Contextual Income Mobility and Individual Health

Sebastian Daza

Center for Demography and Ecology
University of Wisconsin-Madison
sdaza@ssc.wisc.edu

Alberto Palloni

Center for Demography and Health of Aging
University of Wisconsin-Madison
palloni@ssc.wisc.edu

November 1, 2019

*Preliminary draft. The research on which this paper is based was supported by the National Institute on Aging via research project grants (R01 AG016209 [PREHCO], R03 AG015673, R01 AG018016, and MERIT award R37 AG025216), and by a Fogarty International Center award for Global Research Training in Population Health (D43 TW001586). The University of Wisconsin-Madison researchers are supported by core grants to the Center for Demography and Ecology, University of Wisconsin (R24 HD047873) and to the Center for Demography of Health and Aging, University of Wisconsin (P30 AG017266).

Abstract

Despite substantial research, the drivers of the widening gap in life expectancy between rich and poor in the U.S. —the so-called longevity gap— remain unknown. Recent research has suggested that contextual income mobility (e.g., county-level socioeconomic mobility) may play an essential role in explaining the longevity gap. However, previous studies have used mostly aggregate or cross-sectional data to examine the link between exposure to a given income mobility regime and health and mortality. Some of the critical issues of those studies are the ecology fallacy associated with aggregate analyses, but also the overlook of selection processes related to residential mobility over time. This paper aims to extend previous research by estimating the effect of average exposure during childhood and adolescence on health during young adulthood. For that, we use both the National Longitudinal Survey of Youth 1997 (NLSY) and the Panel Study of Income Dynamics (PSID) with geocode data to assess the link between county-level income mobility (Chetty's estimates) and health outcomes and behaviors such as health self-report, BMI, depression, and smoking. Also, we use cohorts that match better the ones used by Chetty's estimates of income mobility in the U.S. (1980-1982) and account for selection and time-varying confounders using marginal structural models (MSM). Thus, we provide a more precise assessment of the hypothesis that exposure to income mobility may determine health later in life and explains the longevity gap.

1 Introduction

The growing life expectancy gap by income represents a fundamental challenge for health policy in the US The best performing counties have life expectancies that are now 20 years greater than the poorest performers. Recent work by Chetty and colleagues in the United States (Chetty et al. 2014) demonstrates that differences in life expectancy (at age 40) between the richest and poorest quartiles of the income distribution grew from 9 years to about 11 among men and from 5.2 years to 6.6 years among women. These gaps are substantial – representing 25 percent of remaining life expectancy among men and 13% among women.

Results from multiple recent analyses suggest that neither access to medical care or socioeconomic factors fully explain observed geographic or income disparities in longevity. Intending to identify new drivers that may explain the longevity gap, scholars have recently suggested that contextual income mobility – defined as the ability of individuals to exceed the income of their parents – may play an essential role in explaining health disparities (Venkataramani et al. 2015, 2016; Daza and Palloni 2018). Low-income mobility, for instance, may harm health by raising despair and diminishing the motivation to engage in healthy behaviors. Economic mobility is distinct from income inequality – individuals living in areas characterized by similarly high degrees of income inequality may experience different probabilities of social mobility - and therefore may have different implications health outcomes. While the association between income inequality and health has been studied as part of a 20-year literature, recent work states that its contribution disparities in longevity may be small. In contrast, the health consequences of economic mobility have been understudied. This gap in the literature is particularly salient given emerging evidence of falling income mobility in the US - among the same birth cohorts currently experiencing divergence in their life expectancies.

Previous evidence on the link between income mobility and health comes from the analysis of aggregate (Venkataramani et al. 2015; Daza and Palloni 2018), and individual cross-sectional data (Venkataramani et al. 2016). We identify three main limitations of previous research. First, associations observed using aggregate data might not be observed at the individual level (i.e., ecology fallacy), mainly when most of the mechanisms proposed in the literature occurred at the individual level (Daza and Palloni 2018). Consequently, a direct way to assess the hypothesis on the link between contextual income mobility and health should use individual data. Second, as the neighborhood effects literature has pointed out (Wodtke et al. 2011, 2016; Sampson et al. 2002), residential mobility might produce spurious associations between contextual variables and individual outcomes. Hence, in order to obtain unbiased estimates of the effect of contextual income mobility on individual health, we need to use both longitudinal data and account for selection due to residential mobility. Finally, previous research has not defined clearly exposure to place's income mobility and when during the life course would be relevant to assess the hypothesis of the link between income mobility and health.

In this paper, we extend previous research by estimating the effect of average exposure during childhood and adolescence on health outcomes and behaviors measured during young adulthood. For that, we use both the National Longitudinal Survey of Youth 1997 (NLSY) and the Panel Study of Income Dynamics (PSID) with geocode data to assess the link between county-level income mobility (Chetty et al. 2014's estimates) and health outcomes and behaviors such as health self-report, BMI, depression, and smoking. Also, we use cohorts that match better the cohorts used by Chetty to estimate of income mobility in the US at the county level (1980-1982), and account for selection due to residential mobility and time-varying confounders using marginal structural models (MSM). Thus, we provide a more precise assessment of the hypothesis that exposure to income mobility may determine health later in life and explains the longevity gap.

2 Individual mechanisms

We briefly discuss potential causal mechanisms that could generate an association between place's income mobility and health. First, we need to define what we are not doing. We examine the relationship between a place's income mobility and health/mortality, that is, the linkage between a contextual characteristic (place's income mobility) and an individual trait such as health and mortality. In other words, we are not assessing the relation between individuals' lifetime income mobility experiences and their adult health – a problem studied in a large and distinguished body of research (Chandola et al. 2003; Illsley 1955; Fox et al. 1982; Blane et al. 1999, 1993; Solon 1992)[1]. What we attempt here is demonstrate that there is an association between an *aggregate* property of the stratification system, on the one hand, and individual experiences, on the other. It is, of course, possible that individuals' experiences of occupation or SES mobility are also influenced by the prevailing aggregate regime of income mobility. Indeed, these experiences may be one of many other pathways through which aggregate income mobility and individual health are related. However, in this paper, we are interested in the *total* effects of places' income mobility on individual health and are not concerned with the precise empirical identification of mediating pathways.

We argue that a link between places' income mobility and mortality could exist if communities with higher income mobility host social and economic environments that reduce mortality risks relative to communities with lower income mobility, *independently of the income level and income inequality*. Individuals and groups who occupy the most vulnerable and exposed social positions within unequal communities may be comparatively better off when they face advantageous income mobility prospects than when they do not. Just as individuals who command lower incomes in communities with more equitable income distributions may experience better health than individuals with similar incomes in societies with higher income inequality, so too could individuals and groups that occupy lower ranked positions in societies with higher income mobility enjoy better health than counterparts in societies with more rigid stratification systems.

In theory, communities could be classified in different combinations of income mobility and inequality, where each combination is characterized by a health and mortality profile. Indeed, in our data we actually observe communities (counties) simultaneously characterized by unequal income distribution and flexible mobility regimes or by generous income distributions and high levels of social rigidity. The standard conjecture is that indicators of mortality and health will be more beneficial in communities with less inequality than in those with high inequality. The new conjecture is that at a given level of income inequality, better health and mortality conditions will be experienced by members of communities with higher income mobility.

We propose four pathways that might produce a link between income mobility and health:

1. *Residential mobility, adult health and mortality*: As stated above, an association between aggregate income mobility and individual health and mortality may be the outcome of a composition effect, namely, places with higher income mobility contain a population composition biased toward individuals who experience mobility (and their health and mortality consequences). In this case, the association between the aggregate property of the stratification system and individual experiences of health and mortality reflects the influence of individual residential mobility patterns and associated selection processes.

2. *Individual early experiences*: A large body of literature on health and mortality disparities demonstrates that SES (income, education) health and mortality gradients are pervasive, persistent and, as of recent, increasing everywhere in high-income countries (Mackenbach 2012; Meara et al. 2008). Further, there is evidence that early conditions and upbringing of individuals matter greatly for adult health and mortality disparities (Palloni et al. 2009; Case et al. 2002). Thus, some of the health differentials between men in low and high ranking positions initially attributable to chronic stress among those in subordinate positions (Marmot 2004; Sapolsky 2005) may be rooted in antecedent health conditions sculpted early in life (Case and Paxson 2011). If early conditions are influential for SES health and mortality disparities, they may also be influential as vehicles that establish relations between income inequality, income mobility, and adult health and mortality.

   During early stages of socialization individuals experience sensitive and critical windows for the acquisition of cognitive and non-cognitive abilities that are the foundation of skills acquired later in life (Knudsen et al. 2006; Shonkoff et al. 2009; Heckman 2007; Cunha and Heckman 2009). Some of these traits involve the development of outlooks and attitudes that influence investments in skill acquisition and health, including propensities to adhere health-related behaviors. Thus, behaviors critically associated with modern chronic illnesses, such as smoking uptake and desistance, alcohol consumption, substance abuse, choices of diet and physical activity, are in part determined by capabilities sculpted early in life. Early avoidance of unhealthy behaviors has large payoffs

[1] The bulk of this literature is concerned with the long-run impact of early occupational (career) shifts or the short-run effects of late occupational (career) shifts. This work is based on empirical research that focuses on patterns of relationships between individuals' occupation (or SES status broadly conceived) at an early point in their adult life and subsequent older adult health and mortality.

in adulthood because these behaviors are closely related and reinforce each other, the physiological and psychological damage they produce are accumulated over time, and they all are strongly non-reversible. Early adoption of healthy behaviors is facilitated by socialization that emphasizes robust future outlooks, self-confidence, and self-reliance, beliefs in the neutrality and fairness of social reward allocation systems, hopefulness and optimism, and incentives to succeed. These are all traits that reduce time discounting so that the addition of one year of healthy life in the future of an individual is endowed with significant rewards and returns (Grossman 2000, 1972).

We know from empirical research that negative affect, chronic stress, subordination, bleak future outlooks associated with poverty lead to increases in time discounting (Haushofer and Fehr 2014). Higher time preferences favors resistance to the adoption of behaviors that may yield immediate rewards but are health-damaging and discourage those that have a more distant and elusive pay-off but are health-preserving (Schlam et al. 2013; Eigsti et al. 2006).

This mechanism alludes to influences that shape environments during critical stages of individuals' upbringing. The conjecture is that a places' income mobility regime is powerful enough to shape those environments. But so is an individual's ancestral income mobility experiences, particularly parental and possibly grand parental mobility. Strictly speaking, these are two very different mechanisms that can be properly identified only if we simultaneously observe both the influences of a place's aggregate income mobility and individuals' familial income mobility experiences.

3. *Community endowments*: Communities with low-income mobility may distort opportunities and incentives, reinforce unequal allocation of favorable traits, undervalue public institutions that contribute to the formation of skills with a high wage premium and, many of them, support non-meritocratic reward allocation strategies. These community properties directly influence the suite of opportunities available to individuals and shapes the way parents socialize children and favor (discourage) the adoption of positive outlooks and the value of skill acquisition. Rigid or weak income mobility fosters individual hopelessness, despair, mistrust, disbelief in a level playing field for all, weaken aspirations and, more generally, diminishes the value of adoption of attitudes and behaviors that promote good health.

3 Data and Measures

We use a data set that results from merging separate data sources. The first is the Health Inequality Project Data (HIPD) created by Chetty and colleagues (Chetty et al. 2016) that contain information on income from tax records for the period 1999 and 2014 by US counties and commuting zones by linking 1.4 billion tax records to Social Security Administration records.[2] The HIPD also include statistics of the income distributions and two indicators of income mobility derived from measures of the association between incomes of children born between 1980 and 1982 and their parents' income.[3] First, we use the index of relative mobility (IRM), rank-rank slope, or the correlation between a child's income rank in her birth cohort income distribution and parents' income rank in their parents' income distribution at the county level.[4] The relative income mobility indicator ranges between -1 and 1, and larger values correspond to lower income mobility (higher rank-rank correlation between parents' and child's income). We also use an absolute upward mobility score or "the mean rank (in the national income distribution) of children whose parents are at the 25$^{\text{th}}$ percentile of the national parent income distribution" (Chetty et al. 2014, p. 7).[5] Absolute upward income mobility ranges from 0 to 1 and higher values correspond to larger income mobility. To facilitate interpretation, we multiply the upward mobility score by -1 so that the meaning and expected association of relative

[2] Chetty et al. (2014)'s core sample data include children who (1) have a valid Social Security number or individual taxpayer identification number, (2) were born between 1980 and 1982, and (3) are US citizens as of 2013. There are approximately 10 million children in the core sample.

[3] We use a *permanent-resident* version of income mobility measures, that is, parents who stay in the same counties between 1996-2012. Note that children who grow up in a county may have outmigrated as adults.

[4] Rank-rank slopes (i.e., Spearman's correlation) have proved to be quite robust across specifications and highly suitable for comparisons across areas (Chetty et al. 2014). *Canonical* measures of relative mobility, such as inter-generational income elasticity (of child income relative to parents' income) tend to be more sensitive to changes in inequality across generations.

[5] Although at the national level both the relative and absolute measure of mobility provide similar information, when studying small areas a child's rank in the national income distribution would be an absolute outcome because income a given area has little impact on the national distribution.

and absolute income mobility with health are the same. Finally, we use the Gini Index (GI) as an indicator of income inequality.

The second database is the National Longitudinal Survey of Youth 1997, a nationally representative sample of 8,984 American youth born between 1980 and 1984. Surveys were conducted annually, beginning in 1997 when the youth were between 12 and 18 years of age. In the first round, both the eligible youth and one of that youth's parents were administrated personal interviews. The restricted NLSY97 geocode data file contains information on the geographic residence of each respondent at age 12 and over time, allowing us to merge it with Chetty's county level. Importantly, the NLSY 97 sample matches the cohorts of the core sample used by Chetty et al. (2014) (1980-1982) so that we can estimate with more precision the effect of early exposure to place's income mobility (from 12 to 20 years old) on health measures during young adulthood (30-36 years old). After merging the two databases, we obtain 8,810 NLSY 97 respondents.

The third database is the Panel Study of Income Dynamics (PSID), a nationally representative sample of US men, women, children, and their families that has been followed for more than 40 years. The PSID began interviewing a sample of approximately 5,000 families in 1968 and were re-interviewed each year through 1997 when interviewing became biennial. Similarly to the NLSY, restricted geographic data allow us to merge individual records with county income mobility measures. Unlike the NLSY 97, the PSID data allows us to estimate the effect of exposure to contextual mobility from birth to age 20, but the number of respondents who match Chetty et al. (2014)'s cohorts is smaller. For instance, between 1977 and 1985, the PSID panel recorded 4044 newborns.[6] Although that cohort does not match exactly the cohort used by Chetty et al. (2014), it offers a reasonable approximation of exposure provided that the mobility regime would not change dramatically before and after 1980-82. We also use the PSID *Well being and Daily Life Supplement* 2016 (WB) based on a self-administered instrument that collects information on topics relevant for this study such as well being, personality traits, and everyday skills. The eligible respondents of this supplement are individuals at least 30 years old by December 2015 that have been a household head or spouse/partner in the 2015 Main PSID.[7] This eligibility criterion reduces the sample considerably from 4,044 to 1,201 respondents.[8] After merging the HIPD to the cohort 1977-1985 of the PSID, we obtain 3,888 respondents and 1,138 WB participants. Although the sample is considerably restricted, we think it is worth to estimate the effects of exposure to contextual income mobility from birth to 20 years old, and compare those results with the NLSY 97.

The use of these data sources offers a broader picture to examine our research questions, and a more precise definition of exposure to contextual income mobility as both of them track the county of residence of respondents over relatively long periods.

4 Analytical Strategy

We estimate the effect of average exposure of income mobility at the county level during childhood and adolescence on health outcomes measured during young adulthood. Outcomes in the PSID and NLSY 97 were measured in the last wave of the study (2015-2017), that is, when respondents were about 30-35 years old. The key independent variable is the average income mobility exposure between ages 0 and 20 for the PSID, and 12 to 20 for the NLSY 97. We also assess the effect of average income inequality exposure (Gini coefficient). For instance, the average exposure for the NLSY 97 is defined as:

$$\frac{\sum_{i=12}^{20} \text{income mobility}_i}{8}$$

[6] These are PSID *gene* respondents. All 1968 sample members have the PSID *gene*, and they are followed in all subsequent waves across their entire lives, regardless of where they live. All individuals born to or adopted by somebody with the PSID *gene* acquires the gene themselves, and therefore are followed.

[7] Eligibility status was confirmed for 10,689 cases.

[8] If we change the period from 1977-1985 to 1971-1985, the PSID newborns with data in the WB supplement increases to 1,733

To deal with selection due to residential mobility and time-varying confounders, we estimate marginal structural models (Hernán and Robins 2006; Wodtke et al. 2011). We create stabilized weights to run models that estimate the effect of income mobility (average exposure) on outcome variables (van der Wal et al. 2011). Dropouts and missing data are addressed using multiple imputation (van Buuren 2018).

5 Preliminary results

Table 1 shows preliminary estimates of the effect of standardized income mobility exposure between ages 12 and 20 among NLSY 97 respondents using 10 imputations. Each coefficient corresponds to an independent model. As can be seen, more systematic effects are observed regarding BMI and smoking: higher rank-rank correlation (less mobility) increases BMI, smoking prevalence and the number of days a respondent have smoked in the last month. Gini coefficients, in contrast, are, most of the time, very imprecise, noisy or negative.

Table 1: Income mobility and inequality exposure models (NLSY 97)

	Self-reported healh	BMI	Depression	Smoking	Smoking last 30 days
Income relative mobility average exposure	0.01	0.45	−0.00	0.10	0.11
	(0.03)	(0.14)	(0.01)	(0.04)	(0.03)
Gini average exposure	−0.02	−0.12	−0.00	−0.11	−0.11
	(0.03)	(0.11)	(0.01)	(0.04)	(0.03)
Observations	8810	8810	8810	8810	8810

Note: Each row represents a model. Self-reported health = ordinal regression, BMI = GLM, Depression = GLM, Smoking = Logistic, Smoking last 30 days = Poisson.

6 Next steps

The next steps of this project include:

1. Estimate models using the PSID data.
2. Sensitivity analysis of multiple imputation models.
3. Sensitivity analysis of models used to define stabilized weights.
4. Use a categorical version of the income mobility variable.
5. Use absolute income mobility as key independent variable.
6. Use a residualized version of the income mobility variable to assess the impact of confounding at the county level.

References

Blane, D., Harding, S., and Rosato, M. (1999). Does social mobility affect the size of the socioeconomic mortality differential?: Evidence from the Office for National Statistics Longitudinal Study. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 162(1):59–70.

Blane, D., Smith, G. D., and Bartley, M. (1993). Social selection: What does it contribute to social class differences in health? *Sociology of Health & Illness*, 15(1):1–15.

van Buuren, S. (2018). *Flexible Imputation of Missing Data*. Interdisciplinary Statistics. Chapman and Hall/CRC, second edition edition.

Case, A., Lubotsky, D., and Paxson, C. (2002). Economic Status and Health in Childhood: The Origins of the Gradient. *The American Economic Review*, 92(5):1308–1334.

Case, A. and Paxson, C. (2011). The Long Reach of Childhood Health and Circumstance: Evidence from the Whitehall II Study*. *The Economic Journal*, 121(554):F183–F204.

Chandola, T., Bartley, M., Sacker, A., Jenkinson, C., and Marmot, M. (2003). Health selection in the Whitehall II study, UK. *Social Science & Medicine*, 56(10):2059–2072.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States. *The Quarterly Journal of Economics*, 129(4):1553–1623.

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A., and Cutler, D. (2016). The Association Between Income and Life Expectancy in the United States, 2001-2014. *JAMA*, 315(16):1750.

Cunha, F. and Heckman, J. J. (2009). The Economics and Psychology of Inequality and Human Development. *Journal of the European Economic Association*, 7(2-3):320–364.

Daza, S. and Palloni, A. (2018). Income Inequality, Social Mobility and Mortality in the U.S. *CDE Working Paper, University of Wisconsin-Madison*, (No. 2016-02).

Eigsti, I.-M., Zayas, V., Mischel, W., Shoda, Y., Ayduk, O., Dadlani, M. B., Davidson, M. C., Aber, J. L., and Casey, B. J. (2006). Predicting Cognitive Control From Preschool to Late Adolescence and Young Adulthood. *Psychological Science*, 17(6):478–484.

Fox, A. J., Goldblatt, P. O., and Adelstein, A. M. (1982). Selection and mortality differentials. *Journal of Epidemiology & Community Health*, 36(2):69–79.

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *Journal of Political Economy*, 80(2):223–255.

Grossman, M. (2000). Chapter 7 - The Human Capital Model*. In Newhouse, A. J. C. a. J. P., editor, *Handbook of Health Economics*, volume 1, Part A of *Handbook of Health Economics*, pages 347–408. Elsevier.

Haushofer, J. and Fehr, E. (2014). On the psychology of poverty. *Science*, 344(6186):862–867.

Heckman, J. J. (2007). The Economics, Technology and Neuroscience of Human Capability Formation. *Proceedings of the National Academy of Sciences*, 104(33):13250–13255.

Hernán, M. A. and Robins, J. M. (2006). Estimating causal effects from epidemiological data. *Journal of Epidemiology and Community Health (1979-)*, 60(7):578–586.

Illsley, R. (1955). Social Class Selection and Class Differences in Relation to Stillbirths and Infant Deaths. *British Medical Journal*, 2(4955):1520–1524.

Knudsen, E. I., Heckman, J. J., Cameron, J. L., and Shonkoff, J. P. (2006). Economic, neurobiological, and behavioral perspectives on building America's future workforce. *Proceedings of the National Academy of Sciences*, 103(27):10155–10162.

Mackenbach, J. P. (2012). The persistence of health inequalities in modern welfare states: The explanation of a paradox. *Social Science and Medicine*, 75(4):761–769.

Marmot, M. (2004). The status syndrome: How social standing affects our health and longevity. 2004. *London: Bloomsbury*.

Meara, E. R., Richards, S., and Cutler, D. M. (2008). The Gap Gets Bigger: Changes In Mortality And Life Expectancy, By Education, 1981-2000. *Health Affairs*, 27(2):350–60.

Palloni, A., Milesi, C., White, R. G., and Turner, A. (2009). Early childhood health, reproduction of economic inequalities and the persistence of health and mortality differentials. *Social Science & Medicine*, 68(9):1574–1582.

Sampson, R. J., Morenoff, J. D., and Gannon-Rowley, T. (2002). Assessing "Neighborhood Effects": Social Processes and New Directions in Research. *Annual Review of Sociology*, 28(1):443–478.

Sapolsky, R. M. (2005). The influence of social hierarchy on primate health. *Science*, 308(5722):648–652.

Schlam, T. R., Wilson, N. L., Shoda, Y., Mischel, W., and Ayduk, O. (2013). Preschoolers' delay of gratification predicts their body mass 30 years later. *The Journal of pediatrics*, 162(1):90–93.

Shonkoff, J. P., Boyce, W. T., and McEwen, B. S. (2009). Neuroscience, molecular biology, and the childhood roots of health disparities: Building a new framework for health promotion and disease prevention. *JAMA*, 301(21):2252–9.

Solon, G. R. (1992). Intergenerational Income Mobility in the United States. *The American Economic Review*, 82(3):393–408.

Venkataramani, A. S., Brigell, R., O'Brien, R., Chatterjee, P., Kawachi, I., and Tsai, A. C. (2016). Economic opportunity, health behaviours, and health outcomes in the USA: A population-based cross-sectional study. *The Lancet. Public Health*, 1(1):e18–e25.

Venkataramani, A. S., Chatterjee, P., Kawachi, I., and Tsai, A. C. (2015). Economic Opportunity, Health Behaviors, and Mortality in the United States. *American Journal of Public Health*, 106(3):478–484.

van der Wal, W. M., Geskus, R. B., et al. (2011). Ipw: An R package for inverse probability weighting. *Journal of Statistical Software*, 43(13):1–23.

Wodtke, G. T., Elwert, F., and Harding, D. J. (2016). Neighborhood Effect Heterogeneity by Family Income and Developmental Period. *American Journal of Sociology*, 121(4):1168–1222.

Wodtke, G. T., Harding, D. J., and Elwert, F. (2011). Neighborhood Effects in Temporal Perspective The Impact of Long-Term Exposure to Concentrated Disadvantage on High School Graduation. *American Sociological Review*, 76(5):713–736.