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Meritocracy-Based Stickiness Measure of Social Mobility

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MERITOCRACY-BASED STICKINESS MEASURE OF SOCIAL MOBILITY

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By

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ABSTRACT

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I measure the stickiness of social mobility in terms of meritocratic assumptions through the first-known Meritocracy-Based Stickiness Measure of Mobility (MBSMoM) using mobility transition matrices and assumptions based on Full Meritocracy (FM) and Lack of Meritocracy (LM). I develop the Simple Stickiness Measure of Mobility (SSMoM) and the Weighted Stickiness Measure of Mobility (WSMoM). In addition, I create the MBSMoM which is calculated from mobility transition matrices of intragenerational, intergenerational, and multigenerational correlations using various measures of status including education, occupation, class, consumption, income, and wealth. Utilizing mobility transition matrices employed by plethora of studies, MBSMoMs are calculated as a percentage between SSMoMs or WSMoMs under assumptions of FM and LM. The MBSMoM is a standalone measure and is interpreted as the percentage between outcomes under FM and LM assumptions. I calculate MBSMoM values for 92 mobility matrices from 22 previous studies of mobility and report individual and group results.

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LIST OF ACRONYMS

BHPS	British Household Panel Survey
CEO	Chief Executive Officer
CHNS	China Health and Nutrition Survey
CNEF	Cross-National Equivalence File
CPS	Current Population Survey
DMR	Downward Mobility Ratio
FM	Full Meritocracy
GC	Gini Coefficient
GSEOP	German Socio-Economic Panel
HRS	Health and Retirement Survey
HSP	Hadamard-Schur Product
IGE	Inter-Generational Elasticities
IHDS	India Human Development Survey
IQ	Intelligent Quotient
IR	Immobility Ratio
LM	Lack of Meritocracy
MBSMoM	Meritocracy-Based Stickiness Measure of Mobility
NCDS	National Child Development Study
NLSY	National Longitudinal Survey of Youth
OCGS	Occupational Change in a Generation Survey

OMS	Oxford Mobility Study
PSID	Panel Study of Income Dynamics
QPM	Quasi-Perfect Mobility
SAD	Social Advantage and Disadvantage
SCF	Surveys of Consumer Finances
SFCC	Survey of the Financial Characteristics of Consumers
SES	Socio-Economic Status
SIPP	Survey of Income and Program Participation
SMoM	Stickiness Measure of Mobility
SOI	Statistics of Income
SSA	Social Security Administration
SSMoM	Simple Stickiness Measure of Mobility
UK	United Kingdom
UMR	Upward Mobility Ratio
US	United States
WSMoM	Weighted Stickiness Measure of Mobility

I. INTRODUCTION

Mobility research has been addressing the concern for inequality for many decades. There is great inequality in the world with over 1.2 billion people living "in extreme poverty," the top one percent owning forty percent of wealth, and the bottom 50 percent owning less than one percent of assets (Mishra, 2018, p. 271). Equality, equality of opportunity, and social mobility are important topics of interest to sociologists, economists, and policy makers. Interestingly, not all forms of inequality are "ethically objectionable" (Roemer & Trannoy, 2016, p. 1288). In fact, by concentrating on equality of opportunity, society demonstrates its willingness to accept some inequality in outcomes (Stokey, 1996). Since outcomes are a result of opportunity, ability, actions, and luck, equality of opportunity implies eradicating differences due to varying opportunities and luck, so ability and effort alone result in outcome inequality (Roemer & Trannoy, 2016; Stokey, 1996). Equality and mobility are different concepts and can coexist at different levels: "rising inequality may (but need not) be accompanied by reduced intergenerational mobility" (Becker et al, 2018, p. S10). For this reason, "today, the literature on intergenerational mobility is integral to the social sciences and draws significant interest from policy circles" (Nybom & Stuhler, 2019, p. 77). Both inequality and mobility are "important indicators used to evaluate and compare the quality of life in modern societies" (Burkhauser & Couch, 2008, p. 522). In fact, mobility researchers often seek the holy grail, "the true rate of social mobility" (Clark, 2013, p. 1). This demonstrates that "assessing the extent to which economic advantages are transmitted across generations is quite a difficult endeavor" (Mitnik et al., 2019, p. 406). There is even disagreement among authors about the basic nature of mobility. Some claim it is variable across social structure, government policy, time, place, and subpopulations while others insist it is "a universal constant across societies, changing little across social systems and epochs" (Clark, 2013, p. 7). Solon (2018) quoted Clark (2013) as asserting that "all social mobility is governed by a simple underlying law, independent of social structure and government policy," even though Clark's thesis is not well supported empirically (pp. F340, F349). Income and wealth are often touted as indicators of mobility (Burkhauser & Couch, 2008; Clark, 2013; Mitnik et al., 2019; Nybom & Stuhler, 2019; Roemer & Trannoy, 2016; Solon, 2018; Stokey, 1996).

Both income and wealth inequality and their growth are often presented as evidence of a lack of meritocracy in the United States (US), especially since the US is considered one of the "least mobile societies among those rich countries" (Corak, 2004, p. 9). Meritocracy is a matter of degree: "However meritocratic most liberal-democracies are, they're far from being fully-fledged meritocracies" (Young, 2015, p. 14). Even today, there is still "the modern view of the United States as one of the least economically mobile countries among advanced economies" so, "the view of the United States as a highly mobile society and a 'land of opportunity' may be unwarranted" (Smeeding, 2018, p. 38). Daniel Markovits claimed that meritocracy "is stifling social mobility" and is leading to an American class war (Damazer, 2019, p. 1). He took the view that, although it was supposed to equalize opportunity, meritocracy has actually concentrated wealth among the few and is the source of transmitting privilege, and is "a lose-lose arrangement" (Voegeli, 2019, pp. 1-2). On the other hand, others have praised the US for its meritocratic atmosphere (Corak, 2004; Damazer, 2019; Smeeding, 2018; Voegeli, 2019; Young, 2015).

Saunders (2010) claimed, "we are much closer to achieving a meritocracy than most pundits or politicians seem to suppose" (p. 9). He claimed that "generally, sociologists have assumed that unequal outcomes…signify unfair selection procedures" (Saunders, 2010, p. 47). Despite the belief that "equal opportunity would lead to true meritocracy, which would be true egalitarianism", inequality and immobility in the US have been blamed for all sorts of social problems even though we still do not fully understand their source and effects (Celarent, 2009, p. 322). Many studies have found a negative relationship between inequality and mobility: "Wealth is rising to the top as a dynastic force that limits intergenerational mobility and preserves economic status" (Smeeding, 2018, p. 38). However, inequality is not necessarily a cause of immobility because institutional forces such as the welfare regime and specific government policy affect both inequality and mobility in society. Before inequality and immobility may be determined as sources of social problems requiring correction, we must understand their nature and workings. This is important because equality of opportunity is vital in economies reliant on human capital—particularly education—for growth and economic efficiency (Corak, 2004). Nonetheless, there is no obvious way of determining the extent of opportunity individuals really have in society (Celarent, 2009; Corak, 2004; Saunders, 2010; Smeeding, 2018).

The purpose of this study is to build on prior research by developing a Simple Stickiness Measure of Mobility (SSMoM), a Weighted Stickiness Measure of Mobility (WSMoM), and a Meritocracy-Based Stickiness Measure of Mobility (MBSMoM) which may be used with mobility transition matrices of intragenerational, intergenerational, and multigenerational correlations of various measures of status including education, occupation, class, consumption, income, and wealth from multiple and varying studies. Intragenerational is within a single generation while intergenerational indicates across two generations and multigenerational spans more than two generations (Hout, 1983; Jäntti and Jenkins, 2013; Torche, 2015).

This research formulates an MBSMoM—a way to use the idea of meritocracy in the measure of mobility in education, class, occupation, consumption, income, and wealth levels which may be used with intragenerational, intergenerational, and multigenerational mobility transition matrices. Using mobility transition matrices similar to those used by many studies, real-world MBSMoMs are calculated as a percentage between SSMoMs or WSMoMs under the assumptions of Full Meritocracy (FM), or "perfect mobility" (represented by equally distributed "generational mobility") and its opposite, Lack of Meritocracy (LM) (represented by an absence of "generational mobility") (Corak, 2004, p. 3; Saunders, 2010, p. 10). One may think of FM, or "perfect mobility," as a society with randomly distributed success characteristics with equal opportunity, leading to randomly distributed education, class, occupation, consumption, income, and wealth outcomes (Saunders, 2010, p. 10). LM is the total absence of any mobility. Of course, FM and LM are polar opposites within which real-world societies fit. It is important not to equate equal opportunity or fairness with intergenerational class, educational, occupational, consumption, income or wealth mobility (Corak, 2004). Otherwise, policy proposals in pursuit of meritocracy may tend to impinge on other values and individual rights (Saunders, 2010). The MBSMoM is a standalone measure and is interpreted as the percentage between outcomes under FM and LM assumptions. The MBSMoM may also be used in research to make comparisons between social structures, governmental policies, and of population subsets, across time, space, and by identity (race, ethnicity, nationality, gender, sexuality, religion, ability, age, etc.) (Corak, 2004; Pfeffer and Killewald, 2018; Saunders, 2010).

II. LITERATURE REVIEW

Equality, equality of opportunity, and social mobility are all related to the American Dream. Urahn et al. (2012) asserted that "the ideal that all Americans have equality of opportunity regardless of their economic status at birth is the crux of the American Dream and a defining element of our national psyche" (p. 1). Even in 1931, James Truslow Adams wrote:

> The American Dream is that dream of a land in which life should be better and richer and fuller for every man, with opportunity for each according to ability or achievement…It is not a dream of motor cars and high wages merely, but a dream of social order in which each man and each woman shall be able to attain to the fullest stature of which they are innately capable, and be recognized by others for what they are, regardless of the fortuitous circumstances of birth or position (Bloom, 2011, p. 1).

In the early part of the twentieth century, the American dream included individual equal opportunity and social meritocracy. Even today, "America's promise is predicated on economic mobility" (Bradbury, 2011, p. 1). Therefore, one of the fundamental questions facing the United States today is "whether there is a sufficient degree of equality of opportunity" (Smeeding, 2018, p. 38). But equality of opportunity can itself lead to a widening gap of inequality (Littler, 2018).

The word meritocracy was first used by Alan Fox in 1956 (Littler, 2018). Two years later, Michael Young popularized the term in *The Rise of the Meritocracy, 1870-2033: An Essay on Education and Equality*, even though he "always found *equality* as a notion extremely difficult" (Young, 1994a, p. 73). Some people in America view meritocracy in terms of income and/or wealth outcomes, but class (social status), educational, and occupational outcomes have also been important. Occupation may be a more stable variable than income or wealth since it could be "less age or year dependent" (Song et al, 2020, p. 257). For example, occupational rank-rank correlations are estimated to be around "0.32" (Song et al., 2020, p. 252). The measurement of income and wealth Inter-Generational Elasticities (IGE) have evolved over time and are currently estimated to be "between 0.30 and 0.60" (Torche, 2015, p. 56). In addition, income and wealth intergenerational correlation coefficients are predicted to be "between 0.50 and 0.60" (Keister, 2014, p. 349). This implies that approximately "half of economic advantages are transmitted from parent to children" (Mitnik et al., 2019, p. 380).

There have been myriad mobility studies conducted in the past 50 years (Bloom, 2011; Bradbury, 2011; Keister, 2014; Littler, 2018; Mitnik et al., 2019; Smeeding, 2018; Song et al., 2020; Torche, 2015; Urahn et al., 2012; Young, 1994a). Studies of mobility have been conducted with widely varied approaches and methods. Solon (2017) summed up what we know concerning mobility: "…the playing field is far from level. Children from poor families are at a substantial disadvantage relative to children from well-off families" (p. 5). Jäntti and Jenkins (2013) pointed out that this disadvantage of a "lack of social mobility implies inequality of opportunity," so mobility, while "socially desirable," in actuality "is an imperfect indicator of the degree of inequality of opportunity" (p. 13). To Michael Young (1958), both "intelligence and effort together make up merit" (p. 94). He "disapproved of equality of opportunity on the grounds that it gave the appearance of fairness to the massive inequalities created by capitalism" (Young, 2015, p. 9). Young (1994a) saw "that equality of opportunity, which had so much more of a following than equality, was itself going to produce greater inequality" (p. 73). As it turned out, meritocracy developed into a positive term rather than keeping the negative connotation Michael Young intended (Young, 2015). In fact, Toby Young (2015), Michael's son said, "the answer is more meritocracy" (p. 10). The idea behind meritocracy is that "even children born into the humblest of circumstances can succeed if they are bright and they work hard" (Saunders, 2010, p. 3). Meritocracy has developed such a strong following mainly because it counters "established hierarchies" and "reacts against inherited privilege" (Littler, 2017, p. 4; Littler, 2018, p. 48). Today, meritocracy is the concept of fairness within society so that one may use their intelligence, ability, talents, and effort to earn their just deserts and achieve success (Damazer, 2019; Littler, 2018; Stokey, 1996). Inequality of outcomes is acceptable because if talent and effort are normally distributed, "so should a meritocratic distribution of wealth and income" (VannPashak, 2019, p. 3). However defined, meritocracy is directly opposed to the "SAD thesis," the belief that "Social Advantage and Disadvantage conferred at birth is what shapes peoples' destinies" (Saunders, 2010, p. 3). The Social Advantage and Disadvantage (SAD) thesis was originally based on a study conducted by Glass (1954), which produced impossible findings using outdated data and flawed statistics (Saunders, 2010, pp. 11-12).

Not everyone agrees that inequality matters, but most are concerned about the magnitude of inequality. Even after the reduction in savings and investment during the 1980s, average income and wealth have increased in the US along with growing inequality. Thomas Hobbes saw no problem with growing inequality if income and wealth were increasing because: “felicity consists in continually prospering” (Ryan, 2002, p. 227). Saunders (2010) found that when accounting for individual Intelligent Quotient (IQ) scores, mobility reflects what would be expected in a complete meritocracy. Of course, IQ scores and Socio-Economic Status (SES) have been shown to be correlated. Even so, about fourteen percent of the top 5 percentiles of IQs come from parents with below-average IQs (Saunders, 2010). Some make the case for “sufficient equality” because too much inequality is just too “unpleasant,” “dysfunctional,” “ugly,” and “stupid” (Galbraith, 2002, p. 201). Others advocate that inequality only matters due to emotions of envy and glory. Still others believe that inequality is only acceptable if based on needs, resources, or abilities. Whether inequality is bad or good, “wealth is systematically related to income, point in the life cycle, and other demographic characteristics. But apart from those differences, there remains great residual heterogeneity in wealth holding” (Hurst et al., 1998, p. 268). While income and wealth have grown overall, not all individuals or groups of people have experienced that growth equally (Galbraith, 2002; Herrnstein and Murray, 1994; Hurst et al., 1998; Murray, 2012; Ryan, 2002; Saunders, 2010).

Even though “much of what happens to individuals in the course of their lifetimes is down to chance and idiosyncratic circumstances,” some authors have hinted at the stickiness of class, education, occupation, consumption, income, and wealth (Saunders, 2010, p. 2). Pfeffer and Killewald (2018) provided “estimates of the multigenerational persistence of family wealth,” and referred to the “intergenerational rigidity of the wealth structure” (pp. 1415, 1416, 1433, 1436). Saunders (2002) alluded to this stickiness when stating that “while class origins have some effect on class destinations (in particular, for those born into the middle class), ability and effort exert a much greater effect” (p. 559). Some researchers have explicitly labelled the persistence in education, occupation, class, consumption expenditures, income, and wealth as being sticky. When discussing class mobility, Saunders (2010) referred to “stickiness” (p. 36). He identified the “stickiness of middle-class downward mobility rates…as the principal weakness in the meritocracy thesis” (Saunders, 2010, p. 89). In contradiction, Urahn et al. (2012) identified the “lack of relative mobility” as “a phenomenon known as stickiness at the ends” (pp. 6, 2). Identifying non-linearities, Pfeffer and Killewald (2015) “hypothesize that wealth positions at the top and bottom of the distribution may be particularly sticky” (p. 4). Authors have also referred to the opposite of stickiness, using the terms “intergenerational fluidity,” “social fluidity,” and “churning in economic position” (Charles and Hurst, 2003, pp. 1155, 1157, 1163, 1179-1180; Torche, 2015, p. 42). In the US, “people are largely faring better than prior generations” which creates “individual well-being even in the face of growing inequality” (Keister, 2014, p. 363). Of course, equality of opportunity and rewards based on merit are still major goals of Americans. Friedrich Hayek, along with others, criticized outcome equality for practical reasons that it is too costly in liberty and human terms (Young, 2015). Regardless of whether inequality matters to everyone, it seems desirable to have a common definition of meritocracy (Arrow et al., 2000; Charles and Hurst, 2003; Galbraith, 2002; Keister, 2014; Pfeffer and Killewald, 2018; Ryan, 2002; Saunders, 2002; Young, 2015).

Meritocracy and Mobility

Unlike the extremes of egalitarianism (equality of outcomes) and libertarianism (just entitlement), "the essence of a meritocratic society is that it offers individuals equal opportunities to become unequal…is inherently competitive and it produces losers as well as winners" (Saunders, 2010, pp. 124, 131-134). Meritocracy works fine for those found with the right merit, but not so well for those who lack what is valued within society (Saunders, 2010). There are multiple accepted definitions of meritocracy. A basic definition of meritocracy in the US is "the ability to get ahead through hard work" (Solt et al., 2016, p. 1). There are two main ways to view equality: opportunity, and outcome. Equality of opportunity and outcome have generally accepted definitions. To sociologists, equality of opportunity refers to equal individual freedom of all to pursue their own development and to "apply themselves to the best of their ability" while equality of outcome means equal access to "rewards and resources" (Johnson, 2000, p. 107). Meritocracy involves a social environment in which personal success depends on individual merits like "talents, abilities and effort," and implies the existence of fair measures of merit and equal opportunity (Johnson, 2000, p. 191). By assuming that merit must be evenly distributed among social classes, income levels, and wealth holdings, some define meritocracy in terms of an open and fair society where everyone has an equal statistical opportunity to rise or fall in order to end up in different social status' (Saunders, 2010).

Operationalizing these concepts in research is much more difficult than understanding the theoretical definitions. One study, referring to the belief in meritocracy, used “three distinctly different measures of meritocracy” (Solt et al., 2016, p. 1). Most research dealing with income and wealth equality within meritocratic ideals has attempted to explain “generational mobility…the relationship between the socio-economic status of parents—more particularly to their income—and the status and income their children will attain in adulthood” (Corak, 2004, p. 3). Some mobility researchers assume that equality of opportunity may be proven if the “conditional distribution of children’s income does not vary across parental incomes” (Mitnik et al., 2019, p. 383).

Meritocracy and fairness are not necessarily the same thing (Corak, 2004; Johnson, 2000; Solt et al., 2016). Meritocracy and fairness have been entangled in research involving the general population, work environments, university admissions, and education in general. Education is particularly sensitive because of the belief that “a meritocratic education underpins a meritocratic society” (Young, 1994b, p. 88). Some observe that inborn talents are undeserved and distributed like a “natural lottery” since “some people are more gifted than others, the same amount of effort will reap different rewards, depending on their natural endowments” (Young, 2015, pp. 10-11). In fact, “Being a member of the ‘lucky sperm club’ confers no moral right to advantage” (Young, 1994b, p. 89). With equality of opportunity, inequality is ethically acceptable if it is “due to differential effort” rather than “differential circumstances” (Dardanoni et al., 2008, p. 2). One approach—value-in-merit—proposes an environment of “equal opportunity and meritocratic outcomes,” and another—multicultural meritocracy—combines “value-in-diversity elements of multiculturalism with the equal opportunity components of a value-in-merit ideology" (Gündemir et al., 2017, p. 34). Elite university admissions processes have long been criticized as inherently unfair and non-meritocratic. But one study found the admissions process at the University of Oxford highly meritocratic and indicated that what may be needed is a more fair "outcomes-based meritocracy" implemented by the University of California because of the inequality that leads to disparate educational outcomes in public schools (Nahai, 2013, p. 681). This has led to advocating for a lottery system for elite university admissions due to the SAT being a source of admission inequality by reproducing class, income, wealth, racial, and gender privilege. What may be needed is to counteract "a meritocracy based on unequal competitor starting points, and in which merit is continuously defined and redefined in ways that favor the dominant social groups" (Nahai, 2013, p. 699). This leads to the belief that affirmative action is required to compensate those who lack non-meritocratic advantages. If we understand that inequality is not necessarily unfair if it is the result of equal opportunity to use one's talent and effort to find a place in society, then meritocracy is a worthy goal (Saunders, 2010). In addition, belief in meritocracy may depend heavily on where in the class, occupation, income, and wealth spectrum people fall (Gündemir, 2017; Nahai, 2013; Soares, 2017; Solt et al., 2016; Walton et al., 2013; Warikoo, 2017).

There are various opinions about the sources and effects of inequality. In fact, some conflate equality and meritocracy. While meritocracy means different things to different people and is not commonly defined, it usually involves the existence of a system that rewards people based on their valued contributions rather than their genealogy. Genealogy may include both history and inheritance. Many researchers associate equality of opportunity with merit-based rewards, which generally leads to eschewing advantages based on birth, except for inborn talents and intellect. Under the condition of equal opportunity, as Young (2015) asserts, cognitive ability is "a better predictor of achievement in school and occupational status than the standard environmental factors singled out by liberal policy-makers" (p. 12). In fact, IQ scores predict SES better than the SES of parents, although parent education is a fair predictor of child education and thus child SES. Peter Saunders (2010) showed that parent education is twice as important than parental class. What many people do not understand is that "merit-based rewards, may, in fact, generate considerable inequality" (Sen, 2000, p. 14). Benabou (2000) believed that equal opportunity within a merit-based system may lead to social and economic mobility but not necessarily to equality of outcomes. In fact, "imposing *equality of outcomes* is unmeritocratic" (Benabou, 2000, p. 320). When advancing to a dynamic measure including intergenerational effects, "parents' outcomes determine children's opportunities" (Benabou, 2000, p. 322).

Measuring mobility is not necessarily easy, given the diverse understandings of the concept (Benabou, 2000; Saunders, 2010; Sen, 2000; Young, 2015). Various methods have been attempted to measure meritocracy. Phillips (2016) investigated meritocracy with an evaluation of new fellows for membership in fellowship societies. He posited that quantitative assessment of objective and subjective elements may be combined in meritocratic measurement of individuals. It is common to measure meritocracy in studies of bureaucracies. Rather than objectively measuring the existence of meritocracy, this branch of the literature has relied on opinion surveys of experts, citizens, and public employees. Charron et al. (2016) showed that evaluating bureaucracies relies on definitions of meritocracy in terms of government employee recruitment and promotion as opposed to political appointment. Goode (2016) developed a six-question inventory of meritocracy endorsement called the Meritocracy Scale, which measures individual attitudes toward meritocracy. Directly measuring meritocracy has eluded us and modeling it has been uncommon (Charron et al., 2016; Goode, 2016; Phillips, 2016).

Roland Benabou (2000) seems to be the only author to theorize a model of meritocracy. He modeled two separate types of meritocracy. The first was meritocracy of opportunity which included comparing the variances of a person's lifetime income resulting from intrinsic qualities compared to their total lifetime income. Benabou's second theoretical construct of meritocracy focused on the meritocracy of outcomes. Meritocracy of outcomes includes the intrinsic qualities income coefficient and the redistribution tax rate. Benabou (2000) combined these two models of meritocracy into an overall construct of meritocracy. While he created a theoretical model involving the oppositional nature of opportunity and outcome, Benabou (2000) did not propose an operational measure of either one.

Patterns of Mobility

Even though "there are multiple concepts of mobility," we will consider social mobility as "the movement of individuals from one position in society to another" (Jäntti and Jenkins, 2013, p. 2; Saunders, 2010, p. 1). Torche (2015) summarized mobility with the following:

> Social scientists operationalize mobility as the extent and pattern of association between parents' and adult children's socioeconomic standing where higher association means less mobility. Socioeconoimc standing is

> captured by different measures—the most common are social class, occupational status, individual earnings, and family income (pp. 37-38).

While sociologists typically concentrate on social class, education, and occupation, economists tend to favor consumption, income, and wealth measures (Solon, 2018; Torche, 2015). Income stability is usually preferred by individuals when all other things are equal (Jäntti and Jenkins, 2013). While inequality is about a static snapshot, mobility is a dynamic look at "status from one time period or generation to another" and may be intragenerational, intergenerational, or multigenerational (Fields & Ok, 1999a, p. 557).

Intragenerational, Intergenerational and Multigenerational Mobility

Intragenerational mobility is concerned with social status changes for individuals: "Intragenerational mobility refers to observed differences in the economic circumstances of individuals over time" (Burkhauser & Couch, 2008, p. 524). Intergenerational mobility is defined in terms of the movement of social status across single generational boundaries like parent to child. "Multigenerational mobility refers to the associations in socio-economic status across three or more generations" (Solon, 2018, p. F340). Pfeffer and Killewald (2015) explained that "demographic shifts" including decreasing fertility rates, increasing longevity, and changes in marriage rates and tenure have been increasing the effect of "extended family networks" (pp. 5-6).

Absolute vs. Relative Mobility

Mobility may be analyzed from an absolute or relative standpoint (Burkhauser & Couch, 2008; Fields & Ok, 1999a; Jäntti and Jenkins, 2013; Pfeffer and Killewald, 2015; Saunders, 2010; Solon, 2018; Torche, 2015). Inequality of outcomes "is not the appropriate yardstick for assessing the fairness of a given allocation or social system"

(Ferreira & Gignoux, 2011, p. 2). As Saunders (2010) pointed out, relative mobility does not necessarily reflect fairness or equal opportunity within society, but mobility could equalize ex-ante opportunities without having any equalizing effect on ex-post outcomes. This is important because "if fairness matters to economic agents and alters their behavior, then understanding fairness ought to matter even to the purest positive economist" (Brunori et al., 2013, p. 2). Equal Opportunity involves the idea that ex ante inequality due to individuals' circumstances such as resources and/or opportunities—race, ethnicity, gender, birthplace, parent's education and/or occupation—is unfair but any inequality as a result of individual ability and effort is acceptable. Therefore, equality of opportunity "implies that differences in status are ethically acceptable if they are due to differential effort but not if they are due to differential circumstances" (Dardanoni et al., 2008, p. 2). These inherited traits may impact intelligence and effort (Brunori et al., 2013; Ferreira & Gignoux, 2011; Lefranc et al., 2006; Stokey, 1996).

Many sociologists and economists simply dismiss heritability as a possible explanation for the stickiness of class, education, occupation, consumption, income, and wealth. Instead, they assume "intelligence is randomly distributed" rather than passed on from parents (Saunders, 2010, p. 50). Economists tend to assume that genetics has a much less impact on mobility than the investment in human capital which may develop into a "human capital elite" (Becker et al., 2018, pp. S8-S9). Others accept both nature and nurture: "richer parents tend to have more favorable endowments, which tend to be passed on to their children through genetic and cultural inheritance" (Solon, 2018, p. F344). Some researchers agree that cognitive ability, which is determined by "both genetics and environment," may have a direct effect on social mobility (Saunders, 2010,

p. 56). Referring to racial gaps, Mazumder (2014) commented that "cognitive skills…are strongly associated with these gaps," but this doesn't necessarily mean that they form at birth (p. 2). Hans Eysenck has claimed that genetics ("perhaps 50 percent") may be twice as strong than environment when it comes to intelligence (Saunders, 2010, pp. 56, 58). Even grandparents' traits may skip a generation and they "may contribute to cultural inheritance" (Solon, 2018, p. F345). Just because correlations of intelligence of approximately 0.50 between children and their parents indicates heritability of mental ability, it does not prove the meritocracy thesis, but is consistent with the data and plausible, along with other explanations (Saunders, 2010). Of course, Hill (2003) who said, "All you are or ever shall become is the result of the use to which you put your mind," would have disagreed with this inheritance hypothesis, since he researched the important characteristics of success and promoted their learned nature (p. xxv).

Absolute mobility means analyzing total mobility or "absolute changes" in social, educational, occupational, consumption, income, or wealth status (Fields & Ok, 1999a, pp. 564, 568). The measures used focus on objective rather than relative measures. For income and wealth, absolute measurement of mobility compares children's amounts to their parents' values (Urahn et al., 2012). When it comes to occupations, absolute mobility has been operationalized as "the change in average occupational status over time" of "the total observed flows between classes of origins and classes of destination" (Torche, 2015, pp. 39, 41). Relative mobility typically uses quantiles that result in a zero-sum game as far as mobility is concerned and often use regression models to estimate persistence coefficients or elasticities (Torche, 2015). Relative mobility refers to…and is a "zero-sum game" because "every increase in upward mobility requires a corresponding increase…in downward mobility" (Voegeli, 2019, p. 3). When it comes to relative measures, groups are divided into equal-sized quantile (percentile, quartile, decile, etc.) groups, show relative reranking, and "are called fractile matrices" (Fields & Ok, 1999a, p. 567; Torche, 2015, p. 51). Most researchers use "strongly relative measures" (Fields & Ok, 1999a, p. 563). While many researchers emphasize relative mobility, most individuals are concerned with absolute mobility for their children: "What matters most to them is that their chance to succeed in life has improved, irrespective of whether everybody else's chances have improved by a similar degree" (Saunders, 2010, p. 22). Structural mobility concerns fluctuations in mobility due to variations in the numbers of positions available in various social classes, while exchange mobility deals with "movement among social classes, for a given distribution of positions among these classes" (Fields & Ok, 1999a, p. 564).

Measures of Mobility

Varying units of measure have been used in mobility research, creating differences between measurements of individuals, families, households, or a combination (Torche, 2015). The principal variables used in mobility research are social class, SES, education, occupation, consumption, earnings, income, and wealth. Even though they are related to individual life chances, social classes are usually aggregated so that they may exclude the measurement of "important variation in socioeconomic advantage" (Saunders, 2010, p. 1; Torche, 2015). Besides using broad occupational categories, researchers use occupational status, which is typically "a weighted average of the mean level of earnings and education of detailed occupations" (Torche, 2015, p. 38). Income or earnings mobility research typically pursues relative mobility by using linear regression of the logarithms of income/earnings or quantile (percentile, decile, quintile, quartile) ranks of these variables (Torche, 2015). Because permanent expected income is the theoretical determinant of consumption and well-being, it is the important theoretical variable which has sometimes avoided practical measurement. Researchers often rely on short- or long-run income averages to approximate permanent income. Researchers have created multiple single-number summaries, referred to as mobility measures or indices, even though they result in loss of information (Trede, 1998).

There has been a proliferation of measures of mobility with "at least 20 mobility measures…used in the literature" (Mishra, 2018, p. 276). A mobility measure may be defined as a function on a mobility transition matrix M, F(M), which maps M into a single scalar. There are some limitations involved in creating summary mobility measures. In order to measure mobility, longitudinal data is required (Fields & Ok, 1996) but "no single mobility statistic has the minimum requirements regarded as essential" (King, 1983, p. 108). There are many descriptive measures of mobility (Chakravarty et al., 1985; Fields, 2010). Since comparing mobility transition matrices from different locations, times, or populations to show mobility relationships is difficult, researchers have created different measures of mobility for different situations (Burkhauser & Couch, 2008). Indices may focus "on positional change, individual…growth, longer-term inequality reduction, or…risk" (Jäntti and Jenkins, 2013, p. 49). It is important to define mobility within one's purpose in order to select the proper method of measurement (Burkhauser & Couch, 2008). As Lundberg and Stewart (2020) assert, "Single-number summaries that capture the relationship of socioeconomic outcomes across generations are a cornerstone of economic mobility research" (p. 2).

But whether single or multiple numbers are used, any values involved in a summary measurement inherently sacrifices information in order to gain parsimony (Lundberg & Stewart, 2020) and is an "oversimplification" (Bartholomew, 1982, p. 30). Measurements of mobility are functions that result in ranking mobility outcomes but trying to account for all aspects of mobility is "destined for failure" (Fields & Ok, 1999a, p. 560). There are multiple aspects of mobility that may be measured. The most obvious is movement, which is important with intragenerational mobility. Origin independence is an idea which applies easily with intergenerational mobility and is often equated with equality of opportunity. Any measurement of mobility should address one of these aspects of mobility (Fields & Ok, 1999a). Since "an outcome can be 'more meritocratic' without being perfectly meritocratic," comparing to meritocracy is important (VannPashak, 2019, p. 1).

There are several important existing measures of mobility (Bartholomew, 1982; Burkhauser & Couch, 2008; Chakravarty et al., 1985; Fields, 2010; Fields & Ok, 1996, 1999a; Jäntti and Jenkins, 2013; King, 1983; Lundberg & Stewart, 2020; Mishra, 2018; VannPashak, 2019). Two commonly used, statistical measures of mobility are the Pearson correlation, r, and the least-squares slope coefficient (elasticity), Beta (β)—neither of which use mobility transition matrices (Jäntti and Jenkins, 2013). Both 1-r and 1- β have been used as mobility indices (Jäntti and Jenkins, 2013). Schiller (1977) used rank-correlation (ρ) as a measure of immobility. Mobility may be measured by 1-ρ. Cowell and Flachaire (2017) asserted that "elasticity and correlation-based indices are inadequate to measure income mobility" (p. 2). Fields and Ok proposed several measures of mobility, including "the per capita aggregate change in log-incomes" (Fields & Ok, 1999b, p. 455), “the sum of the absolute values of income changes” (Fields & Ok, 1996, p. 369), the per capita measure of income changes, and the percentage measure of income changes (Fields & Ok, 1996). None of these measures are related to mobility tables/transition matrices.

Odds ratios for adjacent rows and columns have been a common method used to show the positive or negative associations in a mobility table (Hout, 1983). Edwards (1963) was a proponent of using cross-ratios of matrices to measure association. The Altham Statistic uses all the cross-ratios of two matrices to measure the distance between them. While this distance may be calculated between any two same-sized matrices, typically the second matrix used is that of independence (matrix of all ones) (Long & Ferrie, 2018). The Altham Statistic is equal to zero in the perfectly mobile situation and infinity (∞) under complete immobility (Altham and Ferrie, 2007). While the Altham Statistic measures a quantitative association between two matrices, it does not show “direction of the association” (Altham and Ferrie, 2007, p. 11). Of course, there are many different tables that could have the same Altham Statistic value, so comparing mobility between tables may not be possible in some cases.

Mobility ratios are a method used to show the relationship of actual totals or frequencies to those “expected under the model of perfect mobility” (Hout, 1983, p. 17). Since they compare observed quantities to hypothetical values, they do not reflect any strength of association. A measure of upward mobility is the probability that a child’s quantile rank exceeds that of their parents’ quantile rank (Torche, 2015). Similarly, a measure of downward mobility is the probability that a child’s quantile rank ends up below that of their parents’ quantile rank. Bartholomew (1982) and Scott and Litchfield

(1994) proposed the Average Absolute Jump Index of mobility. It averages the individual class boundaries crossed between the origin and destination timeframes (Mishra, 2018). The normalized Average Jump Index is equal to the Average Absolute Jump Index divided by n/2 (Mishra, 2018). Formby et al. (2004) used a measure of "the average number of income classes crossed by all individuals" (Formby et al., 2004, p. 184).

There are other ways of summarizing mobility using mobility matrices (Bartholomew, 1982; Formby et al., 2004; Hout, 1983; Jäntti and Jenkins, 2013; Mishra, 2018; Scott and Litchfield, 1994; Torche, 2015). Good (1965) "suggested that the algebraic rank of the matrix" should be part of measuring association (Altham, 1970, p. 66). Immobility Ratios (IRs) "summarise how much clustering there is on (or, sometimes, also around) the leading diagonal of a transition matrix—and hence summarize positional change" (Jäntti and Jenkins, 2013, p. 55). In addition, a mobility ratio of 1 – IR may also be used. A simple measure of mobility is using the trace of the mobility transition matrix. The trace is simply the sum of the main diagonal elements and indicate the level of stickiness or immobility (Jäntti and Jenkins, 2013). Prais (1955) and Shorrocks (1978) advocated a measure of mobility using the trace of a mobility transition matrix, referred to as the Normalized Trace (Jäntti and Jenkins, 2013). It takes the form of:

$$P(M) = [n - \text{trace}(M)]/[n - 1],$$

Where n is the size of the n x n matrix M. P(M) is equal to one in the perfectly mobile situation and zero under complete immobility (Burkhauser & Couch, 2008; Shorrocks, 1978). It "measures the average probability across all classes that an individual will leave her initial class in the succeeding period; it is also interpreted as the normalized distance…away from the identity matrix I" (Formby et al., 2004, p. 184). Bartholomew (1982) proposed another measure using the trace of mobility tables and transmission matrices. It takes the form of:

$$B(M) = [\mathrm{trace}(M) - 1]/[n - 1],$$

Where n is the size of the n x n matrix M. Opposite of P(M), B(M) is equal to one under complete immobility and zero in the perfectly mobile situation (Bartholomew, 1982).

Mobility has also been measured by a fraction of the sum of destination entries found off the principal diagonal compared to the sum of all table entries. This measure is also equal to one minus the Immobility Ratio (IR) and may be called the Mobility Ratio (MR). This overall MR may be split into Upward Mobility Ratio (UMR) and Downward Mobility Ratio (DMR) measures by limiting the sum of the off-diagonal entries to those above and below the main diagonal (Altham and Ferrie, 2007; Long and Ferrie, 2013).

Rather than using dollar amounts of income or wealth, intragenerational, intergenerational, and multigenerational transmission may also be measured by movement up or down the income or wealth ladder of individuals—or across generations. One way to measure this inequality is to compare the top to the bottom in the form of a ratio, whether it is by quartile, quintile, decile, or percentile. Another way may be to compare income and wealth distribution to a reference like a time of greatest equality or inequality (Keister, 2014; Kim and Tamborini, 2012; McNamee and Miller, 2014).

Modeling the Relationship between Origin and Destination Status

Besides recording the observed values in mobility tables and transition matrices, researchers create models to predict the cell entries. Linear models typically use least squares regression to model the relationship between origin and destination status (Hout, 1983). Most often, logarithms are used to deal with the skewed nature of income and wealth variables. In this case, all observed values of zero must be discarded, which biases the results. This is less of a problem if lifetime incomes are used rather than a single observation (Lundberg & Stewart, 2020). To overcome this problem, authors have divided the population samples into quantiles and performed additive quantile regression (Jäntti and Jenkins, 2013; Lundberg & Stewart, 2020). Quasi-Perfect Mobility (QPM) attempts to model mobility with a two-step process. A proportion is selected for stayers along the main diagonal and the rest of the population is assigned to destinations randomly, according to origin independence. Thus, some of the original non-stayers are randomly assigned along the main diagonal and added to the selected proportion of stayers (Hout, 1983). The constrained and unconstrained diagonals models are a class of social distance mobility models and are concerned with the "number of occupational categories to be crossed" (Hout, 1983, p. 32). There are seven different models depending on the different available diagonal constraints employed by the analyst (Hout, 1983).

Log-linear models may be expressed as equations for expected frequencies or in logit form. A logit model of mobility is measured by "the log-odds on a high-status destination relative to a lower-status destination given a fixed origin status" (Hout, 1983, p. 34). Chetty et al. (2014) insist that rank-rank specifications provide "a more robust summary of intergenerational mobility than traditional log-log specifications" (p. 143). Topological models are structural in nature and deal with mobility through "quasi-independent subsets of cells ('levels') in the table" (Hout, 1983, p. 37). They involve conditional invariance with “total, row, and column effects” and “only one interaction parameter” that determine cell mobility/immobility relative to other cells (Hout, 1983, p. 38). Latent variables may also be used if researchers suspect there are unobserved variables at play in the association between independent observed variables (Hout, 1983). Saunders (2010) is one of the few authors who have addressed R^2 in mobility research. Most others have simply ignored it. According to Saunders (2010), even a model R^2 of between 0.22 and 0.37 is “fairly weak” and reveals “other factors at work which have little to do with either social advantage/disadvantage or meritocracy” (pp. 77,78). There are very few studies, if any, that exceed this weak explanatory power. No matter how hard researchers try, there will always be measurement error (Chetty et al., 2014; Hout, 1983; Jäntti and Jenkins, 2013; Lundberg & Stewart, 2020; Saunders, 2010).

Measurement Error in Mobility Research

Error is significant in mobility research, estimated to account for “a 15 to 20 percent downward bias in intergenerational association” in occupation (Torche, 2015, p. 40). Measurement error in earnings/income include selection bias (especially the censored sample), functional form, short term measurement, transitory fluctuations, the age at which measurement is taken, and life cycle concerns and is exacerbated by using market-determined outcomes which exclude the welfare of those participating in non-market activities (Mitnik et al., 2019; Torche, 2015). In fact, “those without jobs…tend to be dropped from social mobility studies altogether, or they get subsumed into bigger categories and their distinctiveness is lost” (Saunders, 2010, p. 8). Authors have worried that after accounting for parental socioeconomic status, education, occupation, income, and wealth correlations may be spurious in nature (Killewald et al., 2017). Bias exists when samples are restricted to individuals that are linked through validation systems. Validation systems are less likely to link “those with less education and income, poor English ability, non-employed, non-citizens, non-participants in government programs, and minorities” (Bond et al., 2014, p. 3). In addition to measurement errors, there is considerable random variability in measuring mobility of socioeconomic status. Part of this randomness is due to luck in the real world even after consideration of underlying individual intelligence, ability, talent, and effort. In addition, individual decision-making under similar circumstances is different even for similarly situated people (Clark, 2013). If luck happens to “be correlated across generations,” additional bias may be the result (Shea, 2000, p. 157).

Mobility Tables and Transition Matrices

Consideration of measurement error and bias is important in forming mobility tables and transition matrices (Bond et al., 2014; Clark, 2013; Killewald et al., 2017; Mitnik et al., 2019; Saunders, 2010; Shea, 2000; Torche, 2015). Altham and Ferrie (2007) pointed out that “few tools are as useful to the social historian as the humble contingency table” (p. 3). Otherwise known as mobility tables and transition matrices, they are “a simple but under-used device” for mobility research (Jäntti and Jenkins, 2013, p. 161). Yet, comparing the mobility shown in these tables and matrices is not necessarily an easy task (Burkhauser & Couch, 2008). They are cross-classifications of the values of a variable at two different times and show the movement of subjects between different categories or classes (Fields & Ok, 1999a; Torche, 2015). In fact, transition matrices/mobility tables are “a convenient way of providing a simple snapshot of rank-movements in the sample” but are still a “crude aggregation” (Chen and Cowell, 2017, p. 206). They convey information about the symmetrical and asymmetrical nature of mobility in table form and may be intragenerational (within a single generation), intergenerational (across two generations), or multigenerational (spanning more than two generations) (Hout, 1983; Jäntti and Jenkins, 2013; Torche, 2015). Transition matrices/mobility tables allow one to see "where the rigidities might exist along the earnings distribution" (Mazumder, 2005, p. 91).

Mobility tables show totals of those moving from each origin to every destination, so that individual cells reflect "the counts of persons that share each combination of origin and destination" (Hout, 1983, p. 9). "The same categories are used for origin and destination," while the chosen categories are displayed in the same order on each axis of the table (Hout, 1983, p. 9). The main diagonal entries represent the number who end up right where they started, so were immobile (Burkhauser & Couch, 2008). In empirical studies there is typically excess immobility—that found over and above what is expected under assumptions of origin independence—discovered along the diagonal (Hout, 1983

Transition matrices contain the proportions or probabilities of that movement (Fields & Ok, 1999a; Prais, 1955; Trede, 1998). The row proportions are outflows and column proportions are inflows (Hout, 1983). Of course, "summarizing a distributional transformation by a transition matrix usually results in a loss of information" but tend to be robust within the defined categories, and do not capture any movement within those categories (Fields & Ok, 1999a, p. 566). Because inequality involves multiple dimensions, interpreting mobility transition matrices is not necessarily easy (Atkinson & Bourguignon, 1982; Trede, 1998;). It is important to note that a "perfectly mobile society," or perfect mobility, is represented by the rows of percentages being equal

(Bartholomew, 1982, p. 24; Hout, 1983; Prais, 1955). Saunders (1996) demonstrated that observed rates of mobility were similar to those expected under a meritocratic society. This idea of perfect mobility within a meritocracy is a result of the meritocratic assumptions made within society (Altham and Ferrie, 2007; Atkinson & Bourguignon, 1982; Bartholomew, 1982; Burkhauser & Couch, 2008; Chen and Cowell, 2017; Fields & Ok, 1999a; Hout, 1983; Jäntti and Jenkins, 2013; Mazumder, 2005; Prais, 1955; Saunders, 1996, 2010; Torche, 2015; Trede, 1998).

Trends and Patterns of Mobility Found in Past Studies

Research has been divided into studies that outline measures of mobility, establish estimates of mobility, and look at trends in mobility. Some studies emphasize the lack of mobility observed and others value the mobility discovered. Song et al. (2020) discovered trends in mobility between 1850 and 2015 within the US using an occupational percentile rank mobility measure. They found increasing mobility for Americans born before 1900 and mostly constant mobility rates since. Rank-rank correlations began at about 0.17 with the 1830 cohort and were approximately 0.32 in 1980. Net of the structural change "mostly driven by the movement from farm to factory during industrialization" mobility was flat between 1860 to 1960 (Song et al., 2020, p. 251). Even with the sharp rise in income inequality since 1970, mobility has stayed relatively stable (Song et al., 2020). Other researchers have found the same lack of "major changes in intergenerational mobility" (Lee & Solon, 2009, p. 766). "Since the First World War, relative mobility rates have remained roughly constant, but absolute mobility has increased dramatically" (Saunders, 2010, p. 106). In fact, each succeeding generation enjoyed greater upward mobility than the last because of structural changes that created “more room at the top” (Saunders, 2010, p. 107). More recently, these structural changes have subsided and there is much less upward mobility, especially since “downward mobility is sticky” (Saunders, 2010, p. 109). While “inequality has increased,” “rank-based mobility has remained stable” even with consistent differences across geographic areas in the U.S. (Chetty et al., 2014, pp. 141, 145).

Significant non-linearities have been found in mobility research including “substantial kinks in the distribution” of occupational status (Torche, 2015, p. 40). Mobility transition matrices have shown “an especially high degree of rigidity at the bottom and top of the earnings distribution” (Mazumder, 2005, p. 80). Therefore, a single linear IGE is not a good measure of mobility when there are non-linearities involved (Mitnik et al., 2019). Adding higher order polynomial terms to regressions, using spline functions, and utilizing locally weighted or quantile regressions are all possible ways to deal with this non-linearity. Besides linearity, other functional forms may be more appropriate. Many studies use logarithmic functions (Killewald et al., 2017). Another transformation that has been scarcely used is the inverse hyperbolic sine transformation, which “can incorporate zero and negative values, generating a function that is approximately linear close to zero and approximately logarithmic for large values” (Killewald et al., 2017, p. 382).

Adermon et al. (2018) calculated correlation of intergenerational wealth outcomes over four generations in Sweden. They found rank correlations between parents and children in the range of 0.3 to 0.4 and grandparent-grandchildren between 0.1 to 0.2. Gifts and bequests made up over half of this correlation and education a quarter. In the regressions involving wealth, the R^2 was not above 0.20 but was often below 0.10

(Adermon et al., 2018). Another study done in Sweden by Hällsten (2014) even included first and second cousins. The correlations were found to be relatively low but much higher for families above the ninety-ninth percentile (Adermon et al., 2018; Hällsten, 2014).

In an analysis of the one-percenters—those with income and wealth above the ninety-ninth percentile—Keister (2014) found that their household income and wealth are correlated with coefficients between 0.50 and 0.60. The one-percenter households accounted for seventeen percent of all income and held more than one-third of net worth and financial assets. Most of the top one-percenter research has concentrated on exorbitant Chief Executive Officer (CEO) salaries and has largely ignored wealth and life-course effects. Keister (2014) used the 2001-2010 Surveys of Consumer Finances (SCF) even though the SCF is unable to determine either income or wealth at the very top. In her study, Keister (2014) described the top one percent, next 9 percent, and the other 90 percent shares of income and wealth for what she calls "income earners" and "wealth owners" but reports them as household income and household wealth in her figures (Keister, 2014, pp. 352, 353). This raises the question about individuals versus households when it comes to measuring income and wealth and may complicate comparisons with other earners, households, or the total population. She reports that "members of the one percent are disproportionately male, white, and married" (Keister, 2014, p. 356). But, if income and wealth are being measured at the household level and about half of the one percenters are married, then approximately one quarter of the households would include women, which would contradict the reported top one percent being 97.8 percent (income) and 95.8 percent (wealth) males (Keister, 2014). The distinction between measuring individual and household variables is an important one.

While Keister (2014) did not report any new theoretical or empirical work, she employed the commonly used Gini Coefficient (GC) to describe historical trends in income and wealth distribution. This measure of inequality is a number between zero and one that indicates the gap between perfect equality (GC = 0) and actual income or wealth distribution (Johnson, 2000). Unfortunately, the wealth GC is commonly calculated by setting negative net worth values to zero, which introduces downward bias into wealth inequality measurements (Keister, 2014). Of course, income or wealth equality do not necessarily parallel to mobility or meritocracy. Even though research of income and wealth inequality has been expanding, there are still gaps in the literature (Keister, 2014; Johnson, 2000).

Nettles (2003) stated that "Intelligence is the strongest single factor causing class mobility in contemporary societies that has been identified" (Nettles, 2003, p. 560). When it comes to occupation, "the direct effect of parental status, once education is accounted for, is nonzero but relatively minor," even though "the mediating role of education varies widely across classes" (Torche, 2015, pp. 39, 41). In addition, parenting style has been found to be more important to explaining educational and occupational outcomes than class and income of parents (Saunders, 2010). Socialization is also a "key factor in boosting life chances for those born into disadvantage" (Saunders, 2010, p. 117).

Charles and Hurst (2003) and Pfeffer and Killewald (2018) used regression methods to show intergenerational wealth outcomes over two and three generations using the PSID. They found "substantial intergenerational persistence in wealth" (Charles and

Hurst, 2003, pp. 1179-1180) and “stark differences in wealth mobility between whites and African Americans” (Pfeffer and Killewald, 2018, p. 1434). Both studies used a regression model utilizing prior generation wealth to account for current wealth, age-adjusted for the timing of wealth measurements. They also addressed other explanations of intergenerational wealth transmission including income, education, marriage, home ownership, business ownership, asset ownership, and direct transfers. They both attempted to report inherited or learned family-related variables that account for the differential wealth of individuals. What is left after the family-related variable accounting is the wealth derived from non-family-determined variables. This allows the comparison between family-determined wealth distribution and non-family-determined wealth provision over generations. Unfortunately, intergenerational wealth in these studies only explained between eight and sixteen percent of child wealth outcomes. In addition to regression models resulting in estimates in generational wealth correlations, both studies showed mobility transition matrices to display transmission of wealth between generations.

Need for Meritocracy-Based Measures of Mobility

The need for a single measure to describe mobility has been established for some time. In order to supplement mobility transition matrices, “it is also important to construct a single aggregate mobility index which summarizes the direction and magnitude of…mobility” (Mishra, 2018, p. 276). Cowell and Flachaire (2017) admitted that “it is not so easy to compare two matrices with many different values” (p. 29). Determining from mobility transition matrices “whether there is a large or small amount of mobility” is not “straightforward” (Jäntti and Jenkins, 2013, p. 28). A single measure of mobility summarizing a mobility transition matrix also helps in determining if mobility increases or decreases (Jäntti and Jenkins, 2013). Altham (1970) outlined the convenience of "a single expression for the measure of association" rather than multiple summaries or complete matrices (p. 66). These single measures of mobility allow easy comparisons "across time or countries in order to say whether mobility is greater or smaller" (Jäntti and Jenkins, 2013, p. 2).

Several authors have outlined the reasons we need to measure where a society stands compared to an ideal meritocracy. Prais (1955) compared his measure of the average time spent in a particular social class to the time expected in a "perfectly mobile society" by taking a ratio of the two (pp. 59-60). In addition, "one can judge the present imperfection of a particular society" with a meritocratically-comparable measurement (Allen, 2011, p. 368). In addition, Allen (2011) indicated that measuring mobility in meritocratic terms can indicate progress of different societies across geography and time. He also felt that a measurement involving meritocracy may be used as a proxy for corruption. Solon (2017) outlined the need for a meritocracy-based measure when he stated, "most people would like to know where our own society lies between the extremes" (p. 3). In addition, relating to "a perfectly meritocratic society" would "enable us to compare the reality with the 'perfect' model to gauge the extent to which the reality falls short of the ideal" (Saunders, 2010, p. 60). Without meritocracy-based measurement, there is disagreement about how "far from the perfect mobility of society" we are (Solon, 2017, p. 4). Because the idea of meritocracy and the SAD thesis are diametrically opposed, an objective measure that shows exactly where a society falls between a perfect meritocracy (shown by origin independence) and a perfect non-meritocracy (shown by complete immobility) is needed (Saunders, 2010). Because researchers have found "a clustering of observations along the main diagonal," a stickiness measure of mobility related to meritocracy assumptions makes sense (Altham and Ferrie, 2007, p. 11). Besides meritocracy in mobility measurement being important, there have been different methods employed (Allen, 2011).

Economists and sociologists have used class, education, occupation, consumption, income, and wealth in order to estimate social mobility across generations. In fact, "there is a continuing debate about whether the rate of intergenerational social mobility has remained stagnant or declined in the past fifty years, but few think it has increased" and this immobility has been identified as an important western political problem which needs addressed (Young, 2015, p. 9). This political problem has been perceived as serious even though inequality may not have been on individuals' minds because "even as inequality worsens most people have tended to fare better" (Keister, 2014, p. 363). The assumption is that "societies can't possibly be meritocratic because of the low levels of social mobility" (Young, 2015, p. 11). But even if this assumption is true, it may only indicate a lack of meritocracy in the distribution of inborn talents (Young, 2015). This perception that immobility is a serious problem and is to blame for current social ills must still be tested. It is possible that society, including economists and sociologists are blaming the wrong thing. The common perception is that all democracies are far from being meritocracies (Young, 2015). One way to support or refute this common perception is to create an MBSMoM that shows where a society lies between assumptions of FM and LM. Besides this individual position of society, an MBSMoM will be able to compare class, education, occupation, consumption, income, and wealth mobility over time, geography, and among subpopulations (Keister, 2014; Young, 2015).

Gathering data on income and wealth in the US is a relatively new enterprise, starting in the 1950s (income) and 1980s (wealth) except for the 1962 Survey of the Financial Characteristics of Consumers (SFCC) which measured both. Other sources of income and wealth data include the US Census, the Social Security Administration (SSA), Current Population Survey (CPS), the National Longitudinal Survey of Youth (NLSY), the Panel Study of Income Dynamics (PSID), the Survey of Consumer Finances (SCF), the Health and Retirement Survey (HRS), the Survey of Income and Program Participation (SIPP), Statistics of Income (SOI), Occupational Change in a Generation Survey (OCGS), Federal Income Tax data, and Estate Tax data. In addition, cross national data has been harmonized in the Cross-National Equivalence File (CNEF). The PSID is the ideal dataset because it is “the world’s longest running national household panel survey, collecting data since 1968 from the same families and their descendants” (Smeeding, 2018, p. 29). In order to measure how close a society is to meritocracy, there must exist mobility information (Auten et al., 2013; Jäntti and Jenkins, 2013; Keister, 2014; Long and Ferrie, 2013; Mazumder, 2014; Smeeding, 2018).

This research takes several steps. The first is: develop an SSMoM and WSMoM which may be used with intragenerational, intergenerational, and multigenerational mobility transition matrices. The second is: calculate SSMoM and WSMoM values using real-world transition matrices, and transition matrices under assumptions of FM and its opposite, LM. The third step is: take real-world values of the SSMoM and WSMoM and their values in FM and LM to create an MBSMoM.

III. DATA AND METHODS

Data

Jäntti and Jenkins (2013) recognized that "different data sources and estimation methods may generate different results" (p. 170). Dardanoni et al. (2008) claimed that "there is no compelling reason to use three categories rather than two, four or any other number" (p. 13). Others have disagreed, pointing out that the number of categories leads to different results. For example, "the transition-matrix approach could be sensitive to the merging or splitting of classes or the adjustment of class boundaries" (Cowell and Flachaire, 2017, p. 14). The amount of measured mobility "heavily depends on the number of…groups, or is sensitive to the choice of the range over which movement (i.e., quintiles, deciles, and so on) is measured" (Mishra, 2018, p. 277). These differences may even be driven by the mobility variable chosen—education, occupation, SES, class, consumption, income, or wealth (Jäntti and Jenkins, 2013). Results can vary widely by class, education, occupation, consumption, income, and wealth mobility studies (Torche, 2015). Intragenerational, intergenerational, and multigenerational mobility and mechanisms differ by geography, structural institutions, governments, population subgroups and socioeconomic status, not to mention differences in results from research assumptions, approaches, and methods (Pfeffer, 2014). Mobility research "has produced wildly divergent estimates" (Lee & Solon, 2009, p. 766). When it comes to earnings, measures "over short periods of time may contain a large 'transitory' component" and cannot represent permanent or lifetime income (Mazumder, 2005, p. 81). These transitory shocks have been found to fluctuate over the life cycle, which have resulted in large variations in mobility estimates (Cowell and Flachaire, 2017; Dardanoni et al., 2008; Jäntti and Jenkins, 2013; Lee & Solon, 2009; Mazumder, 2005; Mishra, 2018; Pfeffer, 2014; Torche, 2015).

Methods

The current study uses the MBSMoM in evaluating the results of 22 studies using 92 mobility transition matrices with sample sizes ranging from 799 to 43,701. Appendix Table 1(a) shows a mobility transition matrix under assumptions for an imaginary LM (perfect non-meritocracy), which represents perfect rigidity or complete immobility, indicated by all 100 percent entries in the main diagonal and zeros in all off-diagonal cells of the table (Burkhauser & Couch, 2008; Jäntti and Jenkins, 2013). Appendix Table 1(b) represents the mobility transition outcomes in an imaginary FM (optimal meritocracy), representing origin independence or perfect mobility, assuming randomly distributed natural talent represented by a lack of systemic relationship between origins and destinations (Burkhauser & Couch, 2008; Jäntti and Jenkins, 2013). Perfect mobility means "there is no connection between the children's origins and where they will end up" (Solon, 2017, p. 3). This optimal meritocracy is the opposite of the perfect non-meritocracy shown in Appendix Table 1(a) (Saunders, 2010). However, actual transition matrices almost always lie somewhere between those represented by Appendix Table 1(a) and 1(b) (Bartholomew, 1982). As an illustration, Appendix Table 1(c) presents the wealth mobility results from Charles and Hurst (2003).

I first created two Stickiness Measures of Mobility (SMoMs) which may be used with intragenerational, intergenerational, and multigenerational mobility transition matrices, and applicable to multiple diverse studies. These different ways to measure mobility may be used with data of class, education, occupation, consumption, income, and wealth contained in mobility transition matrices. These SMoMs may be calculated and compared with their values of an ideal FM ("perfect mobility") and its opposite, an LM (perfect immobility) (Saunders, 2010, p. 10). Because stickiness of class, education, occupation, consumption, income, and wealth may be important, these SMoMs bay be used to form an MBSMoM (Charles and Hurst, 2003; Pfeffer and Killewald, 2018; Saunders, 2010).

The SMoMs concentrate on the stickiness of class, education, occupation, consumption, income, and wealth within and across generations. They reflect a measure of the probabilities of remaining in the same category or quantile (quartile, quintile, decile, or percentile) taken across all categories of the mobility transition matrix. The objective was to transform commonly used mobility transition matrices into a Simple Stickiness Measure of Mobility (SSMoM) and/or a Weighted Stickiness Measure of Mobility (WSMoM) and then a Meritocracy-Based Stickiness Measure of Mobility (MBSMoM), using comparisons of these real-world SMoMs with SMoMs associated with FM and LM assumptions.

Mobility transition matrices consist of n by n matrices of numbers representing the proportions of individuals who begin a time period in the *ith* category or quantile (quartile, quintile, decile, or percentile) and end the time period in the *jth* category or quantile (quartile, quintile, decile, or percentile). For quartiles, n is equal to 4. For quintiles, n is equal to 5. Obviously, n is equal to 10 for deciles and 100 when using percentiles. Since this research deals with stickiness, only the principal diagonal of the mobility transition matrices matter because they represent those who begin and end in the same position. This limits the analysis to those entries with *i* equal to *j*.

A mobility matrix M has individual entries m_{ij} where *i* represents the row number and j represents the column number:

$$\begin{vmatrix} m_{11} & m_{12} & m_{13} & m_{14} & m_{15} \\ m_{21} & m_{22} & m_{23} & m_{24} & m_{25} \\ m_{31} & m_{32} & m_{33} & m_{34} & m_{35} \\ m_{41} & m_{42} & m_{43} & m_{44} & m_{45} \\ m_{51} & m_{52} & m_{53} & m_{54} & m_{55} \end{vmatrix}$$

For example, the mobility matrix M calculated by Charles and Hurst (2003) is:

$$\begin{vmatrix} 36 & 29 & 16 & 12 & 7 \\ 26 & 24 & 24 & 15 & 12 \\ 16 & 21 & 25 & 24 & 15 \\ 15 & 13 & 20 & 26 & 26 \\ 11 & 16 & 14 & 24 & 36 \end{vmatrix}$$

Stickiness measures of mobility are only concerned with the principal diagonal of the mobility matrix M, so taking the diagonal, D_M, of mobility matrix, M, results in the matrix (Horst, 1963):

$$\begin{vmatrix} m_{11} & 0 & 0 & 0 & 0 \\ 0 & m_{22} & 0 & 0 & 0 \\ 0 & 0 & m_{33} & 0 & 0 \\ 0 & 0 & 0 & m_{44} & 0 \\ 0 & 0 & 0 & 0 & m_{55} \end{vmatrix}$$

The diagonal, D_M, of mobility matrix, M, may also be calculated by taking the "Hadamard-Schur" Product (HSP) (multiplying each individual element of two same-size matrices, a_{ij} and b_{ij} with each other to form a resultant matrix the same size as those being multiplied) of the matrix, M, and a matrix with all ones along the principal diagonal and zeros elsewhere (Rao and Rao, 1998):

$$\begin{vmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{vmatrix} \quad \begin{vmatrix} m_{11} & m_{12} & m_{13} & m_{14} & m_{15} \\ m_{21} & m_{22} & m_{23} & m_{24} & m_{25} \\ m_{31} & m_{32} & m_{33} & m_{34} & m_{35} \\ m_{41} & m_{42} & m_{43} & m_{44} & m_{45} \\ m_{51} & m_{52} & m_{53} & m_{54} & m_{55} \end{vmatrix}$$

For example, the diagonal, D_M, of mobility matrix M calculated by Charles and Hurst (2003) is:

$$\begin{vmatrix} 36 & 0 & 0 & 0 & 0 \\ 0 & 24 & 0 & 0 & 0 \\ 0 & 0 & 25 & 0 & 0 \\ 0 & 0 & 0 & 26 & 0 \\ 0 & 0 & 0 & 0 & 36 \end{vmatrix}$$

A Simple Stickiness Measure of Mobility (SSMoM) may be calculated as an average mobility rate by taking the trace of the diagonal of the mobility matrix, M, trace(D_M), and dividing it by n. The trace(D_M), is calculated by pre-multiplying and post-multiplying D_M, by vectors consisting of all ones (Horst, 1963):

$$\begin{vmatrix} 1 & 1 & 1 & 1 & 1 \end{vmatrix} \quad \begin{vmatrix} m_{11} & 0 & 0 & 0 & 0 \\ 0 & m_{22} & 0 & 0 & 0 \\ 0 & 0 & m_{33} & 0 & 0 \\ 0 & 0 & 0 & m_{44} & 0 \\ 0 & 0 & 0 & 0 & m_{55} \end{vmatrix} \quad \begin{vmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{vmatrix}$$

$\text{trace}(D_M) = m_{11} + m_{22} + m_{33} + m_{44} + m_{55}$

For example, the Simple Stickiness Measure of Mobility (SSMoM) consisting of the trace(D_M) divided by n calculated for the transition matrix of Charles and Hurst (2003) is:

$$\begin{vmatrix} 1 & 1 & 1 & 1 & 1 \end{vmatrix} \quad \begin{vmatrix} 36 & 0 & 0 & 0 & 0 \\ 0 & 24 & 0 & 0 & 0 \\ 0 & 0 & 25 & 0 & 0 \\ 0 & 0 & 0 & 26 & 0 \\ 0 & 0 & 0 & 0 & 36 \end{vmatrix} \quad \begin{vmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{vmatrix}$$

$\text{SSMoM} = \text{trace}(D_M)/n = (36 + 24 + 25 + 26 + 36)/5 = 147/5 = 29.40$

A Weighted Stickiness Measure of Mobility (WSMoM) may be calculated by pre-multiplying D_M by a set of weights, post-multiplying by a vector of ones, dividing by n, then dividing by the average weight (weight vector multiplied by a vector of ones divided by n):

WSMoM = $(WD_M1/n)/(W1/n)$

Where WD_M1 =

$$\begin{vmatrix} w_1 & w_2 & w_3 & w_4 & w_5 \end{vmatrix} \begin{vmatrix} m_{11} & 0 & 0 & 0 & 0 \\ 0 & m_{22} & 0 & 0 & 0 \\ 0 & 0 & m_{33} & 0 & 0 \\ 0 & 0 & 0 & m_{44} & 0 \\ 0 & 0 & 0 & 0 & m_{55} \end{vmatrix} \begin{vmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{vmatrix}$$

$WD_M1 = w_1m_{11} + w_2m_{22} + w_3m_{33} + w_4m_{44} + w_5m_{55}$

And W1 =

$$\begin{vmatrix} w_1 & w_2 & w_3 & w_4 & w_5 \end{vmatrix} \begin{vmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{vmatrix}$$

$W1 = w_1 + w_2 + w_3 + w_4 + w_5$

Therefore, WSMoM =

$[(w_1m_{11}+w_2m_{22}+w_3m_{33}+w_4m_{44}+w_5m_{55})/n]/((w_1+w_2+w_3+w_4+w_5)/n)$

For example, a WSMoM using declining weights of 5, 4, 3, 2, 1, of the mobility matrix calculated for the transition matrix of Charles and Hurst (2003) is:

WSMoM = $(WD_M1/n)/(W1/n)$

Where WD_M1 =

$$\begin{vmatrix} 5 & 4 & 3 & 2 & 1 \end{vmatrix} \quad \begin{vmatrix} 36 & 0 & 0 & 0 & 0 \\ 0 & 24 & 0 & 0 & 0 \\ 0 & 0 & 25 & 0 & 0 \\ 0 & 0 & 0 & 26 & 0 \\ 0 & 0 & 0 & 0 & 36 \end{vmatrix} \quad \begin{vmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{vmatrix}$$

$WD_M1/n = [5(36) + 4(24) + 3(25) + 2(26) + 1(36)]/5 = 439/5 = 87.8$

And W1 =

$$\begin{vmatrix} 5 & 4 & 3 & 2 & 1 \end{vmatrix} \quad \begin{vmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{vmatrix}$$

$W1 = 5 + 4 + 3 + 2 + 1 = 15$

So $WSMoM = (WD_M1/n)/(W1/n) = (439/5)/(15/5) = 87.8/3 = 29.27$

The SSMoM and WSMoM values calculated from mobility transition matrices will be compared with those calculated under hypothetical outcomes under FM and LM assumptions to gage where in the spectrum they lay. For example, an SSMoM of LM, $SSMoM_{LM}$, assumes that there is a 100 percent chance of remaining in the quantile in which one is born and, for the 5X5 matrix shown in Appendix Table 1(a), may be calculated as (Saunders, 2010):

$$\begin{vmatrix} 1 & 1 & 1 & 1 & 1 \end{vmatrix} \quad \begin{vmatrix} 100 & 0 & 0 & 0 & 0 \\ 0 & 100 & 0 & 0 & 0 \\ 0 & 0 & 100 & 0 & 0 \\ 0 & 0 & 0 & 100 & 0 \\ 0 & 0 & 0 & 0 & 100 \end{vmatrix} \quad \begin{vmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{vmatrix}$$

$SSMoM_{LM} = (100 + 100 + 100 + 100 + 100)/5 = 100$

In addition, an SSMoM of FM, $SSMoM_{FM}$, assumes that there is equal chance to move from each quantile to any other quantile, and, for the 5X5 matrix shown in Appendix Table 1(b), may be calculated as (Saunders, 2010):

$$\begin{vmatrix} 1 & 1 & 1 & 1 & 1 \end{vmatrix} \quad \begin{vmatrix} 20 & 0 & 0 & 0 & 0 \\ 0 & 20 & 0 & 0 & 0 \\ 0 & 0 & 20 & 0 & 0 \\ 0 & 0 & 0 & 20 & 0 \\ 0 & 0 & 0 & 0 & 20 \end{vmatrix} \quad \begin{vmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{vmatrix}$$

$$SSMoM_{FM} = trace(D_M)/n = (20 + 20 + 20 + 20 + 20)/5 = 20$$

Since the values in the principal diagonal of each mobility matrix, M, associated with FM and LM assumptions are equal, the WSMoM for each will have the same value of 100 and 20 respectively, no matter the weights chosen.

A Meritocracy-Based Stickiness Measure of Mobility (MBSMoM) is calculated by taking an SSMoM (or WSMoM) and computing a percentage between its values of $SSMoM_{FM}$ (or $WSMoM_{FM}$) and $SSMoM_{LM}$ (or $WSMoM_{LM}$):

$$MBSMoM_S = (SSMoM - SSMoM_{FM})/(SSMoM_{LM} - SSMoM_{FM})$$

$$MBSMoM_W = (WSMoM - WSMoM_{FM})/(WSMoM_{LM} - WSMoM_{FM})$$

For example, the MBSMoMs calculated for the transition matrix of Charles and Hurst (2003) in Appendix Table 1(c) are:

$$MBSMoM_S = (SSMoM - SSMoM_{FM})/(SSMoM_{LM} - SSMoM_{FM})$$

$$MBSMoM_S = (29.40 - 20)/(100 - 20) = 9.40/0.80 = 11.75$$

$$MBSMoM_W = (WSMoM - WSMoM_{FM})/(WSMoM_{LM} - WSMoM_{FM})$$

$$MBSMoM_W = (29.27 - 20)/(100 - 20) = 9.27/0.80 = 11.59$$

The $MBSMoM_S$ value of 11.75 indicates that the real-world observation of mobility using the SSMoM = 29.40, from the mobility table in Charles and Hurst (2003), is 11.75% away from the value under assumptions of FM. Using the WSMoM = 29.27, mobility lies 11.59% between the values under assumptions of FM and LM.

The MBSMoM may be interpreted as a measure of mobility that is the percentage between the hypothetical mobility table associated with assumptions of FM and the hypothetical mobility table associated with assumptions of LM. In this sense, every MBSMoM conveys information by itself, in addition to allowing comparisons with other MBSMoM calculations. Many existing measures of mobility convey no information by themselves because they may only be used in comparison with other values. Because of the stickiness expectation of class, occupation, income, and wealth mobility, the values of real world calculated SMoMs should have a minimum of 1/n (associated with FM) and may not exceed the value of 1 (associated with LM). With a minimum of 1/n and maximum of 1, actual values of Stickiness SMoMs will fall somewhere in between. Since MBSMoMs are calculated as a percentage, they will range in value between 0 and 1. I selected the mobility studies I found that included mobility matrices.

IV. FINDINGS

The overall results are contained in Appendix Table 2. This table shows the source of each mobility transition matrix evaluated in this study, along with basic information about the sample used and the calculated value of the MBSMoM. First, I will describe the individual results and then make some generalizations about the trends and patterns of mobility based on observations. Authors from 22 studies created 92 mobility transition matrices with sample sizes ranging from 799 to 43,701.

Calculated Values of the MBSMoM

Charles and Hurst (2003)

Charles and Hurst (2003) used the PSID to evaluate relative family wealth mobility in the US. They evaluated 1,491 parent/child pairs in the US using quintiles to measure age-adjusted family wealth of parents in 1984-1989 and their children in 1999.

This mobility transition matrix resulted in an MBSMoM value of 0.1154, meaning that mobility was 11.54 percent away from the mobility under FM assumptions. Charles and Hurst (2003) also controlled for lifetime income and asset composition to evaluate the 1,491 parent/child pairs in the US using quintiles to measure age-adjusted family wealth of parents in 1984-1989 and their children in 1999. This mobility transition matrix resulted in an MBSMoM value of 0.0126, meaning that mobility was 1.26 percent away from the mobility under FM assumptions.

Pfeffer and Killewald (2018)

Pfeffer and Killewald (2018) used the PSID to evaluate relative family wealth mobility in the US. They evaluated 2,001 parent/child pairs in the US using quintiles to measure intergenerational family wealth of parents in 1984 and their children in 2013. This mobility transition matrix resulted in an MBSMoM value of 0.1494, meaning that mobility was 14.94 percent away from the mobility under FM assumptions.

Jäntti and Jenkins (2013)

Jäntti and Jenkins (2013) used the PSID to evaluate relative mobility in intragenerational family income in the US. In order to investigate the effect of the number of divisions (categories or quantiles) chosen for analysis, I repeated the work of Jäntti and Jenkins (2013) with half the quantiles they chose to use. They evaluated income using deciles to measure intragenerational income of families between 1979 and 1988. This mobility transition matrix resulted in an MBSMoM value of 0.1213, meaning that mobility was 12.13 percent away from the mobility under FM assumptions. I re-assessed the Jäntti and Jenkins (2013) family income in the US by dividing their deciles into quintiles by combining deciles 1 and 2, 3 and 4, 5 and 6, 7 and 8, and 9 and 10, to measure family income between 1979 and their sons in 1988. This mobility transition matrix resulted in an MBSMoM value of 0.2206, meaning that mobility was 22.06 percent away from the mobility under FM assumptions. This is almost double (1.82 times) the value obtained using deciles with the same data.

Jäntti and Jenkins (2013) evaluated income using deciles to measure intragenerational income of families between 1989 and 1998. This mobility transition matrix resulted in an MBSMoM value of 0.1444, meaning that mobility was 14.44 percent away from the mobility under FM assumptions. I also re-assessed the Jäntti and Jenkins (2013) family income in the US by dividing their deciles into quintiles by combining deciles 1 and 2, 3 and 4, 5 and 6, 7 and 8, and 9 and 10, to measure family income between 1989 and their sons in 1998. This mobility transition matrix resulted in an MBSMoM value of 0.2580, meaning that mobility was 25.8 percent away from the mobility under FM assumptions. This is almost double (1.79 times) the value obtained using deciles with the same data.

Mazumder (2005)

Mazumder (2005) used SIPP and SSA data to evaluate relative intergenerational income mobility in the US for fathers and sons. In order to investigate the effect of the number of divisions (categories or quantiles) chosen for analysis, I repeated the work of Mazumder (2005) with half the quantiles they chose to use. They evaluated father/son pairs using deciles to measure relative intergenerational income mobility of fathers in 1985 and their sons in 1998. This mobility transition matrix resulted in an MBSMoM value of 0.0721, meaning that mobility was 7.21 percent away from the mobility under FM assumptions. I re-assessed the Mazumder (2005) father/son pairs in the US by dividing their deciles into quintiles by combining deciles 1 and 2, 3 and 4, 5 and 6, 7 and 8, and 9 and 10, to measure income of fathers in 1985 and their sons in 1998. This mobility transition matrix resulted in an MBSMoM value of 0.1160, meaning that mobility was 11.6 percent away from the mobility under FM assumptions. This is 1.61 times the value obtained using deciles with the same data.

Mazumder (2005) evaluated father/son pairs using quartiles to measure relative intergenerational income mobility of fathers in 1985 and their sons in 1998. This mobility transition matrix resulted in an MBSMoM value of 0.1196, meaning that mobility was 11.96 percent away from the mobility under FM assumptions. This is like using quintiles and 1.66 times the value obtained using deciles with the same data.

Corak and Heisz (1999)

Corak and Heisz (1999) used tax data to evaluate relative income mobility in Canada for fathers and sons. In order to investigate the effect of the number of divisions (categories or quantiles) chosen for analysis, I repeated the work of Corak and Heisz (1999) with half the quantiles they chose to use. They evaluated father/son pairs in Canada and used deciles to measure income of fathers in 1982 and their sons in 1995. This mobility transition matrix resulted in an MBSMoM value of 0.0306, meaning that mobility was 3.06 percent away from the mobility under FM assumptions. I re-assessed the Corak and Heisz (1999) father/son pairs in Canada by dividing their deciles into quintiles by combining deciles 1 and 2, 3 and 4, 5 and 6, 7 and 8, and 9 and 10, to measure income of fathers in 1982 and their sons in 1995. This mobility transition matrix resulted in an MBSMoM value of 0.0589, meaning that mobility was 5.89 percent away from the mobility under FM assumptions. This is almost twice (1.92 times) the value obtained using deciles with the same data.

Cowell and Flachaire (2017)

Cowell and Flachaire (2017) used the China Health and Nutrition Survey (CHNS) to evaluate relative intragenerational household income mobility in China. They used quintiles to measure intragenerational household income mobility between 1989 and 2000. This mobility transition matrix resulted in an MBSMoM value of 0.0789, meaning that mobility was 7.89 percent away from the mobility under FM assumptions. Cowell and Flachaire (2017) also used quintiles to measure intragenerational household income mobility between 2000 and 2011. This mobility transition matrix resulted in an MBSMoM value of 0.1127, so mobility was 11.27 percent away from FM assumptions.

Chen and Cowell (2017)

Chen and Cowell (2017) used the China Health and Nutrition Survey (CHNS) to evaluate relative intragenerational mobility of household income throughout all of China, rural China, and urban China. They started with long-term mobility of a 12-year time span. Chen and Cowell (2017) evaluated 2,843 households in China and used quintiles to measure intragenerational mobility of household income between 1989 and 2000. This mobility transition matrix resulted in an MBSMoM value of 0.0789, meaning that mobility was 7.89 percent away from the mobility under FM assumptions. Chen and Cowell (2017) also evaluated 2,600 households in China and used quintiles to measure intragenerational mobility of household income between 2000 and 2011. This mobility transition matrix resulted in an MBSMoM value of 0.1127, meaning that mobility was 11.27 percent away from the mobility under FM assumptions.

Chen and Cowell (2017) evaluated rural households in China and used quintiles to measure intragenerational mobility of household income between 1989 and 2000. This mobility transition matrix resulted in an MBSMoM value of 0.0565, meaning that mobility was 5.65 percent away from the mobility under FM assumptions in rural China. Chen and Cowell (2017) also evaluated rural households in China and used quintiles to measure intragenerational mobility of household income between 2000 and 2011. This mobility transition matrix resulted in an MBSMoM value of 0.0834, meaning that mobility was 8.34 percent away from the mobility under FM assumptions in rural China.

Chen and Cowell (2017) evaluated urban households in China and used quintiles to measure intragenerational mobility of household income between 1989 and 2000. This mobility transition matrix resulted in an MBSMoM value of 0.0938, meaning that in urban China mobility was 9.38 percent away from the mobility under FM assumptions. Chen and Cowell (2017) also evaluated urban households in China and used quintiles to measure intragenerational mobility of household income between 2000 and 2011. This mobility transition matrix resulted in an MBSMoM value of 0.1613, meaning that in urban China mobility was 16.13 percent away from the mobility under FM assumptions.

In addition, Chen and Cowell (2017) evaluated short-term intragenerational income mobility by dividing the 12 years of data into 3-year time spans. They evaluated 3,600 households in China and used quintiles to measure intragenerational mobility of household income between 1989 and 1991. This mobility transition matrix resulted in an MBSMoM value of 0.1882, meaning that mobility was 18.82 percent away from the mobility under FM assumptions. Chen and Cowell (2017) evaluated 3,358 households in China and used quintiles to measure intragenerational mobility of household income between 1991 and 1993. This mobility transition matrix resulted in an MBSMoM value of 0.1768, meaning that mobility was 17.68 percent away from the mobility under FM assumptions. Chen and Cowell (2017) evaluated 3,400 households in China and used quintiles to measure intragenerational mobility of household income between 2004 and 2006. This mobility transition matrix resulted in an MBSMoM value of 0.2061, meaning that mobility was 20.61 percent away from the mobility under FM assumptions. Chen and Cowell (2017) evaluated 3,442 households in China and used quintiles to measure intragenerational mobility of household income between 2009 and 2011. This mobility transition matrix resulted in an MBSMoM value of 0.2239, meaning that mobility was 22.39 percent away from the mobility under FM assumptions.

Formby et. al. (2004)

Formby et. al. (2004) used data from the PSID and the German Socio-Economic Panel (GSEOP) to evaluate both absolute and relative individual intragenerational mobility of earnings in the US and Germany. They evaluated 5,000 individuals in the US using quintiles to measure relative individual intragenerational earnings between 1985 and 1990. This mobility transition matrix resulted in an MBSMoM value of 0.3670, meaning that mobility was 36.7 percent away from the mobility under FM assumptions. Formby et. al. (2004) also evaluated 6,000 individuals in Germany using quintiles to measure relative individual intragenerational earnings between 1985 and 1990. This mobility transition matrix resulted in an MBSMoM value of 0.4131, meaning that mobility was 41.31 percent away from the mobility under FM assumptions.

Formby et. al. (2004) evaluated 5,000 individuals in the US using quintiles to measure absolute individual intragenerational earnings between 1985 and 1990. This mobility transition matrix resulted in an MBSMoM value of 0.3839, meaning that mobility was 38.39 percent away from the mobility under FM assumptions. Formby et. al. (2004) also evaluated 6,000 individuals in Germany using quintiles to measure absolute individual intragenerational earnings between 1985 and 1990. This mobility transition matrix resulted in an MBSMoM value of 0.5086, meaning that mobility was 50,86 percent away from the mobility under FM assumptions.

Mishra (2018)

Mishra (2018) used the India Human Development Survey (IHDS) to evaluate relative intragenerational mobility of household income throughout all India, rural India, and urban India. They evaluated 40,018 households in India and used quintiles to measure intragenerational income of households between 2005 and 2012. This mobility transition matrix resulted in an MBSMoM value of 0.1543, meaning that mobility was 15.43 percent away from the mobility under FM assumptions. Mishra (2018) evaluated rural households in India and used quintiles to measure intragenerational income of households between 2005 and 2012. This mobility transition matrix resulted in an MBSMoM value of 0.1275, meaning that mobility was 12.75 percent away from the mobility under FM assumptions. Mishra (2018) also evaluated urban households in India using quintiles to measure intragenerational income of households between 2005 and 2012. This mobility transition matrix resulted in an MBSMoM value of 0.1525, meaning that mobility was 15.25 percent away from the mobility under FM assumptions.

Long and Ferrie (2018)

Long and Ferrie (2018) used Census data to evaluate absolute mobility in occupations in the US and Britain for different combinations of grandfathers, fathers and sons. Long and Ferrie (2018) evaluated 4,943 father/son pairs in Britain and used four categories to measure occupations of fathers in 1851 and their sons in 1881. This mobility transition matrix resulted in an MBSMoM value of 0.3204, meaning that mobility was 32.04 percent away from the mobility under FM assumptions. Long and Ferrie (2018) also evaluated 4,887 father/son pairs in Britain and used four categories to measure occupations of fathers in 1881 and their sons in 1911. This mobility transition matrix resulted in an MBSMoM value of 0.2424, meaning that mobility was 24.24 percent away from the mobility under FM assumptions. In addition, Long and Ferrie (2018) evaluated 4,002 grandfather/grandson pairs in Britain and used four categories to measure occupations of grandfathers in 1851 and their grandsons in 1911. This mobility transition matrix resulted in an MBSMoM value of 0.1113, meaning that mobility was 11.13 percent away from the mobility under FM assumptions.

Long and Ferrie (2018) evaluated 43,701 father/son pairs in the US and used four categories to measure occupations of fathers in 1850 and their sons in 1880. This mobility transition matrix resulted in an MBSMoM value of 0.2418, meaning that mobility was 24.18 percent away from the mobility under FM assumptions. Long and Ferrie (2018) also evaluated 43,701 father/son pairs in the US and used four categories to measure occupations of fathers in 1880 and their sons in 1910. This mobility transition matrix resulted in an MBSMoM value of 0.2776, meaning that mobility was 27.76 percent away from the mobility under FM assumptions. In addition, Long and Ferrie (2018) evaluated 43,701 grandfather /grandson pairs in the US and used four categories to measure occupations of fathers in 1850 and their grandsons in 1910. This mobility transition matrix resulted in an MBSMoM value of 0.1421, meaning that mobility was 14.21 percent away from the mobility under FM assumptions.

Long and Ferrie (2018) evaluated 1,983 father/son pairs in Britain and used four categories to measure occupations of fathers in 1881 and their sons in 1911 for fathers who ended up in an occupation equal to that of the grandfather. This mobility transition matrix resulted in an MBSMoM value of 0.2227, meaning that mobility was 22.27 percent away from the mobility under FM assumptions. Long and Ferrie (2018) also evaluated 1,043 father/son pairs in Britain and used four categories to measure occupations of fathers in 1881 and their sons in 1911 for fathers who ended up in an occupation higher to that of the grandfather. This mobility transition matrix resulted in an MBSMoM value of 0.0601, so mobility was 6.01 percent away from the mobility under FM assumptions. In addition, Long and Ferrie (2018) evaluated 948 father/son pairs in Britain and used four categories to measure occupations of fathers in 1881 and their sons in 1911 for fathers who ended up in an occupation lower than that of the grandfather. This mobility transition matrix resulted in an MBSMoM value of 0.1198, meaning that mobility was 11.98 percent away from the mobility under FM assumptions.

Altham and Ferrie (2007)

Altham and Ferrie (2007) used Census data to evaluate absolute intergenerational mobility in occupations in the US for fathers and sons. They evaluated 8,999 father/son pairs and used four categories to measure occupations of fathers in 1850 and their sons in 1880. This mobility transition matrix resulted in an MBSMoM value of 0.2045, meaning that mobility was 20.45 percent away from the mobility under FM assumptions. Altham and Ferrie (2007) also evaluated 17,733 father/son pairs using four categories to measure occupations of fathers in 1880 and their sons in 1910. This mobility transition matrix resulted in an MBSMoM value of 0.1875, meaning that mobility was 18.75 percent away from the mobility under FM assumptions.

Neidhöfer and Stockhausen (2019)

Neidhöfer and Stockhausen (2019) used the GSEOP, PSID, and British Household Panel Survey (BHPS) from the Cross-National Equivalent File to evaluate absolute multigenerational mobility of education in Germany, the US, and Britain for grandparents and grandchildren. They evaluated 1,890 German grandparents/ grandchildren pairs from the GSEOP and used three categories to measure education levels of grandparents and their grandchildren between 1960 and 1985. This mobility transition matrix resulted in an MBSMoM value of 0.1698, meaning that mobility was 16.98 percent away from the mobility under FM assumptions. Neidhöfer and Stockhausen (2019) also evaluated 5,554 US grandparents/ grandchildren pairs from the PSID using three categories to measure education levels of grandparents and their grandchildren between 1960 and 1985. This mobility transition matrix resulted in an MBSMoM value of 0.1020, meaning that mobility was 10.2 percent away from the mobility under FM assumptions. In addition, Neidhöfer and Stockhausen (2019) evaluated 5,554 British grandparents/ grandchildren pairs from the BHPS using three categories to measure education levels of grandparents and their grandchildren between 1960 and 1985. This mobility transition matrix resulted in an MBSMoM value of 0.0350, meaning that mobility was 3.5 percent away from FM assumptions mobility.

Long and Ferrie (2013)

Long and Ferrie (2013) used the Oxford Mobility Study (OMS), Occupational Change in a Generation Survey (OCGS), and Census data to evaluate absolute mobility in occupations in Britain and the US for fathers and sons. They evaluated 1,123 father/son pairs from the OMS in Britain and used four categories to measure occupations of fathers in 1949 and their sons in 1972. This mobility transition matrix resulted in an MBSMoM value of 0.2015, meaning that mobility was 20.15 percent away from the mobility under FM assumptions. Long and Ferrie (2013) evaluated 2,988 US father/son pairs from OCGS data using four categories to measure occupations of fathers in 1955 and their sons in 1973. This mobility transition matrix resulted in an MBSMoM value of 0.1493, meaning that mobility was 14.93 percent away from the mobility under FM assumptions.

Long and Ferrie (2013) evaluated 3,076 British father/son pairs from British Census data using four categories to measure occupations of fathers in 1851 and their sons in 1881. This mobility transition matrix resulted in an MBSMoM value of 0.3090, meaning that mobility was 30.9 percent away from the mobility under FM assumptions. Long and Ferrie (2013) evaluated 2,005 US father/son pairs from US Census data using four categories to measure occupations of fathers in 1850 and their sons in 1880. This mobility transition matrix resulted in an MBSMoM value of 0. 0.2161, meaning that mobility was 21.61 percent away from the mobility under FM assumptions. Long and Ferrie (2013) also evaluated 2,632 US father/son pairs from US Census data using four categories to measure occupations of fathers in 1860 and their sons in 1880. This mobility transition matrix resulted in an MBSMoM value of 0. 0.2222, meaning that mobility was 22.22 percent away from the mobility under FM assumptions. In addition, Long and Ferrie (2013) evaluated 2,499 US father/son pairs from US Census data using four categories to measure occupations of fathers in 1880 and their sons in 1900. This mobility transition matrix resulted in an MBSMoM value of 0. 0.2664, meaning that mobility was 26.64 percent away from the mobility under FM assumptions.

Goodman (1965; 1969)

Goodman (1965; 1969) evaluated absolute mobility in occupations in Britain and Denmark for fathers and sons. He evaluated 2,391 father/son pairs in Denmark and used three categories to measure intergenerational occupational mobility of fathers and their sons. This mobility transition matrix resulted in an MBSMoM value of 0.2720, meaning that mobility was 27.2 percent away from the mobility under FM assumptions. Goodman (1965; 1969) also evaluated 3,497 father/son pairs in Britain using three categories to measure intergenerational occupational mobility of fathers and their sons. This mobility transition matrix resulted in an MBSMoM value of 0.2371, meaning that mobility was 23.71 percent away from the mobility under FM assumptions. In addition, Goodman (1965; 1969) evaluated the same 3,497 father/son pairs in Britain using five categories to measure intergenerational occupational mobility of fathers and their sons. This mobility transition matrix resulted in an MBSMoM value of 0.1868, meaning that mobility was 18.68 percent away from the mobility under FM assumptions. Using the same data, the calculated MBSMoM with three categories is 1.27 times the value using five categories.

Pfeffer and Killewald (2015)

Pfeffer and Killewald (2015) used the PSID to evaluate relative intergenerational wealth mobility in the US for parents and their children. They evaluated 1,975 parent/child pairs in the US and used quintiles to measure intergenerational wealth mobility of parents in 1984 and their children in 2013. This mobility transition matrix resulted in an MBSMoM value of 0.1386, meaning that mobility was 13.86 percent away from the mobility under FM assumptions. Pfeffer and Killewald (2015) also evaluated 1,105 White parent/child pairs in the US and used three quantiles to measure intergenerational wealth mobility of parents in 1984 and their children in 2013. This mobility transition matrix resulted in an MBSMoM value of 0.2243, meaning that mobility was 22.43 percent away from the mobility under FM assumptions. In addition, Pfeffer and Killewald (2015) evaluated 799 Black parent/child pairs in the US and used three quantiles to measure intergenerational wealth mobility of parents in 1984 and their children in 2013. This mobility transition matrix resulted in an MBSMoM value of 0.0669, meaning that mobility was 6.69 percent away from the mobility under FM assumptions.

Pfeffer and Killewald (2015) also investigated home ownership as a proxy for wealth. They evaluated 1,428 White grandparent/grandchildren pairs in the US and used two categories to measure multigenerational home ownership mobility of grandparents in 1984 and their grandchildren in 2013. This mobility transition matrix resulted in an MBSMoM value of 0.0750, meaning that mobility was 7.5 percent away from the mobility under FM assumptions. Pfeffer and Killewald (2015) also evaluated 942 Black grandparent/grandchildren pairs in the US and used two categories to measure multigenerational home ownership mobility of grandparents in 1984 and their grandchildren in 2013. This mobility transition matrix resulted in an MBSMoM value of 0.0690, meaning that mobility was 6.9 percent away from the mobility under FM assumptions.

Mazumder (2014)

Mazumder (2014) used the SIPP and SSA data to evaluate relative intergenerational income mobility in the US for parents and sons. They evaluated 14,757 White parent/son pairs in the US and used quintiles to measure intergenerational income mobility of parents in 1986 and their sons in 2007. This mobility transition matrix resulted in an MBSMoM value of 0.0881, meaning that mobility was 8.81 percent away from the mobility under FM assumptions. Mazumder (2014) also evaluated 2,025 Black parent/son pairs in the US and used quintiles to measure intergenerational income mobility of parents in 1986 and their sons in 2007. This mobility transition matrix resulted in an MBSMoM value of 0.0860, meaning that mobility was 8.6 percent away from the mobility under FM assumptions.

Charles et. al. (2014)

Charles et. al. (2014) used the PSID to evaluate relative intergenerational expenditure mobility in the US for parents and children. They evaluated 3,000 parent/child pairs in the US and used quartiles to measure intergenerational expenditure mobility of parents and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1324, meaning that mobility was 13.24 percent away from the mobility under FM assumptions. Charles et. al. (2014) evaluated 3,000 parent/child pairs in the US and used quartiles to measure intergenerational income mobility of parents and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1633, meaning that mobility was 16.33 percent away from the mobility under FM assumptions.

Long (2013)

Long (2013) used Census data to evaluate absolute mobility in occupations in Britain for individual fathers and sons. They evaluated 12,516 father/son pairs in Britain and used five categories to measure occupations of fathers in 1851 and their sons in 1881. This mobility transition matrix resulted in an MBSMoM value of 0.2413, meaning that mobility was 24.13 percent away from the mobility under FM assumptions. Long (2013) also evaluated 4,071 father/son pairs in Britain and used five categories to measure occupations of fathers in 1881 and their sons in 1901. This mobility transition matrix resulted in an MBSMoM value of 0.2007, meaning that mobility was 20.07 percent away from the mobility under FM assumptions. In addition, Long (2013) evaluated 7,749 individuals in Britain and used five categories to measure intragenerational occupational mobility between 1851 and 1881. This mobility transition matrix resulted in an MBSMoM value of 0.3942, meaning that mobility was 39.42 percent away from the mobility under FM assumptions.

Long (2013) evaluated 12,516 father/son pairs in Britain and used nine categories to measure occupations of fathers in 1851 and their sons in 1881. This mobility transition matrix resulted in an MBSMoM value of 0.2369, meaning that mobility was 23.69 percent away from the mobility under FM assumptions. Long (2013) evaluated the same 12,516 father/son pairs in Britain using five categories to measure occupations of fathers in 1851 and their sons in 1881. This mobility transition matrix resulted in an MBSMoM value of 0.2615, meaning that mobility was 26.15 percent away from the mobility under FM assumptions. Using the same data, the calculated MBSMoM with five categories is 1.10 times the value using nine categories.

Long (2013) evaluated 2,483 father/son pairs using Marriage Registry data in Britain and five categories to measure occupations of fathers and their sons between 1859 and 1874. This mobility transition matrix resulted in an MBSMoM value of 0.4845, meaning that mobility was 48.45 percent away from the mobility under FM assumptions. Long (2013) also evaluated 4,153 married individuals in Britain using Census data and five categories to measure intragenerational occupational mobility between 1851 and 1881. This mobility transition matrix resulted in an MBSMoM value of 0.4077, meaning that mobility was 40.77 percent away from the mobility under FM assumptions. In addition, Long (2013) evaluated 2,716 father/son pairs from wage occupational class III using Census data in Britain and five categories to measure occupations of fathers in 1851 and their sons in 1881. This mobility transition matrix resulted in an MBSMoM value of 0.4024, meaning that mobility was 40.24 percent away from the mobility under FM assumptions. Finally, Long (2013) evaluated 3,460 father/son pairs using the OMS in Britain and five categories to measure occupations of fathers and their sons in 1972. This mobility transition matrix resulted in an MBSMoM value of 0.1390, so mobility was 13.9 percent away from the mobility under FM assumptions.

Auten et. al. (2013)

Auten et. al. (2013) used SOI, Tax, and SSA data to evaluate relative intragenerational income mobility in the US for individuals, parents, and children. They evaluated individuals using six quantiles to measure individual intragenerational income mobility between 1987 and 2007. This mobility transition matrix resulted in an MBSMoM value of 0.1735, meaning that mobility was 17.35 percent away from the mobility under FM assumptions. Auten et. al. (2013) also evaluated individuals using quintiles to measure individual intragenerational income mobility between 1987 and 2007. This mobility transition matrix resulted in an MBSMoM value of 0.1904, meaning that mobility was 19.04 percent away from the mobility under FM assumptions. Using the same data, the calculated MBSMoM with five categories is 1.10 times the value using six categories.

Auten et. al. (2013) evaluated parent/child pairs using six quantiles to measure intergenerational income mobility between parents in 1987 and their children in 2007. This mobility transition matrix resulted in an MBSMoM value of 0.0782, meaning that mobility was 7.82 percent away from the mobility under FM assumptions. Auten et. al. (2013) also evaluated parent/child pairs using quintiles to measure intergenerational income mobility between parents in 1987 and their children in 2007. This mobility transition matrix resulted in an MBSMoM value of 0.0741, meaning that mobility was 7.41 percent away from the mobility under FM assumptions. Using the same data, the calculated MBSMoM with six categories is 1.06 times the value using five categories.

Urahn et al. (2012)

Urahn et al. (2012) used the PSID to evaluate relative intergenerational income, earnings, and wealth mobility in the US for parents and children. They evaluated 2,736 parent/child pairs in the US and used quintiles to measure intergenerational income mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1344, meaning that mobility was 13.44 percent away from the mobility under FM assumptions. Urahn et al. (2012) also evaluated 1,014 father/son pairs in the US and used quintiles to measure intergenerational earnings mobility of fathers in 1968 and their sons in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1095, meaning that mobility was 10.95 percent away from the mobility under FM assumptions. In addition, Urahn et al. (2012) evaluated 2,277 parent/child pairs in the US and used quintiles to measure intergenerational wealth mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1615, meaning that mobility was 16.15 percent away from the mobility under FM assumptions.

Urahn et al. (2012) evaluated White parent/child pairs in the US and used quintiles to measure intergenerational income mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1140, meaning that mobility was 11.4 percent away from the mobility under FM assumptions. Urahn et al. (2012) also evaluated Black parent/child pairs in the US and used quintiles to measure intergenerational income mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.0703, meaning that mobility was 7.03 percent away from the mobility under FM assumptions. Urahn et al. (2012) evaluated White parent/child pairs in the US and used terciles to measure intergenerational wealth mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1015, meaning that mobility was 10.15 percent away from the mobility under FM assumptions. In addition, Urahn et al. (2012) evaluated Black parent/child pairs in the US and used terciles to measure intergenerational wealth mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.0267, meaning that mobility was 2.67 percent away from the mobility under FM assumptions.

Urahn et al. (2012) evaluated non-college-graduate parent/child pairs in the US and used terciles to measure intergenerational income mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1087, meaning that mobility was 10.87 percent away from the mobility under FM assumptions. Urahn et al. (2012) also evaluated college-graduate parent/child pairs in the US and used terciles to measure intergenerational income mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.0588, meaning that mobility was 5.88 percent away from the mobility under FM assumptions. Urahn et al. (2012) evaluated non-college-graduate parent/child pairs in the US and used terciles to measure intergenerational wealth mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1354, meaning that mobility was 13.54 percent away from the mobility under FM assumptions. In addition, Urahn et al. (2012) evaluated college-graduate parent/child pairs in the US and used terciles to measure intergenerational wealth mobility of parents in 1968 and their children in 2009. This mobility transition matrix resulted in an MBSMoM value of 0.1333, meaning that mobility was 13.33 percent away from the mobility under FM assumptions.

Eberharter (2013)

Eberharter (2013) used the GSEOP, the PSID, and the BHPS from the CNEF to evaluate relative intergenerational income mobility in Germany, the US, and Britain for parents and children. They evaluated 2,128 parent/child pairs in Germany and used quintiles to measure intergenerational income mobility of parents in 1988-1992 and their children in 2005-2009. This mobility transition matrix resulted in an MBSMoM value of 0.1174, meaning that mobility was 11.74 percent away from the mobility under FM assumptions. Eberharter (2013) also evaluated 2,585 parent/child pairs in the US and used quintiles to measure intergenerational income mobility of parents in 1987-1991 and their children in 2003-2007. This mobility transition matrix resulted in an MBSMoM value of 0.1438, meaning that mobility was 14.38 percent away from the mobility under FM assumptions. In addition, Eberharter (2013) evaluated 1,840 parent/child pairs in Britain and used quintiles to measure intergenerational income mobility of parents in 1991-1995 and their children in 2004-2008. This mobility transition matrix resulted in an MBSMoM value of 0.1529, meaning that mobility was 15.29 percent away from the mobility under FM assumptions.

Dardanoni et al. (2012)

Dardanoni et al. (2012) used the National Child Development Study (NCDS) to evaluate absolute mobility in occupations in Britain for fathers and sons. They evaluated 1,942 father/son pairs in Britain and used three categories to measure occupations of fathers in 1974 and their sons in 1991. This mobility transition matrix resulted in an MBSMoM value of 0.1987, meaning that mobility was 19.87 percent away from the mobility under FM assumptions. Dardanoni et al. (2012) also evaluated 1,104 father/son pairs in Britain and used three categories to measure wage level mobility of fathers in 1974 and their sons in 1991. This mobility transition matrix resulted in an MBSMoM value of 0.0802, meaning that mobility was 8.02 percent away from the mobility under FM assumptions.

Trends and Patterns of Mobility Generalized from the Values of the MBSMoM

With 92 mobility matrices in 22 different studies, the overall mean computed value for the MBSMoM using all the different mobility variables is 0.1714 (Standard Deviation = 0.1030), with a minimum of 0.0126 and a maximum of 0.5086. This indicates that overall mobility is approximately seventeen percent away from the mobility expected under FM assumptions.

When comparing the MBSMoMs of various countries, one finds some interesting differences. With 35 mobility matrices in 13 different studies, the mean computed value for the MBSMoM for the US is 0.1614 (Standard Deviation = 0.0847), with a minimum of 0.0126 and a maximum of 0.3839. This indicates that the US shows mobility that is 16.14 percent away from the mobility expected under FM assumptions. With 20 mobility matrices in 5 different studies, the mean computed value for the MBSMoM for the United Kingdom (UK) is 0.2407 (Standard Deviation = 0.1195), with a minimum of 0.0350 and a maximum of 0.4845. It is possible that the UK has less mobility than the US and is farther away from FM. With 12 mobility matrices in 2 different studies, the mean computed value for the MBSMoM for China is 0.1210 (Standard Deviation = 0.0571), with a minimum of 0.0565 and a maximum of 0.2239. This indicates that China shows more mobility as a percentage between outcomes under assumptions of FM and LM than the US. From 3 mobility matrices in one study, the mean computed value for the MBSMoM for India is 0.1448 (Standard Deviation = 0.0150), with a minimum of 0.1275 and a maximum of 0.1543. This indicates that India falls between China and the US when it comes to mobility as a percentage between FM and LM. Germany, on the other hand shows less mobility as a percentage between FM and LM than any of the other countries. With 3 mobility matrices in 2 different studies, the mean computed value for the MBSMoM for Germany is 0.3638 (Standard Deviation = 0.1747), with a minimum of 0.1698 and a maximum of 0.5086. Germany seems to exhibit less mobility than the US and UK.

Comparing the MBSMoMs of different measures of mobility like income, wealth, and occupation reveals differences between them. With 28 mobility matrices in 5 different studies, the mean computed value for the MBSMoM using occupation as the mobility variable is 0.2342 (Standard Deviation = 0.0919), with a minimum of 0.0801 and a maximum of 0.4845. This indicates that income mobility is approximately 23.42 percent away from the mobility expected under FM assumptions. With 36 mobility matrices in 20 different studies, the mean computed value for the MBSMoM using income as the mobility variable is 0.1613 (Standard Deviation = 0.1076), with a minimum of 0.0306 and a maximum of 0.5086. This indicates that income mobility is approximately 16.13 percent away from the mobility expected under FM assumptions. With 6 mobility matrices in 3 different studies, the mean computed value for the MBSMoM using wealth as the mobility variable is 0.1179 (Standard Deviation = 0.0727), with a minimum of 0.0126 and a maximum of 0.2243. This indicates that wealth mobility is approximately 11.79 percent away from the mobility expected under FM assumptions. The measure of wealth seems to show more mobility than income and income more than occupation.

Comparing the MBSMoMs using different sizes of mobility matrices shows differences. With 15 mobility matrices in 9 different studies, the mean computed value for the MBSMoM using income as the mobility variable in the US and Canada using five income partitions is 0.1610 (Standard Deviation = 0.1038), with a minimum of 0.0589 and a maximum of 0.3839. This indicates that income mobility in the US and Canada with five income partitions is 16.1 percent away from the mobility expected under FM assumptions. With 4 mobility matrices in 3 different studies, the mean computed value for the MBSMoM using income as the mobility variable in the US and Canada using ten income partitions is 0.0921 (Standard Deviation = 0.0509), with a minimum of 0.0306 and a maximum of 0.1444. This indicates that income mobility in the US and Canada with ten income partitions is 9.21 percent away from the mobility expected under FM assumptions. In addition, using the same studies to compare the five and ten income partitions shows a significant difference in the computed values of the MBSMoMs. With 4 mobility matrices in 3 different studies in the US and Canada, the mean computed value for the MBSMoM using income as the mobility variable and five income partitions is 0.1634 (Standard Deviation = 0.0920), with a minimum of 0.0589 and a maximum of 0.2580. With the same 4 mobility matrices in the same 3 studies, the mean computed value for the MBSMoM using income as the mobility variable and ten income partitions is only 0.0921 (Standard Deviation = 0.0509), with a minimum of 0.0306 and a maximum of 0.1444. Mobility seems to be greater when using more partitions, even when using the exact same data.

Comparing the MBSMoMs taken from studies evaluating the 19th and 20th centuries shows a difference in meritocracy-based mobility. With 23 mobility matrices in 4 different studies evaluating time periods during the 19th century, the mean computed value for the MBSMoM is 0.2510 (Standard Deviation = 0.1020), with a minimum of 0.0601 and a maximum of 0.4845. This indicates that mobility during the 19th century was 25.1 percent away from the mobility expected under FM assumptions. With 66 mobility matrices in 18 different studies evaluating time periods during the 20th century, the mean computed value for the MBSMoM is 0.1409 (Standard Deviation = 0.0889), with a minimum of 0.0126 and a maximum of 0.5086. This indicates that mobility during the 20th century was only 14.09 percent away from the mobility expected under

FM assumptions. Mobility seemed to be greater during the 20th century than the 19th century.

Comparing the MBSMoMs taken from studies evaluating intragenerational, intergenerational, and multigenerational data shows differences in meritocracy-based mobility. With 27 mobility matrices in 7 different studies evaluating intragenerational data, the mean computed value for the MBSMoM is 0.2070 (Standard Deviation = 0.1237), with a minimum of 0.0565 and a maximum of 0.5086. This indicates that intragenerational mobility was 20.7 percent away from the mobility expected under FM assumptions. With 58 mobility matrices in 16 different studies evaluating intergenerational data, the mean computed value for the MBSMoM is 0.1634 (Standard Deviation = 0.0918), with a minimum of 0.0126 and a maximum of 0.4845. This indicates that intergenerational mobility was 16.34 percent away from the mobility expected under FM assumptions. With 7 mobility matrices in 3 different studies evaluating multigenerational data, the mean computed value for the MBSMoM is 0.1006 (Standard Deviation = 0.0458), with a minimum of 0.0350 and a maximum of 0.1698. This indicates that multigenerational mobility was 10.06 percent away from the mobility expected under FM assumptions. Mobility seems to be higher when more generations are included.

V. DISCUSSION AND CONCLUSIONS

As mentioned earlier, the MBSMoM suffers from the same limitations as all summary measures using mobility matrices, except that it has a standalone interpretation based on its calculation being a percentage difference between outcomes based on assumptions of FM and LM. I calculated the MBSMoM values for 92 mobility matrices from 22 previous studies of mobility. Averaging the results of all 92 mobility matrices in 22 different studies, results in an overall mean computed value for the MBSMoM of 0.1714. This indicates that the average overall mobility of multiple countries, using multiple variables, over the last two centuries is approximately 17.14 percent away from the mobility expected under FM assumptions.

Dividing mobility matrices from the 22 previous studies into those evaluating different countries indicates, on average, that mobility, in order of highest to lowest, is China (MBSMoM = 0.1210), India (MBSMoM = 0.1448), United States (MBSMoM = 0.1614), United Kingdom (MBSMoM = 0.2407), and Germany (MBSMoM = 0.3638). Germany was farthest away (36.38%) from mobility expected under FM assumptions while China was the closest (12.1%) to mobility expected under FM assumptions. This indicates that mobility may be quite different by country and may be unrelated to the country level of standard of living. Mobility may be related to structural opportunity, degree of inequality, and/or government policies.

Separating mobility matrices from the 22 previous studies into those evaluating occupation, income, and wealth indicates, on average, that mobility using occupation (MBSMoM = 0.2342) is farther away from mobility expected under FM assumptions than mobility using income (MBSMoM = 0.1613). In addition, mobility using income (MBSMoM = 0.1613) is farther away from mobility expected under FM assumptions than mobility using wealth (MBSMoM = 0.1179). This indicates that mobility studies tend to show less mobility using occupation as the study variable than income. In addition, these mobility studies tend to show less mobility using income as the study variable than wealth. Wealth as a study variable tends to result in lower values of MBSMoM than income, and income lower values than occupation, which indicates that the study variable may influence the mobility measured.

Using 15 mobility matrices from the same 9 studies using income as the mobility variable indicates that income mobility with five income partitions is 16.10 percent away from the mobility expected under FM assumptions while the results of 4 mobility matrices from 3 studies using ten income partitions results in income mobility being only 9.21 percent away from the mobility expected under FM assumptions. Using the same 4 mobility matrices from the same 3 studies using income as the mobility variable indicates that income mobility with five income partitions is 16.34 percent away from the mobility expected under FM assumptions while using ten income partitions results in income mobility being only 9.21 percent away from the mobility expected under FM assumptions. The only difference is the number of income partitions, showing that mobility tends to be closer to that expected under assumptions of FM with more partitions.

Separating mobility matrices between the 19^{th} and 20^{th} centuries for these studies indicates, on average, that mobility during the 19^{th} century was 25.1 percent away from the mobility expected under FM assumptions while during the 20^{th} century mobility was only 14.09 percent away from the mobility expected under FM assumptions. Based on this result, it seems that mobility may have moved closer to that expected under assumptions of FM over time.

Separating mobility matrices from the 22 previous studies into those evaluating intragenerational, intergenerational, and multigenerational variables indicates, on average, that mobility using intragenerational variables (MBSMoM = 0.2070) is farther away from mobility expected under FM assumptions than mobility using intergenerational variables (MBSMoM = 0.1634). In addition, mobility using intergenerational variables (MBSMoM = 0.1634) is farther away from mobility expected under FM assumptions than mobility using multigenerational variables (MBSMoM = 0.1006). This indicates that mobility studies tend to show less mobility using intragenerational variables than intergenerational. In addition, these mobility studies tend to show less mobility using intergenerational variables than multigenerational. This is consistent with previous studies and common sense that mobility increases with the number of generations included.

I developed two different SMoMs and an MBSMoM using FM and LM assumptions. Until now, no one has computed a stickiness meritocracy-based measure of mobility using mobility transition matrices calculated as a percentage between outcomes based on FM and LM assumptions. In addition to conveying the percentage between outcomes expected under FM and LM assumptions, the MBSMoM may be used to make comparisons of population subsets, across time and space, and by identity (race, ethnicity, nationality, gender, sexuality, religion, ability, age, etc.). We may compare mobility over time and across geographic boundaries, drawing conclusions about meritocratic differences. The MBSMoM may help further our understanding of the roles of race, ethnicity, gender, sexuality, ability, age, etc. on intragenerational, intergenerational, and multigenerational correlations of class, education, occupation, consumption, income, and wealth in addition to comparisons between different identities over time and geography. The MBSMoM more fully describes the differences in outcomes attributable to these identities. In addition, it may help us better understand the need for interactional variables between the channels of class, occupation, consumption, income, and wealth transmission, such as gifts and bequests, education, marriage, homeownership, and business ownership.

Future Research

There is still a need of much future research in studies of mobility. Keister (2014) identified two important gaps in the income and wealth inequality research. There has been less emphasis on explaining wealth inequality than income inequality and there is little knowledge about the demographics and life course effects on income and wealth. Pfeffer and Killewald (2018) also identified opportunities for future research, including earlier investments made on behalf of children, sources of disparities between Whites and blacks, family size adjustments, home values as asset proxy, neighborhood effects, differences among other minority groups, reverse transfers, causality, and life-cycle effects. Just as Pfeffer and Killewald (2019) found significant disparities in mobility between Whites and Blacks, racial differences in mobility have persisted throughout history whether measured by earnings gap or rank gap (Bayer and Charles, 2018; Pfeffer & Killewald, 2019). There is still “deep-seated and systematic differences in economic outcomes along lines of gender, ethnicity, social class and geographic location” (Allen, 2011, p. 367). While there has been some research regarding the differences between Whites and Blacks regarding intragenerational, intergenerational, and multigenerational mobility, larger samples are needed in order to compare outcomes among various races, ethnicities, genders, sexualities, abilities, ages, etc. (Allen, 2011; Pfeffer and Killewald, 2018). For example, “estimates…by race can provide insight on whether racial differences in the US are likely to be eliminated and, if so, how long it might take" and might "shed light on the mechanisms behind the relatively high degree of intergenerational persistence of inequality in the United States" (Mazumder, 2014, p. 1).

Social mobility research has included intragenerational, intergenerational, and multigenerational transmission of status. Since individuals may continue improving their abilities and climb the social class ladder throughout their lives, combining intergenerational and intragenerational mobility into one theory makes sense for future research (Charles et al., 2013; Cheng & Song, 2019; Saunders, 2010). We may be able to combine intergenerational and intragenerational mobility by creating and comparing different intragenerational mobility transition matrices for those who come from different initial parent categories or quantiles, showing the different paths of mobility from parent to child and across the children's lives. (Burkhauser & Couch, 2008).

It seems that most, if not all, mobility studies have made the same assumption that mobility is randomly and evenly distributed among the population. Future studies may relax this assumption, especially with linked data, to verify who is actually mobile. It may be that the same individuals or households are moving up and down across multiple periods. Intergenerational income and wealth effects research may also concentrate on explaining their transference from parents through inheritance of personal and family traits, various networks, education, and other forms of capital. What may be more important is to concentrate on intergenerational well-being, life-course welfare, equality of opportunity, or real outcomes rather than focusing on relative inequality. There may be several alternative ways to measure class, occupation, income, and wealth mobility, which should be investigated. There is a need to determine the most appropriate time lags for measuring mobility, take account of non-linearities, and the impact of structural systems such as politics, welfare, and cultural values on measuring mobility. No matter the direction taken in future research, an MBSMoM over time and between groups is needed so comparisons of intragenerational, intergenerational, and multigenerational transmission of class, education, occupation, consumption, income, and wealth may have meaning. Not only does an MBSMoM have meaning in comparison between geography and time (like other measures), they also have stand-alone meaning as a measure at a single place and time. They measure the percent distance between optimal mobility (under assumptions of FM) and complete immobility (under assumptions of LM) (Fields, 2010).

REFERENCES

Adermon, A., Lindahl, M., & Waldenström, D. (2018). Intergenerational Wealth Mobility and the Role of Inheritance: Evidence from Multiple Generations. *Economic Journal*, *128*(612), F482-F513.

Allen, A. (2011). Michael Young's The Rise of the Meritocracy: A Philosophical Critique. *British Journal of Educational Studies*, 59(4), 367–382.

Altham, P. M. (1970). The Measurement of Association of Rows and Columns for an r x s Contingency Table. *Journal of the Royal Statistical Society*, 32(1), 63-73.

Altham, P. M. E. & Ferrie, J. P. (2007). Comparing Contingency Tables. *Historical Methods*, 40(1), 3-16.

Arrow, K. J., Bowles, S., & Durlauf, S. N. (2000). *Meritocracy and Economic Inequality*. Princeton, NJ: Princeton University Press.

Atkinson, A. B. and Bourguignon, F. (1982). The Comparison of Multi-Dimensioned Distributions of Economic Status. *Review of Economic Studies*, XLIX, 183-201.

Auten, G., Gee, G., & Turner, N. (2013). Income Inequality, Mobility, and Turnover at the Top in the US, 1987-2010. *American Economic Review: Papers & Proceedings*, 103(3), 168-172.

Bartholomew, D. J. (1982). *Stochastic Models for Social Processes* (3rd ed). London: Wiley.

Bayer, P. & Charles, K. K. (2018). Divergent Paths: A New Perspective on Earnings Differences Between Black and White Men Since 1940. *Quarterly Journal of Economics*. 1459-1501.

Becker, G. S., Murphy, K. M., Kominers, S. D., & Spenkuch, J. L. (2018). A Theory of Intergenerational Mobility. *Journal of Political Economy*, 126 (S1), S7–S25.

Benabou, R. & Ok, E. A. (2001). Mobility as Progressivity: Ranking Income Processes According to Equality of Opportunity. *NBER Working Paper Series*. Working Paper 8431.

Benabou, R. (2000). Meritocracy, Redistribution, and the Size of the Pie. In K. Arrow, S. Bowles, & S. Durlauf (Eds.), *Meritocracy and Economic Inequality* (pp. 317–339). Princeton, NJ: Princeton University Press.

Bloom, M. (2011). The Meritocracy Myth. Retrieved from https://wellbeing.nd.edu/assets/169463/meritocracy_myth.pdf

Bond, B., Brown, J. D., Luque, A., & O'hara, A. (2014). The Nature of the Bias When Studying Only Linkable Person Records: Evidence from the American Community Survey. *CARRA Working Paper Series*. Working Paper #2014-08.

Bradbury, K. (2011). Trends in U.S. Family Income Mobility, 1969-2006. *Federal Reserve Bank of Boston Working Papers*. Working Paper No. 11-10.

Brunori, P., Ferreira, F. H. G., & Peragine, V. (2013). Inequality of Opportunity, Income Inequality and Economic Mobility. *World Bank Policy Research Working Paper 6304*.

Burkhauser, R. V., & Couch, K. A. (2009). Intragenerational Inequality and Intertemporal Mobility. In W.Salverda, , B.Nolan, , & T. M.Smeeding (eds.), *The*

Oxford handbook of economic inequality (pp. 522-545). Oxford: Oxford University Press.

Celarent, B. (2009). The Rise of the Meritocracy, 1870-2033. *American Journal of Sociology*, 115(1), 322.

Chakravarty, S. R., Dutta, B., & Weymark, J. A. (1985). Ethical Indices of Income Mobility. *Social Choice and Welfare*, 2(1), 1-21.

Charles, K. K., Hurst, E., & Killewald, A. (2013). Marital Sorting and Parental Wealth. *Demography*, 50(1), 51-70.

Charles, K. K., Danziger, S., Li, G., & Schoeni, R. (2014). The Intergenerational Correlation of Consumption Expenditures. *American Economic Review: Papers & Proceedings*, 104(5), 136-140.

Charles, K. K., & Hurst, E. (2003). The Correlation of Wealth across Generations. *Journal of Political Economy*, (6), 1155-1182.

Charron, N., Dahlström, C., & Lapuente, V. (2016). Measuring Meritocracy in the Public Sector in Europe: A New National and Sub-National Indicator. *European Journal on Criminal Policy & Research*, 22(3), 499–523.

Chen, Y., & Cowell, F. A. (2017). Mobility in China. *Review of Income & Wealth*, 63(2), 203–218.

Cheng, S. & Song, X., (2019). Linked Lives, Linked Trajectories: Intergenerational Association of Intragenerational Income Mobility. *American Sociological Review*, 84(6), 1037-1068.

Chetty, R., Hendren, N., Kline, P., Saez, E., & Turner, N. (2014). Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility. *The American Economic Review*, (5), 141-147.

Clark, G. (2013). What is the True Rate of Social Mobility? Evidence from the Information Content of Surnames. Retrieved from https://pdfs.semanticscholar.org/7a10/72d491feee204dac612c634f72636e80c1a9.pdf?_ga=2.197587183.171663119.1588635080-2006937851.1579704800

Corak, M., & Heisz, A. (1999). The Intergenerational Earnings and Income Mobility of Canadian Men: Evidence from Longitudinal Income Tax Data. *Journal of Human Resources*, 34(3), 504–533.

Corak M. (ed.). (2004). Generational Income Mobility in North America and Europe. Cambridge, New York, and Melbourne: Cambridge University Press.

Cowell, F. A. & Flachaire, E. (2017). *Measuring Mobility*.

Damazer, M. (2019). Why We Get Our Unjust Deserts. *New Statesman*, 148(5487), 42–44.

Dardanoni V., Fiorini, M., & Forcina, A. (2008). Stochastic Monotonicity in Intergenerational Mobility Tables. *Working Paper Series 156, Finance Discipline Group, UTS Business School, University of Technology, Sydney*.

Dardanoni, V., Fiorini, M., & Forcina, A. (2012). Stochastic Monotonicity in Intergenerational Mobility Tables. *Journal of Applied Econometrics*, 27(1), 85–107.

Eberharter, V. V. (2013). The Intergenerational Dynamics of Social Inequality: Empirical Evidence from Europe and the United States. *SOEP papers on Multidisciplinary Panel Data Research*, No. 588.

Edwards, A. W. F. (1963). The Measure of Association in a 2 x 2 Table. *Journal of the Royal Statistical Society*, 126, 109-114.

Featherman, D. L., & Hauser, R. M. (1976). Changes in the Socioeconomic Stratification of the Races, 1962-73. *American Journal of Sociology*, 82(3), 621–651.

Ferreira, F. H. G. & Gignoux, J. (2011). The Measurement of Inequality of Opportunity: Theory and An Application to Latin America. *Review of Income and Wealth*, 1-36.

Fields, G. S. (2010). Does Income Mobility Equalize Longer-Term Incomes? New Measures of an Old Concept. *Journal of Economic Inequality*, 8, 409-427.

Fields, G. S. & Ok, E. A. (1996). The Meaning and Measurement of Income Mobility. *Journal of Economic Theory*, 71, 349-377.

Fields, G. & Ok, E. (1999a). The Measurement of Income Mobility: An Introduction to the Literature. In J. Silber (Ed.), *Handbook on Income Inequality Measurement* (pp. 557-596). Norwell, MA: Kluwer Academic Publishers.

Fields, G. S. & Ok, E. A. (1999b). Measuring Movement of Incomes. *Economica*, 66, 455-471.

Formby, J. P., Smith, W. J., & Zheng, B. (2004). Mobility Measurement, Transition Matrices and Statistical Inference. *Journal of Econometrics*, 120, 181-205.

Glass, D. V. (1954). *Social Mobility in Britain*. London: Routledge & Kegan Paul Ltd.

Good, I. J. (1965). The Estimation of Probabilities: An Essay on Modern Bayesian Methods. *Research Monographs No. 30*. Cambridge: MIT Press.

Goode, C., & Keefer, L. A. (2016). Meritocracy Scale. *PsycTESTS*.

Goodman, L. A. (1965). On the Statistical Analysis of Mobility Tables. *The American Journal of Sociology*, 70, 564-585.

Goodman, L. A. (1969). On the Measurement of Social Mobility: An Index of Status Persistence. *American Sociological Review,* 34(6), 831-850.

Gündemir, S., Homan, A. C., Usova, A., & Galinsky, A. D. (2017). Multicultural Meritocracy: The Synergistic Benefits of Valuing Diversity and Merit. *Journal of Experimental Social Psychology*, 73, 34–41.

Hällsten, M. (2014). Inequality Across Three and Four Generations in Egalitarian Sweden: 1st and 2nd Cousin Correlations in Socio-economic Outcomes. *Research in Social Stratification and Mobility,* 35 (Inequality Across Multiple Generations), 19-33.

Herrnstein, R. J., & Murray, C. (1994). *The Bell Curve: Intelligence and Class Structure in American Life*. New York: The Free Press.

Hill, N. (2003). *Law of Success: The 21st-Century Edition*. Los Angeles: Highroads Media.

Horst, P. (1963). *Matrix Algebra for Social Scientists*. New York: Holt, Rinehart and Winston.

Hout, M. (1983). *Mobility Tables*. Beverly Hills: Sage Publications.

Hurst, E., Luoh, M. C., & Stafford, F. P. (1998). The Wealth Dynamics of American Familites, 1984-94. *Brookings Papers on Economic Activity,* 1998(1).

Jäntti, M., & Jenkins, S. P. (2013). Income Mobility. *The Institute for the Study of Labor Discussion Paper No. 7730*.

Johnson, A. G. (2000). *The Blackwell Dictionary of Sociology: A User's Guide to Sociological Language*. Malden, MA: Blackwell Publishers.

Keister, L. A. (2014). The One Percent. *Annual Review of Sociology*, 40, 347-67.

Killewald, A., Pfeffer, F. T., & Schachner, J. N. (2017). Wealth Inequality and Accumulation. *Annual Review of Sociology*, 43, 379–404.

Kim, C., & Tamborini, C. R. (2012) Do Survey Data Estimate Earnings Inequality Correctly? Measurement Errors Among Black and White Male Workers. *Social Forces*, 90 (4), 1157-1181.

King, M. A. (1983). An Index of Inequality: With Applications to Horizontal Equity and Social Mobility. *Econometrica*, 51(1), 99-115.

Lee, C. & Solon, G. (2009). Trends in Intergenerational Income Moblity. *Review of Economics and Statistics*, 91(4), 766-772.

Lefranc, A., Pistolesi, N., & Trannoy, A. (2006). Inequality of Oportunities Vs. Inequality of Outcomes: Are Western Societies All Alike? *ECINEQ*, 2006-54.

Littler, J. (2017). Meritocracy: The Great Delusion that Ingrains Inequality. *The Guardian*, March 20, 2017. Retrieved from https://www.theguardian.com/commentisfree/2017/mar/20/meritocracy-inequality-theresa-may-donald-trump

Littler, J. (2018). Narratives and Values: Young and old meritocracy: from radical critique to neoliberal tool. *Renewal*, 26(1), 40–51.

Long, J. (2013). The Surprising Social Mobility of Victorian Britain. *European Review of Economic History*, 17(1), 1-23.

Long, J. & Ferrie, J. (2018). Grandfathers Matter(ed): Occupational Mobility Across Three Generations in the US and Britain, 1850-1911. *Economic Journal*, 128(July), F422-F445.

Long, J. & Ferrie, J. P. (2013). Intergenerational Occupational Mobility in Britain and the U.S. since 1850. *American Economic Review*, 103(4), 1109-1137.

Lundberg, I., & Stewart, B. (2020). Comment: Summarizing Income Mobility with Multiple Smooth Quantiles Instead of Parameterized Means. Retrieved from https://scholar.princeton.edu/sites/default/files/bstewart/files/lundbergstewart_commenton_mitnikgrusky.pdf

Mazumder, B. (2014). Black-White Differences in Intergenerational Economic Mobility in the United States. *Federal Reserve Bank of Chicago Economic Perspectives*, 1Q, 1-18.

Mazumder, B. (2005). The Apple Falls Even Closer to the Tree than We Thought: New and Revised Estimates of the Intergenerational Inheritance of Earnings. In S. Bowles, H. Gintis, & M. O. Groves (Eds.), *Unequal chances: Family background and economic success* (pp. 80–99). Princeton, NJ: Princeton University Press.

McNamee, S. J., & Miller, R. K. (2014). *The Meritocracy Myth*. Lanham, MD: Rowman & Littlefield.

Mishra, A. K. (2018). Household Income Inequality and Income Mobility: Implications Towards Equalizing Longer-Term Incomes in India. *International Economic Journal*, 32(2), 271-290.

Mitnik, P. A., Bryant, V., & Weber, M. (2019). The Intergenerational Transmission of Family-Income Advantages in the United States. *Sociological Science*, 6, 380-415.

Murray, C. (2012). *Coming Apart: The State of White America 1960-2010*. New York: Crown Forum.

Nahai, R. N. (2013). Is meritocracy fair? A qualitative case study of admissions at the University of Oxford. *Oxford Review of Education*, 39(5), 681–701.

Neidhöfer, G. & Stockhausen, M., (2019). Dynastic Inequality Compared: Multigenerational Mobility in the United States, the United Kingdom, and Germany. *Review of Income and Wealth*, 65(2), 383-414.

Nettles, D. (2003). Intelligence and Class Mobility in the British Population. *British Journal of Psychology*, 94, 551-61.

Nybom, M., & Stuhler, J. (2019). Steady-State Assumptions in Intergenerational Mobility Research. *The Journal of Economic Inequality*, 17, 77-97.

Pfeffer, F. T. (2014). Multigenerational Approaches to Social Mobility: A Multifaceted Research Agenda. *Research in Social Stratification and Mobility*, 35, 1–12.

Pfeffer, F. T., & Killewald, A. (2019). Intergenerational Wealth Mobility and Racial Inequality. *Socius: Sociological Research for a Dynamic World*, 5. 1-2.

Pfeffer, F. T., & Killewald, A. (2018). Generations of Advantage: Multigenerational Correlations in Family Wealth. *Social Forces*, 96(4), 1411-1441.

Pfeffer, F. T., & Killewald, A. (2015). How Rigid is the Wealth Structure and Why? Inter- and Multi-generational Associations in Family Wealth. *Populations Studies Center Research Report* 15-845.

Phillips, P. C. B. (2016). Meritocracy Voting: Measuring the Unmeasurable. *Econometric Reviews*, 35(1), 2–40.

Prais, S. J. (1955). Measuring Social Mobility. *Journal of the Royal Statistical Society*, Series A (General), 118(1), 56-66.

Rao, C. R. & Rao, M. B. (1998). *Matrix Algebra and Its Applications to Statistics and Econometrics*. New Jersey: World Scientific.

Roemer J. E. & Trannoy, A. (2016). Equality of Opportunity: Theory and Measurement. *Journal of Economic Literature*, 54(4), 1288-1332.

Ryan, A. (2002). Does Inequality Matter—For its Own Sake? In E. Paul, F. Miller, & J. Paul (Eds.), *Should Differences in Income and Wealth Matter?* (pp. 225–243). Cambridge; New York: Cambridge University Press.

Saunders, P. (1996). *Unequal But Fair? A Study of Class Barriers in Britain*. London: Institute of Economic Affairs, Health & Welfare Unit.

Saunders, P. (2002). Reflections on the Meritocracy Debate in Britain: A Response to Richard Breen & John Goldthorpe. *British Journal of Sociology*, 53(4), 559-574.

Saunders, P. (2010). *Social Mobility Myths*. London: Civitas: Institute for the Study of Civil Society.

Schiller, B. R. (1977). Relative Earnings Mobility in the US. *American Economic Review*, 67, 926-941.

Scott, C. D. & Litchfield, J. A. (1994). Inequality, Mobility and the Determinants of Income Among the Rural Poor in Chile, 1968-1986. *Discussion Paper 53, Development Economics Research Programme, London School of Economics*.

Sen, A. (2000). Merit and Justice. In K. Arrow, S. Bowles, & S. Durlauf (Eds.), *Meritocracy and Economic Inequality* (pp. 5–16). Princeton, NJ: Princeton University Press.

Shea, J. (2000). Does Parents' Money Matter? *Journal of Public Economics*, 77, 155-184.

Shorrocks, A. F. (1978). The Measurement of Mobility. *Econometrica*, 46(5), 1013-1024.

Smeeding, T. M. (2018). The PSID in Research and Policy. *Annals of the American Academy of Political & Social Science*, 680(1), 29–47.

Soares, J. A. (2017). Meritocracy Dismissed. *Ethnic & Racial Studies*, 40(13), 2300–2307.

Solon, G. (2017). Intergenerational Transmission of Income Inequality: What Do We Know? *Focus*, 33(2), 3-5.

Solon, G. (2018). What Do We Know So Far About Multigenerational Mobility? *The Economic Journal*, 128(July), F340-F352.

Solt, F., Hu, Y., Hudson, K., Song, J., & Yu, D. E. (2016). Economic Inequality and Belief in Meritocracy in the United States. *Research & Politics*, 3, 1-7.

Song, X., Massey, C. G., Rolf, K. A., Ferrie, J. P. Roghbaum, J. L., & Xie, Y. (2020). Long-Term Decline in Intergenerational Mobility in the United States Since the 1850s. *PNAS*, 117(1), 251-258.

Stokey, N. L. (1996). *Shirtsleeves to Shirtsleeves: The Economics of Social Mobility*. Nancy L. Schwartz Lecture. University of Chicago. Retrieved from http://home.uchicago.edu/~nstokey/papers/im22.pdf

Torche, F. (2015). Analyses of Intergenerational Mobility: An Interdisciplinary Review. *Annals of the American Academy of Political and Social Science*, 657, 37–62.

Trede, M. (1998). Making Mobility Visible: A Graphical Device. *Economics Letters*, 59, 77-82.

Urahn, S. K., Currier, E., Elliott, D., Wechsler, L., Wilson, D., & Colbert, D. (2012). *Pursuing the American Dream: Economic Mobility Across Generations*. Washington D.C: Pew Charitable Trusts.

VannPashak, J. (2019). Measuring Meritocracy: The Simple Version. *Medium*, September 9, 2019. Retrieved from https://medium.com/@jvannpashak/measuring-meritocracy-c1ce2ec42feb

Voegeli, W. (2019). Meritocracy and its Discontents. *National Review*, 71(19), 46-48.

Walton, G. M., Spencer, S. J., & Erman, S. (2013). Affirmative Meritocracy. *Social Issues & Policy Review*, 7(1), 1–35.

Warikoo, N. (2017). A research Agenda on Race and Meritocracy. *Ethnic & Racial Studies*, 40(13), 2308–2315.

Young, M. (1958). *The Rise of the Meritocracy, 1870-2033*. London: Thames and Hudson.

Young, M. (1994a). Looking Back on Meritocracy. *Political Quarterly*, 77(S1), 73–77.

Young, M. (1994b). Meritocracy Revisited, *Society*, 31(6), 87.

Young T. (2015). The Fall of the Meritocracy, *Quadrant Magazine*, 59(9), 9–17.

APPENDIX

Table 1. Mobility Transition Matrices

(a) Mobility Transition Matrix (%) for LM

Parental Wealth Quintile	Child's Wealth Quintile				
	1	2	3	4	5
	Lowest	Quintile 2	Quintile 3	Quintile 4	Highest
Lowest	100.0	0.0	0.0	0.0	0.0
Quintile 2	0.0	100.0	0.0	0.0	0.0
Quintile 3	0.0	0.0	100.0	0.0	0.0
Quintile 4	0.0	0.0	0.0	100.0	0.0
Highest	0.0	0.0	0.0	0.0	100.0

(b) Mobility transition matrix (%) for FM

Parental Wealth Quintile	Child's Wealth Quintile				
	1	2	3	4	5
	Lowest	Quintile 2	Quintile 3	Quintile 4	Highest
Lowest	20.0	20.0	20.0	20.0	20.0
Quintile 2	20.0	20.0	20.0	20.0	20.0
Quintile 3	20.0	20.0	20.0	20.0	20.0
Quintile 4	20.0	20.0	20.0	20.0	20.0
Highest	20.0	20.0	20.0	20.0	20.0

(c) Wealth Mobility transition matrix (%) from Charles and Hurst (2003)

Parental Wealth Quintile	Child's Wealth Quintile				
	1	2	3	4	5
	Lowest	Quintile 2	Quintile 3	Quintile 4	Highest
Lowest	36.0	29.0	16.0	12.0	7.0
Quintile 2	26.0	24.0	24.0	15.0	12.0
Quintile 3	16.0	21.0	25.0	24.0	15.0
Quintile 4	15.0	13.0	20.0	26.0	26.0
Highest	11.0	16.0	14.0	24.0	36.0

Table 2. Studies of Mobility Transition Matrices

Study	Database	Sample Description	Sample Size	Measure	Location	Quan n	Origin Time Period	Destination Time Period	Gen Span	MBSMoM Value
Charles and Hurst (2003)	PSID		1,491	Wealth	USA	5	1984-1989	1999	2	0.1154
Charles and Hurst (2003)	PSID		1,491	Wealth	USA	5	1984-1989	1999	2	0.0126
Pfeffer and Killewald (2018)	PSID		2,001	Wealth	USA	5	1984	2013	2	0.1494
Jäntti and Jenkins (2013)	PSID		N/R	Income	USA	10	1979	1988	1	0.1213
Jäntti and Jenkins (2013)	PSID		N/R	Income	USA	5	1979	1988	1	0.2206
Jäntti and Jenkins (2013)	PSID		N/R	Income	USA	10	1989	1998	1	0.1444
Jäntti and Jenkins (2013)	PSID		N/R	Income	USA	5	1989	1998	1	0.2580
Mazumder (2005)	SIPP/SSA		N/R	Income	USA	10	1985	1998	2	0.0721
Mazumder (2005)	SIPP/SSA		N/R	Income	USA	5	1985	1998	2	0.1160
Mazumder (2005)	SIPP/SSA		N/R	Income	USA	4	1985	1998	2	0.1196
Corak and Heisz (1999)	Tax		N/R	Income	Canada	10	1982	1995	2	0.0306
Corak and Heisz (1999)	Tax		N/R	Income	Canada	5	1982	1995	2	0.0589
Cowell (2017)	CHNS		N/R	Income	China	5	1989	2000	1	0.0789
Cowell (2017)	CHNS		N/R	Income	China	5	2000	2011	1	0.1127
Chen and Cowell (2017)	CHNS		2,843	Income	China	5	1989	2000	1	0.0789
Chen and Cowell (2017)	CHNS		2,600	Income	China	5	2000	2011	1	0.1127
Chen and Cowell (2017)	CHNS		N/R	Income	China-Rural	5	1989	2000	1	0.0565
Chen and Cowell (2017)	CHNS		N/R	Income	China-Rural	5	2000	2011	1	0.0834
Chen and Cowell (2017)	CHNS		N/R	Income	China-Urban	5	1989	2000	1	0.0938
Chen and Cowell (2017)	CHNS		N/R	Income	China-Urban	5	2000	2011	1	0.1613
Chen and Cowell (2017)	CHNS		3,600	Income	China	5	1989	1991	1	0.1882
Chen and Cowell (2017)	CHNS		3,358	Income	China	5	1991	1993	1	0.1768
Chen and Cowell (2017)	CHNS		3,400	Income	China	5	2004	2006	1	0.2061
Chen and Cowell (2017)	CHNS		3,442	Income	China	5	2009	2011	1	0.2239
Formby et. al. (2004)	PSID		5,000	Earnings	USA	5	1985	1990	1	0.3670
Formby et. al. (2004)	GSOEP		6,000	Earnings	Germany	5	1985	1990	1	0.4131
Formby et. al. (2004)	PSID		5,000	Earnings	USA	5	1985	1990	1	0.3839
Formby et. al. (2004)	GSOEP		6,000	Earnings	Germany	5	1985	1990	1	0.5086
Mishra (2018)	IHDS		40,018	Income	All India	5	2005	2012	1	0.1543
Mishra (2018)	IHDS		N/R	Income	Rural India	5	2005	2012	1	0.1275
Mishra (2018)	IHDS		N/R	Income	Urban India	5	2005	2012	1	0.1525
Long & Ferrie (2018)	Census		4,943	Occupation	Britain	4	1851	1881	2	0.3204
Long & Ferrie (2018)	Census		4,887	Occupation	Britain	4	1881	1911	2	0.2424
Long & Ferrie (2018)	Census		4,002	Occupation	Britain	4	1851	1911	3	0.1113
Long & Ferrie (2018)	Census		43,701	Occupation	USA	4	1850	1880	2	0.2418
Long & Ferrie (2018)	Census		43,701	Occupation	USA	4	1880	1910	2	0.2776
Long & Ferrie (2018)	Census		43,701	Occupation	USA	4	1850	1910	3	0.1421
Long & Ferrie (2018)	Census		1,983	Occupation	Britain	4	1881	1911	2	0.2227
Long & Ferrie (2018)	Census		1,043	Occupation	Britain	4	1881	1911	2	0.0601
Long & Ferrie (2018)	Census		948	Occupation	Britain	4	1881	1911	2	0.1198
Altham & Ferrie (2007)	Census		8,999	Occupation	USA	4	1850	1880	2	0.2045
Altham & Ferrie (2007)	Census		17,733	Occupation	USA	4	1880	1910	2	0.1875
Neidhöfer & Stockhausen (2019)	GSEOP/CNEF		1,890	Education	Germany	3	Parent/Grand	1960-1985	3	0.1698
Neidhöfer & Stockhausen (2019)	PSID/CNEF		5,554	Education	USA	3	Parent/Grand	1960-1985	3	0.1020
Neidhöfer & Stockhausen (2019)	BHPS/CNEF		1,392	Education	UK	3	Parent/Grand	1960-1985	3	0.0350
Long & Ferrie (2013)	OMS		1,123	Occupation	Britain	4	1949	1972	2	0.2015
Long & Ferrie (2013)	OCGS		2,988	Occupation	USA	4	1955	1973	2	0.1493
Long & Ferrie (2013)	Census		3,076	Occupation	Britain	4	1851	1881	2	0.3090
Long & Ferrie (2013)	Census		2,005	Occupation	USA	4	1850	1880	2	0.2161
Long & Ferrie (2013)	Census		2,632	Occupation	USA	4	1860	1880	2	0.2222
Long & Ferrie (2013)	Census		2,499	Occupation	USA	4	1880	1900	2	0.2664
Goodman (1965, 1969)	N/R		3,497	Occupation	Britain	3	N/R	N/R	2	0.2371
Goodman (1965, 1969)	N/R		2,391	Occupation	Denmark	3	N/R	N/R	2	0.2720
Goodman (1965, 1969)	N/R		3,497	Occupation	Britain	5	N/R	N/R	2	0.1868
Pfeffer & Killewald (2015)	PSID	Population	1,975	Wealth	USA	5	1984	2013	2	0.1386
Pfeffer & Killewald (2015)	PSID	White	1,105	Wealth	USA	3	1984	2013	2	0.2243
Pfeffer & Killewald (2015)	PSID	Black	799	Wealth	USA	3	1984	2013	2	0.0669
Pfeffer & Killewald (2015)	PSID	White	1,428	Home Own	USA	2	1984	2013	3	0.0750
Pfeffer & Killewald (2015)	PSID	Black	942	Home Own	USA	2	1984	2013	3	0.0690
Mazumder (2014)	SIPP/SSA	White	14,757	Income	USA	5	1986	2007	2	0.0881
Mazumder (2014)	SIPP/SSA	Black	2,025	Income	USA	5	1986	2007	2	0.0860
Charles, et. al. (2014)	PSID		3,000	Expenditure	USA	4	Parents	2009	2	0.1324
Charles, et. al. (2014)	PSID		3,000	Income	USA	4	Parents	2009	2	0.1633

Long (2013)	Census		12,516	Occupation	Britain	5	1851	1881	2	0.2413
Long (2013)	Census		4,071	Occupation	Britain	5	1881	1901	2	0.2007
Long (2013)	Census		7,749	Occupation	Britain	5	1851	1881	1	0.3942
Long (2013)	Census		12,516	Occupation	Britain	9	1851	1881	2	0.2369
Long (2013)	Linked Census		12,516	Occupation	Britain	5	1851	1881	2	0.2615
Long (2013)	Marriage Reg		2,483	Occupation	Britain	5	Father	1859-1874	2	0.4845
Long (2013)	OMS		3,460	Occupation	Britain	5	Father	1972	2	0.1390
Long (2013)	Census	Married	4,153	Occupation	Britain	5	1851	1881	1	0.4077
Long (2013)	Census	Wage, Class III	2,716	Wage Level	Britain	5	1851	1881	2	0.4024
Auten, et. al. (2013)	SOI-Tax-SSA		N/R	Income	USA	6	1987	2007	1	0.1735
Auten, et. al. (2013)	SOI-Tax-SSA		N/R	Income	USA	5	1987	2007	1	0.1904
Auten, et. al. (2013)	SOI-Tax-SSA		N/R	Income	USA	6	1987	2007	2	0.0782
Auten, et. al. (2013)	SOI-Tax-SSA		N/R	Income	USA	5	1987	2007	2	0.0741
Pew (2012)	PSID		2,736	Income	USA	5	1968	2009	2	0.1344
Pew (2012)	PSID		1,014	Earnings	USA	5	1968	2009	2	0.1095
Pew (2012)	PSID		2,277	Wealth	USA	5	1968	2009	2	0.1615
Pew (2012)	PSID	White	N/R	Income	USA	5	1968	2009	2	0.1140
Pew (2012)	PSID	Black	N/R	Income	USA	5	1968	2009	2	0.0703
Pew (2012)	PSID	White	N/R	Wealth	USA	3	1968	2009	2	0.1015
Pew (2012)	PSID	Black	N/R	Wealth	USA	3	1968	2009	2	0.0267
Pew (2012)	PSID	Non-CG	N/R	Income	USA	3	1968	2009	2	0.1087
Pew (2012)	PSID	College Grad	N/R	Income	USA	3	1968	2009	2	0.0588
Pew (2012)	PSID	Non-CG	N/R	Wealth	USA	3	1968	2009	2	0.1354
Pew (2012)	PSID	College Grad	N/R	Wealth	USA	3	1968	2009	2	0.1333
Eberharter (2013)	GSOEP/CNEF		2,128	Income	Germany	5	1988-1992	2005-2009	2	0.1174
Eberharter (2013)	PSID/CNEF		2,585	Income	USA	5	1987-1991	2003-2007	2	0.1438
Eberharter (2013)	BHPS/CNEF		1,840	Income	Britain	5	1991-1995	2004-2008	2	0.1529
Dardanoni, et al. (2008)	NCDS		1,942	Occupation	Britain	3	1974	1991	2	0.1987
Dardanoni, et al. (2008)	NCDS		1,104	Wage Level	Britain	3	1974	1991	2	0.0802
Average:			6369			5	1949	1973	2	0.1714
Minimum:			799			2	1850	1880	1	0.0126
Maximum:			43701			10	2009	2013	3	0.5086
STD:			10166			2	57	50	1	0.1030

PSID	Panel Study of Income Dynamics
SIPP	Survey of Income and Program Participation
SSA	Social Security Administration
CHNS	China Health and Nutrition Survey
GSOEP	German Socio-Economic Panel
IHDS	India Human Development Survey
BHPS	British Household Panel Survey
CNEF	Cross-National Equivalent File
OMS	Oxford Mobility Study
OCGS	Occupational Change in a Generation Survey
NLSY	National Longitudinal Survery of Youth
SOI	Statistics of Income
NCDS	National Child Development Study