Beyond the Diagonal Reference Model: Critiques and New Directions

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Abstract

There has recently been an increase in the number of quantitative studies examining the consequences of individual-level socioeconomic mobility. Nearly all of these studies have used Sobel's (1981; 1985) diagonal reference model. Here, we critically examine the properties of the model, and show mathematically and via simulation that, under plausible values of mobility effects, it tends to generate results that implicitly force the mobility linear effect to zero. As such, the model has little advantage over Duncan's square additive model, which has been abandoned for similar reasons. We conclude with a caution to researchers interested in using the diagonal reference model. The resulting estimated mobility effects are, in part, an artifact of the model and should be interpreted judiciously. In general, when using the technique researchers should decompose the mobility parameters using orthogonal projection, which will reveal the potentially strong assumptions underlying the model.

1 Background and Motivation

1.1 Introduction

Interest in the consequences of social mobility is long-standing (for reviews, see Hope 1971; Hendrickx et al. 1993). From its earliest days, the scientific literature on social mobility has debated its individual-level effects. The sociologist Pitrim Sorokin (1927), for example, hypothesized negative effects of both upward *and* downward social mobility on individuals' well-being, as those who attain a status different from that of their parents may suffer from the cultural gap between their attained position and family origins. Nearly a century later, the large body of quantitative sociological research on mobility effects has rendered a clear but puzzling verdict — social mobility has virtually no effect on a strikingly wide range of outcomes, including individuals' well-being, attitudes, and behaviors (Weakliem 1992; Breen 2001; Tolsma et al. 2009; Houle and Martin 2011; Zang and Dirk de Graaf 2016; Chan 2018; Daenekindt 2017; Schuck and Steiber 2018).

The null findings on mobility effects not only contradicts longstanding sociological theory, but also calls into question much of the work on social mobility conducted by demographers and sociologists. Since the influential work by Lipst and Bendix (1959), international teams of researchers have conducted a number of important, widely-cited studies explaining differing rates of social mobility across countries. However, as Lipset and Zetterberg (1959) point out, "unless variations in mobility rates and in the subjective experience of mobility make a difference for society or for the behavior pattern of an individual, knowledge concerning rates of mobility will be of purely academic interest" (6). It appears that generations of sociologists and demographers have attempted to explain an outcome that is, on the whole, of no consequence for the individual.[1]

In this paper we demonstrate that such conclusions about the individual-level consequences of social mobility, although consistent with a wide range of studies, are premature. The initial wave of research, influenced by Duncan's seminal work on the topic, showed no effect of social mobility on a range of outcomes. This model was later recognized to implicitly assume that the linear effect of mobility is zero. Another wave of research has resulted from Sobel's (1981; 1985) diagonal reference model, which is seen as the "gold standard" for mobility effects research. As Houle and Martin (2011) point out, the diagonal reference model "is the only method used in modern mobility effects research" (197). In recent years, sociologists have used Sobel's model to explain various outcomes, including subjective well-being, political extremism, obesity, and so on. However, as we show, like Duncan's model, the diagonal reference model relies on on strong assumptions about the linear effect of social mobility, effectively building in the conclusion that social mobility is of no consequence.

The rest of this paper is organized as follows. First, we outline the identification challenge, clarifying what can be known from the data without additional constraints. Second, we discuss Sobel's diagonal reference model, comparing it with Duncan's square additive model. Third, we show, mathematically and with simulations, that the diagonal reference model fails to capture the true effect of social mobility in a number of plausible scenarios. Finally, we conclude with a call for caution when using diagonal reference models to estimate mobility effects. Ultimately any model attempting to separate the effects of social mobility from those of origin and destination must use explicit, carefully-reasoned assumptions. The conclusions are necessarily tentative and subject to revision depending on new theoretical insights and/or the inclusion of additional data (i.e., data other than that from a single mobility table).

1.2 Identification Challenge

Progress in empirically identifying the effects of social mobility on individuals has been hampered by a fundamental methodological challenge. Social mobility (M) is the difference between individuals' social origins (O), e.g., parental social class, and their social destinations (D), e.g., their own social class. As a result, any model of mobility effects is underidentified and cannot be estimated using conventional statistical techniques. In contrast to problems of statistical inference, which involve understanding how sampling variability can affect conclusions based on samples of limited size, problems of identification entail understanding what conclusions can be drawn even with a sample of unlimited size. The lack of a unique solution of mobility effects is a classic identification problem, because it cannot be resolved by collecting larger samples. A variety of techniques have been proposed for analyzing mobility effects. Sobel's diagonal reference model remains, especially over the past decade, the most commonly-used technique for analyzing mobility effects in sociology and demography.[2]

[1]One may attempt to save the situation by claiming that social mobility has effects only at the macro-level, not the micro-level. However, this renders ambiguous the likely mechanisms linking social mobility rates with macro-level outcomes; moreover, any analysis could easily be the product of the ecological fallacy.

[2]In this paper we will use "diagonal reference model" to refer to Sobel's "simple diagonal reference model." We do not consider the DM-1 and DM-2 models because, as pointed out by Weakliem (1992) and Hendrickx (1993), they will conflate the mobility effects with the effects of origin and destination, respectively.

2 The Methodological Challenge

2.1 Modeling Mobility Effects

The typical model for origin, destination, and mobility effects is an additive model for a particular outcome. Suppose we have a set of categorical variables for $i = 1, \ldots I$ origin groups, $j = 1, \ldots, J$ destination groups, and $k = j - i + I, \ldots K$ mobility groups.[3] For simplicity, and without loss of generality, we will assume that the origin and destination categories are of equal width. Let $\mathbf{M} = [\mu_{ijk} : i = 1, \ldots, I; j = 1, \ldots, J; k = j - i + I, \ldots K]$ denote a mobility table (i.e., a matrix) of means with I rows and J columns. The index $k = j - i + I, \ldots, K$ denotes the diagonals running from the upper-left to lower-right of the table, beginning with the cell in the lower-left corner. The basic mobility effects model (e.g., see Blalock 1966: 130) is

$$\mu_{ijk} = \mu + \alpha_i + \beta_j + \delta_k + \epsilon_{ijk}, \tag{1}$$

where μ is the intercept (or overall mean), α_i is the ith origin effect, β_j is the jth destination effect, δ_k is the kth cohort effect, and ϵ_{ijk} is the error term.[4]

To express the model using matrix notation, we can group the means into an $(I \times J) \times 1$ vector $\boldsymbol{\mu}$. We can also group the intercept, origin, destination, and mobility effects into a $(1+I+J+K) \times 1$ vector $\boldsymbol{\gamma}$, where

$$\boldsymbol{\gamma}^T = (\mu, \boldsymbol{\alpha}^T, \boldsymbol{\beta}^T, \boldsymbol{\delta}^T) = (\mu, \alpha_1, \ldots, \alpha_I, \beta_1, \ldots, \beta_J, \delta_1, \ldots, \delta_K). \tag{2}$$

For an appropriate design matrix $\mathbf{X}$ of dimension $(I \times J) \times (1 + I + J + K)$, the vector of means in an $I \times J$ mobility table $\mathbf{M}$ is generated by $\boldsymbol{\mu} = \mathbf{X}\boldsymbol{\gamma}$.[5]

Unfortunately, this model suffers from two identification problems. The first issue is that, with an intercept in the model, there is one more level than can be estimated so an additional constraint is required. This is a relatively tractable identification problem common to all linear models using categorical variables as inputs. In the discussion that follows, we will assume that sum-to-zero constraints are applied, such that $\sum_{i=1}^{I} \alpha_i = \sum_{j=1}^{J} \beta_j = \sum_{k=1}^{K} \delta_k = 0$. The second identification problem is considerably more troublesome. Even after applying a constraint to identify the intercept, the linear effects of the three variables are not identified (Blalock 1966; Blalock 1967; Hendrickx et al. 1993). That is, the design matrix $\mathbf{X}$ is rank deficient one even after applying a constraint to identify the intercept. Thus, a regular inverse of $\mathbf{X}^T\mathbf{X}$ does not exist and accordingly there is no unique least-squares solution $\mathbf{b}_{\text{OLS}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\boldsymbol{\mu}$, where the superscript -1 denotes a regular inverse.

2.2 Formalizing the Identification Challenge

More formally, note that, in a particular mobility table $\mathbf{M}$, the cell-specific means μ_{ijk} are generated by the model $\mu + \alpha_i + \beta_j + \delta_k + \epsilon_{ijk}$. These cell-specific means are invariant with respect to a set of transformations on the parameters, reflecting the non-identifiability of the overall levels of the origin, destination, and mobility variables as well as their unique linear effects (cf. Carstensen 2007; Kuang et al. 2008). Following Kuang et al. (2008), we denote this set of transformations $F = [f : f\boldsymbol{\gamma} = (f\mu, f\boldsymbol{\alpha}, f\boldsymbol{\beta}, f\boldsymbol{\delta})]$, where

[3] Note that I is added to $j - i$ so that the mobility index begins at $k = 1$. This ensures that, for example, $i = j = k = 1$ refers to the first group for all three variables. One could just as easily index the mobility groups using $k = j - i$, but this identity would be lost.

[4] If we had data on a set of individuals indexed from $n = 1, \ldots, N$, then we would have individual-specific means μ_{ijkn} and individual-specific error terms ϵ_{ijkn}. However, the identification problems discussed above still hold.

[5] Without loss of generality, we will generally assume that there are no disturbances such that $\boldsymbol{\epsilon} = \mathbf{0}$, where $\boldsymbol{\epsilon}$ is an $(I \times J) \times 1$ vector of error terms ϵ_{ijk} and $\mathbf{0}$ is an $(I \times J) \times 1$ vector of zeros.

$$f\mu = \mu - a - b - c + (I-1)v \tag{3}$$
$$f\boldsymbol{\alpha} = [\alpha_i + a + (i-1)v]_{i=1}^{I}, \tag{4}$$
$$f\boldsymbol{\beta} = [\beta_j + b - (j-1)v]_{j=1}^{J}, \tag{5}$$
$$f\boldsymbol{\gamma} = [\delta_k + c + (k-1)v]_{k=1}^{K}. \tag{6}$$

The quantities a, b, c, and v are scalars that can take on any real number. Specifically, the values of a, b, and c indicate, respectively, the unknown overall levels of the origin, destination, and mobility effects, while v is an unknown overall linear component. Crucially, the set of means collected in the mobility table $\mathbf{M}$ are invariant with respect to the transformations $f\mu$, $f\boldsymbol{\alpha}$, $f\boldsymbol{\beta}$, and $f\boldsymbol{\gamma}$. That is, for any f, it is the case that

$$\begin{aligned} \mu_{ijk}(f\boldsymbol{\gamma}) &= \mu_{ijk}(f\mu, f\alpha_i, f\beta_j, f\delta_k) && (7)\\ &= \mu_{ijk}(\mu, \alpha_i, \beta_j, \delta_k) && (8)\\ &= \mu_{ijk}(\boldsymbol{\gamma}). && (9) \end{aligned}$$

To see this, note that $k = j - i + I$ and that we can therefore write the following:

$$\begin{aligned} \mu_{ijk}(f\mu, f\alpha_i, f\beta_j, f\delta_k) = (&\mu - a - b - c + (I-1)v && (10)\\ &+ [\alpha_i + a + (i-1)v]_{i=1}^{I} && (11)\\ &+ [\beta_j + b - (j-1)v]_{j=1}^{J} && (12)\\ &+ [\delta_{j-i+I} + c + (j-i+I-1)v]_{i=1,j=1}^{i=I,j=J}. && (13) \end{aligned}$$

Because the scalars a, b, c, and v cancel out, it can be concluded that

$$\begin{aligned} \mu_{ijk}(f\mu, f\alpha_i, f\beta_j, f\delta_k) &= \mu + \alpha_i + \beta_j + \delta_k && (14)\\ &= \mu_{ijk}(\mu, \alpha_i, \beta_j, \delta_k). && (15) \end{aligned}$$

In other words, the data likelihood is invariant to a set of transformations on the origin, destination, and mobility parameters. Thus, the levels of origin, destination, and mobility effects are not identifiable without fixing a, b, and c by, for example, applying sum-to-zero constraints.[6] Likewise, the linear effects are not identifiable without setting a particular value of v or, equivalently, applying an appropriate constraint on the linear effects.

3 The Square Additive and Diagonal Reference Models

Most contemporary work on mobility effects has attempted to separate the effects of mobility from origin and destination using one of two models: the *square additive model* (Duncan 1966) or the *diagonal reference model* (Sobel 1981; Sobel 1985). Both models begin with a baseline set of estimated origin and destination effects. The square additive model entails the following baseline parameterization:

$$\mu_{ijk} = \mu + \alpha_i + \beta_j + \epsilon_{ijk} \tag{16}$$

where μ is the intercept, α_i is the ith origin effect, β_j is the jth destination effect, and ϵ_{ijk} denotes the error term. To estimate mobility effects, Duncan (1966: 95) proposed estimating

$$\mu_{ijk} = \mu + \alpha_i + \beta_j + \omega_{ij} + \epsilon_{ijk}, \tag{17}$$

where ω_{ij} denotes the interaction between the ith and jth origin and destination categories. Duncan claimed that mobility effects should be considered present whenever there are statistically significant interactions in Equation 17.

As an alternative approach, Sobel (1981; 1985) proposed the following model as a baseline:

$$\mu_{ijk} = \mu + p_1\mu_i + p_2\mu_j + \epsilon_{ijk} \tag{18}$$

[6]Note that we must apply three sum-to-zero constraints, one for each effect, i.e. origin, destination, and mobility.

with

$$p_1 = \frac{e^{\xi_1}}{e^{\xi_1} + e^{\xi_2}} \text{ and } p_2 = 1 - p_1 = \frac{e^{\xi_2}}{e^{\xi_1} + e^{\xi_2}}$$

where μ is the intercept, p_1 is the weight for the effect of origin, p_2 is the weight for the destination effect which is equal to $1 - p_1$, ξ_1 is the origin parameter used to calculate the weights, ξ_2 is the destination parameter used to calculate the weights, μ_i is the expected mean outcome for the ith origin category, μ_j is the expected mean outcome for the jth destination category, and ϵ_{ijk} is the error term.[7] Unlike the square additive model, the diagonal reference model estimates the origin and destination effects indirectly. Note that, because Equation 18 is nonlinear, it cannot be estimated using ordinary least squares. Formally, for nonlinear models, at least one of the derivatives of the expectation function with respect to the parameters depends on at least one of the parameters. The joint origin and destination effects for the cells on the main diagonal, representing non-mobile individuals, are given by the parameters μ_i (or, equivalently, μ_j). The joint origin and destination effects for the cells off the main diagonal, representing mobile individuals, are given by $p_1\mu_i + p_2\mu_j$, where p_1 and p_2 can be interpreted as the relative salience of the origin and destination categories, respectively. Above the baseline model, mobility effects can be parameterized as a set of categorical variables:

$$\mu_{ijk} = \mu + p_1\mu_i + p_2\mu_j + \delta_k + \epsilon_{ijk} \tag{19}$$

where the weights are the same as before, and δ_k denotes the set of mobility effect parameters. Sobel (1981: 902) suggests that mobility effects are present whenever the δ_k's in Equation 19 are statistically significant.

4 Limitations of the Diagonal Reference Model

Unfortunately, the square additive and diagonal reference models suffer from three fundamental problems that hindered the scientific understanding of mobility effects. First, both have generated a body of null findings on mobility effects, contradicting longstanding social science theory (Lipset and Bendix 1959; Smelser 1966; Sorokin 1927; Tumin 1957) as well as a growing body of qualitative evidence (e.g., see Friedman 2012; Friedman 2014; Friedman 2016; Goldthorpe et al. 1987; Paulson 2018). Second, both models rely on statistical significance tests and fit statistics to make conclusions about the extent of origin, destination, and mobility effects (Duncan 1966; Sobel 1981; Sobel 1985; Weakliem 1992). However, because the linear effects are unidentified, they are already captured by the baseline models by the inclusion of origin and destination effects, so such tests and fit statistics are uninformative about the magnitude or direction of the true, unknown linear effects. Finally, most problematically, both models are based on *ad hoc*, implicit constraints on the linear origin, destination, and mobility effects. To reiterate, as shown in Equations 3 to 15, the data likelihood is invariant with respect to a set of transformations on the linear effects of origin, destination, and mobility. Accordingly, both models are only identified to the extent that the very specific assumptions they entail about the linear effects are valid. For example, the diagonal reference model assumes that the linear effects of origin and destination are correctly captured by $p_1\mu_i + p_2\mu_j$, which cannot be verified from the data from a mobility table. Similarly, the square additive model implicitly assumes that the linear mobility effect is zero, because the linear effect of mobility is already captured by the set of α_i origin and β_j destination effects (Hope 1971; Hope 1975).[8] In fact, the *ad hoc* assumptions of *both* models implicitly force the mobility linear effects to zero, which explains the repeated null findings in the most recent quantitative literature (e.g., see Houle and Martin 2011; Daenekindt 2017).

[7] Typically the intercept is dropped from Equation 18, but we retain it here to allow for comparison with the square additive model (e.g., see Hendrickx et al. 1993: 342).

[8] In other words, the interaction terms capture nonlinearities in the mobility effect, but not the linear component.

To understand the constraints applied to the diagonal reference model, note that the diagonal effects are given by $\mu_{i=1} \ldots \mu_{i=I}$ if indexed by the origin categories. Equivalently, the diagonal effects can be indexed by the destination categories, such that $\mu_{j=1} \ldots \mu_{j=J}$. Each effect on the diagonal can be decomposed into an overall linear effect and a nonlinear effect. For example, the diagonal effect corresponding to the ith origin category can be decomposed as $\mu_i = \psi + \widetilde{\mu}_i$, where ψ is the overall linear effect and $\widetilde{\mu}_i$ is the ith nonlinearity. Alternatively, the diagonal effect corresponding to the jth destination category can be decomposed as $\mu_j = \psi + \widetilde{\mu}_j$. Lastly, the kth mobility effect can be decomposed as $\delta_k = \delta + \widetilde{\delta}_k$, where δ is the linear effect. In this way, we can rewrite Equation 19 as:

$$\mu_{ijk} = \mu + p_1(\psi + \widetilde{\mu}_i) + p_2(\psi + \widetilde{\mu}_j) + (\delta + \widetilde{\delta}_k) + \epsilon_{ijk} \tag{20}$$

or

$$\mu_{ijk} = \mu + p_1\psi + p_2\psi + \delta + p_1\widetilde{\mu}_i + p_2\widetilde{\mu}_j + \widetilde{\delta}_k + \epsilon_{ijk}. \tag{21}$$

Because the origin, destination, and mobility linear effects are not identified, any set of constrained estimates will differ based on an unknown scalar v. In terms of the basic mobility effects model, this can be represented as $\alpha^* = \alpha + v$, $\beta^* = \beta - v$, and $\delta^* = \delta + v$, where the asterisk denotes the estimated linear effect under some particular constraint. Similarly, in terms of the diagonal reference model, the non-identifiability of the linear effects can be represented as $p_1^*\psi^* = p_1\psi + v$, $p_2^*\psi^* = p_2\psi - v$, and $\delta^* = \delta + v$. When estimating the mobility effects model, which is necessarily a constrained estimator, we are in fact estimating:

$$\widehat{\mu}_{ijk} = \mu + p_1^*\psi^* + p_2^*\psi^* + \delta^* + p_1\widetilde{\mu}_i + p_2\widetilde{\mu}_j + \widetilde{\delta}_k + \epsilon_{ijk} \tag{22}$$

or

$$\widehat{\mu}_{ijk} = \mu + (p_1\psi + v) + (p_2\psi - v) + (\delta + v) + p_1\widetilde{\mu}_i + p_2\widetilde{\mu}_j + \widetilde{\delta}_k + \epsilon_{ijk}. \tag{23}$$

If, as proposed by Sobel, $p_2 = 1 - p_1$, Equation 23 is equal to:

$$\widehat{\mu}_{ijk} = \mu + (p_1\psi + v) + (\psi - p_1\psi - v) + (\delta + v) + p_1\widetilde{\mu}_i + (1 - p_1)\widetilde{\mu}_j + \widetilde{\delta}_k + \epsilon_{ijk} \tag{24}$$

or

$$\widehat{\mu}_{ijk} = \mu + \psi + (\delta + v) + p_1\widetilde{\mu}_i + (1 - p_1)\widetilde{\mu}_j + \widetilde{\delta}_k + \epsilon_{ijk}. \tag{25}$$

Equation 25 is crucial to understanding the diagonal reference model. The joint linear effect of origin and destination, given by ψ, is identified. In fact, there are three unknown quantities, δ, v, and p_1; all other quantities in the equation are fully identified from the data. In Sobel's main model, we assume $p_1 = 1 - p_2$. However, the mobility linear effect equals $\delta + v$. Because v can take on any value from positive to negative infinity, the model is not identified. That is, identical sets of predicted values (i.e., the $\widehat{\mu}_{ijk}$'s) from a diagonal reference model can be obtained by simply altering the value of v, which is unknown.

Mathematically the diagonal reference model is fixing a particular value of v. Using simulations (to be presented), we demonstrate that the model will set values of v such that the mobility linear effect (δ) is forced to zero. This is because the model is already saturated in terms of the baseline linear effect, which is ψ. It has been claimed that the diagonal reference model allows one "to simultaneously estimate effects of social position of origin, social position of destination, and social mobility" (Daenekindt 2017: 23). This is only the case if the mobility linear effect is, in fact, zero in the population. This is an assumption that can only be justified by appealing to sociological theories of social mobility and is not information directly available from a mobility table.

5 Conclusion

Studies of social mobility have typically used the diagonal reference model, especially in a wave of recently-published research. These studies, similar to an older wave of studies using Duncan's square additive model, have shown that, on the whole, mobility has no effect on a range of important outcomes. We have shown, both mathematically and with simulations, that these conclusions are an artifact of the diagonal reference model. When using the diagonal reference model, we recommend using orthogonal projection to decompose the linear from the nonlinear effects. Doing so will reveal the exact nature of the assumptions involved.

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