the researcher thinks may be relatively homogeneous with respect to outcomes. Another case occurs if the effect of mobility depends on the timing of the mobility transition. For example, if respondent ℓ completes a bachelor's degree at age 21, the effect of her educational mobility on earnings at the time at which earnings are measured may be different than had she completed her degree at age 27. Let $Y_{\ell t}(d, t_d)$ denote ℓ's potential outcome at time $t > t_d$ were she, possibly counterfactually, to have moved to destination d at time t_d: then $Y_{\ell t}(d) \equiv Y_{\ell t}(d, t_d)$, where t_d denotes the possibly counterfactual time at which ℓ transitioned to d. Alternatively, depending on the analysis, t_d might refer to a respondent's age or to a date in time. The "treatments" (d, t_d) can then be grouped into subsets α_ℓ, as in the previous analysis of directional mobility.

5.4.3 Interference

A number of previous authors have argued that the relative salience of origin and destinations could depend on the density of respondents in the respective origin and destination statuses. This suggests that the effect of mobility on respondents moving, possibly counterfactually, to destination d could depend on the proportion of respondents who move to this destination, in which case ℓ's potential outcomes depend not only on her destination, but the destinations of others. Suppose there are N units in the population, and let Ω_D^N denote the set of all destination vectors $\mathbf{D} = (D_1, ..., D_N)$. The no interference assumption (Cox 1958) states that for all respondents $\ell = 1, ..., N$, and for all $\mathbf{d}$ and $\mathbf{d'}$ in Ω_D^N, with $d_\ell = d'_\ell$, $Y_\ell(\mathbf{d}) = Y_\ell(\mathbf{d'})$. For some outcomes, this assumption will be reasonable, e.g., consider the effect of mobility on respondents' health status. For other outcomes, e.g., political attitudes, one might expect that if ℓ is the only respondent to move to d her attitudes may differ from the case where 90 % of respondents move, possibly counterfactually, to destination d; this is the result of spillover.

Starting with Halloran and Struchiner (1995), Hong and Raudenbush (2006), Sobel (2006), there has subsequently been enormous interest in this topic. Statisticians have made headway primarily by imposing constraints on the pattern of interference; for example, in cluster randomized experiments or observational studies with units nested in larger groupings, it is assumed that outcomes depend only on the interference within the cluster in which one is located (e.g., Hudgens and Halloran (2008), Qu et al. (2022)); the analogue here would be to treat destinations as clusters. See also Aronow and Samii (2017). As with mediation, the intent here is only to indicate that interference is something that future researchers working on mobility effects will need to address: doing so is both a challenge and an opportunity.

6 Conclusions

Social and behavioral scientists have long been interested in the consequences of social mobility for health, psychological functioning, cultural, economic outcomes, and even social stability. This paper focused on the sociological literature and the mobility effects hypothesis in particular. For the past 40 years, this hypothesis has typically been investigated using the DMM. We trace the origins and development of the DMM, then describe a representative collection of applications. Although empirical researchers using the DMM often failed to find mobility "effects", the model, in the absence of mobility "effects", decomposes mobility outcomes using origin and destination weights that capture the relative salience of these statuses, a question of some independent interest to researchers. Thus, several extensions of the model are also proposed, for multiple and continuous statuses, and for various types of longitudinal data.

At about the same time the DMM was conceptualized, statisticians were developing an approach to causal inference based on a counterfactual view of the causal relation. This approach, now widely disseminated to other disciplines, regards what earlier researchers would have deemed mobility "effects" as associations between mobility and its subsequent correlates. While these associations may actually be of primary interest for many research questions, questions where one wants to know what would have happened, if possibly counterfactually, respondents had experienced a different mobility profile than that they actually experienced, may also be of interest sometimes to both researchers and policy makers. We, therefore, develop this approach in the mobility context, putting forth a number of causal estimands that may be of interest. We also discuss the challenges in identifying these estimands.

The extensions of the DMM and the causal estimands herein are more illustrative than definitive. We did not discuss the identification and estimation of the DMM extensions, though these can be treated within the generalized linear (and mixed) model framework. A related extension that might be further developed is De Graaf (1991), who modeled the relationship between status inconsistency and material consumption in several Eastern European countries, with separate sets of weights for the husband's education, the wife's education, and household income. We also want to make clear that although the frameworks we have provided for studying effects and associations of mobility with outcomes are useful, there are many questions of interest and approaches to studying mobility that do not readily fit into this framework. In some instances, it may be useful to extend and/or adapt these questions and approaches to encompass the relationship between mobility and its consequences. As an example, Song et al. (2022) applied a group-based trajectory approach to classify individual income trajectories as immobile, upwardly mobile, or downwardly mobile. A natural extension would be to model the relationship between the trajectories and outcomes, e.g., mental health. Readers who are not familiar with this approach might see Zang and Max (2020) for an introduction and a Bayesian approach. As a second example, we have highlighted the difficulty of identifying the causal estimands put forth in this paper. Since randomized mobility trials are infeasible to conduct, and as the identification conditions discussed in the text will be difficult to meet, researchers may need to take advantage of experimental and quasi-experimental studies intended for other purposes. Several examples of encouragement designs were discussed in the text, e.g., the school voucher study by Barnard et al. (2003), and regression discontinuity studies were also mentioned. Recently Jia and Li (2021) used Chinese College Entrance Exam scores to compare students just above and below the thresholds for entry into elite colleges, using this to estimate the effect of elite college admission on subsequent wages. Coupled with information on social origins, such data might be used to estimate the effect of social mobility on wages, at least in a local neighborhood of the thresholds.

Finally, the distinction between effects of mobility and associations of mobility with outcomes is important. We hope that the explicit treatment herein will help future researchers think more carefully about the questions they wish to ask, and to use appropriate tools to address these. We also hope that future workers will further develop the ideas herein, and explore innovative designs and methods, coupling these with appropriate data to address important questions of substance and policy relevance.

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