Partial Identification of Economic Mobility: With an Application to the United States

Daniel L. Millimet*

Southern Methodist University & IZA

Hao Li

Southern Methodist University

Punarjit Roychowdhury

Shiv Nadar University

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Abstract

The global rise in inequality has brought renewed attention to the economic mobility of individuals and households. While many measures of economic mobility exist, reliance on transition matrices remains pervasive due to simplicity and ease of interpretation. However, estimation of transition matrices is complicated by the well-acknowledged problem of measurement error in self-reported and even administrative data. Existing methods of addressing measurement error are complex, rely on numerous strong assumptions, and often require data from more than two periods. In this paper, we investigate what can be learned about economic mobility as measured via transition matrices while formally accounting for measurement error in a reasonably transparent manner. To do so, we develop a nonparametric partial identification approach to bound transition probabilities under various assumptions on the measurement error and mobility processes. This approach is applied to panel data from the United States to explore short-run mobility before and after the Great Recession.

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*The authors are grateful for helpful comments from Elira Kuka, Xun Tang, and conference participants at Texas Econometrics Camp XXII. Corresponding author: Daniel Millimet, Department of Economics, Box 0496, Southern Methodist University, Dallas, TX 75275-0496. Tel: (214) 768-3269. Fax: (214) 768-1821. E-mail: millimet@smu.edu.

1 Introduction

There has been substantial interest of late in the related topics of inequality, intragenerational mobility, and intergenerational mobility. Atkinson and Bourguignon (2015, p. xvii) state that inequality has become "very much centre stage," while Dang et al. (2014, p. 112) state that mobility "is currently at the forefront of policy debates around the world." In addition, the public has become acutely aware of issues related to the income distribution. An article in the *Washington Post* (October 6, 2016) states that "social mobility ... has become a major focus of political discussion, academic research and popular outrage in the years since the global financial crisis," while the *New York Times* (December 6, 2016) states that "inequality has been a defining national issue for nearly a decade."[1,2]

While inequality and mobility are often "lumped together," they represent distinct characterizations of the income distribution (*New York Times*, April 3, 2015).[3] Inequality is predominantly a cross-sectional phenomenon, describing the shape of the income distribution at a snapshot in time. Mobility, in contrast, is inherently dynamic and invokes a "complementary perspective on income distribution" (Jäntti and Jenkins 2015, p. 808). In this paper, we study the analysis of mobility while accounting for measurement error in income data. As discussed below, measurement error in income data is known to be pervasive, even in administrative data. However, existing studies of mobility either ignore the issue or utilize complex solutions that invoke strong (and often non-transparent) identification assumptions and have data requirements that are quite limiting.

Our focus is on mobility for several reasons. First, while there is convincing evidence that income inequality has been increasing in the US and elsewhere, the welfare impacts of this rise in inequality depend crucially on the level of economic mobility.[4] Shorrocks (1978, p. 1013) argues that "evidence on inequality of incomes or wealth cannot be satisfactorily evaluated without knowing, for example, how many of the less affluent will move up the distribution later in life." Glewwe (2012, p. 236-7) states that "the distribution of income at one point in time may not be the key issue" and that "shifting concern for equity from short-run to long-run inequality leads directly to mobility." Kopczuk et al. (2010, p. 91-2) conclude that "a comprehensive analysis of disparity requires studying both inequality and mobility" as "annual earnings inequality might substantially exaggerate the extent of true economic disparity among individuals."

Second, and related, the degree of income mobility in an economy is often used as a metric to gauge the efficiency and equity in an economy. Mobility, especially across generations, is frequently interpreted as a measure of equality of opportunity (Jäntti and Jenkins 2015). However, too much mobility may be indicative of large and frequent economic shocks, leading to fluctuating incomes and insecurity (Jarvis and

[1] See `https://www.washingtonpost.com/news/wonk/wp/2016/10/06/striking-new-research-on-inequality-whatever-you-thought-its-wors` `?utm_term=.83d37c53195b`.

[2] See `https://www.nytimes.com/2016/12/06/business/economy/a-bigger-economic-pie-but-a-smaller-slice-for-half-of-the-us.html`.

[3] See `https://www.nytimes.com/2015/04/05/upshot/its-not-the-inequality-its-the-immobility.html`.

[4] The level of income inequality in the US has followed a U-shaped pattern over the past century (Picketty and Saez 2003; Kopczuk et al. 2010; Atkinson and Bourguignon 2015).

Jenkins 1998).

Finally, owing to the rise in inequality and concern over poverty, policies increasingly contain distributional objectives (Atkinson and Bourguignon 2015). This has occurred in spite of the "paucity of evidence on the duration of poverty and on income mobility," particularly in developing countries (Dang et al. 2014, p. 112). Glewwe (2012) and Dang et al. (2014) articulate the importance of such evidence for the creation of effective policy. On the one hand, if mobility is low, such that individuals may find themselves caught in a poverty trap, then policy should perhaps target the acquisition of assets by low income households. On the other hand, if mobility is high, but individuals are unable to smooth consumption during periods of low income, then policy may be more effective if it targets sources of income volatility and/or credit and insurance markets.

Given the reasons to be interested in mobility, many measures have been proposed, often reflecting different underlying definitions of mobility itself (Burkhauser and Couch 2009; Jäntti and Jenkins 2015; Jenderny 2016). Benabou and Ok (2001, p. 2) summarize the literature at the time, stating that "the measurement of mobility remains in a state of flux, with the literature showing a somewhat bewildering array of approaches and concepts." In this paper, we focus on transition matrices (and summary measures derived therefrom). We do so for three reasons. First, transition matrices are an obvious starting point in the measurement of mobility. Jäntti and Jenkins (2015, p. 822) argue that, when measuring mobility across two points in time, "the bivariate joint distribution of income contains all the information there is about mobility, so a natural way to begin is by summarizing the joint distribution in tabular or graphical form." Second, transition matrices are easily understood by policymakers and the general public and thus are frequently referenced within these domains. The importance of this cannot be oversold. For example, a recent article in *The New Yorker* (March 26, 2014) argued that an "essential part" of the work by Piketty and others as it relates to inequality is the presentation of the data in a manner that is "easier to understand" through the avoidance of "clever but complicated statistics ... which attempted to reduce the entire income distribution to a single number."[5] Third, transition matrices, in contrast to mobility measures that yield a single number, allow one to examine mobility at different parts of the income distribution (Lee et al. 2017).

While transition matrices are easily understood and trivial to estimate given the availability of accurate data at two points in time for a random sample, it is well-known that income data are not error-free. This is true regardless of whether the data come from a survey or administrative records. In survey data, measurement error arises for two main reasons: misreporting (particularly with retrospective data) and imputation of missing data (Jäntti and Jenkins 2015). It is now taken as given that self-reported income in survey data contain significant measurement error, and that the measurement error is nonclassical in the sense that it is mean-reverting and serially correlated (Duncan and Hill 1985; Bound and Krueger 1991; Bound et al. 1994; Pischke 1995; Pedace and Bates 2000; Bound et al. 2001; Kapteyn and Ypma 2007; Gottschalk and Huynh 2010). Compounding matters, Meyer et al. (2015) find that both problems – nonresponse and

[5] See `http://www.newyorker.com/news/john-cassidy/pikettys-inequality-story-in-six-charts`.

accuracy conditional on answering – are worsening over time. In administrative data, measurement error arises for three main reasons: misreporting (tax evasion or filing errors), conceptual differences between the desired and available income measures, and processing errors (Bound et al. 1994; Bound et al. 2001; Kapteyn and Ypma 2007; Pavlopoulos et al. 2012; Abowd and Stinson 2013; Meyer et al. 2015; Obserski et al. 2016). Even if administrative data are entirely accurate, they are only available in a handful of developed countries.

In light of this, addressing measurement error in the study of mobility should no longer be optional. Nonetheless, the most frequent response to measurement error is to mention it as a caveat (Dragoset and Fields 2006). While the usual assumption is that measurement error will lead to upward bias in measures of mobility, the complexity of various mobility measures along with the nonclassical nature of the measurement error makes the direction of any bias uncertain. Glewwe (2012, p. 239) states that "all indices of relative mobility tend to exaggerate mobility if income is measured with error," yet others offer a different opinion. Dragoset and Fields (2006, p. 1) contend that "very little is known about the degree to which earnings mobility estimates are affected by measurement error." Gottschalk and Huynh (2010, p. 302) note that "the impact of nonclassical measurement error on mobility is less clear since mobility measures are based on the joint distribution of reported earnings in two periods."

In this paper, we offer a new approach to addressing measurement error in the estimation of transition matrices. Specifically, we abandon point identification and instead concentrate on the partial identification of such matrices. We provide informative bounds on the transition probabilities using a variety of nonparametric assumptions. To our knowledge, this is the first study to extend recent developments in the literature on partial identification to the study of transition matrices (see, e.g., Horowitz and Manski 1995; Manski and Pepper 2000; Kreider and Pepper 2007, 2008; Gundersen and Kreider 2008, 2009; Kreider et al. 2012). Within this environment, we first derive sharp bounds on transition probabilities under minimal assumptions on the measurement error process. We then show how the bounds may be narrowed by imposing more structure via shape restrictions, level set restrictions that relate transition probabilities across observations with different attributes (Manski 1990; Lechner 1999), and monotone instrumental variable (MIV) restrictions that assume monotonic relationships between the true income and certain observed covariates (Manski and Pepper 2000).

In contrast to existing approaches to handle measurement error in studies of mobility (discussed in Section 2), our approach has several distinct advantages. First, the assumptions invoked to obtain a given set of the bounds are transparent, easily understood by a wide audience, and easy to impose or not impose depending on the particular context. Moreover, bounds on the elements of transition matrices extend naturally to bounds on mobility measures derived from transition matrices. Second, our approach only requires data at two points in time. Third, our approach is easy to implement (through our creation of a generic Stata command).[6] Fourth, our approach extends easily to applications other than income, such as dynamics related

[6] Available at `http://faculty.smu.edu/millimet/code.html`.

to consumption, wealth, occupational status, labor force status, health, student achievement, etc.

The primary drawback to our approach is the lack of point identification of transition probabilities. Two responses are in order. First, our approach should be viewed as a complement to, not a replacement for, existing approaches. Indeed, one usefulness of our approach is to provide bounds with which point estimates derived via alternative estimation techniques may be compared. Second, many existing approaches to deal with measurement error in mobility studies end up producing bounds even though the solutions are not couched as a partial identification approach (e.g., Dang et al. 2014; Lee et al. 2017). This arises due to an inability to identify all parameters in some structural model of observed and actual incomes.

We illustrate our approach examining intragenerational mobility in the United States using data from the Survey of Income and Program Participation (SIPP) for the United States. Specifically, we examine mobility over two four-year periods, 2004 to 2008 and then 2008 to 2012. We find some striking results. First, our analysis shows that relatively small amounts of measurement error leads to bounds that can be quite wide in the absence of other information or restrictions. Second, the restrictions considered contain significant identifying power as the bounds can be severely narrowed. Finally, allowing for misclassification errors in up to 10% of the sample, we find that the probability of remaining in poverty (out of poverty) in the initial and terminal years in the sample is at least 36% (89%) under our most restrictive set of assumptions.

The rest of the paper is organized as follows. Section 2 provides a brief literature review of existing approaches to address measurement error in studies of mobility. Section 3 presents our partial identification approach. Section 4 contains the empirical applications. Section 5 concludes.

2 Literature Review

Burkhauser and Couch (2009) and Jäntti and Jenkins (2015) provide excellent reviews of the numerous mobility measures. Bound et al. (2001) and Meyer et al. (2015) offer excellent surveys regarding measurement error in microeconomic data. Here, we focus on approaches that have been taken to address (or not address) measurement error in analyses of economic mobility. We identify three general approaches in the existing literature: (i) ignore it, (ii) *ad hoc* data approaches, and (iii) *structural* approaches.

The first, and most common, approach is to note the problem and then ignore it. Pavlopoulos et al. (2012, p. 750) state that "despite the enormous bias that measurement error can cause in the estimation of wage dynamics, most relevant studies ignore this phenomenon." Lee et al. (2017, p. 37) write that "most studies of income and poverty dynamics have ignored potential measurement error biases in the transition matrices, although the presence of measurement error in both income and expenditure survey data has been widely acknowledged."

The second general strategy we refer to as *ad hoc* data approaches. Trimming is one example and refers to the practice of deleting a fraction (say, 1%) of the poorest and richest observations in the sample. Jäntti and Jenkins (2015, p. 862) note that trimming has been "applied in virtually every study cited in our discussion." The motivation for trimming is the removal of outliers that may represent measurement error (e.g., Maasoumi and Trede 2001). The drawbacks to this procedure include the fact that outliers may arise for reasons other than measurement error and that it does nothing to address measurement error outside the tails of the distribution.

A second example of an *ad hoc* approach is to average income data over several years. Thus, when computing mobility between two points in time, income in the initial (terminal) period is taken as, say, the three-year average around the true initial (terminal) period. Such a strategy was popularized in Solon (1992); see Bhattacharya and Mazumder (2011) and Bradbury (2016) for more recent examples. The motivation for averaging income over several periods is to smooth away measurement error. However, there are several drawbacks to this procedure. First, averaging smooths away all time-varying idiosyncratic sources of income variation, regardless of whether the variation arises from measurement error or legitimate shocks to income. As such, some mobility is lost. Second, averaging will not remove measurement error that is persistent over time. Finally, averaging requires data from more than two time periods, a requirement that may be prohibitive, especially in developing country contexts.

A third example of an *ad hoc* approach is the pseudo-panel estimator in Antman and McKenzie (2007), although the approach can also be applied with genuine panel data. Here, rather than averaging income over several periods for each observation, income is averaged over individuals assigned to the same cohort within each time period. Measures of mobility are then computed using panel data at the cohort level. As in the preceding case, the motivation for averaging income within cohorts and time periods is to smooth away measurement error. Again, though, there are several drawbacks. First, averaging smooths away all time-varying idiosyncratic sources of income variation, regardless of whether the variation arises from legitimate shocks to income. Second, cohorts must remain stable over time, which is not assured when using pseudo-panel data, and cohorts must be large. Finally, the definition of cohorts is arbitrary and shrinks the effective sample size.

The final general strategy used in the extant literature we refer to as *structural* approaches. Approaches falling under this category represent the forefront of the literature and can be sub-divided into two groups. The first group seeks to estimate a scalar measure of mobility: either the correlation coefficient between (true) log incomes in the initial and terminal periods, denoted by ρ, or the elasticity of (true) terminal period income with respect to (true) initial period income, denoted by β in the following simple linear regression model

$$\ln(y^*_{1i}) = \alpha + \beta \ln(y^*_{0i}) + \varepsilon_i, \tag{1}$$

where y^*_{0i} (y^*_{1i}) is income in the true initial (terminal) period for observation i. Glewwe (2012) notes that if we define β_R as the coefficient in the reverse regression, given by

$$\ln(y^*_{0i}) = \alpha_R + \beta_R \ln(y^*_{1i}) + \eta_i, \tag{2}$$

then

$$\text{plim}\sqrt{\widehat{\beta}\cdot\widehat{\beta}_R} = \rho, \tag{3}$$

where $\widehat{\beta}$ and $\widehat{\beta}_R$ denote the ordinary least squares (OLS) estimate of the corresponding population parameters.

With measurement error, the researcher observes y_{0i} and y_{1i}. As such, $\widehat{\beta}$ and $\widehat{\beta}_R$ are inconsistent and the square root of their product provides a consistent estimate of the correlation between the logs of *observed* income, not *true* income. The solution proffered in the literature is to recover consistent estimates of β, β_R, and ρ via instrumental variables (IV). There are two drawbacks to this approach. First and foremost, obtaining credible instruments is extremely difficult (if not impossible). Antman and McKenzie (2007) and Glewwe (2012) offer detailed examinations of this issue. Second, even if consistent estimates of ρ and β could be obtained, they are of limited use as measures of mobility as their scalar nature preclude examinations of mobility at different parts of the distribution.

The second group under the heading of *structural* approaches pursues a different strategy. Instead of focusing on a specific measure of mobility, such as ρ or β, structural methods are used to simulate error-free income, denoted by $\widehat{y}^*_{0i}$ and $\widehat{y}^*_{1i}$. Armed with such estimates, any mobility measure may be computed, including transition matrices. Clearly, the validity of this approach rests on the quality of the simulated error-free data. Obtaining simulated values of error-free data is not trivial and typically relies on complex models invoking a number of fairly opaque assumptions.

Studies pursuing this strategy include McGarry (1995), Glewwe and Dang (2011), Pavlopoulos et al. (2012), Dang et al. (2014), and Lee et al. (2017). McGarry (1995) posits a variance components model to isolate the portion of observed income that represents measurement error. Upon simulating error-free income, conditional staying probabilities for the poor are examined. The results indicate substantially less mobility in the simulated data. However, the model defines measurement error as the individual-level, time-varying, serially *uncorrelated* component of income. Thus, all time-varying idiosyncratic sources of income variation are removed. Moreover, the individual-level, time-varying, serially *correlated* component of income is not considered measurement error. Finally, parametric distributional assumptions are required for identification in practice.

Glewwe and Dang (2011) begin with the assumption that log income follows an AR(1) process as in (1). The authors then combine OLS and IV estimates of the forward and reverse regressions, along with assumptions about the variance components of the model, to simulate error-free income. The simulated data are then used to assess income growth across the distribution. As in McGarry (1995), the results suggest substantial bias from measurement error. However, as in McGarry (1995), identification of error-free income relies on strong assumptions for identification, such as serially *uncorrelated* measurement error, particular functional forms, and valid instrumental variables.

Pavlopoulos et al. (2012) build on Rendtel et al. (1998) and specify a mixed latent Markov model to examine error-free transitions between low pay, high pay, and non-employment. The model requires data from at least three periods, as well as requires perhaps strong assumptions concerning unobserved heterogeneity and initial conditions. In addition, serial correlation in measurement error is difficult to address and extending the model to more than three states is problematic. Nonetheless, the results align with the preceding studies in that mobility is dampened once measurement error is addressed.

Dang et al. (2014) consider the measurement of mobility using pseudo-panel data. Since the same individuals are not observed in multiple periods, the authors posit a static model of income using only time invariant covariates available in all periods. The model estimates, along with various assumptions concerning how unobserved determinants of income are correlated over time, are used to bound measures of a two-by-two poverty transition matrix. This approach implicitly addresses measurement error through the imputation process as missing data can be considered an extreme form of measurement error. However, measurement error in observed incomes used to estimate the static model and compute the poverty transition matrix is not addressed. Moreover, it is not clear how one could extend the method to estimate more disaggregate transition matrices.

Finally, Lee et al. (2017) estimates a complex model based on an AR(1) model of consumption dynamics with time invariant and time-varying sources of measurement error to simulate error-free consumption and estimate transition matrices. Consistent with the preceding studies, significantly less mobility is found in the simulated data. While the authors' model has some advantages compared to earlier attempts to simulate error-free outcomes, these advantages come at a cost of increased complexity, decreased transparency of the identifying assumptions, and a need for four periods of data. In addition, bounds are obtained as not all parameters required for the simulations are identified.

In summary, the literature on addressing measurement error in studies of mobility has witnessed significant growth in the past decade. Indeed, the most recent approaches move well past early *ad hoc* approaches. However, there remains much scope for additional work. Methods addressing measurement error in the context of using ρ or β to capture mobility rely on strong and perhaps implausible assumptions concerning the validity of instrumental variables. Simulation-based methods return the focus to transition matrices, but are complex, lack transparency, rely on strong functional form and distributional assumptions, and often require more than two years of data (limiting their usefulness in studies of intergenerational mobility). Moreover, the common reliance in the majority of the simulation approaches on an AR(1) model of income or consumption dynamics is worrisome. Lee et al. (2017, p. 38) acknowledge that "this model is not so much derived from a well-developed theory, but it is a convenient reduced-form model." Finally, the reliance on precise assumptions concerning the nature of the variance components is unappealing in light of Kapteyn and Ympa's (2007, p. 535) finding that "substantive conclusions may be affected quite a bit by changes in assumptions on the nature of error in survey and administrative data."

Our proposed approach complements these existing approaches. In contrast to approaches focused on estimating ρ or β, we are concerned with estimating transition matrices. In contrast to simulation approaches, which often end up with bounds on transition probabilities, we set out to estimate bounds from the beginning, making it transparent exactly how the bounds are affected by each assumption one may wish to impose. Furthermore, the assumptions imposed to narrow the bounds are much easier for non-experts to comprehend.

3 Model

3.1 Setup

Let y^*_{it}, denote the true income for observation i, $i = 1, ..., N$, in period t, $t = 0, 1$. An observation may refer to an individual or household observed at two points in time in the case of intragenerational mobility or a parent-child pair observed at two points in time in the case of intergenerational mobility. Further, let $F_{0,1}(y^*_0, y^*_1)$ denote the joint (bivariate) cumulative distribution function (CDF), where $y^*_t \equiv [y^*_{1t} \cdots y^*_{Nt}]$.

While movement through the distribution from an initial period, 0, to a subsequent period, 1, is completely captured by $F_{0,1}(y^*_0, y^*_1)$, this is not practical. Moreover, policymakers and the media often focus on more easily understood transition matrices. A $K \times K$ transition matrix, $P^*_{0,1}$, summarizes this joint distribution and is given by

$$P^*_{0,1} = \begin{bmatrix} p^*_{11} & \cdots & \cdots & p^*_{1K} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ p^*_{K1} & \cdots & \cdots & p^*_{KK} \end{bmatrix}. \tag{4}$$

Elements of this matrix have the following form

$$\begin{aligned} p^*_{kl} &= \frac{\Pr(\zeta^0_{k-1} \le y^*_0 < \zeta^0_k,\ \zeta^1_{l-1} \le y^*_1 < \zeta^1_l)}{\Pr(\zeta^0_{k-1} \le y^*_0 < \zeta^0_k)} \\ &= \frac{\Pr(y^*_0 \in k,\ y^*_1 \in l)}{\Pr(y^*_0 \in k)} \qquad k, l = 1, ..., K, \end{aligned} \tag{5}$$

where the ζs are cutoff points between the K partitions such that $0 = \zeta^t_0 < \zeta^t_1 < \zeta^t_2 < \cdots < \zeta^t_{K-1} < \zeta^t_K < \infty$, $t = 0, 1$.[7] Thus, p^*_{kl} gives the fraction of observations in partition k in period 0 who are in partition l in period 1. Note, inclusion of the denominator in (5) standardizes elements of the transition matrix. A complete lack of mobility implies p^*_{kl} equals unity if $k = l$ and zero otherwise.[8] Finally, we can define *conditional* transition matrices, conditioned upon $X = x$, where X denotes a vector of observation attributes. Denote the conditional transition matrix as $P^*_{0,1}(x)$, with elements given by

$$\begin{aligned} p^*_{kl}(x) &= \frac{\Pr(\zeta^0_{k-1} \le y^*_0 < \zeta^0_k,\ \zeta^1_{l-1} \le y^*_1 < \zeta^1_l | X = x)}{\Pr(\zeta^0_{k-1} \le y^*_0 < \zeta^0_k | X = x)} \\ &= \frac{\Pr(y^*_0 \in k,\ y^*_1 \in l | X = x)}{\Pr(y^*_0 \in k | X = x)} \qquad k, l = 1, ..., K. \end{aligned} \tag{6}$$

[7] For example, if $K = 5$, then the cutoff points might correspond to quintiles within the two marginal distributions of y^*_0 and y^*_1.

[8] In contrast, 'perfect' mobility may be characterized by origin-destination independence, implying $p^*_{kl} = 1/K$ for all k, l, or by complete rank reversal, implying $p^*_{kl} = 1$ if $k + l = K + 1$ and zero otherwise. See Jäntti and Jenkins (2015) for discussion.

Implicit in this definition is the assumption that X includes only time invariant attributes.[9]

For clarity, throughout the paper we consider two types of transition matrices: (i) those with equal-sized partitions and (ii) those with unequal-sized partitions. With equal-sized partitions, the ζs are chosen such that each partition contains $1/K$ of the population. For example, equal-sized partitions with $K = 5$ corresponds to a quintile transition matrix. In this case, $P^*_{0,1}$ is bistochastic and mobility is necessarily zero-sum (i.e., if an observation is misclassified in the upward direction, there must be at least one observation misclassified in the downward direction). With unequal-sized partitions, only the rows of $P^*_{0,1}$ sum to one and mobility is not zero-sum. For example, we shall consider the case of a 2×2 poverty transition matrix, where ζ^t_1 is the poverty line in period t.

Given the definition of $P^*_{0,1}$ or $P^*_{0,1}(x)$, our objective is to learn something about its elements. With a random sample $\{y^*_{it}, x_i\}$ and a choice of K and the ζs, the transition probabilities are point identified as they are functions of nonparametrically estimable quantities. The corresponding plug-in estimator is consistent. However, as stated previously, ample evidence indicates that income is measured with error. Let y_{it} denote the observed income for observation i in period t. With data $\{y_{it}, x_i\}$ and a choice of K and the ζs, the empirical transition probabilities are inconsistent for p^*_{kl} and $p^*_{kl}(x)$.

With access only to data containing measurement error, our goal is to bound the probabilities given in (5) and (6). The relationships between the true partitions of $\{y^*_{it}\}^1_{t=0}$ and the observed partitions of $\{y_{it}\}^1_{t=0}$ are characterized by the following joint probabilities:

$$\theta^{(k'-k,l'-l)}_{(k,l)} = \Pr(y_0 \in k',\ y_1 \in l',\ y^*_0 \in k,\ y^*_1 \in l) \tag{7}$$

where the subscript (k, l) indexes the true partitions in period 0 and 1 and the superscript $(k' - k, l' - l)$ indicates the degree of misclassification given by the differences between the observed partitions k' and l' and true partitions k and l. If $k' - k, l' - l > 0$, then there is *upward* misclassification in both periods. If $k' - k, l' - l < 0$, then there is *downward* misclassification in both periods. If $k' - k$ and $l' - l$ are of different signs, then the direction of misclassification changes across periods. $\theta^{(0,0)}_{(k,l)}$ represents the probability of no misclassification in either period for an observation with true income in partitions k and l.[10]

[9] Note, while the probabilities are conditional on X, the cutoff points ζ are not. Thus, we are capturing movements within the *overall* distribution among those with $X = x$.

[10] Of course, $\theta^{(0,0)}_{(k,l)}$ may be strictly positive even though income is misreported in either or both periods (i.e., $y_{it} \neq y^*_{it}$ for at least some i and t) as long as the misreporting is not so severe as to invalidate the observed partitions (i.e., $k' = k$ and $l' = l$ regardless). Throughout the paper, we shall use the term *measurement error* to refer to errors in observed income ($y_{it} \neq y^*_{it}$) and *misclassification* to refer to errors in the observed partition ($k' \neq k$ or $l' \neq l$).

With this notation, we can now rewrite the elements of $P^*_{0,1}$ as

$$\begin{aligned} p^*_{kl} &= \frac{\Pr(y^*_0 \in k, y^*_1 \in l)}{\Pr(y^*_0 \in k)} \\ &= \frac{\Pr(y_0 \in k, y_1 \in l) + \sum\limits_{\substack{k',l'=1,2,\ldots,K \\ (k'-k,l'-l)\neq(0,0)}} \theta^{(k'-k,l'-l)}_{(k,l)} - \sum\limits_{\substack{\widetilde{k},\widetilde{l}=1,2,\ldots,K \\ (\widetilde{k},\widetilde{l})\neq(k,l)}} \theta^{(k-\widetilde{k},l-\widetilde{l})}_{(\widetilde{k},\widetilde{l})}}{\Pr(y_0 \in k) + \sum\limits_{\substack{k',l',\widetilde{l}=1,2,\ldots,K \\ k'\neq k}} \theta^{(k'-k,l'-\widetilde{l})}_{(k,\widetilde{l})} - \sum\limits_{\substack{\widetilde{k},l',\widetilde{l}=1,2,\ldots,K \\ \widetilde{k}\neq k}} \theta^{(k-\widetilde{k},l'-\widetilde{l})}_{(\widetilde{k},\widetilde{l})}} \qquad (8) \\ &= K\left[\Pr(y_0 \in k, y_1 \in l) + \sum\limits_{\substack{k',l'=1,2,\ldots,K \\ (k'-k,l'-l)\neq(0,0)}} \theta^{(k'-k,l'-l)}_{(k,l)} - \sum\limits_{\substack{\widetilde{k},\widetilde{l}=1,2,\ldots,K \\ (\widetilde{k},\widetilde{l})\neq(k,l)}} \theta^{(k-\widetilde{k},l-\widetilde{l})}_{(\widetilde{k},\widetilde{l})}\right], \qquad (9) \end{aligned}$$

where the final line holds only in the case of equal-sized partitions.[11] The transition probabilities are not identified from the data alone. The data identify $\Pr(y_0 \in k, y_1 \in l)$ and $\Pr(y_0 \in k)$, but not the misclassification parameters, θ.

In principal, one can compute sharp bounds by searching across the unknown misclassification parameters. There are $K^2(K^2-1)$ misclassification parameters in $P^*_{0,1}$. However, the following constraints must hold

(i) $0 \leq \sum\limits_{\substack{\widetilde{k},\widetilde{l}=1,2,\ldots,K \\ (\widetilde{k},\widetilde{l})\neq(k,l)}} \theta^{(k-\widetilde{k},l-\widetilde{l})}_{(\widetilde{k},\widetilde{l})} \leq \Pr(y_0 \in k, y_1 \in l) \equiv r_{kl}, \quad k,l = 1,\ldots,K$

(ii) $0 \leq \sum\limits_{\substack{\widetilde{k},l',\widetilde{l}=1,2,\ldots,K \\ \widetilde{k}\neq k}} \theta^{(k-\widetilde{k},l'-\widetilde{l})}_{(\widetilde{k},\widetilde{l})} \leq \Pr(y_0 \in k) \equiv p_k, \quad k = 1,\ldots,K$

(iii) $0 \leq \sum\limits_{\substack{k',\widetilde{k},\widetilde{l}=1,2,\ldots,K \\ \widetilde{l}\neq l}} \theta^{(k-\widetilde{k},l'-\widetilde{l})}_{(\widetilde{k},\widetilde{l})} \leq \Pr(y_0 \in l) \equiv p_l, \quad l = 1,\ldots,K$

The K^2 inequality constraints in (i) must hold since the fraction of observations incorrectly classified as belonging to partition (k,l) cannot exceed the fraction of observations classified as belonging to this partition. The K inequality constraints in (ii) and (iii) must hold since the fraction of observations incorrectly classified as belonging to partition k in period 0 or partition l in period 1 cannot exceed the fraction of observations classified as belonging to these partitions.

In addition, the following constraints must hold in the case of equal-sized partitions:

(iv.a) $\sum\limits_{\substack{k',l',\widetilde{l}=1,2,\ldots,K \\ k'\neq k}} \theta^{(k'-k,l'-\widetilde{l})}_{(k,\widetilde{l})} - \sum\limits_{\substack{\widetilde{k},l',\widetilde{l}=1,2,\ldots,K \\ \widetilde{k}\neq k}} \theta^{(k-\widetilde{k},l'-\widetilde{l})}_{(\widetilde{k},\widetilde{l})} = 0, \quad k = 1,\ldots,K$

(v.a) $\sum\limits_{\substack{k',\widetilde{k},l'=1,2,\ldots,K \\ l'\neq l}} \theta^{(k'-\widetilde{k},l'-l)}_{(\widetilde{k},l)} - \sum\limits_{\substack{k',\widetilde{k},\widetilde{l}=1,2,\ldots,K \\ \widetilde{l}\neq l}} \theta^{(k'-\widetilde{k},l-\widetilde{l})}_{(\widetilde{k},\widetilde{l})} = 0, \quad l = 1,\ldots,K$

[11] The expression in (8) is identical to that in Gundersen and Kreider (2008, p. 368) when $K = 2$.

$$\text{(vi.a)} \quad -r_{kl} \leq \sum_{\substack{k',l'=1,2,...,K \\ (k'-k,l'-l)\neq(0,0)}} \theta_{(k,l)}^{(k'-k,l'-l)} - \sum_{\substack{\widetilde{k},\widetilde{l}=1,2,...,K \\ (\widetilde{k},\widetilde{l})\neq(k,l)}} \theta_{(\widetilde{k},\widetilde{l})}^{(k-\widetilde{k},l-\widetilde{l})} \leq \frac{1}{K} - r_{kl}, \qquad k,l = 1,...,K$$

The constraints in (iv.a) and (v.a) follow from the fact that $\Pr(y_0 \in k) = \Pr(y_1 \in l) = 1/K$. The constraints in (vi.a) follow from the fact that $r^*_{kl} \equiv \Pr(y^*_0 \in k, y^*_1 \in l) \in [0, 1/K]$.

If the partitions are of unequal size, then the following constraints must hold:

$$\text{(iv.b)} \quad -p_k \leq \sum_{\substack{k',l',\widetilde{l}=1,2,...,K \\ k'\neq k}} \theta_{(k,\widetilde{l})}^{(k'-k,l'-\widetilde{l})} - \sum_{\substack{\widetilde{k},l',\widetilde{l}=1,2,...,K \\ \widetilde{k}\neq k}} \theta_{(\widetilde{k},\widetilde{l})}^{(k-\widetilde{k},l'-\widetilde{l})} \leq 1 - p_k, \qquad k = 1,...,K$$

$$\text{(v.b)} \quad -p_l \leq \sum_{\substack{k',\widetilde{k},l'=1,2,...,K \\ l'\neq l}} \theta_{(\widetilde{k},l)}^{(k'-\widetilde{k},l'-l)} - \sum_{\substack{k',\widetilde{k},\widetilde{l}=1,2,...,K \\ \widetilde{l}\neq l}} \theta_{(\widetilde{k},\widetilde{l})}^{(k'-\widetilde{k},l-\widetilde{l})} \leq 1 - p_l, \qquad l = 1,...,K$$

$$\text{(vi.b)} \quad -r_{kl} \leq \sum_{\substack{k',l'=1,2,...,K \\ (k'-k,l'-l)\neq(0,0)}} \theta_{(k,l)}^{(k'-k,l'-l)} - \sum_{\substack{\widetilde{k},\widetilde{l}=1,2,...,K \\ (\widetilde{k},\widetilde{l})\neq(k,l)}} \theta_{(\widetilde{k},\widetilde{l})}^{(k-\widetilde{k},l-\widetilde{l})} \leq 1 - r_{kl}, \qquad k,l = 1,...,K$$

The constraints in (iv.b) and (v.b) follow from the fact that $p^*_k \equiv \Pr(y^*_0 \in k) \in [0,1]$ and $p^*_l \equiv \Pr(y^*_1 \in l) \in [0,1]$. Finally, the constraints in (vi.b) follow from the fact that $r^*_{kl} \equiv \Pr(y^*_0 \in k, y^*_1 \in l) \in [0,1]$.

Even with these constraints, obtaining informative bounds on the transition probabilities is not possible without further restrictions. Section 3.2 considers assumptions on the θs. Section 3.3 considers restrictions regarding the underlying mobility process.

3.2 Misclassification

3.2.1 Assumptions

Given the presence of measurement error, we obtain bounds on the elements of $P^*_{0,1}$, given in (8).[12] We consider the following misclassification assumptions.

Assumption 1 (Rank Preserving Measurement Error)**.** *Misreporting does not alter an observation's rank in the income distribution in either period. Formally, defining $F_t(y_{it})$ and $F^*_t(y^*_{it})$, $t = 0,1$, as the marginal CDFs of observed and true income in each period, then*

$$\begin{aligned} & F_t(y_{it}) = F^*_t(y^*_{it}) \quad \forall i,t \\ \implies \quad & \theta_{(k,l)}^{(k'-k,l'-l)} = 0 \quad \forall k'-k, l'-l \neq 0. \end{aligned}$$

Thus, the total number of misclassification parameters is reduced to zero.

Assumption 1 is similar to Heckman et al.'s (1997) rank invariance assumption in the context of the distribution of potential outcomes in a treatment effects framework. Although this assumption places strong restrictions about the joint distribution of y_{it} and y^*_{it}, it is a useful benchmark.

[12] In the interest of brevity, we focus attention from here primarily on the unconditional transition matrix. We return to the conditional transition matrix in Section 3.3.

Assumption 2 (Maximum Misclassification Rate)**.**

(i) The total misclassification rate in the data is bounded from above by $Q \in (0,1)$*. Formally,*

$$\sum_{\substack{k,k',l,l'=1,2,\ldots,K \\ (k'-k,l'-l)\neq(0,0)}} \theta_{(k,l)}^{(k'-k,l'-l)} \leq Q. \tag{10}$$

(ii) The total misclassification rate in the data is bounded from above by $Q \in (0,1)$ *and is uniformly distributed across partitions. Formally,*

$$\sum_{\substack{k',l,l'=1,2,\ldots,K \\ (k'-k,l'-l)\neq(0,0)}} \theta_{(k,l)}^{(k'-k,l'-l)} \leq \frac{Q}{K} \quad \forall k \tag{11}$$

$$\sum_{\substack{k,k',l'=1,2,\ldots,K \\ (k'-k,l'-l)\neq(0,0)}} \theta_{(k,l)}^{(k'-k,l'-l)} \leq \frac{Q}{K} \quad \forall l. \tag{12}$$

For the case of equal-sized partitions, misclassification is necessarily zero-sum; upward misclassification of some observations necessarily implies downward misclassification of others. Thus, even if measurement error in income is uni-directional, misclassification errors must be bi-directional. However, for the case of unequal-sized partitions, this need not be the case. In such cases, we also consider adding the following assumption.

Assumption 3 (Uni-Directional Misclassification)**.** *Misclassification occurs strictly in the upward direction. Formally,*

$$\theta_{(k,l)}^{(k'-k,l'-l)} \begin{cases} \geq 0 & \text{if } k' \geq k \text{ and } l' \geq l \\ = 0 & \text{otherwise} \end{cases} .$$

Note, Assumption 3 is consistent with mean-reverting measurement error as long as the negative measurement errors for observations with high income are not sufficient to lead to misclassification in the downward direction. For example, if $P^*_{0,1}$ is a 2×2 poverty transition matrix, Assumption 3 permits observations with true incomes exceeding the poverty threshold to underreport income, but not to a degree whereby they are misclassified as in poverty.

3.2.2 Bounds

Rank Preserving Measurement Error (Assumption 1) Under Assumption 1 the sampling process identifies the transition probabilities despite the presence of measurement error. Specifically, the transition probabilities in (5) are nonparametrically identified by replacing the terms in (5) with their sample analogs.

The estimator is given by

$$\widehat{p}_{kl} = \frac{\sum_i \mathrm{I}(y_{0i} \in k, y_{1i} \in l)}{\sum_i \mathrm{I}(y_{0i} \in k)} \tag{13}$$

$$= \frac{K}{N} \sum_i \mathrm{I}(y_{0i} \in k, y_{1i} \in l) \tag{14}$$

where the final line holds under equal-sized partitions.

Maximum Misclassification Rate (Assumption 2) Under Assumption 2 if $Q = 0$, then each θ must be equal to zero and the sampling process identifies the transition probabilities. Specifically, (13) is a consistent estimator. If $Q > 0$, then the transition probabilities are not nonparametrically identified.

Consider first the case of equal-sized partitions. Sharp bounds for p^*_{kl} are given by

$$\max\{K(r_{kl} - Q), 0\} \leq p^*_{kl} \leq \min\{K(r_{kl} + Q), 1\}, \tag{15}$$

under Assumption 2(i) and

$$\max\{K(r_{kl} - Q/K), 0\} \leq p^*_{kl} \leq \min\{K(r_{kl} + Q/K), 1\}. \tag{16}$$

under Assumption 2(ii). These bounds are analogous to those in Kreider and Pepper (2008, p. 335) and follow from Horowitz and Manski (1995, Corollary 1.2). The bounds are estimated by replacing r_{kl} with its sample analog. The estimator is consistent. Note, for a given transition probability, p^*_{kl}, the bounds are completely uninformative if $Q \geq \max\{r_{kl}, (1/K) - r_{kl}\}$ under Assumption 2(i) and $Q \geq \max\{r_{kl}K, 1 - r_{kl}K\}$ under Assumption 2(ii). Since $r_{kl} \in [0, 1/K]$, this implies that the bounds are always completely uninformative under Assumption 2(i) if $Q \geq 1/K$. The bounds are only assured of being uninformative under Assumption 2(ii) if $Q = 1$.

Consider now the case of unequal-sized partitions. The expression in (8) may be re-written as

$$p^*_{kl} = \frac{r_{kl} + Q_1 - Q_2}{p_k + Q_3 - Q_4}, \tag{17}$$

where

$$
\begin{aligned}
Q_1 &\equiv \sum_{\substack{k',l'=1,2,\ldots,K \\ (k'-k,l'-l)\neq(0,0)}} \theta_{(k,l)}^{(k'-k,l'-l)} \\
Q_2 &\equiv \sum_{\substack{\widetilde{k},\widetilde{l}=1,2,\ldots,K \\ (\widetilde{k},\widetilde{l})\neq(k,l)}} \theta_{(\widetilde{k},\widetilde{l})}^{(k-\widetilde{k},l-\widetilde{l})} \\
Q_3 &\equiv \sum_{\substack{k',l',\widetilde{l}=1,2,\ldots,K \\ k'\neq k}} \theta_{(k,\widetilde{l})}^{(k'-k,l'-\widetilde{l})} \\
Q_4 &\equiv \sum_{\substack{\widetilde{k},l',\widetilde{l}=1,2,\ldots,K \\ \widetilde{k}\neq k}} \theta_{(\widetilde{k},\widetilde{l})}^{(k-\widetilde{k},l'-\widetilde{l})}
\end{aligned}
$$

The lower bound is obtained by replacing r_{kl} and p_k with their sample analogs, setting $Q_1 = Q_4 = 0$, and minimizing the righthand side of (17) with respect to Q_2 and Q_3 subject to the following inequality constraints

$$
\begin{aligned}
0 \leq \quad & Q_2 \quad \leq r_{kl} \\
0 \leq \quad & Q_3 \quad \leq 1 - p_k
\end{aligned}
$$

and $Q_2 + Q_3$ must be less than or equal to Q or Q/K under Assumption 2(i) or 2(ii), respectively. The upper bound is obtained by setting $Q_2 = Q_3 = 0$ and maximizing the righthand side of (17) with respect to Q_1 and Q_4 subject to the following inequality constraints

$$
\begin{aligned}
0 \leq \quad & Q_1 \quad \leq 1 - r_{kl} \\
0 \leq \quad & Q_4 \quad \leq p_k
\end{aligned}
$$

and $Q_1 + Q_4$ must be less than or equal to Q or Q/K under Assumption 2(i) or 2(ii), respectively.

Uni-Directional Misclassification (Assumption 3) For simplicity, we only consider Assumption 3 in the case of a 2×2 poverty transition matrix. The bounds on the four elements of the transition matrix are

$$\max\left\{\frac{r_{11}}{\min\{p_1+Q,1\}},0\right\} \leq \quad p_{11}^* \quad \leq \min\left\{\frac{\min\{r_{11}+Q,1\}}{p_1},1\right\} \tag{18}$$

$$\max\left\{\frac{r_{12}}{\min\{p_1+Q,1\}},0\right\} \leq \quad p_{12}^* \quad \leq \min\left\{\frac{\min\{r_{12}+Q,1\}}{p_1},1\right\} \tag{19}$$

$$\max\left\{\frac{\max\{r_{21}-Q,0\}}{\max\{p_2-Q,0\}},0\right\} \leq \quad p_{21}^* \quad \leq \min\left\{\frac{\min\{r_{21}+Q_1,1\}}{\max\{p_2-Q_2,0\}},1\right\} \tag{20}$$

$$\max\left\{\frac{\max\{r_{22}-Q,0\}}{p_2},0\right\} \leq \quad p_{22}^* \quad \leq \min\left\{\frac{r_{22}}{\min\{p_2-Q,0\}},1\right\} \tag{21}$$

under Assumption 2(i), where $p_k \equiv \Pr(y_0 \in k)$, $k = 1, 2$. These bounds are straightforward to estimate using the appropriate sample analogs with the exception of the upper bound for p^*_{21}. In this case, the bound is maximized with respect to Q_1 and Q_2 subject to the constraints that each term is non-negative and $Q_1 + Q_2 = Q$. Replacing Assumption 2(i) with Assumption 2(ii) entails replacing Q with $Q/2$ in (18)-(21).

3.3 Restrictions

Under Assumption 2(i) or 2(ii) with $Q > 0$ and with equal-sized partitions, the bounds are given in (15) or (16), respectively. With unequal-sized partitions, the bounds are given by the appropriate minimum and maximum of (17) under Assumption 2(i) or 2(ii) alone and (18)-(21) under Assumption 3 as well. Here, we explore the identifying power of additional restrictions on the mobility process itself. The restrictions may be imposed alone or in combination.

3.3.1 Shape Restrictions

Shape restrictions place inequality constraints on the population transition probabilities. Here, we consider imposing shape restrictions related to the fact that large transitions are less likely than smaller ones. This leads us to the following assumption.

Assumption 4 (Shape Restrictions)**.** *The transition probabilities are weakly decreasing in the size of the transition. Formally, p^*_{kl} is weakly decreasing in the absolute difference between k and l.*

This assumption implies that within each row or each column of the transition matrix, the diagonal element (i.e., the conditional staying probability) is the largest. The remaining elements decline weakly monotonically moving away from the diagonal element.

Denote the bounds on p^*_{kl} under some combination of Assumptions 2-3 as

$$LB_{kl} \leq p^*_{kl} \leq UB_{kl}.$$

Imposing Assumption 4 tightens the bounds to

$$\max\left\{\sup_{l' \neq l} LB_{kl'}, \sup_{k' \neq k} LB_{k'l}\right\} \leq p^*_{kl} \quad \leq \quad UB_{kl} \text{ if } k = l \tag{22}$$

$$\max\left\{\sup_{l' > l} LB_{kl'}, \sup_{k' < k} LB_{k'l}\right\} \leq p^*_{kl} \quad \leq \quad \min\left\{\inf_{k \leq l' < l} UB_{kl'}, \inf_{k < k' \leq l} UB_{k'l}\right\} \text{ if } k < l \tag{23}$$

$$\max\left\{\sup_{l' < l} LB_{kl'}, \sup_{k' > k} LB_{k'l}\right\} \leq p^*_{kl} \quad \leq \quad \min\left\{\inf_{l < l' \leq k} UB_{kl'}, \inf_{l \leq k' < k} UB_{k'l}\right\} \text{ if } k > l \tag{24}$$

Estimates of the bounds in (22)-(24) are biased as plug-in estimators relying on infima and suprema are biased in finite samples, producing bounds that are too narrow (Kreider and Pepper 2008). To circumvent this issue, a bootstrap bias correction is typically used in the literature on partial identification. Denote the plug-in estimators of the lower and upper bounds in (22)-(24) as $\widehat{LB}$ and $\widehat{UB}$, respectively. The bootstrap bias corrected estimates are given by

$$\begin{aligned}\widehat{LB}_c &= 2\widehat{LB} - \mathrm{E}^*\left[\widehat{LB}\right] \\ \widehat{UB}_c &= 2\widehat{UB} - \mathrm{E}^*\left[\widehat{UB}\right],\end{aligned}$$

where $\widehat{LB}_c$ and $\widehat{UB}_c$ denote the bootstrap bias corrected estimates and $\mathrm{E}^*[\cdot]$ denotes the expectation operator with respect to the bootstrap distribution. See Kreider and Pepper (2008) and the references therein. However, there is an added complication here. Because we are estimating bounds on probabilities, the upper (lower) bound is constrained by one (zero). It is well known that the traditional bootstrap does not work for parameters at or near the boundary of the parameter space (Andrews 2000). Instead, we employ subsampling, using replicate samples with $N/2$ observations (Andrews and Guggenberger 2009; Martínez-Muñoz and Suáreza 2010).[13]

3.3.2 Level Set Restrictions

Level set restrictions place equality constraints on population transition probabilities across observations with different observed attributes (Manski 1990; Lechner 1999). In the present context, this leads to the following assumption.

Assumption 5 (Level Set Restrictions). *The conditional transition probabilities, given in (6), are constant across a range of conditioning values. Formally,* $p^*_{kl}(x)$ *is constant for all* $x \in \mathcal{A}_x \subset \mathcal{R}_m$*, where* x *is an* m*-dimensional vector.*

For instance, if x denotes the age of an individual in years, one might wish to assume that $p^*_{kl}(x)$ is constant for all x within a five-year window around x.

Denote the bounds for $p^*_{kl}(x)$ under some combination of Assumptions 2-3 as

$$LB(x) \leq p^*_{kl}(x) \leq UB(x). \tag{25}$$

Imposing Assumption 5 tightens the bounds to

$$\sup_{z \in \mathcal{A}_x} LB(z) \leq p^*_{kl}(x) \leq \inf_{z \in \mathcal{A}_x} UB(z). \tag{26}$$

Bounds on the unconditional transition probabilities, p^*_{kl}, are obtained using the law of total probability

[13] We employ sub-sampling (without replacement) rather than an m-bootstrap (with replacement), where $m < N$, as sub-sampling is valid under weaker assumptions (Horowitz 2001). Noneless, our Stata code allows for both options. Moreover, we set $m = N/2$ as it is unlikely that an optimal, data-driven choice of m is available (or computationally feasible in the present context). Politis et al. (1999, p. 61) state that "subsampling has some asymptotic validity across a broad range of choices for the subsample size" as long as $m/N \to 0$ and $m \to \infty$ as $N \to \infty$. Martínez-Muñoz and Suáreza (2010, p. 143) note that setting $m = N/2$ is "typical."

(Manski and Pepper 2000). Specifically,

$$\sum_x \Pr(X=x)\left(\sup_{z\in\mathcal{A}_x} LB(z)\right) \leq p^*_{kl} \leq \sum_x \Pr(X=x)\left(\inf_{z\in\mathcal{A}_x} UB(z)\right). \tag{27}$$

Implicit in this formulation is that X is discrete. As in the case of bounds under shape restrictions, estimates of the bounds in (26) or (27) are biased in finite samples. Again, a subsampling bias correction is used.

To operationalize (26) or (27), bounds on the conditional transition probabilities in the absence of level set restrictions, shown in (25), must be obtained. From (6) and (8), we have

$$p^*_{kl}(x) = \frac{\Pr(y_0\in k, y_1\in l|X=x) + \sum\limits_{\substack{k',l'=1,2,\ldots,K\\(k'-k,l'-l)\neq(0,0)}} \theta^{(k'-k,l'-l)}_{(k,l)}(x) - \sum\limits_{\substack{\widetilde{k},\widetilde{l}=1,2,\ldots,K\\(\widetilde{k},\widetilde{l})\neq(k,l)}} \theta^{(k-\widetilde{k},l-\widetilde{l})}_{(\widetilde{k},\widetilde{l})}(x)}{\Pr(y_0\in k|X=x) + \sum\limits_{\substack{k',l',\widetilde{l}=1,2,\ldots,K\\k'\neq k}} \theta^{(k'-k,l'-\widetilde{l})}_{(k,\widetilde{l})}(x) - \sum\limits_{\substack{\widetilde{k},l',\widetilde{l}=1,2,\ldots,K\\\widetilde{k}\neq k}} \theta^{(k-\widetilde{k},l'-\widetilde{l})}_{(\widetilde{k},\widetilde{l})}(x)} \tag{28}$$

where now the misclassification parameters may vary across x. To derive the bounds on (28), let us first introduce a new assumption on the misclassification parameters.

Assumption 6 (Independence)**.** *Misclassification rates are independent of the observed attributes of observations. Formally,*

$$\begin{aligned}\theta^{(k'-k,l'-l)}_{(k,l)}(x) &= \Pr(y_0\in k',\ y_1\in l',\ y^*_0\in k,\ y^*_1\in l|X=x)\\ &= \Pr(y_0\in k',\ y_1\in l',\ y^*_0\in k,\ y^*_1\in l)\\ &= \theta^{(k'-k,l'-l)}_{(k,l)}.\end{aligned}$$

We now proceed by first deriving the bounds for the case of partitions of equal size under various assumptions including Assumption 6. We then drop Assumption 6. Finally, we perform the same exercise for the case of partitions of unequal size.

Consider first the case of partitions of equal size. Under Assumption 6, the denominator in (28) reduces to $p_k(x)\equiv\Pr(y_0\in k|X=x)$ and is therefore identified by the data. This simplification follows from the fact that the sum of the misclassification parameters in the denominator of (28) is equal to the sum of the misclassification parameters in the denominator of (8) under Assumption 6, and the latter is equal to zero in the case of partitions of equal size. The bounds on $p^*_{kl}(x)$ are given by

$$\max\left\{\frac{1}{p_k(x)}(r_{kl}(x)-Q),0\right\} \leq p^*_{kl}(x) \leq \min\left\{\frac{1}{p_k(x)}(r_{kl}(x)+Q),1\right\} \tag{29}$$

under Assumption 2(i) and

$$\max\left\{\frac{1}{p_k(x)}(r_{kl}(x)-Q/K),0\right\} \leq p^*_{kl}(x) \leq \min\left\{\frac{1}{p_k(x)}(r_{kl}(x)+Q/K),1\right\} \tag{30}$$

under Assumption 2(ii), where $r_{kl}(x) \equiv \Pr(y_0 \in k, y_1 \in l | X = x)$. These bounds can be further tightened by adding Assumption 4 and using the formulas in (22)-(24) where now everything is conditional on x. Once final bounds are obtained for $p^*_{kl}(x)$, sharp bounds under Assumption 5 are given in (26) for the conditional transition probabilities and (27) for unconditional transition probabilities.

Absent Assumption 6, the denominator in (28) is not identified by the data alone. In this case, the expression in (28) may be re-written as

$$p^*_{kl}(x) = \frac{r_{kl}(x) + Q_1(x) - Q_2(x)}{p_k(x) + Q_3(x) - Q_4(x)}. \tag{31}$$

where

$$\begin{aligned}
Q_1(x) &\equiv \sum_{\substack{k',l'=1,2,\ldots,K \\ (k'-k,l'-l)\neq(0,0)}} \theta^{(k'-k,l'-l)}_{(k,l)}(x) \\
Q_2(x) &\equiv \sum_{\substack{\widetilde{k},\widetilde{l}=1,2,\ldots,K \\ (\widetilde{k},\widetilde{l})\neq(k,l)}} \theta^{(k-\widetilde{k},l-\widetilde{l})}_{(\widetilde{k},\widetilde{l})}(x) \\
Q_3(x) &\equiv \sum_{\substack{k',l',\widetilde{l}=1,2,\ldots,K \\ k'\neq k}} \theta^{(k'-k,l'-\widetilde{l})}_{(k,\widetilde{l})}(x) \\
Q_4(x) &\equiv \sum_{\substack{\widetilde{k},l',\widetilde{l}=1,2,\ldots,K \\ \widetilde{k}\neq k}} \theta^{(k-\widetilde{k},l'-\widetilde{l})}_{(\widetilde{k},\widetilde{l})}(x).
\end{aligned}$$

The lower bound is obtained replacing $r_{kl}(x)$ and $p_k(x)$ with their sample analogs, setting $Q_1(x) = Q_4(x) = 0$, and minimizing the righthand side of (31) with respect to $Q_2(x)$ and $Q_3(x)$ subject to the following inequality constraints

$$\begin{aligned}
0 \leq Q_2(x) &\leq r_{kl}(x) \\
0 \leq Q_3(x) &\leq \min\left\{1 - p_k(x), \frac{1}{K \cdot \Pr(X = x)} - p_k(x)\right\}
\end{aligned}$$

and $Q_2(x) + Q_3(x)$ must be less than or equal to the minimum of unity and $Q/\Pr(X = x)$ or $Q/[K \cdot \Pr(X = x)]$ under Assumption 2(i) or 2(ii), respectively. The constraints follow from the fact that conditional probabilities must lie in the unit interval and the fact that conditional probabilities must be consistent with unconditional probabilities. The upper bound is obtained by setting $Q_2(x) = Q_3(x) = 0$ and maximizing the righthand side of (31) with respect to $Q_1(x)$ and $Q_4(x)$ subject to the following inequality constraints

$$\begin{aligned}
0 \leq Q_1(x) &\leq 1 - r_{kl}(x) \\
0 \leq Q_4(x) &\leq \min\left\{p_k(x), p_k(x) - \frac{\frac{1}{K} - [1 - \Pr(X = x)]}{\Pr(X = x)}\right\}
\end{aligned}$$

and $Q_1(x)+Q_4(x)$ must be less than or equal to the minimum of unity and $Q/\Pr(X=x)$ or $Q/[K \cdot \Pr(X=x)]$ under Assumption 2(i) or 2(ii), respectively. The resulting bounds on (31) can be further tightened by adding Assumption 4 and using the formulas in (22)-(24) where now everything is conditional on x.[14]

Consider now the case where the partitions are not of equal size. Under Assumption 6 the expression in (28) may be re-written as

$$p^*_{kl}(x) = \frac{r_{kl}(x) + Q_1 - Q_2}{p_k(x) + Q_3 - Q_4}, \tag{32}$$

where Q_j, $j = 1, ..., 4$, are defined above. The lower bound is obtained replacing $r_{kl}(x)$ and $p_k(x)$ with their sample analogs, setting $Q_1 = Q_4 = 0$, and minimizing the righthand side of (31) with respect to Q_2 and Q_3 subject to the following inequality constraints

$$\begin{aligned} 0 \leq \quad & Q_2 \quad \leq r_{kl}(x) \\ 0 \leq \quad & Q_3 \quad \leq 1 - p_k(x) \end{aligned}$$

and $Q_2 + Q_3$ must be less than or equal to Q or Q/K under Assumption 2(i) or 2(ii), respectively. The upper bound is obtained by setting $Q_2 = Q_3 = 0$ and maximizing the righthand side of (31) with respect to Q_1 and Q_4 subject to the following inequality constraints

$$\begin{aligned} 0 \leq \quad & Q_1 \quad \leq 1 - r_{kl}(x) \\ 0 \leq \quad & Q_4 \quad \leq p_k(x) \end{aligned}$$

and $Q_1 + Q_4$ must be less than or equal to Q or Q/K under Assumption 2(i) or 2(ii), respectively.

Absent Assumption 6, the expression in (28) may be re-written as in (31). The lower bound is obtained replacing $r_{kl}(x)$ and $p_k(x)$ with their sample analogs, setting $Q_1(x) = Q_4(x) = 0$, and minimizing the righthand side of (31) with respect to $Q_2(x)$ and $Q_3(x)$ subject to the following inequality constraints

$$\begin{aligned} 0 \leq \quad & Q_2(x) \quad \leq r_{kl}(x) \\ 0 \leq \quad & Q_3(x) \quad \leq 1 - p_k(x) \end{aligned}$$

and $Q_2(x)+Q_3(x)$ must be less than or equal to the minimum of unity and $Q/\Pr(X=x)$ or $Q/[K \cdot \Pr(X=x)]$ under Assumption 2(i) or 2(ii), respectively. The upper bound is obtained by setting $Q_2(x) = Q_3(x) = 0$ and maximizing the righthand side of (31) with respect to $Q_1(x)$ and $Q_4(x)$ subject to the following inequality

[14] Note, there is no assurance that the bounds under Assumption 5, but without Assumption 6, will be narrower than the corresponding bounds without Assumption 5.

constraints

$$\begin{aligned} 0 \leq \quad & Q_1(x) \quad \leq 1 - r_{kl}(x) \\ 0 \leq \quad & Q_4(x) \quad \leq p_k(x) \end{aligned}$$

and $Q_1(x)+Q_4(x)$ must be less than or equal to the minimum of unity and $Q/\Pr(X = x)$ or $Q/[K\cdot\Pr(X = x)]$ under Assumption 2(i) or 2(ii), respectively.

If we add Assumption 3 in the case of a 2×2 poverty transition matrix, the bounds on $p^*_{kl}(x)$ are given by

$$\max\left\{\frac{r_{11}(x)}{\min\{p_1(x)+Q,1\}},0\right\} \leq p^*_{11}(x) \quad \leq \quad \min\left\{\frac{\min\{r_{11}(x)+Q,1\}}{p_1(x)},1\right\} \tag{33}$$

$$\max\left\{\frac{r_{12}(x)}{\min\{p_1(x)+Q,1\}},0\right\} \leq p^*_{12}(x) \quad \leq \quad \min\left\{\frac{\min\{r_{12}(x)+Q,1\}}{p_1(x)},1\right\} \tag{34}$$

$$\max\left\{\frac{\max\{r_{21}(x)-Q,0\}}{\max\{p_2(x)-Q,0\}},0\right\} \leq p^*_{21}(x) \quad \leq \quad \min\left\{\frac{\min\{r_{21}(x)+\widetilde{Q}_1,1\}}{\max\{p_2(x)-\widetilde{Q}_2,0\}},1\right\} \tag{35}$$

$$\max\left\{\frac{\max\{r_{22}(x)-Q,0\}}{p_2(x)},0\right\} \leq p^*_{22}(x) \quad \leq \quad \min\left\{\frac{r_{22}(x)}{\min\{p_2(x)-Q,0\}},1\right\} \tag{36}$$

subject to $\widetilde{Q}_1 + \widetilde{Q}_2 = Q$ under Assumptions 2(i) and 6. Under Assumptions 2(ii) and 6, Q is replaced by $Q/2$. Absent Assumption 6, Q is replaced by Q is replaced by $Q/\Pr(X = x)$ or $Q/[K \cdot \Pr(X = x)]$ under Assumption 2(i) or 2(ii), respectively.

Once bounds on $p^*_{kl}(x)$ are obtained under some combination of Assumptions 2-3 and 6, the bounds may be further tightened by adding Assumption 4 and using the formulas in (22)-(24), where now everything is conditional on x.[15].

Before continuing, it is worth noting that a special case of level set restrictions occurs when the conditioning variable, x, represents time. For example, one might separately bound transition matrices from $t = 0 \rightarrow 1$ and $t = 1 \rightarrow 2$ and then impose the restriction that mobility is constant across the two time periods. In this case, the level set restriction is identical to a stationarity assumption about the markov process governing the outcome variable.

3.3.3 Monotonicity Assumptions

Next, we explore the identifying power of monotonicity assumptions. Monotonicity restrictions place inequality constraints on population transition probabilities across observations with different observed attributes (Manski and Pepper 2000. In the present context, this leads to the following assumption.

Assumption 7 (Monotonicity)**.** *The probability of upward mobility is weakly increasing in a vector of attributes, u, and the probability of downward mobility is weakly decreasing in the same vector of attributes.*

[15] Again, there is no assurance that the bounds under Assumption 5, but without Assumption 6, will be narrower than the corresponding bounds without Assumption 5.

Formally, if $u_2 \geq u_1$*, then*

$$\begin{aligned} p^*_{kl}(u_1) &\leq p^*_{kl}(u_2) \;\; \forall l > k \\ p^*_{kl}(u_1) &\geq p^*_{kl}(u_2) \;\; \forall l < k \\ p^*_{11}(u_1) &\geq p^*_{11}(u_2) \\ p^*_{KK}(u_1) &\leq p^*_{KK}(u_2). \end{aligned}$$

For instance, if u denotes the education of an individual, one might wish to assume that the probability of upward (downward) mobility is no lower (higher) for individuals with more education. Note, the monotonicity assumption provides no information on the conditional staying probabilities, $p^*_{kk}(u)$, for $k = 2, ..., K-1$.

By extension of Manski and Pepper (2000, Proposition 1 and Corollary 1), Assumption 7 implies

$$\sup_{u_1 \leq u} LB(u_1) \leq p^*_{kl}(u) \leq \inf_{u \leq u_2} UB(u_2) \;\; \forall l > k \tag{37}$$

$$\sup_{u \leq u_1} LB(u_1) \leq p^*_{kl}(u) \leq \inf_{u_2 \leq u} UB(u_2) \;\; \forall l < k \tag{38}$$

$$\sup_{u \leq u_1} LB(u_1) \leq p^*_{11}(u) \leq \inf_{u_2 \leq u} UB(u_2) \tag{39}$$

$$\sup_{u_1 \leq u} LB(u_1) \leq p^*_{KK}(u) \leq \inf_{u \leq u_2} UB(u_2) \tag{40}$$

where u represents a monotone instrumental variables (MIV). Bounds on the unconditional transition probabilities, p^*_{kl}, are obtained using the law of total probability (Manski and Pepper 2000). Assumption 7 and the resulting bounds, given in (37) – (40), may be combined with any of the prior assumptions.

To proceed, partition u into J cells, $j = 1, ..., J$ and let P_j denote the sample fraction in cell j. Next, estimate the bounds for $p^*_{kl}(u)$ for each cell under some combination of Assumptions 2-6. Denote the lower and upper bounds as LB_j and UB_j, respectively. Finally, the overall bounds on p^*_{kl} under Assumption 7 are given by

$$\textstyle\sum_j P_j \left(\sup_{j' \leq j} LB_{j'} \right) \leq p^*_{kl} \leq \sum_j P_j \left(\inf_{j' \geq j} UB_{j'} \right) \tag{41}$$

As in the case of bounds under level set restrictions, estimates of the bounds in (41) are biased in finite samples. Again, a subsampling bias correction is used.

3.4 Inference

The estimated bounds, obtained under some set of assumptions, are estimates. Inference is handled via subsampling and the Imbens-Manski (2004) correction to obtain 90% confidence intervals (CIs). As with the bias correction, we set the size of the replicate samples to $N/2$.

3.5 Summary Mobility Measures

Upon obtaining bounds on the elements of the transition matrix, bounds on various measures derived from these elements follow automatically. The Prais (1955) measure of mobility is based on the mean exit time from partition k, given by

$$\frac{1}{1-p^*_{kk}},\ k=1,...,K. \tag{42}$$

Shorrocks (1978) defines the Immobility Ratio measure as

$$IR=\frac{K-\mathrm{tr}(P^*_{0,1})}{K-1} \tag{43}$$

where $\mathrm{tr}(\cdot)$ is the trace of a matrix. Finally, Bradbury (2016) defines measures of upward and downward mobility that account for the size of the partitions. The upward mobility measure is given by

$$UM=\frac{K}{K-1}(1-p^*_{11}); \tag{44}$$

downward mobility is given by

$$DM=\frac{K}{K-1}(1-p^*_{KK}). \tag{45}$$

Mobility is decreasing in the value of the Prais measure; increasing in the remaining three measures. In all cases, the measures can be bounded using the lower and upper bounds on the conditional staying probabilities.

4 U.S. Mobility

4.1 Data

To assess U.S. intragenerational mobility, we use panel data from the Survey of Income and Program Participation (SIPP). Collected by the U.S. Census Bureau, SIPP is a rotating, nationally representative longitudinal survey of households. Begun in 1984, SIPP collects detailed income data as well as data on a host of other economic and demographic attributes. Households in the SIPP are surveyed over a multi-year period ranging from two and a half years to four years. Then, a new sample of households are drawn. The sample sizes range from approximately 14,000 to 52,000 households. Here, we use the 2004 and 2008 panels to examine mobility leading up to the Great Recession and during the early recovery period. For the 2004 panel, the initial period is November 2003 and the terminal period is October 2007. For the 2008 panel, the initial period is June 2008 and the terminal period is September 2012. Thus, we investigate household-level income dynamics over two separate four-year windows. We also assess mobility pooling the two panels.

For the analysis, the outcome variable is derived from total monthly household income (variable THTOTINC). This includes income from all household members and sources: labor market earnings, pensions, social security income, interest dividends, and other income sources. When analyzing the 2×2 poverty matrix, we determine poverty status for each household in each period by comparing income with the SIPP-reported poverty threshold for the household (variable RHPOV). When analyzing general mobility, we estimate 3×3 matrices based on terciles of the income distribution in each period. However, to adjust for household size, we construct three different measures of equivalized household income.[16] Adjusting income for household size when drawing welfare or policy conclusions is known to be crucial (e.g., Chiappori 2016). In our baseline analysis, we use OECD equivalized household income (OECD 1982). As alternatives, we also construct OECD-modified equivalized household income (Haagenars et al. 1994) and per capita household income. Specifically, the OECD (OECD-modified) equivalence scale assigns a value of one to the first household member, 0.7 (0.5) to each additional adult, and of 0.5 (0.3) to each child. In contrast, the per capita measure assigns a value of one to all household members. In the interest of brevity, results based on these alternative equivalence scales are relegated to the appendix.

When assessing the two panels separately and imposing level set restrictions, we use age of the household head in the initial period. Specifically, we group households into five-year age bins (25-29, 30-34, ..., 60-65) and impose the restriction that mobility is constant across adjacent bins. For example, we tighten the bounds on mobility for households where the head is, say, 30-34 by assuming that mobility is constant across households where the head is 25-39, 30-34, and 35-39. When pooling the two panels and imposing level set restrictions, we combine the age of household head restriction used in the case of separate panels with a stationarity assumption that mobility is constant across the two panels. For example, we tighten the bounds on mobility for households where the head is, say, 30-34 in the initial period of the 2004 panel by assuming that mobility is constant across households where the head is 25-39, 30-34, and 35-39 in the 2004 and 2008 panels.

When imposing the monotonicity restrictions, we use the education level of the household head in the initial period. Here, households are grouped into three bins (high school graduate and below, some college but less than a four-year degree, and at least a four-year college degree).

In constructing our estimation sample, we use only the initial and terminal wave for each panel. The sample, by necessity, must be balanced. Households with any invalid or missing information on the relevant variables are excluded. Finally, we restrict the sample to households where the head is between 25 and 65 years old in the initial period. The sample size for the 2004 panel is 7,834 and for the 2008 panel is 16,006.[17] Summary statistics are presented in Table 1.

[16] There is no need to adjust income for household size when estimating the poverty transition matrix since the poverty threshold already accounts for differences in household composition.

[17] The 2004 panel contains 10,503 households observed in the initial and terminal periods. Two observations are dropped due to negative household income. The remainder are dropped because the household head is outside the 25-65 year old age range. The 2008 panel panel contains 21,616 households observed in the initial and terminal periods. 88 observations are dropped due to negative or missing household income. The remainder are dropped because the household head is outside the 25-65 year old age range.

4.2 Results

4.2.1 Poverty Transition Matrix

Results for the 2×2 poverty transition matrix are presented in Tables 2-4.[18] Overall, the observed poverty rate declined from 11.8% to 10.7% in the first panel (November 2003 to October 2007) and held constant at 12.6% in the second panel (June 2008 to September 2012); see Table 1. Turning to mobility, under the baseline assumption of Rank-Preserving Measurement Error (Table 2, Panel I) the probability of a household remaining in poverty across the initial and terminal periods in the first (second) SIPP panel is 0.448 (0.462), while the probability of remaining out of poverty is 0.939 (0.923).[19] Thus, observed transitions out of (into) poverty are higher in the first (second) SIPP panel (transition out of poverty: 0.552 versus 0.538; transitions into poverty: 0.061 versus 0.0677). This is not surprising since the second SIPP panel spans the end of the Great Recession and the early part of the recovery.

Misclassification Assumptions Panels II and III in Table 2 allow for misclassification, but impose Assumption 2(i) and 2(ii), respectively. The assumed maximum misclassification rate is 10% ($Q = 0.10$).[20] Under arbitrary misclassification, the bounds are completely uninformative on the mobility of households in poverty in the initial period in both SIPP panels. Thus, a relatively small amount of (arbitrary) misclassification results, in the absence of other information, an inability to say anything about the four-year mobility rates of households initially in poverty. For households initially above the poverty line, the probability of remaining out of poverty four years later is at least 0.825 (0.808) in the first (second) SIPP panel.[21] Moreover, in the second SIPP panel, we are able to rule out the possibility (at the 90% confidence level) that no households move into poverty over the four years spanned by the second SIPP panel.

Assuming that misclassification is uniform across the rows and columns of the transition matrix, rather than arbitrary, has some identifying power. Under this assumption, the probability of escaping poverty is at least 0.130 (0.142) in the first (second) SIPP panel. The probability of remaining out of poverty is at least 0.882 (0.865) in the first (second) SIPP panel.

Panels IV and V in Table 2 add the assumption that misclassification is only in the upward direction. This assumption has no identifying power on the transition probabilities for households above the poverty

[18] In all cases, we use 25 replicate samples for the subsampling bias correction and 100 replicate samples to construct 90% Imbens-Manski (2004) confidence intervals via subsampling using $m = N/2$ without replacement. For brevity, we do not report bounds based on all possible combinations of restrictions. Unreported results are available upon request.

[19] Throughout the analysis, poverty status is measured only at the initial and terminal period. Thus, for example, "remaining in poverty" does not mean a household is necessarily continuously in poverty over the four-year period. For expositional purposes, however, we describe the results in terms of remaining in or out of poverty.

[20] A misclassification rate of 10% in the SIPP seems reasonable. For example, Pedace and Bates (2000) compare self-reported earnings in the 1992 SIPP longitudinal file to respondents' earnings as documented in the Social Security Administration's Summary Earnings Record (SER), where over 50,000 respondents are able to be matched using Social Security numbers. The authors find that 3.6% (6.4%) of the final sample report no (positive) earnings in the SIPP despite having positive (no) earnings in the SER. A similar exercise using Swedish data on older individuals in Kapteyn and Ypma (2007) finds that 18.2% (4.6%) report no (positive) earnings in the survey data despite having positive (no) earnings in the administrative records. See also Bound et al. (2001).

[21] Throughout the discussion of the results, we focus on the point estimates for simplicity. The confidence intervals are generally not much wider than the point estimates of the bounds.

line in the initial period. However, it is useful in tightening the bounds on the transition probabilities for households in poverty in the initial period. With arbitrary and uni-directional misclassification, bounds on the probability of remaining in poverty four years later are $[0.243, 0.701]$ in the first SIPP panel and $[0.258, 0.757]$ in the second SIPP panel. Under uniform and uni-directional misclassification, bounds on the probability of remaining in poverty four years later are further tightened to $[0.315, 0.612]$ in the first SIPP panel and $[0.331, 0.614]$ in the second SIPP panel. While the assumptions of uniformity and uni-directional misclassification certainly tighten the bounds, the width of the bounds under the assumption of 10% misclassification makes it clear than even relatively small amounts of misclassification adds considerable uncertainty to estimates of income mobility.

Level Set Restrictions Table 3 allows for misclassification, but imposes different combinations of Assumptions 2–6.[22] For the separate SIPP panels, the level set restrictions are based on the age of the household head in the initial period. For the pooled panels, the level set restrictions are based on the age of the household head as well as a stationarity restriction that mobility is constant across the two SIPP panels. In Panel I, the level set restrictions are not combined with any shape restrictions. In Panel II, shape restrictions are imposed on top of the level set restrictions. This assumption corresponds to the restriction that households are more likely to maintain the same poverty status over the four-year period than change status. With each panel, we present results based on different types of misclassification errors.

Several findings stand out. First, under arbitrary, independent errors (Panels IA and IIA), the level set and shape restrictions have little identifying power. There is some tightening of the lower bounds relative to Panel II in Table 2, but it is modest. Second, under uniform, independent errors (Panels IB and IIB), the level set and shape restrictions have substantial identifying power. For example, bounds on the probability of remaining in poverty over the four-year period in the first SIPP panel under uniform errors alone are $[0.026, 0.870]$ (Table 2, Panel III), under level set restrictions with independent errors are $[0.100, 0.810]$ (Table 3, Panel IB), and under level set and shape restrictions with independent errors is $[0.183, 0.810]$ (Table 3, Panel IIB). In addition, if we impose a stationarity assumption, the bounds are further tightened to $[0.199, 0.821]$ (Table 3, Panel IIB). Under these assumptions, which seem plausible, at least 1 in 5 impoverished households in the initial period remain in poverty four years later. Finally, adding the assumption of uni-directional misclassification errors has considerable identifying power on the transition probabilities for households above the poverty line in the initial period. Now the bounds on the probability of remaining in poverty over the four-year period in the first SIPP Panel are $[0.422, 0.576]$, implying that at least 2 in 5 impoverished households in the initial period remain in poverty four years later.

Monotonicity Restriction Table 4 is similar to Table 3, but adds Assumption 7.[23] The monotonicity restriction requires upward mobility to be weakly increasing in the household head's education level in the

[22] For brevity, not all combinations are presented. Full results are available upon request.
[23] For brevity, not all combinations are presented. Full results are available upon request.

initial period. In general, the monotonicity assumption has little identifying power in this application as the bounds are only modestly tightened, if at all. For instance, assuming uniform, independent, and unidirectional misclassification and imposing both the shape restrictions and level set restrictions based on age of the household head and stationarity, adding the monotonicity restriction tightens the bounds on the probability of remaining in poverty across the initial and terminal periods from $[0.421, 0.575]$ to $[0.446, 0.555]$ (Panel IIC in Table 3 and 4). Nonetheless, the tightness of this interval around the observed probability of remaining in poverty, 0.457 (Panel I in Table 2) shows that much can still be learned in the presence of misclassification through the imposition of several arguably plausible restrictions.

4.2.2 Tercile Transition Matrix

Results for the 3×3 tercile transition matrix based on OECD equivalized household income are presented in Tables 5-7. These tables are analogous to Tables 2-4 except we no longer consider the assumption of unidirectional misclassification since now any upward misclassification must induce downward misclassification as well. Results based on alternative equivalence scales are reported in the appendix, Tables A1-A8.

Under the baseline assumption of Rank-Preserving Measurement Error (Table 5, Panel I) the conditional staying probabilities in the first (second) SIPP panel are 0.683, 0.533, and 0.692 (0.685, 0.538, and 0.685) for terciles 1, 2, and 3, respectively. Thus, the four-year conditional staying probabilities do not vary much across the two panels. Furthermore, we find that the probability of larger movements in the income distribution are less likely than smaller movements. For example, pooling the two panels together, the probability of moving from the first to second tercile is 0.245 and the first to third tercile is 0.071. Similarly, the probability of moving from the third to second tercile is 0.217 and the third to first tercile is 0.095.

Misclassification Assumptions Panels II and III in Table 5 allow for misclassification, but impose Assumption 2(i) and 2(ii), respectively. The assumed maximum misclassification rate continues to be at most 10% ($Q = 0.10$). Under arbitrary misclassification, the width of the bounds is 0.6 ($= 2KQ$) unless the bounds hit one of the boundaries. Under uniform misclassification, the width is 0.2 ($= 2Q$) unless the bounds hit one of the boundaries. Thus, the bounds are guaranteed to be at least somewhat informative in both cases, but the assumption of uniform misclassification has significant identifying power. This assumption is reasonable if misclassification is equally likely in the upward and downward direction. With mean-reverting measurement error in income, this is plausible.

Focusing on the pooled results, as these differ very little from the individual panel results, we find that the bounds on the conditional staying probabilities are $[0.385, 0.985]$, $[0.238, 0.838]$, and $[0.388, 0.988]$ across terciles 1, 2, and 3 under arbitrary misclassification. The bounds tighten to $[0.585, 0.785]$, $[0.438, 0.638]$, and $[0.588, 0.788]$ under uniform misclassification. Bounds on the off-diagonal elements, while generally lower as one moves further from the diagonal, cannot rule out the possibility that large movements in the income distribution are more likely than smaller movements (conditional on changing terciles).

Level Set Restrictions Table 6 allows for misclassification, but imposes different combinations of Assumptions 2–6.[24] Because of the similarity of the results across the two SIPP panels in Table 5, we focus on the results for the pooled sample where the stationarity restriction is imposed. In Panel I, the level set restrictions are not combined with any shape restrictions. In Panel II, shape restrictions are imposed on top of the level set restrictions. This assumption corresponds to the restriction that households are more likely to make smaller movements in the income distribution than larger movements.

Several findings stand out. First, under arbitrary, independent errors (Panels IA and IIA), the level set restrictions have some identifying power. The shape restrictions do not add new information. As stated previously, the bounds under arbitrary errors in Table 5 have a width of 0.6 unless the boundary comes into play. After imposing the level set restrictions, the width of the bounds on the conditional staying probabilities falls to around 0.5. Thus, while still wide, there is some information in the level set restrictions. Second, under uniform, independent errors (Panels IB and IIB), the level set restrictions continue to have some identifying power. The shape restrictions continue to add no new information. The bounds under uniform errors in Table 5 have a width of 0.2 unless the boundary comes into play. After imposing the level set restrictions, the width of the bounds on the conditional staying probabilities falls to around 0.12. For example, bounds on the probability of remaining in the bottom tercile over the four-year period in the pooled sample under uniform errors alone are $[0.585, 0.785]$ (Table 5, Panel III), but under level set restrictions with independent errors are $[0.623, 0.732]$ (Table 6, Panel IB). Finally, under uniform and independent errors with the level set restrictions (including the stationarity assumption), the bounds on the probabilities of extreme income mobility − both upward and downward − exclude zero. However, under arbitrary and independent errors, the bounds include zero. Thus, we can rule out the possibility that there is no movement from the first to third or third to first tercile over the two four-year periods (at the 90% confidence level) only under the assumption of uniform and independent errors.

Monotonicity Restriction Table 7 adds the monotonicity assumption. Two findings emerge. First, the monotonicity assumption has only modest identifying power under arbitrary, independent errors (Panels IA and IIA). For instance, the bounds on the probability of remaining in the bottom tercile across the initial and terminal periods in the pooled sample tighten from $[0.449, 0.907]$ to $[0.449, 0.888]$ (Panel IA in Table 6 and 7). Second, the monotonicity assumption has more identifying power, in relative terms, under uniform, independent errors (Panels IB and IIB). Here, the bounds on the probability of remaining in the bottom tercile across the initial and terminal periods in the pooled sample tighten from $[0.623, 0.732]$ to $[0.623, 0.706]$ (Panel IB in Table 6 and 7). The bounds on the probability of remaining in the top tercile across the initial and terminal periods in the pooled sample tighten from $[0.635, 0.764]$ to $[0.635, 0.719]$ (Panel IB in Table 6 and 7). In both cases, the bounds are fairly tight around the observed conditional staying probabilities of 0.685 and 0.688, respectively (Table 5, Panel I).

[24] For brevity, not all combinations are presented. Full results are available upon request.

Summary Mobility Measures Bounds on the summary mobility measures are reported in Table 8.[25] Generally speaking, three conclusions can be drawn by this exercise. First, relative the baseline assumption of Rank-Preserving Measurement Error, one can assess the dramatic increase in uncertainty once misclassification rates of up to 10% are allowed. For example, the 90% confidence interval for Shorrocks (1978) Immobility Ratio measure based on the first SIPP panel is $[0.529, 0.563]$. Under the assumption of arbitrary errors (with $Q = 0.10$), the confidence interval is $[0.084, 1.009]$. Second, our strictest set of assumptions – uniform, independent errors under level set, shape, and monotonicity – can tighten these bounds. Under these assumptions, the 90% confidence interval for Shorrocks (1978) Immobility Ratio measure based on the first SIPP panel is $[0.435, 0.659]$. Finally, the bounds differ very little across the two SIPP panels.

5 Conclusion

That self-reported income contains complex, nonclassical measurement error is a well-established fact. That administrative data on income is imperfect is also relatively uncontroverted. As such, addressing measurement error in the study of income mobility should no longer be optional. Nonetheless, the most frequent response to measurement error is to mention it as a caveat. Nonetheless, several recent attempts to address measurement error have been put forth. Here, we offer a new and complementary approach based on the partial identification of transition matrices.

Among others, our approach has the advantage of transparency, as the assumptions used to tighten the bounds are easily understood and may be imposed or not depending on the particular context. Moreover, our approach only requires data at two points in time. Finally, our approach extends easily to applications other than income. The primary drawback to our approach is the lack of point identification. Consequently, our approach should be viewed as a complement to alternative approaches that produce point estimates under more stringent (or, at least, alternative) identifying assumptions. Using data from the SIPP, we show that relatively small amounts of measurement error leads to bounds that can be quite wide in the absence of other information or restrictions. However, the restrictions we consider contain significant identifying power. We are hopeful that future work will consider additional restrictions that may be used to further tighten the bounds on transition probabilities.

[25] For brevity, Table 8 displays only the 90% confidence intervals and not the point estimates of the bounds. In addition, only the results for the individual panels are provided. All results are available upon request.

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Table 1. Summary Statistics.

	2004-2008 Panel				2008-2012 Panel			
	Initial		Terminal		Initial		Terminal	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Household Income (Monthly)								
Total Income	5432	5481	5904	5768	6146	5875	6173	5985
Per Capita Income	2233	2452	2427	2440	2605	2693	2600	2689
Equalized Income (OECD Scale)	2720	2801	2937	2791	3145	3039	3121	3030
Equalized Income (Modified OECD Scale)	3158	3168	3401	3172	3631	3413	3597	3402
Below Poverty Line (1 = Yes)	0.118	0.323	0.107	0.309	0.126	0.332	0.126	0.332
Household Size								
Total	2.847	1.495	2.787	1.512	2.764	1.508	2.755	1.537
Number of Adults	2.029	0.843	2.077	0.908	2.001	0.853	2.092	0.945
Number of Children Less Than 18	0.819	1.139	0.710	1.102	0.763	1.127	0.663	1.079
Age (Household Head)								
25-29 (1 = Yes)	0.058	0.233	0.058	0.233	0.056	0.230	0.056	0.230
30-34 (1 = Yes)	0.089	0.285	0.089	0.285	0.081	0.273	0.081	0.273
35-39 (1 = Yes)	0.125	0.331	0.125	0.331	0.107	0.309	0.107	0.309
40-44 (1 = Yes)	0.150	0.357	0.150	0.357	0.133	0.340	0.133	0.340
45-49 (1 = Yes)	0.155	0.362	0.155	0.362	0.151	0.358	0.151	0.358
50-54 (1 = Yes)	0.156	0.363	0.156	0.363	0.161	0.367	0.161	0.367
55-59 (1 = Yes)	0.134	0.340	0.134	0.340	0.149	0.356	0.149	0.356
60-65 (1 = Yes)	0.132	0.339	0.132	0.339	0.163	0.369	0.163	0.369
Education (Household Head)								
High School or Less (1 = Yes)	0.346	0.476	0.346	0.476	0.321	0.467	0.321	0.467
Some College (1 = Yes)	0.367	0.482	0.367	0.482	0.354	0.478	0.354	0.478
Bachelor's Degree or More (1 = Yes)	0.288	0.453	0.288	0.453	0.325	0.469	0.325	0.469
N	7834		7834		16006		16006	

Notes: Samples from the Survey of Income and Program Participation (SIPP).

Table 2. Poverty Transition Matrices: Misclassification Assumptions.

2004-2008 Panel			2008-2012 Panel			Pooled Panels		
I. Rank-Preserving Measurement Error								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.448,0.448]	[0.552,0.552]	**Below**	[0.462,0.462]	[0.538,0.538]	**Below**	[0.457,0.457]	[0.543,0.543]
Poverty	[0.424,0.472]	[0.528,0.576]	**Poverty**	[0.442,0.482]	[0.518,0.558]	**Poverty**	[0.444,0.471]	[0.529,0.556]
Above	[0.061,0.061]	[0.939,0.939]	**Above**	[0.077,0.077]	[0.923,0.923]	**Above**	[0.072,0.072]	[0.928,0.928]
Poverty	[0.056,0.067]	[0.933,0.944]	**Poverty**	[0.074,0.081]	[0.919,0.926]	**Poverty**	[0.069,0.075]	[0.925,0.931]
II. Arbitrary Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.000,1.000]	[0.000,1.000]	**Below**	[0.000,0.991]	[0.009,1.000]	**Below**	[0.000,0.991]	[0.009,1.000]
Poverty	[0.000,1.000]	[0.000,1.000]	**Poverty**	[0.000,0.997]	[0.003,1.000]	**Poverty**	[0.000,0.996]	[0.004,1.000]
Above	[0.000,0.175]	[0.825,1.000]	**Above**	[0.002,0.192]	[0.808,0.998]	**Above**	[0.001,0.186]	[0.814,0.999]
Poverty	[0.000,0.179]	[0.821,1.000]	**Poverty**	[0.001,0.195]	[0.805,0.999]	**Poverty**	[0.001,0.189]	[0.811,0.999]
III. Uniform Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.026,0.870]	[0.130,0.974]	**Below**	[0.066,0.858]	[0.142,0.934]	**Below**	[0.053,0.862]	[0.138,0.947]
Poverty	[0.006,0.896]	[0.104,0.994]	**Poverty**	[0.046,0.877]	[0.123,0.954]	**Poverty**	[0.040,0.877]	[0.123,0.960]
Above	[0.005,0.118]	[0.882,0.995]	**Above**	[0.020,0.135]	[0.865,0.980]	**Above**	[0.015,0.129]	[0.871,0.985]
Poverty	[0.001,0.122]	[0.878,0.999]	**Poverty**	[0.017,0.137]	[0.863,0.983]	**Poverty**	[0.013,0.132]	[0.868,0.987]
IV. Arbitrary, Uni-Directional Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.243,0.701]	[0.299,0.757]	**Below**	[0.258,0.700]	[0.300,0.742]	**Below**	[0.253,0.700]	[0.300,0.747]
Poverty	[0.233,0.713]	[0.287,0.767]	**Poverty**	[0.248,0.709]	[0.291,0.752]	**Poverty**	[0.247,0.707]	[0.293,0.753]
Above	[0.000,0.175]	[0.825,1.000]	**Above**	[0.000,0.192]	[0.808,1.000]	**Above**	[0.000,0.186]	[0.814,1.000]
Poverty	[0.000,0.179]	[0.821,1.000]	**Poverty**	[0.000,0.195]	[0.805,1.000]	**Poverty**	[0.000,0.189]	[0.811,1.000]
V. Uniform, Uni-Directional Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.315,0.612]	[0.388,0.685]	**Below**	[0.331,0.614]	[0.386,0.669]	**Below**	[0.326,0.614]	[0.386,0.674]
Poverty	[0.302,0.626]	[0.374,0.698]	**Poverty**	[0.319,0.626]	[0.374,0.681]	**Poverty**	[0.318,0.622]	[0.378,0.682]
Above	[0.005,0.118]	[0.882,0.995]	**Above**	[0.021,0.135]	[0.865,0.979]	**Above**	[0.016,0.129]	[0.871,0.984]
Poverty	[0.001,0.122]	[0.878,0.999]	**Poverty**	[0.018,0.137]	[0.863,0.982]	**Poverty**	[0.014,0.132]	[0.868,0.986]

Notes: Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See text for further details.

Table 3. Poverty Transition Matrices: Level Set Restrictions.

	2004-2008 Panel			2008-2012 Panel			Pooled Panels	
I. No Shape Restrictions								
A. Arbitrary, Independent Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.000,1.000]	[0.000,1.000]	**Below**	[0.000,0.991]	[0.009,1.000]	**Below**	[0.000,0.991]	[0.009,1.000]
Poverty	[0.000,1.000]	[0.000,1.000]	**Poverty**	[0.000,0.997]	[0.003,1.000]	**Poverty**	[0.000,0.996]	[0.004,1.000]
Above	[0.000,0.171]	[0.829,1.000]	**Above**	[0.002,0.184]	[0.816,0.998]	**Above**	[0.001,0.171]	[0.829,0.999]
Poverty	[0.000,0.175]	[0.825,1.000]	**Poverty**	[0.001,0.187]	[0.813,0.999]	**Poverty**	[0.001,0.176]	[0.824,0.999]
B. Uniform, Independent Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.100,0.810]	[0.190,0.900]	**Below**	[0.119,0.830]	[0.170,0.881]	**Below**	[0.129,0.821]	[0.179,0.871]
Poverty	[0.059,0.844]	[0.156,0.941]	**Poverty**	[0.097,0.854]	[0.146,0.903]	**Poverty**	[0.103,0.844]	[0.156,0.897]
Above	[0.009,0.116]	[0.884,0.991]	**Above**	[0.028,0.127]	[0.873,0.972]	**Above**	[0.028,0.116]	[0.884,0.972]
Poverty	[0.004,0.120]	[0.880,0.996]	**Poverty**	[0.024,0.131]	[0.869,0.976]	**Poverty**	[0.024,0.120]	[0.880,0.976]
C. Uniform, Independent, Uni-Directional Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.343,0.576]	[0.424,0.657]	**Below**	[0.362,0.589]	[0.411,0.638]	**Below**	[0.360,0.575]	[0.425,0.640]
Poverty	[0.318,0.598]	[0.402,0.682]	**Poverty**	[0.347,0.603]	[0.397,0.653]	**Poverty**	[0.345,0.591]	[0.409,0.655]
Above	[0.010,0.116]	[0.884,0.990]	**Above**	[0.030,0.127]	[0.873,0.970]	**Above**	[0.030,0.116]	[0.884,0.970]
Poverty	[0.004,0.120]	[0.880,0.996]	**Poverty**	[0.025,0.131]	[0.869,0.975]	**Poverty**	[0.026,0.120]	[0.880,0.974]
II. With Shape Restrictions								
A. Arbitrary, Independent Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.000,1.000]	[0.000,1.000]	**Below**	[0.000,0.991]	[0.009,1.000]	**Below**	[0.000,0.991]	[0.009,1.000]
Poverty	[0.000,1.000]	[0.000,1.000]	**Poverty**	[0.000,0.997]	[0.003,1.000]	**Poverty**	[0.000,0.996]	[0.004,1.000]
Above	[0.000,0.171]	[0.829,1.000]	**Above**	[0.002,0.184]	[0.816,0.998]	**Above**	[0.001,0.171]	[0.829,0.999]
Poverty	[0.000,0.175]	[0.825,1.000]	**Poverty**	[0.001,0.187]	[0.813,0.999]	**Poverty**	[0.001,0.176]	[0.824,0.999]
B. Uniform, Independent Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.183,0.810]	[0.190,0.817]	**Below**	[0.208,0.830]	[0.170,0.792]	**Below**	[0.199,0.821]	[0.179,0.801]
Poverty	[0.153,0.844]	[0.156,0.847]	**Poverty**	[0.185,0.854]	[0.146,0.815]	**Poverty**	[0.177,0.844]	[0.156,0.823]
Above	[0.009,0.116]	[0.884,0.991]	**Above**	[0.028,0.127]	[0.873,0.972]	**Above**	[0.028,0.116]	[0.884,0.972]
Poverty	[0.004,0.120]	[0.880,0.996]	**Poverty**	[0.024,0.131]	[0.869,0.976]	**Poverty**	[0.024,0.120]	[0.880,0.976]
C. Uniform, Independent, Uni-Directional Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.422,0.576]	[0.424,0.578]	**Below**	[0.424,0.589]	[0.411,0.576]	**Below**	[0.421,0.575]	[0.425,0.579]
Poverty	[0.401,0.598]	[0.402,0.599]	**Poverty**	[0.409,0.603]	[0.397,0.591]	**Poverty**	[0.406,0.591]	[0.409,0.594]
Above	[0.009,0.116]	[0.884,0.990]	**Above**	[0.030,0.127]	[0.873,0.970]	**Above**	[0.030,0.116]	[0.884,0.970]
Poverty	[0.004,0.120]	[0.880,0.996]	**Poverty**	[0.025,0.131]	[0.869,0.975]	**Poverty**	[0.026,0.120]	[0.880,0.974]

Notes: Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. Level set restrictions in 2004-2008 and 2008-2012 panels based age of household held using 5-year age intervals and rolling windows of plus/minus one interval. Level set restrictions in pooled panel based age of household held using 5-year age intervals and rolling windows of plus/minus one interval both within and across panels. See text for further details.

Table 4. Poverty Transition Matrices: Monotonicity + Level Set Restrictions.

	2004-2008 Panel			2008-2012 Panel			Pooled Panels	
I. No Shape Restrictions								
A. Arbitrary, Independent Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.021,0.982]	[0.018,0.979]	**Below**	[0.040,0.991]	[0.009,0.960]	**Below**	[0.039,0.981]	[0.019,0.961]
Poverty	[0.007,1.000]	[0.000,0.993]	**Poverty**	[0.032,0.997]	[0.003,0.968]	**Poverty**	[0.030,0.996]	[0.004,0.970]
Above	[0.000,0.169]	[0.831,1.000]	**Above**	[0.008,0.184]	[0.816,0.992]	**Above**	[0.009,0.167]	[0.833,0.991]
Poverty	[0.000,0.174]	[0.826,1.000]	**Poverty**	[0.005,0.187]	[0.813,0.995]	**Poverty**	[0.006,0.172]	[0.828,0.994]
B. Uniform, Independent Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.102,0.731]	[0.269,0.898]	**Below**	[0.134,0.744]	[0.256,0.866]	**Below**	[0.136,0.723]	[0.277,0.864]
Poverty	[0.083,0.766]	[0.234,0.917]	**Poverty**	[0.121,0.770]	[0.230,0.879]	**Poverty**	[0.122,0.756]	[0.244,0.878]
Above	[0.019,0.112]	[0.888,0.981]	**Above**	[0.036,0.127]	[0.873,0.964]	**Above**	[0.041,0.107]	[0.893,0.959]
Poverty	[0.014,0.117]	[0.883,0.986]	**Poverty**	[0.032,0.131]	[0.869,0.968]	**Poverty**	[0.036,0.113]	[0.887,0.964]
C. Uniform, Independent, Uni-Directional Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.343,0.569]	[0.431,0.657]	**Below**	[0.362,0.589]	[0.411,0.638]	**Below**	[0.360,0.564]	[0.436,0.640]
Poverty	[0.318,0.594]	[0.406,0.682]	**Poverty**	[0.347,0.603]	[0.397,0.653]	**Poverty**	[0.345,0.587]	[0.413,0.655]
Above	[0.020,0.112]	[0.888,0.980]	**Above**	[0.038,0.127]	[0.873,0.962]	**Above**	[0.032,0.114]	[0.886,0.968]
Poverty	[0.015,0.117]	[0.883,0.985]	**Poverty**	[0.034,0.131]	[0.869,0.966]	**Poverty**	[0.027,0.120]	[0.880,0.973]
II. With Shape Restrictions								
A. Arbitrary, Independent Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.025,0.982]	[0.018,0.975]	**Below**	[0.041,0.986]	[0.014,0.959]	**Below**	[0.040,0.981]	[0.019,0.960]
Poverty	[0.013,1.000]	[0.000,0.987]	**Poverty**	[0.032,0.992]	[0.008,0.968]	**Poverty**	[0.031,0.994]	[0.006,0.969]
Above	[0.000,0.169]	[0.831,1.000]	**Above**	[0.008,0.184]	[0.816,0.992]	**Above**	[0.009,0.167]	[0.833,0.991]
Poverty	[0.000,0.174]	[0.826,1.000]	**Poverty**	[0.005,0.187]	[0.813,0.995]	**Poverty**	[0.006,0.172]	[0.828,0.994]
B. Uniform, Independent Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.166,0.731]	[0.269,0.834]	**Below**	[0.168,0.744]	[0.256,0.832]	**Below**	[0.166,0.723]	[0.277,0.834]
Poverty	[0.140,0.766]	[0.234,0.860]	**Poverty**	[0.151,0.770]	[0.230,0.849]	**Poverty**	[0.144,0.756]	[0.244,0.856]
Above	[0.020,0.112]	[0.888,0.981]	**Above**	[0.036,0.127]	[0.873,0.964]	**Above**	[0.041,0.107]	[0.893,0.959]
Poverty	[0.014,0.117]	[0.883,0.986]	**Poverty**	[0.032,0.131]	[0.869,0.968]	**Poverty**	[0.036,0.113]	[0.887,0.964]
C. Uniform, Independent, Uni-Directional Misclassification (Q = 0.10)								
	Below Poverty	**Above Poverty**		**Below Poverty**	**Above Poverty**		**Below Poverty**	**Above Poverty**
Below	[0.410,0.568]	[0.432,0.590]	**Below**	[0.436,0.589]	[0.411,0.564]	**Below**	[0.446,0.555]	[0.445,0.554]
Poverty	[0.391,0.591]	[0.409,0.609]	**Poverty**	[0.420,0.603]	[0.397,0.580]	**Poverty**	[0.430,0.574]	[0.426,0.570]
Above	[0.020,0.112]	[0.888,0.980]	**Above**	[0.038,0.127]	[0.873,0.962]	**Above**	[0.032,0.114]	[0.886,0.968]
Poverty	[0.015,0.117]	[0.883,0.985]	**Poverty**	[0.034,0.131]	[0.869,0.966]	**Poverty**	[0.027,0.120]	[0.880,0.973]

Notes: Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. Level set restrictions in 2004-2008 and 2008-2012 panels based age of household held using 5-year age intervals and rolling windows of plus/minus one interval. Level set restrictions in pooled panel based age of household held using 5-year age intervals and rolling windows of plus/minus one interval both within and across panels. Monotonicity restrictions based on education level of household held using four categories (less than high school, high school degree, some college, and four-year college degree or more). See text for further details.

Table 5. Tercile Transition Matrices: Misclassification Assumptions.

	2004-2008 Panel				2008-2012 Panel				Pooled Panels		
I. Rank-Preserving Measurement Error											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.683,0.683]	[0.246,0.246]	[0.071,0.071]	**1**	[0.685,0.685]	[0.242,0.242]	[0.073,0.073]	**1**	[0.685,0.685]	[0.245,0.245]	[0.071,0.071]
	[0.671,0.695]	[0.236,0.257]	[0.063,0.079]		[0.677,0.694]	[0.234,0.250]	[0.067,0.078]		[0.679,0.691]	[0.239,0.252]	[0.067,0.076]
2	[0.231,0.231]	[0.533,0.533]	[0.236,0.236]	**2**	[0.220,0.220]	[0.538,0.538]	[0.242,0.242]	**2**	[0.220,0.220]	[0.538,0.538]	[0.240,0.240]
	[0.221,0.241]	[0.522,0.543]	[0.225,0.247]		[0.213,0.227]	[0.528,0.547]	[0.234,0.250]		[0.215,0.226]	[0.531,0.545]	[0.234,0.246]
3	[0.087,0.087]	[0.221,0.221]	[0.692,0.692]	**3**	[0.095,0.095]	[0.220,0.220]	[0.685,0.685]	**3**	[0.095,0.095]	[0.217,0.217]	[0.688,0.688]
	[0.077,0.096]	[0.210,0.232]	[0.681,0.704]		[0.089,0.101]	[0.213,0.228]	[0.677,0.693]		[0.091,0.099]	[0.211,0.222]	[0.682,0.694]
II. Arbitrary Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.383,0.983]	[0.000,0.546]	[0.000,0.371]	**1**	[0.385,0.985]	[0.000,0.542]	[0.000,0.373]	**1**	[0.385,0.985]	[0.000,0.545]	[0.000,0.371]
	[0.374,0.992]	[0.000,0.554]	[0.000,0.378]		[0.379,0.992]	[0.000,0.548]	[0.000,0.377]		[0.380,0.990]	[0.000,0.551]	[0.000,0.375]
2	[0.000,0.531]	[0.233,0.833]	[0.000,0.536]	**2**	[0.000,0.520]	[0.238,0.838]	[0.000,0.542]	**2**	[0.000,0.520]	[0.238,0.838]	[0.000,0.540]
	[0.000,0.538]	[0.225,0.841]	[0.000,0.545]		[0.000,0.526]	[0.230,0.845]	[0.000,0.549]		[0.000,0.525]	[0.232,0.843]	[0.000,0.545]
3	[0.000,0.387]	[0.000,0.521]	[0.392,0.992]	**3**	[0.000,0.395]	[0.000,0.520]	[0.385,0.985]	**3**	[0.000,0.395]	[0.000,0.517]	[0.388,0.988]
	[0.000,0.394]	[0.000,0.529]	[0.383,1.000]		[0.000,0.399]	[0.000,0.526]	[0.378,0.991]		[0.000,0.398]	[0.000,0.521]	[0.384,0.993]
III. Uniform Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.583,0.783]	[0.146,0.346]	[0.000,0.171]	**1**	[0.585,0.785]	[0.142,0.342]	[0.000,0.173]	**1**	[0.585,0.785]	[0.145,0.345]	[0.000,0.171]
	[0.574,0.792]	[0.138,0.354]	[0.000,0.178]		[0.579,0.792]	[0.136,0.348]	[0.000,0.177]		[0.580,0.790]	[0.140,0.351]	[0.000,0.175]
2	[0.131,0.331]	[0.433,0.633]	[0.136,0.336]	**2**	[0.120,0.320]	[0.438,0.638]	[0.142,0.342]	**2**	[0.120,0.320]	[0.438,0.638]	[0.140,0.340]
	[0.123,0.338]	[0.425,0.641]	[0.128,0.345]		[0.114,0.326]	[0.430,0.645]	[0.136,0.349]		[0.116,0.325]	[0.432,0.643]	[0.136,0.345]
3	[0.000,0.187]	[0.121,0.321]	[0.592,0.792]	**3**	[0.000,0.195]	[0.120,0.320]	[0.585,0.785]	**3**	[0.000,0.195]	[0.117,0.317]	[0.588,0.788]
	[0.000,0.194]	[0.113,0.329]	[0.583,0.802]		[0.000,0.199]	[0.114,0.326]	[0.578,0.791]		[0.000,0.198]	[0.113,0.321]	[0.584,0.793]

Notes: Outcome = OECD equivalized income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See text for further details.

Table 6. Tercile Transition Matrices: Level Set Restrictions.

	2004-2008 Panel			2008-2012 Panel			Pooled Panels		
I. No Shape Restrictions									
A. Arbitrary, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.437,0.942]	[0.000,0.501]	[0.000,0.339]	[0.422,0.977]	[0.000,0.511]	[0.000,0.348]	[0.449,0.907]	[0.029,0.484]	[0.000,0.303]
	[0.422,0.958]	[0.000,0.515]	[0.000,0.347]	[0.413,0.988]	[0.000,0.518]	[0.000,0.354]	[0.435,0.922]	[0.013,0.496]	[0.000,0.312]
2	[0.000,0.519]	[0.259,0.815]	[0.000,0.516]	[0.000,0.507]	[0.260,0.828]	[0.000,0.525]	[0.000,0.468]	[0.292,0.831]	[0.000,0.526]
	[0.000,0.531]	[0.244,0.832]	[0.000,0.530]	[0.000,0.516]	[0.249,0.836]	[0.000,0.534]	[0.000,0.483]	[0.276,0.843]	[0.000,0.538]
3	[0.000,0.337]	[0.000,0.460]	[0.466,0.978]	[0.000,0.378]	[0.000,0.484]	[0.422,0.951]	[0.000,0.360]	[0.000,0.464]	[0.432,0.938]
	[0.000,0.347]	[0.000,0.475]	[0.451,0.993]	[0.000,0.385]	[0.000,0.494]	[0.411,0.960]	[0.000,0.368]	[0.000,0.474]	[0.419,0.947]
B. Uniform, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.621,0.756]	[0.171,0.318]	[0.000,0.157]	[0.611,0.774]	[0.146,0.327]	[0.000,0.158]	[0.623,0.732]	[0.205,0.317]	[0.000,0.140]
	[0.605,0.770]	[0.156,0.331]	[0.000,0.164]	[0.603,0.783]	[0.137,0.333]	[0.000,0.163]	[0.612,0.747]	[0.190,0.327]	[0.000,0.150]
2	[0.147,0.321]	[0.454,0.614]	[0.140,0.326]	[0.127,0.307]	[0.458,0.624]	[0.151,0.327]	[0.139,0.278]	[0.485,0.627]	[0.181,0.330]
	[0.134,0.333]	[0.440,0.630]	[0.128,0.338]	[0.117,0.316]	[0.448,0.632]	[0.143,0.336]	[0.130,0.291]	[0.470,0.637]	[0.163,0.341]
3	[0.001,0.163]	[0.138,0.285]	[0.642,0.757]	[0.004,0.193]	[0.136,0.296]	[0.608,0.767]	[0.012,0.173]	[0.136,0.286]	[0.635,0.764]
	[0.000,0.173]	[0.122,0.300]	[0.627,0.775]	[0.000,0.199]	[0.127,0.305]	[0.598,0.775]	[0.006,0.185]	[0.128,0.303]	[0.621,0.773]
II. With Shape Restrictions									
A. Arbitrary, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.437,0.942]	[0.000,0.501]	[0.000,0.339]	[0.422,0.977]	[0.000,0.511]	[0.000,0.348]	[0.449,0.907]	[0.029,0.484]	[0.000,0.303]
	[0.422,0.958]	[0.000,0.515]	[0.000,0.347]	[0.413,0.988]	[0.000,0.518]	[0.000,0.354]	[0.435,0.922]	[0.013,0.496]	[0.000,0.312]
2	[0.000,0.519]	[0.259,0.815]	[0.000,0.514]	[0.000,0.507]	[0.260,0.828]	[0.000,0.506]	[0.000,0.468]	[0.292,0.831]	[0.000,0.469]
	[0.000,0.531]	[0.244,0.832]	[0.000,0.525]	[0.000,0.516]	[0.249,0.836]	[0.000,0.514]	[0.000,0.483]	[0.276,0.843]	[0.000,0.483]
3	[0.000,0.337]	[0.000,0.460]	[0.466,0.978]	[0.000,0.378]	[0.000,0.484]	[0.422,0.951]	[0.000,0.360]	[0.000,0.464]	[0.432,0.938]
	[0.000,0.347]	[0.000,0.475]	[0.451,0.993]	[0.000,0.385]	[0.000,0.494]	[0.411,0.960]	[0.000,0.368]	[0.000,0.474]	[0.419,0.947]
B. Uniform, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.621,0.756]	[0.171,0.318]	[0.000,0.157]	[0.611,0.774]	[0.146,0.327]	[0.000,0.158]	[0.623,0.732]	[0.205,0.317]	[0.000,0.140]
	[0.605,0.770]	[0.156,0.331]	[0.000,0.164]	[0.603,0.783]	[0.137,0.333]	[0.000,0.163]	[0.612,0.747]	[0.190,0.327]	[0.000,0.150]
2	[0.147,0.321]	[0.454,0.614]	[0.140,0.324]	[0.127,0.307]	[0.458,0.624]	[0.151,0.309]	[0.139,0.278]	[0.485,0.627]	[0.181,0.279]
	[0.134,0.333]	[0.440,0.630]	[0.128,0.334]	[0.117,0.316]	[0.448,0.632]	[0.143,0.317]	[0.130,0.291]	[0.470,0.637]	[0.163,0.291]
3	[0.001,0.163]	[0.138,0.285]	[0.642,0.757]	[0.004,0.193]	[0.136,0.296]	[0.608,0.767]	[0.012,0.173]	[0.136,0.286]	[0.635,0.764]
	[0.000,0.173]	[0.122,0.300]	[0.627,0.775]	[0.000,0.199]	[0.127,0.305]	[0.598,0.775]	[0.006,0.185]	[0.128,0.303]	[0.621,0.773]

Notes: Outcome = OECD equivalized income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See Table 3 and text for further details.

Table 7. Tercile Transition Matrices: Monotonicity + Level Set Restrictions.

	2004-2008 Panel			**2008-2012 Panel**			**Pooled Panels**		
I. No Shape Restrictions									
A. Arbitrary, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.437,0.916]	[0.058,0.501]	[0.000,0.277]	[0.422,0.941]	[0.015,0.511]	[0.000,0.314]	[0.449,0.888]	[0.078,0.484]	[0.000,0.262]
	[0.422,0.931]	[0.041,0.515]	[0.000,0.303]	[0.413,0.952]	[0.003,0.518]	[0.000,0.322]	[0.435,0.905]	[0.062,0.496]	[0.000,0.289]
2	[0.003,0.403]	[0.270,0.805]	[0.009,0.361]	[0.000,0.393]	[0.262,0.818]	[0.001,0.401]	[0.002,0.383]	[0.299,0.791]	[0.043,0.380]
	[0.000,0.425]	[0.253,0.819]	[0.000,0.384]	[0.000,0.405]	[0.252,0.829]	[0.000,0.413]	[0.000,0.395]	[0.285,0.805]	[0.027,0.399]
3	[0.000,0.337]	[0.005,0.460]	[0.466,0.928]	[0.000,0.344]	[0.005,0.484]	[0.422,0.920]	[0.000,0.332]	[0.006,0.464]	[0.432,0.920]
	[0.000,0.347]	[0.000,0.475]	[0.451,0.947]	[0.000,0.356]	[0.000,0.494]	[0.411,0.931]	[0.000,0.346]	[0.000,0.474]	[0.419,0.944]
B. Uniform, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.621,0.751]	[0.183,0.318]	[0.000,0.037]	[0.611,0.740]	[0.159,0.327]	[0.000,0.013]	[0.623,0.706]	[0.205,0.317]	[0.000,0.052]
	[0.605,0.768]	[0.168,0.331]	[0.000,0.062]	[0.603,0.752]	[0.148,0.333]	[0.000,0.029]	[0.612,0.720]	[0.190,0.327]	[0.000,0.065]
2	[0.147,0.279]	[0.466,0.602]	[0.153,0.271]	[0.127,0.284]	[0.460,0.612]	[0.175,0.268]	[0.139,0.263]	[0.490,0.595]	[0.184,0.268]
	[0.134,0.297]	[0.450,0.620]	[0.141,0.283]	[0.117,0.293]	[0.450,0.623]	[0.166,0.281]	[0.130,0.272]	[0.476,0.608]	[0.174,0.276]
3	[0.020,0.124]	[0.163,0.278]	[0.642,0.719]	[0.021,0.114]	[0.164,0.296]	[0.608,0.721]	[0.024,0.114]	[0.167,0.258]	[0.635,0.719]
	[0.009,0.148]	[0.142,0.294]	[0.627,0.741]	[0.013,0.132]	[0.151,0.305]	[0.598,0.734]	[0.015,0.130]	[0.150,0.276]	[0.621,0.734]
II. With Shape Restrictions									
A. Arbitrary, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.437,0.916]	[0.058,0.501]	[0.000,0.277]	[0.422,0.941]	[0.015,0.511]	[0.000,0.314]	[0.449,0.888]	[0.078,0.484]	[0.000,0.262]
	[0.422,0.931]	[0.041,0.515]	[0.000,0.303]	[0.413,0.952]	[0.003,0.518]	[0.000,0.322]	[0.435,0.905]	[0.062,0.496]	[0.000,0.289]
2	[0.003,0.403]	[0.270,0.805]	[0.009,0.361]	[0.000,0.393]	[0.262,0.818]	[0.001,0.401]	[0.002,0.383]	[0.299,0.791]	[0.043,0.380]
	[0.000,0.425]	[0.253,0.819]	[0.000,0.384]	[0.000,0.405]	[0.252,0.829]	[0.000,0.413]	[0.000,0.395]	[0.285,0.805]	[0.027,0.399]
3	[0.000,0.337]	[0.005,0.460]	[0.466,0.928]	[0.000,0.344]	[0.009,0.484]	[0.422,0.920]	[0.000,0.332]	[0.006,0.464]	[0.432,0.920]
	[0.000,0.347]	[0.000,0.475]	[0.451,0.947]	[0.000,0.356]	[0.000,0.494]	[0.411,0.931]	[0.000,0.346]	[0.000,0.474]	[0.419,0.944]
B. Uniform, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.621,0.751]	[0.183,0.318]	[0.000,0.037]	[0.611,0.740]	[0.159,0.327]	[0.000,0.013]	[0.623,0.706]	[0.205,0.317]	[0.000,0.052]
	[0.605,0.768]	[0.168,0.331]	[0.000,0.062]	[0.603,0.752]	[0.148,0.333]	[0.000,0.029]	[0.612,0.720]	[0.190,0.327]	[0.000,0.065]
2	[0.147,0.279]	[0.466,0.602]	[0.153,0.261]	[0.127,0.284]	[0.460,0.612]	[0.175,0.268]	[0.139,0.263]	[0.490,0.595]	[0.186,0.262]
	[0.134,0.297]	[0.450,0.620]	[0.141,0.271]	[0.117,0.293]	[0.450,0.623]	[0.166,0.281]	[0.130,0.272]	[0.474,0.608]	[0.176,0.271]
3	[0.020,0.124]	[0.163,0.278]	[0.642,0.719]	[0.021,0.114]	[0.164,0.296]	[0.608,0.719]	[0.024,0.114]	[0.167,0.258]	[0.635,0.719]
	[0.009,0.148]	[0.142,0.294]	[0.627,0.741]	[0.013,0.132]	[0.151,0.305]	[0.598,0.732]	[0.015,0.129]	[0.150,0.276]	[0.621,0.734]

Notes: Outcome = OECD equivalized income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See Table 4 and text for further details.

Table 8. Tercile Transition Matrices: Summary Mobility Measures.

2004-2008 Panel		2008-2012 Panel	
I. Expected Exit Time: [Q1,Q1]		I. Expected Exit Time: [Q1,Q1]	
RPME	[3.039,3.275]	RPME	[3.096,3.266]
AM	[1.596,120.725]	AM	[1.610,122.294]
UM	[2.345,4.809]	UM	[2.375,4.807]
LSR + Shape + AIM	[1.730,23.947]	LSR + Shape + AIM	[1.704,82.719]
LSR + Shape + UIM	[2.534,4.343]	LSR + Shape + UIM	[2.519,4.615]
M + LSR + Shape + AIM	[1.730,14.426]	M + LSR + Shape + AIM	[1.704,20.923]
M + LSR + Shape + UIM	[2.534,4.308]	M + LSR + Shape + UIM	[2.519,4.032]
II. Expected Exit Time: [Q3,Q3]		II. Expected Exit Time: [Q3,Q3]	
RPME	[3.131,3.380]	RPME	[3.092,3.259]
AM	[1.621, .]	AM	[1.609,115.444]
UM	[2.399,5.039]	UM	[2.372,4.792]
LSR + Shape + AIM	[1.822,133.865]	LSR + Shape + AIM	[1.698,25.025]
LSR + Shape + UIM	[2.683,4.443]	LSR + Shape + UIM	[2.490,4.449]
M + LSR + Shape + AIM	[1.822,18.790]	M + LSR + Shape + AIM	[1.698,14.521]
M + LSR + Shape + UIM	[2.683,3.862]	M + LSR + Shape + UIM	[2.490,3.737]
III. Immobility Ratio		III. Immobility Ratio	
RPME	[0.529,0.563]	RPME	[0.533,0.559]
AM	[0.084,1.009]	AM	[0.086,1.006]
UM	[0.383,0.709]	UM	[0.386,0.706]
LSR + Shape + AIM	[0.108,0.941]	LSR + Shape + AIM	[0.108,0.963]
LSR + Shape + UIM	[0.413,0.664]	LSR + Shape + UIM	[0.405,0.675]
M + LSR + Shape + AIM	[0.152,0.937]	M + LSR + Shape + AIM	[0.144,0.962]
M + LSR + Shape + UIM	[0.435,0.659]	M + LSR + Shape + UIM	[0.446,0.674]
IV. Upward Mobility		IV. Upward Mobility	
RPME	[0.458,0.494]	RPME	[0.459,0.484]
AM	[0.012,0.940]	AM	[0.012,0.932]
UM	[0.312,0.640]	UM	[0.312,0.632]
LSR + Shape + AIM	[0.063,0.867]	LSR + Shape + AIM	[0.018,0.880]
LSR + Shape + UIM	[0.345,0.592]	LSR + Shape + UIM	[0.325,0.595]
M + LSR + Shape + AIM	[0.104,0.867]	M + LSR + Shape + AIM	[0.072,0.880]
M + LSR + Shape + UIM	[0.348,0.592]	M + LSR + Shape + UIM	[0.372,0.595]
V. Downward Mobility		V. Downward Mobility	
RPME	[0.444,0.479]	RPME	[0.460,0.485]
AM	[0.000,0.925]	AM	[0.013,0.932]
UM	[0.298,0.625]	UM	[0.313,0.632]
LSR + Shape + AIM	[0.011,0.823]	LSR + Shape + AIM	[0.060,0.883]
LSR + Shape + UIM	[0.338,0.559]	LSR + Shape + UIM	[0.337,0.602]
M + LSR + Shape + AIM	[0.080,0.823]	M + LSR + Shape + AIM	[0.103,0.883]
M + LSR + Shape + UIM	[0.388,0.559]	M + LSR + Shape + UIM	[0.401,0.602]

Notes: Outcome = OECD equivalized income. RPME = rank-preserving measurement error. AM = arbitrary misclassification. UM = uniform misclassification. I = independence. LSR = level set restrictions. M = monotonicity. 90% confidence intervals for bounds provided in brackets based on estimates in Tables 5-7. See text for further details.

Table A1. Tercile Transition Matrices: Misclassification Assumptions.

	2004-2008 Panel				2008-2012 Panel				Pooled Panels		
I. Rank-Preserving Measurement Error											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.688,0.688]	[0.243,0.243]	[0.070,0.070]	**1**	[0.687,0.687]	[0.241,0.241]	[0.076,0.076]	**1**	[0.685,0.685]	[0.243,0.243]	[0.073,0.073]
	[0.676,0.701]	[0.231,0.255]	[0.061,0.078]		[0.679,0.695]	[0.234,0.249]	[0.071,0.081]		[0.678,0.691]	[0.237,0.249]	[0.068,0.077]
2	[0.221,0.221]	[0.540,0.540]	[0.239,0.239]	**2**	[0.218,0.218]	[0.536,0.536]	[0.242,0.242]	**2**	[0.221,0.221]	[0.539,0.539]	[0.240,0.240]
	[0.210,0.233]	[0.527,0.553]	[0.227,0.251]		[0.210,0.226]	[0.528,0.544]	[0.234,0.250]		[0.214,0.227]	[0.532,0.547]	[0.235,0.245]
3	[0.091,0.091]	[0.218,0.218]	[0.692,0.692]	**3**	[0.095,0.095]	[0.222,0.222]	[0.682,0.682]	**3**	[0.095,0.095]	[0.218,0.218]	[0.687,0.687]
	[0.082,0.100]	[0.206,0.229]	[0.680,0.703]		[0.089,0.102]	[0.214,0.230]	[0.674,0.690]		[0.089,0.100]	[0.212,0.224]	[0.681,0.693]
II. Arbitrary Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.388,0.988]	[0.000,0.543]	[0.000,0.370]	**1**	[0.387,0.987]	[0.000,0.541]	[0.000,0.376]	**1**	[0.385,0.985]	[0.000,0.543]	[0.000,0.373]
	[0.378,0.998]	[0.000,0.552]	[0.000,0.376]		[0.381,0.993]	[0.000,0.547]	[0.000,0.380]		[0.379,0.990]	[0.000,0.547]	[0.000,0.376]
2	[0.000,0.521]	[0.240,0.840]	[0.000,0.539]	**2**	[0.000,0.518]	[0.236,0.836]	[0.000,0.542]	**2**	[0.000,0.521]	[0.239,0.839]	[0.000,0.540]
	[0.000,0.530]	[0.229,0.850]	[0.000,0.548]		[0.000,0.524]	[0.230,0.842]	[0.000,0.548]		[0.000,0.526]	[0.233,0.845]	[0.000,0.544]
3	[0.000,0.391]	[0.000,0.518]	[0.392,0.992]	**3**	[0.000,0.395]	[0.000,0.522]	[0.382,0.982]	**3**	[0.000,0.395]	[0.000,0.518]	[0.387,0.987]
	[0.000,0.398]	[0.000,0.526]	[0.383,1.000]		[0.000,0.400]	[0.000,0.529]	[0.376,0.988]		[0.000,0.399]	[0.000,0.522]	[0.382,0.992]
III. Uniform Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.588,0.788]	[0.143,0.343]	[0.000,0.170]	**1**	[0.587,0.787]	[0.141,0.341]	[0.000,0.176]	**1**	[0.585,0.785]	[0.143,0.343]	[0.000,0.173]
	[0.578,0.798]	[0.134,0.352]	[0.000,0.176]		[0.581,0.793]	[0.136,0.347]	[0.000,0.180]		[0.579,0.790]	[0.138,0.347]	[0.000,0.176]
2	[0.121,0.321]	[0.440,0.640]	[0.139,0.339]	**2**	[0.118,0.318]	[0.436,0.636]	[0.142,0.342]	**2**	[0.121,0.321]	[0.439,0.639]	[0.140,0.340]
	[0.112,0.330]	[0.429,0.650]	[0.129,0.348]		[0.112,0.324]	[0.430,0.642]	[0.136,0.348]		[0.116,0.326]	[0.433,0.645]	[0.136,0.344]
3	[0.000,0.191]	[0.118,0.318]	[0.592,0.792]	**3**	[0.000,0.195]	[0.122,0.322]	[0.582,0.782]	**3**	[0.000,0.195]	[0.118,0.318]	[0.587,0.787]
	[0.000,0.198]	[0.109,0.326]	[0.583,0.800]		[0.000,0.200]	[0.116,0.329]	[0.576,0.788]		[0.000,0.199]	[0.114,0.322]	[0.582,0.792]

Notes: Outcome = modified OECD equivalized income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See text for further details.

Table A2. Tercile Transition Matrices: Level Set Restrictions.

	2004-2008 Panel				2008-2012 Panel				Pooled Panels		
I. No Shape Restrictions											
A. Arbitrary, Independent Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.451,0.962]	[0.000,0.487]	[0.000,0.335]	**1**	[0.415,0.973]	[0.000,0.513]	[0.000,0.349]	**1**	[0.453,0.913]	[0.017,0.477]	[0.000,0.312]
	[0.435,0.977]	[0.000,0.500]	[0.000,0.345]		[0.405,0.983]	[0.000,0.523]	[0.000,0.355]		[0.438,0.928]	[0.005,0.490]	[0.000,0.321]
2	[0.000,0.505]	[0.270,0.832]	[0.000,0.506]	**2**	[0.000,0.512]	[0.255,0.826]	[0.000,0.535]	**2**	[0.000,0.476]	[0.268,0.830]	[0.000,0.518]
	[0.000,0.518]	[0.252,0.848]	[0.000,0.522]		[0.000,0.520]	[0.245,0.836]	[0.000,0.545]		[0.000,0.487]	[0.255,0.841]	[0.000,0.527]
3	[0.000,0.340]	[0.000,0.463]	[0.460,0.979]	**3**	[0.000,0.368]	[0.000,0.490]	[0.418,0.947]	**3**	[0.000,0.359]	[0.000,0.479]	[0.434,0.941]
	[0.000,0.351]	[0.000,0.477]	[0.445,0.991]		[0.000,0.377]	[0.000,0.499]	[0.408,0.955]		[0.000,0.366]	[0.000,0.487]	[0.424,0.949]
B. Uniform, Independent Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.632,0.763]	[0.160,0.306]	[0.000,0.153]	**1**	[0.600,0.775]	[0.155,0.325]	[0.000,0.163]	**1**	[0.620,0.746]	[0.186,0.312]	[0.000,0.150]
	[0.618,0.779]	[0.146,0.318]	[0.000,0.161]		[0.591,0.785]	[0.145,0.334]	[0.000,0.168]		[0.607,0.757]	[0.175,0.322]	[0.000,0.158]
2	[0.135,0.311]	[0.463,0.635]	[0.169,0.310]	**2**	[0.123,0.310]	[0.457,0.623]	[0.150,0.334]	**2**	[0.132,0.284]	[0.461,0.627]	[0.172,0.319]
	[0.122,0.323]	[0.447,0.650]	[0.152,0.324]		[0.115,0.318]	[0.448,0.633]	[0.141,0.343]		[0.124,0.292]	[0.448,0.635]	[0.159,0.327]
3	[0.005,0.165]	[0.123,0.288]	[0.635,0.768]	**3**	[0.006,0.185]	[0.141,0.297]	[0.618,0.757]	**3**	[0.016,0.178]	[0.133,0.293]	[0.628,0.764]
	[0.000,0.174]	[0.111,0.301]	[0.621,0.783]		[0.000,0.193]	[0.133,0.306]	[0.608,0.765]		[0.011,0.185]	[0.127,0.303]	[0.617,0.771]
II. With Shape Restrictions											
A. Arbitrary, Independent Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.451,0.962]	[0.000,0.487]	[0.000,0.335]	**1**	[0.415,0.973]	[0.000,0.513]	[0.000,0.349]	**1**	[0.453,0.913]	[0.017,0.477]	[0.000,0.312]
	[0.435,0.977]	[0.000,0.500]	[0.000,0.345]		[0.405,0.983]	[0.000,0.523]	[0.000,0.355]		[0.438,0.928]	[0.005,0.490]	[0.000,0.321]
2	[0.000,0.505]	[0.270,0.832]	[0.000,0.506]	**2**	[0.000,0.512]	[0.255,0.826]	[0.000,0.514]	**2**	[0.000,0.476]	[0.268,0.830]	[0.000,0.473]
	[0.000,0.518]	[0.252,0.848]	[0.000,0.522]		[0.000,0.520]	[0.245,0.836]	[0.000,0.522]		[0.000,0.487]	[0.255,0.841]	[0.000,0.484]
3	[0.000,0.340]	[0.000,0.463]	[0.460,0.979]	**3**	[0.000,0.368]	[0.000,0.490]	[0.418,0.947]	**3**	[0.000,0.359]	[0.000,0.479]	[0.434,0.941]
	[0.000,0.351]	[0.000,0.477]	[0.445,0.991]		[0.000,0.377]	[0.000,0.499]	[0.408,0.955]		[0.000,0.366]	[0.000,0.487]	[0.424,0.949]
B. Uniform, Independent Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.632,0.763]	[0.160,0.306]	[0.000,0.153]	**1**	[0.600,0.775]	[0.155,0.325]	[0.000,0.163]	**1**	[0.620,0.746]	[0.186,0.312]	[0.000,0.150]
	[0.618,0.779]	[0.146,0.318]	[0.000,0.161]		[0.591,0.785]	[0.145,0.334]	[0.000,0.168]		[0.607,0.757]	[0.175,0.322]	[0.000,0.158]
2	[0.135,0.311]	[0.463,0.635]	[0.169,0.310]	**2**	[0.123,0.310]	[0.457,0.623]	[0.150,0.312]	**2**	[0.132,0.284]	[0.461,0.627]	[0.172,0.281]
	[0.122,0.323]	[0.447,0.650]	[0.152,0.324]		[0.115,0.318]	[0.448,0.633]	[0.141,0.319]		[0.124,0.292]	[0.448,0.635]	[0.159,0.290]
3	[0.005,0.165]	[0.123,0.288]	[0.635,0.768]	**3**	[0.006,0.185]	[0.141,0.297]	[0.618,0.757]	**3**	[0.016,0.178]	[0.133,0.293]	[0.628,0.764]
	[0.000,0.174]	[0.111,0.301]	[0.621,0.783]		[0.000,0.193]	[0.133,0.306]	[0.608,0.765]		[0.011,0.185]	[0.127,0.303]	[0.617,0.771]

Notes: Outcome = modified OECD equivalized income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See Table 3 and text for further details.

Table A3. Tercile Transition Matrices: Monotonicity + Level Set Restrictions.

	2004-2008 Panel			2008-2012 Panel			Pooled Panels		
I. No Shape Restrictions									
A. Arbitrary, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.451,0.947]	[0.020,0.487]	[0.000,0.276]	[0.415,0.931]	[0.039,0.513]	[0.000,0.310]	[0.453,0.888]	[0.063,0.477]	[0.000,0.289]
	[0.435,0.966]	[0.002,0.500]	[0.000,0.301]	[0.405,0.945]	[0.022,0.523]	[0.000,0.322]	[0.438,0.905]	[0.046,0.490]	[0.000,0.308]
2	[0.000,0.387]	[0.270,0.815]	[0.010,0.357]	[0.000,0.403]	[0.255,0.824]	[0.002,0.379]	[0.000,0.394]	[0.283,0.808]	[0.023,0.369]
	[0.000,0.406]	[0.253,0.831]	[0.000,0.378]	[0.000,0.414]	[0.245,0.836]	[0.000,0.392]	[0.000,0.407]	[0.272,0.820]	[0.012,0.382]
3	[0.000,0.338]	[0.000,0.463]	[0.460,0.894]	[0.000,0.357]	[0.010,0.490]	[0.418,0.915]	[0.000,0.339]	[0.009,0.479]	[0.434,0.918]
	[0.000,0.351]	[0.000,0.477]	[0.445,0.920]	[0.000,0.368]	[0.000,0.499]	[0.408,0.931]	[0.000,0.353]	[0.000,0.487]	[0.424,0.932]
B. Uniform, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.632,0.760]	[0.173,0.306]	[0.000,0.033]	[0.600,0.740]	[0.167,0.325]	[0.000,0.031]	[0.620,0.731]	[0.202,0.312]	[0.000,0.048]
	[0.618,0.778]	[0.156,0.318]	[0.000,0.062]	[0.591,0.752]	[0.155,0.334]	[0.000,0.047]	[0.607,0.743]	[0.185,0.322]	[0.000,0.064]
2	[0.135,0.262]	[0.468,0.607]	[0.169,0.271]	[0.124,0.267]	[0.457,0.617]	[0.160,0.277]	[0.141,0.267]	[0.477,0.597]	[0.180,0.272]
	[0.122,0.277]	[0.453,0.626]	[0.152,0.282]	[0.116,0.277]	[0.448,0.629]	[0.152,0.288]	[0.132,0.277]	[0.468,0.610]	[0.171,0.280]
3	[0.017,0.080]	[0.147,0.288]	[0.635,0.732]	[0.027,0.081]	[0.174,0.297]	[0.618,0.724]	[0.022,0.120]	[0.172,0.266]	[0.628,0.719]
	[0.005,0.106]	[0.130,0.301]	[0.621,0.751]	[0.020,0.100]	[0.162,0.306]	[0.608,0.738]	[0.013,0.141]	[0.159,0.280]	[0.617,0.732]
II. With Shape Restrictions									
A. Arbitrary, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.451,0.947]	[0.020,0.487]	[0.000,0.276]	[0.415,0.931]	[0.039,0.513]	[0.000,0.310]	[0.453,0.888]	[0.063,0.477]	[0.000,0.289]
	[0.435,0.966]	[0.002,0.500]	[0.000,0.301]	[0.405,0.945]	[0.022,0.523]	[0.000,0.322]	[0.438,0.905]	[0.046,0.490]	[0.000,0.308]
2	[0.000,0.387]	[0.270,0.815]	[0.010,0.357]	[0.000,0.403]	[0.255,0.824]	[0.002,0.379]	[0.000,0.394]	[0.283,0.808]	[0.023,0.368]
	[0.000,0.406]	[0.253,0.831]	[0.000,0.378]	[0.000,0.414]	[0.245,0.836]	[0.000,0.392]	[0.000,0.407]	[0.272,0.820]	[0.012,0.381]
3	[0.000,0.335]	[0.000,0.463]	[0.460,0.894]	[0.000,0.357]	[0.010,0.490]	[0.418,0.915]	[0.000,0.339]	[0.009,0.479]	[0.434,0.918]
	[0.000,0.350]	[0.000,0.477]	[0.445,0.920]	[0.000,0.368]	[0.000,0.499]	[0.408,0.931]	[0.000,0.353]	[0.000,0.487]	[0.424,0.932]
B. Uniform, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.632,0.760]	[0.173,0.306]	[0.000,0.033]	[0.600,0.740]	[0.167,0.325]	[0.000,0.030]	[0.620,0.731]	[0.202,0.312]	[0.000,0.048]
	[0.618,0.778]	[0.156,0.318]	[0.000,0.058]	[0.591,0.752]	[0.155,0.334]	[0.000,0.045]	[0.607,0.743]	[0.185,0.322]	[0.000,0.064]
2	[0.135,0.262]	[0.468,0.607]	[0.169,0.242]	[0.124,0.267]	[0.457,0.617]	[0.161,0.276]	[0.141,0.267]	[0.477,0.597]	[0.183,0.261]
	[0.122,0.277]	[0.453,0.626]	[0.152,0.256]	[0.116,0.277]	[0.448,0.629]	[0.152,0.286]	[0.132,0.277]	[0.468,0.610]	[0.174,0.270]
3	[0.017,0.080]	[0.147,0.288]	[0.635,0.732]	[0.027,0.081]	[0.174,0.297]	[0.618,0.724]	[0.022,0.120]	[0.172,0.266]	[0.628,0.719]
	[0.005,0.106]	[0.130,0.301]	[0.621,0.751]	[0.020,0.100]	[0.162,0.306]	[0.608,0.738]	[0.013,0.141]	[0.159,0.280]	[0.617,0.732]

Notes: Outcome = modified OECD equivalized income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See Table 4 and text for further details.

Table A4. Tercile Transition Matrices: Summary Mobility Measures.

	2004-2008 Panel		2008-2012 Panel
I. Expected Exit Time: [Q1,Q1]		I. Expected Exit Time: [Q1,Q1]	
RPME	[3.082,3.341]	RPME	[3.117,3.275]
AM	[1.609,401.781]	AM	[1.615,142.383]
UM	[2.372,4.949]	UM	[2.386,4.830]
LSR + Shape + AIM	[1.771,44.263]	LSR + Shape + AIM	[1.681,57.381]
LSR + Shape + UIM	[2.618,4.518]	LSR + Shape + UIM	[2.443,4.645]
M + LSR + Shape + AIM	[1.771,29.798]	M + LSR + Shape + AIM	[1.681,18.090]
M + LSR + Shape + UIM	[2.618,4.496]	M + LSR + Shape + UIM	[2.443,4.026]
II. Expected Exit Time: [Q3,Q3]		II. Expected Exit Time: [Q3,Q3]	
RPME	[3.129,3.365]	RPME	[3.071,3.227]
AM	[1.620,2560.332]	AM	[1.603,86.107]
UM	[2.397,5.009]	UM	[2.359,4.726]
LSR + Shape + AIM	[1.801,114.361]	LSR + Shape + AIM	[1.690,22.464]
LSR + Shape + UIM	[2.638,4.614]	LSR + Shape + UIM	[2.548,4.262]
M + LSR + Shape + AIM	[1.801,12.468]	M + LSR + Shape + AIM	[1.690,14.400]
M + LSR + Shape + UIM	[2.638,4.019]	M + LSR + Shape + UIM	[2.548,3.811]
III. Immobility Ratio		III. Immobility Ratio	
RPME	[0.522,0.559]	RPME	[0.535,0.559]
AM	[0.077,1.005]	AM	[0.088,1.007]
UM	[0.376,0.705]	UM	[0.388,0.707]
LSR + Shape + AIM	[0.092,0.934]	LSR + Shape + AIM	[0.113,0.971]
LSR + Shape + UIM	[0.394,0.657]	LSR + Shape + UIM	[0.408,0.677]
M + LSR + Shape + AIM	[0.141,0.933]	M + LSR + Shape + AIM	[0.144,0.971]
M + LSR + Shape + UIM	[0.423,0.654]	M + LSR + Shape + UIM	[0.441,0.677]
IV. Upward Mobility		IV. Upward Mobility	
RPME	[0.449,0.487]	RPME	[0.458,0.481]
AM	[0.004,0.932]	AM	[0.011,0.929]
UM	[0.303,0.632]	UM	[0.311,0.629]
LSR + Shape + AIM	[0.034,0.847]	LSR + Shape + AIM	[0.026,0.892]
LSR + Shape + UIM	[0.332,0.573]	LSR + Shape + UIM	[0.323,0.614]
M + LSR + Shape + AIM	[0.050,0.847]	M + LSR + Shape + AIM	[0.083,0.892]
M + LSR + Shape + UIM	[0.334,0.573]	M + LSR + Shape + UIM	[0.373,0.614]
V. Downward Mobility		V. Downward Mobility	
RPME	[0.446,0.479]	RPME	[0.465,0.488]
AM	[0.001,0.926]	AM	[0.017,0.936]
UM	[0.299,0.626]	UM	[0.319,0.636]
LSR + Shape + AIM	[0.013,0.833]	LSR + Shape + AIM	[0.067,0.888]
LSR + Shape + UIM	[0.325,0.569]	LSR + Shape + UIM	[0.352,0.589]
M + LSR + Shape + AIM	[0.120,0.833]	M + LSR + Shape + AIM	[0.104,0.888]
M + LSR + Shape + UIM	[0.373,0.569]	M + LSR + Shape + UIM	[0.394,0.589]

Notes: Outcome = modified OECD equivalized income. RPME = rank-preserving measurement error. AM = arbitrary misclassification. UM = uniform misclassification. I = independence. LSR = level set restrictions. M = monotonicity. 90% confidence intervals for bounds provided in brackets based on estimates in Tables 5-7. See text for further details.

Table A5. Tercile Transition Matrices: Misclassification Assumptions.

	2004-2008 Panel				2008-2012 Panel				Pooled Panels		
I. Rank-Preserving Measurement Error											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.689,0.689]	[0.244,0.244]	[0.068,0.068]	**1**	[0.685,0.685]	[0.242,0.242]	[0.073,0.073]	**1**	[0.689,0.689]	[0.241,0.241]	[0.070,0.070]
	[0.677,0.700]	[0.232,0.255]	[0.060,0.076]		[0.678,0.692]	[0.235,0.250]	[0.067,0.078]		[0.683,0.695]	[0.234,0.248]	[0.066,0.074]
2	[0.221,0.221]	[0.550,0.550]	[0.229,0.229]	**2**	[0.216,0.216]	[0.535,0.535]	[0.248,0.248]	**2**	[0.217,0.217]	[0.540,0.540]	[0.243,0.243]
	[0.209,0.234]	[0.535,0.564]	[0.216,0.242]		[0.209,0.224]	[0.526,0.544]	[0.241,0.256]		[0.211,0.224]	[0.532,0.548]	[0.237,0.249]
3	[0.090,0.090]	[0.207,0.207]	[0.703,0.703]	**3**	[0.099,0.099]	[0.222,0.222]	[0.679,0.679]	**3**	[0.094,0.094]	[0.219,0.219]	[0.687,0.687]
	[0.082,0.099]	[0.195,0.219]	[0.691,0.715]		[0.092,0.105]	[0.215,0.230]	[0.671,0.687]		[0.088,0.099]	[0.213,0.225]	[0.681,0.693]
II. Arbitrary Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.389,0.989]	[0.000,0.544]	[0.000,0.368]	**1**	[0.385,0.985]	[0.000,0.542]	[0.000,0.373]	**1**	[0.389,0.989]	[0.000,0.541]	[0.000,0.370]
	[0.379,0.998]	[0.000,0.553]	[0.000,0.374]		[0.380,0.990]	[0.000,0.548]	[0.000,0.377]		[0.384,0.994]	[0.000,0.546]	[0.000,0.373]
2	[0.000,0.521]	[0.250,0.850]	[0.000,0.529]	**2**	[0.000,0.516]	[0.235,0.835]	[0.000,0.548]	**2**	[0.000,0.517]	[0.240,0.840]	[0.000,0.543]
	[0.000,0.531]	[0.238,0.861]	[0.000,0.539]		[0.000,0.522]	[0.228,0.842]	[0.000,0.554]		[0.000,0.522]	[0.234,0.846]	[0.000,0.547]
3	[0.000,0.390]	[0.000,0.507]	[0.403,1.000]	**3**	[0.000,0.399]	[0.000,0.522]	[0.379,0.979]	**3**	[0.000,0.394]	[0.000,0.519]	[0.387,0.987]
	[0.000,0.397]	[0.000,0.516]	[0.393,1.000]		[0.000,0.404]	[0.000,0.528]	[0.372,0.985]		[0.000,0.398]	[0.000,0.524]	[0.382,0.992]
III. Uniform Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.589,0.789]	[0.144,0.344]	[0.000,0.168]	**1**	[0.585,0.785]	[0.142,0.342]	[0.000,0.173]	**1**	[0.589,0.789]	[0.141,0.341]	[0.000,0.170]
	[0.579,0.798]	[0.134,0.353]	[0.000,0.174]		[0.580,0.790]	[0.137,0.348]	[0.000,0.177]		[0.584,0.794]	[0.136,0.346]	[0.000,0.173]
2	[0.121,0.321]	[0.450,0.650]	[0.129,0.329]	**2**	[0.116,0.316]	[0.435,0.635]	[0.148,0.348]	**2**	[0.117,0.317]	[0.440,0.640]	[0.143,0.343]
	[0.112,0.331]	[0.438,0.661]	[0.119,0.339]		[0.111,0.322]	[0.428,0.642]	[0.142,0.354]		[0.112,0.322]	[0.434,0.646]	[0.138,0.347]
3	[0.000,0.190]	[0.107,0.307]	[0.603,0.803]	**3**	[0.000,0.199]	[0.122,0.322]	[0.579,0.779]	**3**	[0.000,0.194]	[0.119,0.319]	[0.587,0.787]
	[0.000,0.197]	[0.097,0.316]	[0.593,0.812]		[0.000,0.204]	[0.117,0.328]	[0.572,0.785]		[0.000,0.198]	[0.114,0.324]	[0.582,0.792]

Notes: Outcome = per capita income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See text for further details.

Table A6. Tercile Transition Matrices: Level Set Restrictions.

	2004-2008 Panel			2008-2012 Panel			Pooled Panels		
I. No Shape Restrictions									
A. Arbitrary, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.451,0.955]	[0.000,0.494]	[0.000,0.327]	[0.456,0.976]	[0.000,0.488]	[0.000,0.326]	[0.467,0.917]	[0.024,0.473]	[0.000,0.314]
	[0.440,0.971]	[0.000,0.505]	[0.000,0.334]	[0.447,0.986]	[0.000,0.496]	[0.000,0.331]	[0.458,0.931]	[0.013,0.483]	[0.000,0.319]
2	[0.000,0.492]	[0.289,0.837]	[0.000,0.484]	[0.000,0.479]	[0.261,0.826]	[0.000,0.534]	[0.000,0.457]	[0.287,0.825]	[0.009,0.507]
	[0.000,0.504]	[0.273,0.853]	[0.000,0.498]	[0.000,0.490]	[0.249,0.835]	[0.000,0.542]	[0.000,0.468]	[0.273,0.837]	[0.009,0.507]
3	[0.000,0.348]	[0.000,0.445]	[0.479,0.965]	[0.000,0.373]	[0.000,0.482]	[0.414,0.946]	[0.000,0.364]	[0.000,0.463]	[0.438,0.939]
	[0.000,0.360]	[0.000,0.459]	[0.464,0.979]	[0.000,0.380]	[0.000,0.491]	[0.404,0.954]	[0.000,0.369]	[0.000,0.472]	[0.429,0.947]
B. Uniform, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.631,0.781]	[0.159,0.313]	[0.000,0.142]	[0.636,0.751]	[0.152,0.309]	[0.000,0.146]	[0.651,0.735]	[0.193,0.296]	[0.000,0.145]
	[0.621,0.796]	[0.147,0.324]	[0.000,0.151]	[0.627,0.760]	[0.143,0.317]	[0.000,0.151]	[0.635,0.749]	[0.178,0.306]	[0.000,0.153]
2	[0.133,0.310]	[0.487,0.636]	[0.152,0.292]	[0.128,0.303]	[0.454,0.627]	[0.167,0.327]	[0.142,0.277]	[0.480,0.632]	[0.182,0.308]
	[0.119,0.322]	[0.472,0.651]	[0.138,0.304]	[0.118,0.313]	[0.443,0.636]	[0.159,0.336]	[0.132,0.287]	[0.466,0.642]	[0.169,0.317]
3	[0.002,0.148]	[0.132,0.267]	[0.660,0.759]	[0.011,0.165]	[0.147,0.292]	[0.604,0.760]	[0.014,0.153]	[0.151,0.279]	[0.635,0.749]
	[0.000,0.164]	[0.116,0.280]	[0.646,0.775]	[0.005,0.177]	[0.136,0.301]	[0.594,0.770]	[0.009,0.166]	[0.140,0.288]	[0.624,0.760]
II. With Shape Restrictions									
A. Arbitrary, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.451,0.955]	[0.000,0.494]	[0.000,0.327]	[0.456,0.976]	[0.000,0.488]	[0.000,0.326]	[0.467,0.917]	[0.024,0.473]	[0.000,0.314]
	[0.440,0.971]	[0.000,0.505]	[0.000,0.334]	[0.447,0.986]	[0.000,0.496]	[0.000,0.331]	[0.458,0.931]	[0.013,0.483]	[0.000,0.319]
2	[0.000,0.492]	[0.289,0.837]	[0.000,0.484]	[0.000,0.479]	[0.261,0.826]	[0.000,0.500]	[0.000,0.457]	[0.287,0.825]	[0.009,0.463]
	[0.000,0.504]	[0.273,0.853]	[0.000,0.498]	[0.000,0.490]	[0.249,0.835]	[0.000,0.510]	[0.000,0.468]	[0.273,0.837]	[0.000,0.474]
3	[0.000,0.348]	[0.000,0.445]	[0.479,0.965]	[0.000,0.373]	[0.000,0.482]	[0.414,0.946]	[0.000,0.364]	[0.000,0.463]	[0.438,0.939]
	0.000,0.360]	[0.000,0.459]	[0.464,0.979]	[0.000,0.380]	[0.000,0.491]	[0.404,0.954]	[0.000,0.369]	[0.000,0.472]	[0.429,0.947]
B. Uniform, Independent Misclassification (Q = 0.10)									
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	[0.631,0.781]	[0.159,0.313]	[0.000,0.142]	[0.636,0.751]	[0.152,0.309]	[0.000,0.146]	[0.651,0.735]	[0.193,0.296]	[0.000,0.145]
	[0.621,0.796]	[0.147,0.324]	[0.000,0.151]	[0.627,0.760]	[0.143,0.317]	[0.000,0.151]	[0.635,0.749]	[0.178,0.306]	[0.000,0.153]
2	[0.133,0.310]	[0.487,0.636]	[0.152,0.289]	[0.128,0.303]	[0.454,0.627]	[0.167,0.305]	[0.142,0.277]	[0.480,0.632]	[0.182,0.277]
	[0.119,0.322]	[0.472,0.651]	[0.138,0.300]	[0.118,0.313]	[0.443,0.636]	[0.159,0.314]	[0.132,0.287]	[0.466,0.642]	[0.169,0.286]
3	[0.002,0.148]	[0.132,0.267]	[0.660,0.759]	[0.011,0.165]	[0.147,0.292]	[0.604,0.760]	[0.014,0.153]	[0.151,0.279]	[0.635,0.749]
	[0.000,0.164]	[0.116,0.280]	[0.646,0.775]	[0.005,0.177]	[0.136,0.301]	[0.594,0.770]	[0.009,0.166]	[0.140,0.288]	[0.624,0.760]

Notes: Outcome = per capita income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See Table 3 and text for further details.

Table A7. Tercile Transition Matrices: Monotonicity + Level Set Restrictions.

	2004-2008 Panel				2008-2012 Panel				Pooled Panels		
I. No Shape Restrictions											
A. Arbitrary, Independent Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.451,0.933]	[0.035,0.494]	[0.000,0.306]	**1**	[0.456,0.935]	[0.011,0.488]	[0.000,0.317]	**1**	[0.467,0.892]	[0.058,0.473]	[0.000,0.265]
	[0.440,0.952]	[0.017,0.505]	[0.000,0.329]		[0.447,0.948]	[0.000,0.496]	[0.000,0.324]		[0.458,0.907]	[0.041,0.483]	[0.000,0.288]
2	[0.007,0.386]	[0.304,0.818]	[0.011,0.368]	**2**	[0.001,0.373]	[0.271,0.823]	[0.012,0.426]	**2**	[0.000,0.362]	[0.293,0.789]	[0.041,0.397]
	[0.000,0.404]	[0.287,0.834]	[0.000,0.388]		[0.000,0.383]	[0.260,0.833]	[0.003,0.439]		[0.000,0.373]	[0.280,0.804]	[0.028,0.412]
3	[0.000,0.340]	[0.001,0.445]	[0.479,0.930]	**3**	[0.000,0.339]	[0.027,0.482]	[0.414,0.901]	**3**	[0.000,0.320]	[0.031,0.463]	[0.438,0.891]
	[0.000,0.352]	[0.000,0.459]	[0.464,0.952]		[0.000,0.349]	[0.014,0.491]	[0.404,0.916]		[0.000,0.333]	[0.017,0.472]	[0.429,0.916]
B. Uniform, Independent Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.631,0.756]	[0.179,0.307]	[0.000,0.074]	**1**	[0.636,0.733]	[0.175,0.309]	[0.000,0.043]	**1**	[0.651,0.710]	[0.215,0.296]	[0.000,0.068]
	[0.621,0.773]	[0.163,0.323]	[0.000,0.100]		[0.627,0.745]	[0.164,0.317]	[0.000,0.062]		[0.635,0.726]	[0.200,0.306]	[0.000,0.082]
2	[0.143,0.297]	[0.501,0.612]	[0.152,0.275]	**2**	[0.131,0.260]	[0.461,0.614]	[0.184,0.288]	**2**	[0.144,0.257]	[0.485,0.587]	[0.182,0.278]
	[0.127,0.309]	[0.483,0.628]	[0.139,0.287]		[0.124,0.270]	[0.451,0.625]	[0.174,0.301]		[0.133,0.268]	[0.471,0.601]	[0.169,0.286]
3	[0.010,0.148]	[0.178,0.260]	[0.660,0.696]	**3**	[0.021,0.081]	[0.153,0.292]	[0.604,0.734]	**3**	[0.021,0.075]	[0.171,0.274]	[0.635,0.722]
	[0.002,0.164]	[0.158,0.274]	[0.646,0.718]		[0.012,0.100]	[0.138,0.301]	[0.594,0.749]		[0.013,0.098]	[0.156,0.288]	[0.624,0.737]
II. With Shape Restrictions											
A. Arbitrary, Independent Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.451,0.933]	[0.035,0.494]	[0.000,0.306]	**1**	[0.456,0.935]	[0.011,0.488]	[0.000,0.317]	**1**	[0.467,0.892]	[0.058,0.473]	[0.000,0.265]
	[0.440,0.952]	[0.017,0.505]	[0.000,0.329]		[0.447,0.948]	[0.000,0.496]	[0.000,0.324]		[0.458,0.907]	[0.041,0.483]	[0.000,0.288]
2	[0.007,0.386]	[0.304,0.818]	[0.011,0.368]	**2**	[0.001,0.373]	[0.271,0.823]	[0.012,0.416]	**2**	[0.000,0.362]	[0.293,0.789]	[0.041,0.390]
	[0.000,0.404]	[0.288,0.834]	[0.000,0.388]		[0.000,0.383]	[0.260,0.833]	[0.003,0.430]		[0.000,0.373]	[0.280,0.804]	[0.028,0.405]
3	[0.000,0.340]	[0.001,0.445]	[0.479,0.930]	**3**	[0.000,0.339]	[0.027,0.482]	[0.414,0.901]	**3**	[0.000,0.320]	[0.031,0.463]	[0.438,0.891]
	[0.000,0.352]	[0.000,0.459]	[0.464,0.952]		[0.000,0.349]	[0.014,0.491]	[0.404,0.916]		[0.000,0.333]	[0.017,0.472]	[0.429,0.916]
B. Uniform, Independent Misclassification (Q = 0.10)											
	1	**2**	**3**		**1**	**2**	**3**		**1**	**2**	**3**
1	[0.631,0.756]	[0.179,0.307]	[0.000,0.074]	**1**	[0.636,0.733]	[0.175,0.309]	[0.000,0.043]	**1**	[0.651,0.710]	[0.215,0.296]	[0.000,0.066]
	[0.621,0.773]	[0.163,0.323]	[0.000,0.100]		[0.627,0.745]	[0.164,0.317]	[0.000,0.062]		[0.635,0.726]	[0.200,0.306]	[0.000,0.080]
2	[0.143,0.297]	[0.501,0.612]	[0.152,0.260]	**2**	[0.131,0.260]	[0.461,0.614]	[0.184,0.263]	**2**	[0.144,0.257]	[0.485,0.587]	[0.182,0.257]
	[0.127,0.309]	[0.484,0.628]	[0.139,0.273]		[0.124,0.270]	[0.451,0.625]	[0.174,0.275]		[0.133,0.268]	[0.472,0.601]	[0.169,0.264]
3	[0.010,0.148]	[0.178,0.260]	[0.660,0.696]	**3**	[0.021,0.081]	[0.153,0.292]	[0.604,0.733]	**3**	[0.021,0.075]	[0.171,0.274]	[0.635,0.722]
	[0.002,0.164]	[0.158,0.274]	[0.646,0.718]		[0.012,0.100]	[0.138,0.301]	[0.594,0.748]		[0.013,0.098]	[0.156,0.288]	[0.624,0.737]

Notes: Outcome = per capita income. Point estimates for bounds provided in brackets obtained using 25 subsamples of size N/2 for bias correction. 90% Imbens-Manski confidence intervals for the bounds provided in parentheses obtained using 100 subsamples of size N/2. See Table 4 and text for further details.

Table A8. Tercile Transition Matrices: Summary Mobility Measures.

2004-2008 Panel		2008-2012 Panel	
I. Expected Exit Time: [Q1,Q1]		I. Expected Exit Time: [Q1,Q1]	
RPME	[3.093,3.338]	RPME	[3.108,3.245]
AM	[1.611,439.364]	AM	[1.612,103.865]
UM	[2.377,4.946]	UM	[2.379,4.770]
LSR + Shape + AIM	[1.785,34.829]	LSR + Shape + AIM	[1.809,71.620]
LSR + Shape + UIM	[2.639,4.909]	LSR + Shape + UIM	[2.682,4.165]
M + LSR + Shape + AIM	[1.785,20.824]	M + LSR + Shape + AIM	[1.809,19.092]
M + LSR + Shape + UIM	[2.639,4.403]	M + LSR + Shape + UIM	[2.682,3.914]
II. Expected Exit Time: [Q3,Q3]		II. Expected Exit Time: [Q3,Q3]	
RPME	[3.235,3.503]	RPME	[3.036,3.196]
AM	[1.649, .]	AM	[1.594,67.830]
UM	[2.460,5.318]	UM	[2.339,4.657]
LSR + Shape + AIM	[1.865,47.537]	LSR + Shape + AIM	[1.678,21.964]
LSR + Shape + UIM	[2.821,4.446]	LSR + Shape + UIM	[2.465,4.355]
M + LSR + Shape + AIM	[1.865,20.878]	M + LSR + Shape + AIM	[1.678,11.856]
M + LSR + Shape + UIM	[2.821,3.551]	M + LSR + Shape + UIM	[2.465,3.967]
III. Immobility Ratio		III. Immobility Ratio	
RPME	[0.511,0.549]	RPME	[0.539,0.562]
AM	[0.071,0.994]	AM	[0.091,1.010]
UM	[0.365,0.694]	UM	[0.391,0.710]
LSR + Shape + AIM	[0.098,0.912]	LSR + Shape + AIM	[0.112,0.950]
LSR + Shape + UIM	[0.389,0.631]	LSR + Shape + UIM	[0.417,0.668]
M + LSR + Shape + AIM	[0.131,0.904]	M + LSR + Shape + AIM	[0.152,0.945]
M + LSR + Shape + UIM	[0.440,0.625]	M + LSR + Shape + UIM	[0.441,0.664]
IV. Upward Mobility		IV. Upward Mobility	
RPME	[0.449,0.485]	RPME	[0.462,0.483]
AM	[0.003,0.931]	AM	[0.014,0.930]
UM	[0.303,0.631]	UM	[0.314,0.630]
LSR + Shape + AIM	[0.043,0.840]	LSR + Shape + AIM	[0.021,0.829]
LSR + Shape + UIM	[0.306,0.568]	LSR + Shape + UIM	[0.360,0.559]
M + LSR + Shape + AIM	[0.072,0.840]	M + LSR + Shape + AIM	[0.079,0.829]
M + LSR + Shape + UIM	[0.341,0.568]	M + LSR + Shape + UIM	[0.383,0.559]
V. Downward Mobility		V. Downward Mobility	
RPME	[0.428,0.464]	RPME	[0.469,0.494]
AM	[0.000,0.910]	AM	[0.022,0.941]
UM	[0.282,0.610]	UM	[0.322,0.641]
LSR + Shape + AIM	[0.032,0.804]	LSR + Shape + AIM	[0.068,0.894]
LSR + Shape + UIM	[0.337,0.532]	LSR + Shape + UIM	[0.344,0.608]
M + LSR + Shape + AIM	[0.072,0.804]	M + LSR + Shape + AIM	[0.127,0.894]
M + LSR + Shape + UIM	[0.422,0.532]	M + LSR + Shape + UIM	[0.378,0.608]

Notes: Outcome = per capita income. RPME = rank-preserving measurement error. AM = arbitrary misclassification. UM = uniform misclassification. I = independence. LSR = level set restrictions. M = monotonicity. 90% confidence intervals for bounds provided in brackets based on estimates in Tables 5-7. See text for further details.