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Social Mobility in a High Inequality Regime

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Abstract

At several critical junctures in U.S. history, scholars and other commentators have become concerned that opportunities to get ahead may be growing more unequal. Although these concerns have never been borne out, the recent takeoff in income inequality has revived them yet again. There is strikingly little evidence on whether such concerns are warranted. Unfortunately, a host of methodological problems immediately emerge in attempting to establish recent trends in social mobility. These obstacles can, however, be overcome by searching for trend among those age groups and social classes that are most likely to evince trend. Although the data are sparse and caution is clearly warranted, the key conclusion coming out of this analysis is that the General Social Survey data do indeed reveal a recent increase in intergenerational association among young and even middle-age adults, driven by an increased advantage of the professional-managerial class relative to all other classes. The observed pattern of trend is largely consistent with what we call the “top-income hypothesis” and, more generally, with the predictions coming out of a two-factor model featuring the effects of (a) the expansion of mass education, and (b) the takeoff in income inequality. Just as this model implies, the association-over-time curve has the expected convex shape in the two younger age groups, while the change in association appears to be accelerating in the most recent decade. These results suggest that the takeoff in income inequality may account in part for the decline in mobility.

At several critical junctures in U.S. history, scholars and other commentators have become concerned that opportunities to get ahead may be growing more unequal, a hypothesis that was prominent during the Depression years, the postwar period, and then again in the 1950s (Hertzler 1952; Sibley 1942). Although these concerns have never been borne out, the recent takeoff in income inequality has revived them yet again (e.g., DeParle 2012; Foorohar 2001; Franke-Ruta 2012; *The Economist* 2010). We have strikingly little evidence on whether such concerns are finally warranted.

The main goal of this paper is to eke out as much evidence on these concerns as the available data will allow. This descriptive objective might at first blush seem easily achieved. To the contrary, a host of methodological problems immediately emerge in attempting to establish recent trends in social mobility, not least of which is that the takeoff in income inequality has not been in play long enough to affect the upbringing of all that many current workers. It is equally problematic that the available survey samples are too small to reliably detect anything but the broadest trends. We overcome these obstacles in this paper by searching for trend among those age groups and social classes that are most likely to evince trend.

If our paper is largely descriptive in focus, this is not to suggest that we lack hypotheses about what might be driving trends. The key explanation lurking behind our descriptive interests is that the takeoff in income inequality may be producing a historic decline in social fluidity. We will not be able to directly assess this hypothesis. We will, however, provide indirect evidence by developing a framework that has changes in social fluidity resulting from the operation of just two forces, educational expansion and the inequality takeoff. This framework allows us to advance expectations about the pattern of trend that exploit variation in the rate of educational upgrading and in the intensity of expected income-inequality effects across age-gender groups and time periods.

The paper is organized as follows. We lead off our discussion by reaffirming the normative implications of social mobility against old and new objections that stress the role of factors other than opportunity in generating the data in a mobility table. In the sections that follow, we present our analytical framework, review the (scarce) evidence available on recent mobility trends, and introduce a key revision of the conventional inequality hypothesis that better reflects the likely effects of rising income inequality on social mobility. This discussion is followed by a section on data and measures and on the empirical strategy and models we employ. We then turn to our results and their implications for the simple hypothesis that income inequality is reducing social fluidity.

For those who prefer some foreshadowing, we can reveal now that our analyses suggest a substantial decline in social fluidity in recent decades, a decline that *may* be attributable to the takeoff in income inequality. These results, which are sometimes at borderline levels of significance, must be interpreted cautiously. It is nonetheless striking that our results are quite inconsistent with the prevailing view that social fluidity tends to increase under late industrialism (e.g., Breen 2004).

Why Should We Care about Social Mobility?

Because the study of intergenerational mobility has fallen out of fashion among U.S. sociologists, it is perhaps necessary to remind ourselves why we have historically cared about it. There are all manner of motives underlying the social scientific interest in mobility (see Grusky and Cumberworth 2010 for a review), but we mainly care about it because it speaks to the extent to which life chances depend on social class origins. The mobility table is accordingly valued for the evidence it provides on the extent to which our commitment to equal opportunity has been realized.

There is a long history of caveats to the effect that some portion of the origin-destination association may result from differences in talent or preferences that, although correlated with class origins, should not be understood as producing inequality of opportunity (e.g., Breen 2010b). If, for example, the daughters and sons of musicians tend to be bestowed at birth with a "great musical ear" and to become musicians themselves, then some scholars would not treat the resulting immobility as an expression of unequal opportunity. It is of course unclear whether an innate "musical ear," in and of itself, is all that important in determining musical success. Indeed, because most capacities require considerable cultivation to be parlayed into a job, the intergenerational association has to be understood, in part, as reflecting a collective decision to allow unequal innate capacities to be realized rather than attenuated through compensatory training. Moreover, insofar as genetic differences are associated with class origins, this association again reflects the operation of complex social processes that played out in the prior generation (e.g., assortative mating). It follows that even the "genetic lottery" is shaped by class-based unequal opportunities in a quite fundamental way (cf. Swift 2005).

It is likewise problematic to treat preferences as wholly exogenous to one's class origins. For example, those with a preference for "delayed gratification" have likely developed that preference, at least in part, because of their social class environment. In some social classes, we may find cultural rules-of-thumb implying that one should "live for the day," prescriptions that may have developed in part because long-term investments in training tend not to pay off within those classes. The intergenerational association generated by these and other similarly class-dependent preferences is relevant to judgments about equality of opportunity.

We cannot discuss here the lengthy literature on the relationship between equality of opportunity, talents, and preferences (see Roemer 2012; 2004; 1998). It suffices to reiterate that, even if part of the origin-destination association is the result of differences in innate talents and preferences, this does not automatically make that association less informative with respect to concerns about equality of opportunity. Although we do not deny that there *may* be preferences that are correlated with class of origin, affect destination class, and are irrelevant for equality of opportunity, our arguments do at least suggest that the part of the origin-destination association that may result from that type of preferences is likely to be very small. The implication is that any observed changes in the association between origins and destinations are largely determined, directly or indirectly, by true differences in opportunities.

Without a doubt, there is much more that needs to be known about equality of opportunity than what mobility tables can tell us, but they do tell us a good deal. It follows that, notwithstanding the interpretive complications that the role of preferences and talents may entail, there are good normative reasons to be concerned that the gross origin-by-destination association may be increasing in the United States.

The foregoing takes for granted a social commitment to equalizing opportunity and simply suggests that, insofar as such a commitment exists, the association parameters coming out of a mobility table provide one important measure of the extent to which that commitment has been realized. It is especially important to monitor this commitment given its role in justifying inequality. In the U.S., there is still a widespread belief that opportunities to get ahead are openly available (rather than dependent on birth), a presumption that plays a central role in legitimating the soaring inequality of our times. We look to social science to establish whether, consistent with such an account, inequality is indeed the outcome of a fair and open contest rather than some "rigged competition."

Countervailing Effects on Mobility

In explaining trends in social mobility, a host of factors may of course be relevant, but two stand out as especially important. The "education hypothesis," which has long been featured in accounts of trend (see Hout 1998), focuses on the effects of mass education in reducing the intergenerational transmission of class. The "income hypothesis" suggests, to the contrary, that the rise in income inequality amounts to an unprecedented infusion of additional resources among the higher reaches of the class structure, an infusion that will work to increase the amount of reproduction. We review each of these competing hypotheses in turn.

The simplest form of the education hypothesis operates through a decline in the effects of class origins on educational attainment. If a college education becomes increasingly open to children from all classes, then we can expect a corresponding decline in the association in a mobility table. Although some evidence for this mechanism has been found in several countries (e.g., Breen and Jonsson 2007; Breen et al. 2009; cf. Shavit and Blossfeld 1993; Shavit, et al. 2007), there is little, if any, evidence of a reduction in the effects of class origins in the U.S. case (Hout and Janus 2011; Hout and Dohan 1995; Pfeffer 2008; Roksa et al. 2007; also see Gamoran 2001; Hout, Raftery, and Bell 1993; Morgan and Kim 2006). The influence of class of origin may in fact be growing within the U.S. (e.g., Duncan et al. 2012; Reardon 2011).

The main way, therefore, in which mass education has instead exerted its effects is through a simple compositional effect. In a classic paper, Hout (1988) showed that the association between origin and destination withers away among college graduates, the implication being that educational upgrading shifts the population toward a low-association regime (see also Breen 2004; Vallet 2004). This line of reasoning led Beller and Hout (2006:28) to conclude that the rising share of U.S. men with college degrees is "one major reason for the declining correlation between fathers' and sons' occupations." There is also evidence that in other countries, such as England, a compositional effect of this sort has been the *only* driver of the observed reduction in intergenerational association (Breen 2010a).

The evidence for the compositional argument may be strong, but Torche (2011) has recently shown that it takes on a somewhat weaker form within the population of advanced degree-holders. For those holding such degrees, Torche finds that the intergenerational association is no longer zero, although for our purposes the more important point is that the association within the advanced-degree population is still weaker than that prevailing among those without college. The latter result means that the overall compositional effect should grow weaker as an increasing share of the college population holds an advanced degree.

It follows that, all else equal, the association between origins and destinations should follow the trend in the proportion of the population with a college degree.[1] In Figure 1, we have graphed this proportion between 1950 and 2010 (for those aged 25-60), a graph that will likely surprise few. As it reveals, there is a rapid increase between 1950 and 1980 in the college-educated share of men, whereas thereafter this share continues to grow but at a much slower pace. Among women, the share with college barely changes between 1950 and 1960, then increases at a slower pace than the men's share over the following decade, and ultimately takes on a fast and steady growth rate between 1970 and 2010.

We next consider the income hypothesis. Although it is newer than the education hypothesis, it is also more frequently featured in contemporary speculation about mobility trends (Andrews and Leigh 2009; Corak 2013; Krueger 2012; OECD 2010; see also Burtless and Jencks 2003). The relationship between income inequality and class mobility nonetheless remains rather poorly developed in the literature. Insofar as it has been discussed, the main argument is that rising inequality provides privileged families with more resources that can then be lavished on their children, resources that raise their chances of securing desirable class positions for themselves (e.g., Jonsson et al. 2011).[2] By this logic, inequality of condition and of opportunity are now understood as varying together, even though scholars have typically been at pains to stress that they are analytically distinct.[3]

How might parents in privileged classes use their newfound income? The available evidence (see Kornrich and Furstenberg 2011) suggests that they will increase the human, cultural, and social capital of their children via high-quality childcare and preschool, educational toys and books, after-school training and test preparation, science-related summer camps, elite preparatory schools, prestigious college degrees, a "finishing school" vacation in Europe, and stipends or allowances that free them from the need to work during high school and college. As the takeoff plays out, privileged parents can also more readily afford privileged residential neighborhoods, with accordingly improved access to high-quality public schools, neighborhood amenities that assist in human-capital formation (e.g., libraries), and peers that can provide all manner of career advantages (Durlauf, 1996; cf. Mayer 2001).[4]

The latter responses to the takeoff take place when children are still living with their parents (e.g., paying for after-school classes) or are pursuing their college degree (e.g., paying for tuition). Although we suspect that the takeoff will have its strongest effects on adults who were exposed to it as children, we certainly cannot rule out the possibility that it also affects the opportunities of adult children. We can imagine that well-off parents may decide (a) to finance, via loans or gifts, a late-adult professional degree, or (b) to provide in-kind or direct economic support when their adult children are unemployed, support that then allows their children to maintain a high reservation wage (rather than settle quickly for a lesser position). In some cases, parents might also help their adult children pursue entrepreneurial opportunities by providing start-up resources, physical space, or implicit insurance in case of failure. If the takeoff indeed affects adult opportunities in this way, its effects will register without the prolonged lag that arises when it operates exclusively on children (who must then age into the labor force).

This line of reasoning implies that, all else equal, the trend in social fluidity should follow the trend in income inequality, with a lag that depends on the extent to which these "adult mechanisms" are operating. The well-known trend in family income inequality is shown in Figure 2 (see also Atkinson, Piketty, and Saez 2011; Grusky and Cumberworth 2013). It bears noting that this trend takes a rather different form than that pertaining to college completion (Figure 1). Even if the takeoff in income inequality has the effects we have outlined, this means that the gross association between origins and destinations will not necessarily *increase* in recent decades (i.e., "rigidification"). We may instead find that the takeoff simply slows down the education-generated decline in that association. It is precisely this ambiguity about the outcome of the contest between education and income inequality that motivates our analyses. Although it is unlikely that *none* of the takeoff-induced processes outlined above are operative, what remains unclear is whether they are strong enough to undermine the largely countervailing effects of the expansion of mass education. It is also unclear how other forces affecting trend may play out. In stressing the special role of education and inequality, we do not mean to rule out the further complicating effects of yet other forces, such as the rise of cohabitation, blended families, and other more complicated family forms.[5]

Previous Research on Trend

When concerns about rigidification have previously surfaced in U.S. history, they invariably have proven overblown. The evidence from other countries and earlier time periods indicates that mobility regimes change only slowly and, insofar as a trend in social fluidity has been teased out, it is typically in the direction of increasing equality of opportunity (e.g., Breen et al. 2009; Breen 2010a; Vallet 2001). Is there any reason to believe that there is now a trend in the opposite direction?

This question has been addressed most frequently within the literature on income and earnings mobility. In fact, there has been a minor resurgence of such analyses, a development that has been partly motivated by concerns about the effects of rising income inequality (e.g., Aaronson and Mazumder 2008; Bloome and Western 2011; Hertz 2007; Lee and Solon 2009; Levine and Mazumder 2007; Mayer and Lopoo 2004, 2005; Mazumder 2012; also see Harding et al. 2005; Hauser 1998; Torche 2011).[6] These studies of income and earnings mobility are of immense interest, but they have produced very mixed evidence, making it difficult to draw any clear conclusion on trend. As Lee and Solon (2009) pointed out in a recent review, available estimates of trend in economic mobility are highly imprecise, mainly because the typically-used surveys (e.g., Panel Study of Income Dynamics) are based on small samples. The evidence taken from analyses of income or earnings mobility could in any event only be suggestive. This is because the intergenerational elasticities (IGEs) between the income or earnings of children and parents do not correspond in any direct way to the measures of social fluidity typically estimated in analyses of class mobility. Most importantly, IGEs are sensitive to cross-generation changes in the variances of the earnings or income distributions, meaning that they cannot of course be interpreted as measures of association.[7]

It is accordingly useful to consider the relatively few studies that have examined trends in occupational or class mobility during the post-takeoff period or some part of it (Beller and Hout 2006; Beller 2009; Pollak et al. 2011). Notably, Pollak et al. (2011) have analyzed trends in social fluidity between 1962 and 2006, using data from several national surveys. Because they relied on highly disaggregate classifications, the power of their models was limited, and it proved difficult to reach any definitive conclusion about trend. In an earlier analysis, Beller (2009) sought to demonstrate that the mother's class matters in intergenerational mobility, but in the course of carrying out those analyses she also provided, perhaps for the first time, some evidence of decreasing social fluidity in the United States during our period of interest. Using social class measures for both parents, Beller found that the intergenerational association between 1994 and 2006 was substantially larger for men from the 1965-79 birth cohorts than for men in two older cohorts. The results for women, however, are less clear.[8] As we discuss in more detail below, Beller's important finding relies on strong assumptions regarding the age-profile of class membership, assumptions that we will avoid in our own analyses.

Because there is relatively little direct evidence on mobility trends, concerns about rigidification have been fueled mainly by indirect evidence that speaks to some of the mechanisms through which the income hypothesis may be operating. For instance, Reardon (2011) documents a growing performance gap in math and reading achievement between high-income and low-income children, while Kornrich and Furstenberg (2011) show a marked increase in the amount of money that parents in the top income decile spend on such goods and services as high-quality daycare and babysitting, private schooling, books and tutoring, and college tuition and fees. Although spending on children also increased at the bottom of the income distribution, this increase is far smaller in both absolute and relative terms (also see Kaushal, Magnuson, and Waldfogel 2011). As best as we can tell, upper-class parents are indeed spending ever more on the "reproduction project," and it is at least plausible that this spending is achieving its intended effect (but cf. Mayer 1997).

The latter indirect evidence is suggestive, but it cannot of course substitute for direct measurements of trend in social mobility. The small number of available direct measurements (esp. Beller 2009) are also worrying, but should clearly be supplemented with an analysis that directly focuses on the takeoff. We turn to that analysis after introducing an amendment to the simple income hypothesis featured to this point.

The Top Income Hypothesis

The income-inequality hypothesis implies a proportional "stretching out" of the inter-class gaps in family income that should make all types of exchange less common (see Pollak et al. 2011). By this interpretation, one expects an across-the-board increase in the association between class origins and destinations of the sort that might be teased out, for example, with a conventional association model (e.g., Xie 1992). We will label this formulation as the "simple income hypothesis."

It is perhaps more plausible, however, that the effects of the takeoff will register principally within the upper regions of the class distribution. This modification of the income hypothesis is attractive because the professional-managerial class was far and away the biggest beneficiary of the inequality takeoff. Whereas average family income rose within this class by a full 31.8 percent between 1979 and 2010 (i.e., from $80,490 to $106,120), it rose within the other classes by just 4.9 percent over that same period (i.e., from $56,890 to $59,690). As Figure 3 shows, the income gap between the professional-managerial class and all other classes is now very large, whereas the income gaps among the remaining classes are not much different from what prevailed in 1979.[9] The implication is simple: If rising income inequality is indeed driving changes in mobility, we would expect its effects to register almost exclusively in the divide between the professional-managerial class and all other classes.[10] We refer to this second interpretation as the "top income hypothesis."[11]

The mechanical distributional effect just discussed is not the only rationale for the top income hypothesis. There is, after all, a long tradition of scholarship suggesting that professional-managerial culture and institutions are tailor-made for reproductive purposes (e.g., Bourdieu and Passeron 1977). Within this literature, the professional-managerial class is not just represented as especially oriented toward and anxious about reproduction (if only for loss aversion reasons), but also especially skilled in realizing its agenda by choosing the right neighborhoods, buying high-quality preschool, purchasing after-school training, and otherwise engaging in "concerted cultivation" (Lareau 2003). The top income hypothesis thus suggests that, by virtue of increasing the resources at the disposal of professionals and managers, the takeoff works to potentiate their natural reproductive tendencies.

The methodological implication of this hypothesis is that the takeoff should register most prominently in the odds ratio pertaining to the advantage of the professional-managerial class relative to all other classes. The simple income hypothesis directs us, alternatively, to average across all odds ratios, an approach that will blunt our capacity to detect change insofar as the top income hypothesis is indeed on the mark. We will carry out tests aimed at discriminating between these two hypotheses.

Data, Measurement, and Design

We analyze data drawn from the 1972-2010 General Social Surveys (GSS; see Davis, Smith, and Marsden 2010). Because the annual and biannual samples of the GSS are too small to conduct analyses by gender and age group, we are obliged to pool the data into four periods, one for each decade (i.e., 1972-1980, 1982-1990, 1991-2000, and 2002-2010). In Table 1, the decade-specific sample sizes and descriptive statistics are provided, with the right panel reserved for the "two-parent" variable that is available only for the last two decades (see below for details on the construction of this variable).

We have coded age into overlapping categories (25-40, 32-50, 42-60) because the data are very sparse. This decision to resort to overlapping categories entails no methodological complication given that our key comparisons are across periods but within age groups. For those who prefer non-overlapping categories, it is merely a matter of confining attention to our youngest and oldest age groups. In the Appendix, Figure A1 offers a graphical representation of the respondents in our sample by listing their age, birth cohort, years observed, and the years in which they are 16 to 18 years old.

The GSS provides information on father's occupation, mother's occupation, respondent's occupation (at the time of the survey), sex, age, and other variables that aid in coding social class (e.g., employment status). Unfortunately, the GSS does not include a quantitative measure of parental income, thus making it impossible to carry out a direct individual-level test of the income hypothesis. Although the GSS does include a subjective measure of relative income, a measure of this sort is unusable for our purposes because changes in inequality may leave rank in the income distribution unaffected.

For the sake of comparability with most research in this area, we use an approximation to the Erikson, Goldthorpe, and Portacarero (EGP) class scheme (see, e.g., Erikson and Goldthorpe 1992).[12] This scheme includes the following class categories: (a) professionals and managers (EGP I/II); (b) routine white collar workers (EGP IIIa); (c) self-employed (nonfarm) workers with and without employees (EGP IVab); (d) skilled manual workers and supervisors of manual workers (EGP V/VI); (e) unskilled manual and nonmanual workers (EGP VIIa/IIIb); and (f) self-employed farmers and farm laborers (EGP IVc/VIIb).[13]

We have made small adjustments to the EGP categories to prevent various types of selective processes from affecting our assessments of trend. Rather than excluding respondents who, at age 16, had one or more absent parents, we have added a new category to the EGP scheme, labeled "non-resident parent." Likewise, rather than excluding mothers who are out of the labor force, we have again treated "out of the labor force" as a distinct class category. The resulting expanded scheme appears in Table 2.

The results that Beller (2009) reports make it clear that, whenever possible, it is important to use information from both parents simultaneously. Although it is conventional to simply take the "dominant occupation" and characterize the family's class situation in terms of it, we think it is important to more fully exploit the information that mixed-class families convey. At the same time, because our samples are too small to use the full cross-classification of father's and mother's categories, we have instead developed a symmetric scheme that aggregates across each possible type of a mixed-class family. The family with a professional father and self-employed mother is, for example, coded into the same category as a family with a professional mother and self-employed father. This approach, which yields a total of 34 class categories (see Table 1), allows us to take seriously Beller's (2009) injunction that mothers matter while also recognizing that, given the GSS data, sample-size constraints are binding. We will refer to the resulting classification as our "two-parent" scheme.

The top income hypothesis implies that the strongest evidence of change will be found in the odds ratios pertaining to the professional-managerial class. This hypothesis can be tested by creating subtables that isolate the odds ratios that it identifies as most and least affected by the takeoff. We thus proceed by creating four types of mobility tables: (a) "full class" tables that use all categories of the class schemes of Table 2; (b) residual "NPM tables" that are formed by excluding all origin and destination categories pertaining to the professional-managerial class;[14] (c) extended professional-managerial tables ("PM-1 tables") that collapse the routine white collar, self-employed, skilled/supervisor, unskilled, and farm categories into a single non-PM category and retain all other categories (including "non-resident" and "out of labor force");[15] and (d) reduced professional-managerial tables ("PM-2 tables") that combine the non-PM category in the PM-1 tables with all other categories ("non-resident," "out of labor force") and thus take a simple 2x2 form.[16]

If the top income hypothesis is on the mark, the trend should be strongest in those tables that isolate the odds ratios pertaining to the professional-managerial class (i.e., the PM-1 and PM-2 tables). By contrast, the "full class" tables provide a blunter tool with which to detect trend, as they also incorporate odds ratios that, under the top income hypothesis, are not expected to change very much. Finally, the top income hypothesis implies that the NPM tables should reveal very little evidence of a takeoff-induced trend, as they do not contain the very odds ratios (i.e., those pertaining to the professional-managerial class) that are most affected by rising inequality. If, on the other hand, the simple income hypothesis is on the mark, the odd ratios in the full, NPM, and PM tables should change at roughly the same pace.[17]

We restrict the analysis to male and female respondents between 25 and 60 years old (inclusive) who have nonmissing responses on age, gender, social class, and parental class (for either the father-only or two-class schemes). For each of the above types of mobility table, we have constructed separate cross-classifications for all combinations of gender, age group, and period. This yields a total of 24 mobility tables for our analyses based on father's class and a total of 12 mobility tables for our analyses based on the two-parent scheme. We have only 12 tables in the latter case because a measure of mother's occupation is only available within the GSS for the last two time periods (i.e., starting in 1994).

As noted above, our analyses will be based on age-specific tables for each period, an approach that privileges age and period over cohort. It is of course more common to apply a cohort approach when studying trends in social fluidity (e.g., Breen and Johnson 2007). When Beller (2009), for example, analyzed trends in social fluidity, she adopted a cohort approach that involved applying controls for age and its square in her models. These controls are needed to statistically adjust for the widely different ages at which members from different cohorts are observed. There are, however, two important drawbacks to her approach: (a) the validity of the estimates depends on getting the class-age profile right (see Hertz 2007 for a related point in the context of economic mobility); and (b) the biasing effects of changes in the process of selection into the labor force could be substantial (especially of course for women).

How, then, do we proceed? Unlike Beller (2009), we rely on cross-period comparisons of respondents falling within the *same* age group, with a particular focus on the 25-40 age group. This group is of special interest because, for the latest period, virtually all of its members were exposed to the takeoff while still children. By contrast, the vast majority of those 25-40 years old in the 1970s and 1980s became 18 before 1980, which means that they grew up before the takeoff in income inequality unfolded (see Figure A1). The 1990s is an intermediary period because only about half of those in the 25-40 age group during the 1990s grew up during the takeoff. Even when privileged children did experience the takeoff before becoming adults, they were nonetheless often teenagers when it commenced, which means that their parents typically did not receive their extra infusion of money in time to make early human capital investments (such as purchasing high-quality preschool). Moreover, this group experienced the initial part of the takeoff, when better-off parents were not yet receiving as much additional income as they later did. The upshot is that, within our young age group, the effects of the takeoff might start to operate in the 1980s (through "adult mechanisms" exclusively), should begin to show up with some force in the 1990s, and will register far more prominently in the 2000s.

We have to bear in mind, however, that two main forces are likely affecting the trend, not just exposure to the takeoff (i.e., the "income hypothesis") but also to educational expansion (i.e., the "education hypothesis"). Although we could have proceeded by disaggregating our mobility tables by education (e.g., Breen 2010a), it is infeasible to do so with the full-class tables, given how small our samples are. The fallback solution is to at least examine the relevant age-specific time series on college education (see Figure 4). As Figure 4 indicates, both women and men experienced a sharp upward trend in the proportion with college degrees, although the upward trend is more pronounced for women than for men (until the last decade).

The foregoing commentary can be formalized in the six testable hypotheses listed in Table 6. The first hypothesis expresses the relatively wide range of trend lines that the countervailing forces of educational expansion and rising inequality might produce. If the effects of the takeoff are exceedingly strong, they may more than offset the effects of educational expansion, thus producing an accelerating rigidification of the sort featured in the direst predictions. If, however, the effects of the takeoff are comparatively weak, we will only find a slowdown in the rate of decline in the origin-destination association. It follows that the association might (a) increase at an accelerating rate between the 1970s and the 2000s, (b) decrease at a decreasing rate between the 1970s and 2000s, or (c) stop decreasing and start increasing as the inequality takeoff unfolds. These three possibilities all imply that, between the 1970s and 2000s, the trend in association is convex towards the time axis. We therefore label it the "convexity hypothesis."

The second hypothesis follows from our argument that the 2000s are the home ground of the income hypothesis. In this most recent decade, the youngest age group was exposed to the takeoff from a very young age and in its more advanced and extreme stages, meaning that the intergenerational association will either increase more sharply or decline less sharply than in prior periods. We have thus labeled it the "accelerating change hypothesis."

The third hypothesis notes that, because the educational expansion was markedly more prominent for women than men between the 1970s and 1980s (see Figure 4), the decline in the association parameter should likewise be more prominent. This hypothesis assumes that, between the 1970s and 1980s, it was too early for the takeoff to have had any significant effects and that the education expansion was accordingly the main force behind change. The fourth hypothesis states that, because men and women experienced roughly the same educational expansion after the 1990s, we should not expect any major gender difference in the trend line for the association parameters. These two hypotheses thus refer to "gender-specific" change in the early decades and "gender-neutral" change in the more recent periods.

The final two hypotheses in Table 6 pertain to the locus of the takeoff's effects. The top-income hypothesis assumes that the takeoff mainly affects the advantage accruing to the professional-managerial class, while the simple income hypothesis assumes that the takeoff affects exchange among all classes. We adjudicate between these two hypotheses by determining whether the trends pertaining to the professional-managerial odds ratios are especially prominent.

Evidence for the Young Age Group

We proceed by estimating simple association models that condition on a common pattern of odds ratios but allow the strength of these odds ratios to vary across periods (Xie 1992; Erikson and Goldthorpe 1992). The resulting "unidiff model" may be represented as follows:

$$\log(F_{ijk}) = \lambda + \lambda_i^O + \lambda_j^D + \lambda_k^P + \lambda_{ik}^{OP} + \lambda_{jk}^{DP} + \psi_{ij}\phi_k$$

where λ is the intercept, λ_i^O is the marginal effect for the i[th] origin class, λ_j^D is the marginal effect for the j[th] destination class, λ_k^P is the marginal effect for the k[th] period, λ_{ik}^{OP} captures changes across periods in the origin marginal effects, λ_{jk}^{DP} captures changes across periods in the destination marginal effects, ψ_{ij} refers to the interactions between origin and destination class, and ϕ_k indexes the extent to which those interactions grow weaker or stronger across periods. In most cases, we report the estimate for ϕ_k/ϕ_{1990s}, as the 1990s is a convenient contrast category in assessing many of the hypotheses discussed above. We instead report ϕ_k/ϕ_{1970s} whenever doing so suits the hypothesis we seek to test. For purposes of comparison, we will also fit (a) the model of conditional independence (which drops $\psi_{ij}\phi_k$), and (b) the model of constant association (which drops ϕ_k). We will carry out one-tail tests of our hypotheses, as appropriate, within the PM-2 tables (see Table 6). The derivation for these tests can be found in the Appendix.

The results from our analysis are presented in Tables 3a to 3g, Tables 4 and 5, and Figures 5a to 5f. The fit statistics for the models are available in Tables 3a to 3g; the estimates of ϕ_k/ϕ_{1990s} or ϕ_k/ϕ_{1970s} are available in Table 4; one-sided tests of change between the 1990s and 2000s are available in Table 5; and line graphs of estimates of ϕ_k/ϕ_{1990s} are available in Figures 5a to 5f. Because the results and fit statistics for the PM-1 and PM-2 models are very similar, we will only discuss the results for the PM-2 models.

We begin by evaluating our first two hypotheses. As may be recalled, these two hypotheses express the key argument that educational expansion drives the trend at the beginning of the time series, whereas the effects of rising income inequality increasingly express themselves at the end of the time series. This formulation leads to the hypothesis that the trend in association is convex to the time axis (i.e., hypothesis 1) and that the association-increasing effects of the takeoff become increasingly prominent at the end of the time series (i.e., hypothesis 2). Is there any evidence in support of these hypotheses?

There indeed is. If one turns to Figures 5a and 5b, the left panel pertains to the trend in phi within the father-only tables (for sons and daughters respectively). In all cases, the point estimates reveal a curve that is convex to the time axis, a result that is consistent with the presumption that the effects of the takeoff are revealing themselves increasingly over time. For sons, the phi parameter in the full-class table drops from 1.05 in the 1970s to 0.94 in the 1980s, but then increases from 1.00 in the 1990s to 1.14 in the 2000s (Table 4, ages 25-40, row 1). In the PM-2 table, phi is roughly constant in the early decades (ranging from .92 in the 1970s to 1.00 in the 1990s), but then increases to 1.22 in the 2000s (Table 4, ages 25-40, row 4). The curve appears to be yet more convex for daughters. In the full-class table, phi drops from 1.68 in the 1970s to 1.08 and 1.00 in the 1980s and 1990s, but then goes back up to 1.29 in the 2000s (Table 4, ages 25-40, row 1). This “U-turn” assumes a near-perfect form in the corresponding PM-2 table. As Figure 5b and Table 4 reveal, phi drops from 1.46 in the 1970s to 0.97 and 1.00 in the 1980s and 1990s, but then restores to 1.45 in the 2000s (Table 4, ages 25-40, row 4). We are thus seeing convex curves within the father-only tables that are consistent with our first and second hypotheses.

Are these changes significant? Although the null hypothesis of no change in the association can only be rejected at conventional levels of significance in the models for daughters (see Tables 3a and 3d, left panels), that particular test is blunt and imperfect for the purposes of assessing whether the curve is convex.[18] Moreover, when we carry out one-sided tests in the PM-2 tables, we find that the null hypothesis of no change between the 1990s and 2000s is rejected at p = 0.061 for sons and p = 0.007 for daughters (see Table 5).

When we turn to the two-parent tables, we of course cannot estimate the full curve, as data are only available for the last two decades. The rate of change over these two decades is, however, roughly the same as shows up within our full father-only tables. These results, which appear in the right panels of Figures 5a and 5b, reveal a non-trivial increase in the point estimates from the 1990s to the 2000s. For sons, the estimate of phi for the full-class model increases 19 percent from the 1990s to the 2000s (Table 4, ages 25-40, row 13), an increase that is significant in our two-sided test at p = 0.108 (Table 3e, left panel). Within the PM-2 table, the corresponding estimate of phi increases 21 percent over this period (Table 4, ages 25-40, row 16), an increase that is significant at p = 0.081 in the one-sided test (Table 5). For daughters, the estimate of phi increases 19 percent in the full-class table (Table 4, ages 25-40, row 13), a change that is only significant at p = 0.130 in our two-sided test (Table 3e, left panel). By contrast, the estimate increases by 40 percent in the PM-2 table (Table 4, ages 25-40, row 16), with the corresponding one-sided test significant at p = 0.020 (Table 5).

It is clear by now that the recent change is usually larger and more significant (at conventional levels) in analyses pertaining to the professional-managerial odds ratios (i.e., PM-2 tables). This result, which is directly consistent with the top income hypothesis, shows up even more clearly when attention turns to the NPM tables (which exclude the professional-managerial categories). As Figure 5a and 5b reveal, all evidence of an increase in association disappears in the NPM tables, a result that implies that the takeoff is mainly working to increase professional-managerial reproduction. Within the NPM tables for sons, phi increases by 3% between the 1990s and 2000s in the father-only analyses (Table 4, ages 25-40, row 1), while it decreases by 7% over this period in the two-parent analyses (Table 4, ages 25-40, row 14). Within the NPM tables for daughters, phi decreases by 24% between the 1990s and 2000s in the father-only analyses (Table 4, ages 25-40, row 1), while it decreases by 48% over this period in the two-parent analyses (Table 4, ages 25-40, row 14). These results provide strong support for the top income hypothesis.

The only remaining hypotheses of interest pertain to the gender interactions. We have argued that, because the early expansion of education played out especially prominently for women, they would likely experience a correspondingly prominent initial decline in association. This gender interaction should, however, wither away in the more recent decade, when the rate of expansion became roughly the same for men and women. Are the data consistent with these expectations?

We do indeed find evidence of an initial decline in association that is more prominent for women than for men. When the left panels of Figure 5a and 5b are compared, we see that the association for sons changes only barely between the 1970s and 1980s, whereas the association for daughters drops substantially, just as their dramatic increase in college education would imply. These declines are significant for women (Table 4, ages 25-40, rows 5 & 8; Table 3g; Table 5). Moreover, when we test the null hypothesis that the log odds ratio is changing equally for women and men (in the PM-2 tables), that test is rejected with p = 0.058.

We care more, however, about trends in the recent period, when the takeoff in income inequality is in play. During this period, the educational expansion is no more prominent for women than for men (see Figure 4), which leads us to believe that the effect of the takeoff should register equivalently for each gender. The point estimates, which we have already presented, instead suggest a rather more prominent uptick in association for daughters (compare Figures 5a and 5b). Although the point estimates are thus inconsistent with our expectations, we also cannot reject the claim that the trend is the same across genders. That is, when we test the null hypothesis that the log odds ratio is changing equally for women and men (in the PM-2 tables), that hypothesis cannot be rejected in either the father-only tables (p

= 0.403) or the two-parent tables (p = 0.479).[19] The most appropriate conclusion given these results is to withhold judgment on this hypothesis.

Evidence from Older Age Groups

The foregoing evidence from the young age group is consistent with the argument that the takeoff in inequality has increased the intergenerational association. For sons and daughters alike, we find evidence that phi changes along a convex curve, a pattern that becomes even more pronounced for the tables pertaining to the professional-managerial odds ratios. The latter result is consistent with the top income hypothesis.

We can provide further evidence on the top income hypothesis by comparing these results to those that obtain for the two older age groups. As Figure 4 shows, education is again expanding within both of these older age groups, although in the last decade, that expansion slows down for women and disappears for men. The education effect, by itself, should therefore lead to a decline within these older groups in the intergenerational association (albeit not for men in the last decade). In the oldest age group, one would not expect any substantial countervailing effect of the takeoff, given that these respondents mainly grew up before the takeoff was in play (even when they were observed in the 2000s). If any effects of the takeoff are to be found for this group, they would therefore mainly reflect the growing capacity of aging parents to assist their adult children, a type of takeoff effect that is likely to be comparatively minor. The same is not the case, however, for the intermediary group of 32 to 50 year olds. Within the 2000s sample, approximately two-thirds of this age group became 18 *after* 1980, meaning that those with privileged origins could have benefited, as children, from the infusion of cash that their parents were beginning to receive. It follows that we should find some evidence of a takeoff effect within this intermediary age group, at least in the 2000s.

The results are largely consistent with these expectations. If we consider first the oldest age group (i.e., 42-60 years old), the estimate for phi declines from 1.16 to .89 for the full father-by-son tables and from 1.70 to 0.98 for the full father-by-daughter tables (Table 4, ages 42-60, row 1). The test statistics in Table 3a reveal that this change is significant at p = .109 for sons and p = .000 for daughters. The corresponding PM-2 tables show a steep decline for sons but not for daughters, whereas the point estimates for the two-parent tables are highly variable, with some suggesting a decline, others suggesting stability, and yet others suggesting an increase. The null hypothesis of no change in association cannot be rejected at any conventional significance level for the latter two-parent tables (see Tables 3e and 3f).
Taken together, we see *some* evidence of an overall decline in association, just as the education hypothesis would suggest. As anticipated, the origin-destination association does not appear to have increased in the 2000s, presumably because this age group is too old to have experienced the takeoff as a child.

If the middle age group (i.e., 32-50 years old) is considered next, here we expect to find *some* evidence of the takeoff's effects in the 2000s, as members of this age group did frequently experience it while still a child. We may expect, therefore, results that are midway between those of the youngest age group and those of the oldest age group. This is indeed what we largely find. If we consider, for example, the change in the full-class association between the 1990s and the 2000s, we see a 14 percent increase for young sons, a 2 percent increase for middle-aged sons, and an 11 percent decrease for older sons. The corresponding results for daughters are a 29 percent increase (young), 8 percent increase (middle-aged), and 2 percent decrease (old). The middle age group likewise assumes an intermediary position for the PM-2 association within father-only tables (between the 1990s and the 2000s). In this case, we see a 22 percent increase for young sons, a 14 percent increase for middle-aged sons, and a 10 percent decrease for old sons. The coefficients for daughters likewise reveal a 45 percent increase (young), 9 percent increase (middle aged), and 3 percent increase (old). These results are consistent with the view that the takeoff's effects are attenuated within the intermediary age group because a smaller proportion of that group experienced the takeoff as a child.

Conclusions

We have provided the first comprehensive evidence on the frequently-rehearsed claim that the takeoff in income inequality is reducing class mobility in the U.S. This hypothesis is difficult to test because the takeoff, although now some 40 years old, is not likely to register its full effects on mobility except among relatively recent entrants to the labor force. Because of this difficulty, some scholars have attempted to make inferences about trend on the basis of indirect evidence, such as (a) the association between class origins and academic performance (Reardon 2011), (b) the distribution of parental spending on children (Kornrich and Furstenberg 2011), or (c) the effects of income inequality on mobility within a cross-section of countries (Krueger 2012).

We have instead proceeded by searching for trend within the GSS data among those age groups and social classes that are most likely to evince trend. Although the data are sparse and caution is clearly warranted, our key conclusion is that the GSS data do indeed reveal a recent increase in the intergenerational association among young and even middle-age adults. We cannot of course establish the mechanisms by which this rigidification has been generated, but the factual status of this result is independent of whether the takeoff in income inequality produced it. It is nonetheless relevant that the observed pattern of trend is largely consistent with the predictions coming out of our two-factor model featuring the effects of (a) the expansion of mass education, and (b) the takeoff in income inequality. Just as this model implies, the association curve has the expected convex shape in the two younger age groups, and the change in association also appears to be accelerating in the most recent decade (presumably as the full effects of the takeoff register). These results suggest that the takeoff may be implicated, but of course we can hardly deliver a direct test without a direct measure of family income. In the ideal design, the mobility tables would be disaggregated by both family income and respondent's education, thus allowing the two-factor model to be properly evaluated.

The main predictions coming out of our two-factor model were on the mark save in one respect. For the most recent period, the model does not imply any differences in trend across genders, yet our point estimates did nonetheless reveal some differences (entailing a larger change for women). To be sure, this seeming anomaly may reflect nothing more than sampling variability, indeed we could not reject the null hypothesis that the fall in social fluidity is the same for men and women. It is also possible, however, that there are real differences in trend for men and women. These differences might have arisen because daughters born into the professional-managerial class have been especially able to exploit the new infusion of resources that their parents received. It is also possible, however, that the gender interaction results from the operation of mechanisms completely unrelated to the takeoff.

The increase in association uncovered by our models takes the form of rising professional-managerial reproduction. We have thus rejected the simple income hypothesis in favor of what we have dubbed the "top income" hypothesis. There are two reasons why one might expect the takeoff to principally affect reproduction in the professional-managerial class. Most obviously, this class was the main beneficiary of the takeoff, whereas the income gaps between other classes remained roughly the same. This mechanical effect may also combine powerfully with the special anxiety about reproduction that professional-managerial parents are often presumed to have. Because this class cares about reproduction, once additional resources become available it will likely commit them to reproductive ends, such as buying into high-end neighborhoods with good schools and advantageous networks. The takeoff has in this sense allowed the professional-managerial class to more reliably realize its strong interest in reproduction.

Appendix

An important advantage of the PM-2 tables is that, when only two periods are compared, they allow us to conduct one-sided or one-tailed tests. If "P diff" denotes the p-value of the chi-square test of the difference in G^2 between the constant association and unidiff models, the p-value of the one-sided tests can be computed as follows:

$\mathbf{H_0}$	$\mathbf{p-value}$
$\frac{\phi_{2000s}}{\phi_{1990s}} \leq 1$	$\begin{cases} \frac{P\ diff}{2} & if\ \frac{\phi_{2000s}}{\phi_{1990s}} \geq 1 \\ 1-\frac{P\ diff}{2} & if\ \frac{\phi_{2000s}}{\phi_{1990s}} \leq 1 \end{cases}$
$\frac{\phi_{2000s}}{\phi_{1990s}} \geq 1$	$\begin{cases} 1-\frac{P\ diff}{2} & if\ \frac{\phi_{2000s}}{\phi_{1990s}} \geq 1 \\ \frac{P\ diff}{2} & if\ \frac{\phi_{2000s}}{\phi_{1990s}} \leq 1. \end{cases}$

One way of deriving these one-sided tests is by observing that, given a PM-2 table with only two periods, let's say 1990s and 2000s, we can drop $\psi_{pm,pm}\phi_{1990s}$ + $\psi_{pm,pm}\phi_{2000s}$ from the unidiff model and substitute instead $\eta_{pm,pm}$+ $\eta_{pm,pm}^{2000}$ to represent association. It is easy to see that this model and the unidiff model are just re-parameterizations of each other, with $\eta_{pm,pm} = \psi_{pm,pm}\phi_{1990s}$ and $\eta_{pm,pm}^{2000} = \psi_{pm,pm}(\phi_{2000s} - \phi_{1990s})$. Indeed, the 1990s log odds ratio is represented in these two modes as $\psi_{pm,pm}\phi_{1990s}$ and $\eta_{pm,pm}$, respectively, while the 2000s log odds ratio is represented as $\psi_{pm,pm}\phi_{2000s}$ and $\eta_{pm,pm} + \eta_{pm,pm}^{2000}$. Hence we have:

$$\eta_{pm,pm} = \psi_{pm,pm}\phi_{1990s}$$

$$\eta_{pm,pm} + \eta_{pm,pm}^{2000} = \psi_{pm,pm}\phi_{2000s}$$

$$\psi_{pm,pm}\phi_{1990s} + \eta_{pm,pm}^{2000} = \psi_{pm,pm}\phi_{2000s}$$

$$\eta_{pm,pm}^{2000} = \psi_{pm,pm}(\phi_{2000s} - \phi_{1990s}).$$

In turn, this means that, as long as $\psi_{pm,pm} > 0$ (which is an assumption without which the unidiff model cannot be estimated), the chi-square test of the difference in G^2 between the constant association and unidiff models is both a test of the null hypothesis that $\phi_{2000s} = \phi_{1990s}$ and a test of the null hypothesis that $\eta_{pm,pm}^{2000} = 0$. Therefore, as the square of a variable with a standard normal distribution is a variable with a chi-squared distribution with 1 degree of freedom, it follows that we can compute the p-value of one-sided tests as follows:

$\mathbf{H_0}$	$\mathbf{p-value}$
$(\phi_{2000s} - \phi_{1990s}) \leq 0$	$1 - \Phi(sign(\phi_{2000s} - \phi_{1990s})\ (x^2)^{1/2}$
$(\phi_{2000s} - \phi_{1990s}) \geq 0$	$\Phi(sign(\phi_{2000s} - \phi_{1990s})\ (x^2)^{1/2}$

where x^2 is the chi-square statistic from the difference in G^2 between the constant association and unidiff models, $\Phi(z)$ is the cumulative distribution function of the standard normal distribution, and sign(y) is the sign function, which returns a positive sign if its argument is positive and a negative sign otherwise. Mathematically, however, these formulas are identical to the ones provided above, which can be computed more directly. We have the following equalities:

$$\Phi\left((x^2)^{\frac{1}{2}}\right) = 1 - \frac{F(x^2, 1)}{2}$$

$$\Phi\left(-(x^2)^{\frac{1}{2}}\right) = \frac{F(x^2, 1)}{2},$$

where $F(z, 1)$ is the cumulative distribution function of the chi-square distribution with 1 degree of freedom. Therefore, for the null that $(\phi_{2000s} - \phi_{1990s}) \leq 0$, if $sign(\phi_{2000s} - \phi_{1990s}) > 0$, we have:

$$1 - \Phi(\ (x^2)^{\frac{1}{2}} = 1 - 1 + \frac{F(x^2, 1)}{2} = \frac{F(x^2, 1)}{2} = \frac{P\ diff}{2}$$

and, if $sign(\phi_{2000s} - \phi_{1990s}) < 0$,

$$1 - \Phi(-\ (x^2)^{\frac{1}{2}} = 1 - \frac{F(x^2, 1)}{2} = 1 - \frac{P\ diff}{2},$$

which are the formulas used above for this null hypothesis. The formulas for the null that $(\phi_{2000s} - \phi_{1990s}) \geq 0$ follow immediately.

Endnotes

[1] This conclusion assumes, in particular, that neither the association between origin class and education or between education and outcome class is increasing. As already indicated, previous research suggests the former condition holds in the U.S., but we know less about the latter condition (see, e.g., Jackson et al. 2008).

[2] This argument relies on the well-known result that income inequality has grown not just within social classes but also between them (see Weeden et al. 2007; Moew and Kalleberg 2010; cf. Kim and Sakamoto 2008).

[3] It has long been argued (e.g., Tawney 1930) that access to class positions becomes increasingly unequal as the conditions under which children are raised become increasingly unequal.

[4] There are any number of possible long-term effects of rising inequality. It is possible, for example, that high-income parents will opt to send their children to private schools and hence become less supportive of public schools (see, for recent relevant evidence, Corcoran and Evans 2010; also see Mayer 2001; Goldin and Katz 1997).

[5] A list of additional confounding factors might include (a) growing immigration and the consequent realignment of the nation's racial and ethnic composition; (b) the mass incarceration of African American men (via the effects of a criminal record on subsequent labor-market opportunities); (c) the large increase in dual-career families and changes in assortative mating; (d) the emergence and growth of new types of educational and training institutions (e.g., home schooling, charter schools, for-profit universities, on-line universities and skill-certification programs); (e) an increase in the association between educational investments and class outcomes; and (f) the decline of the manufacturing sector.

[6] In Hauser (1998), occupations are indexed by their average income with the goal of generating estimates of economic mobility.

[7] The relationship between the IGE and the intergenerational correlation is given by

$$\rho = \frac{\sigma_p}{\sigma_c} IGE,$$

where ρ is the correlation coefficient and σ_p and σ_c are the standard deviations of the income or earnings distributions of parents and children, respectively. The IGE is not a measure of income or earnings *association* but a measure of average income or earnings *persistence* (e.g., Jantti et al. 2006:8).

[8] The results for women are less clear because, in the sample without single-parent families, the immobility parameters and the overall association parameter do not change in the same direction. In the sample with single-parent families, the immobility and overall association parameters are (a) sometimes zero, (b) sometimes suggestive of rigidification but quite small in size, and (c) sometimes suggestive of growing fluidity (see Beller 2009, Table 4).

[9] This figure is based on a mapping of occupation and employment status (self-employed, employed for salary or wages) into an approximation of the Erikson, Goldthorpe, and Portacarero (EGP) class scheme. This mapping was developed by Michael Hout. In constructing this figure, we used (a) the occupation and employment status of the current job for those who are employed, and (b) the occupation of the last job for those who are not employed. We used income in the last calendar year for the Census analyses, and we used income in the last 12 months for the ACS analyses. Because income was top-coded in 1950, 1960, 1970, 1980 and 2000, we replaced the top-coded values with their estimated means under the assumption that the tail of the income distribution follows a Pareto distribution (see, e.g., Fichtenbaum and Shahidi 1988). We estimated separate means for families headed by men and women.

[10] The coefficient of variation (standard deviation/mean) of average class income across all classes increased 46 percent between 1979 and 2010 (from 0.17 to 0.24). The same measure, when applied to all classes but professional and managers, stayed at 0.11 over this period.

[11] The professional-managerial class is numerically large. In the United States, almost 40 percent of those aged 25-64 in 2010 are in the professional-managerial class, a result that reflects, in part, the very generous definition of this class within the EGP scheme. It follows that the top-income hypothesis, as operationalized here, is not about mobility barriers at the very top of the income distribution. Rather, it is a hypothesis about mobility barriers at the top of the class distribution, barriers that arise because the "top class" garners ever more income with the takeoff. We could perfectly well have dubbed it the "professional-managerial income hypothesis," but decided against doing so for the sake of readability.

[12] We used a protocol developed by Michael Hout (see previous endnote) to map occupation and employment status into our class scheme. This protocol was designed for use with the 1980 Census Occupational Classification (COC). Because the 1988 GSS only codes occupations using the 1970 COC, we employed the Census Bureau's crosswalk (plus additional information from other sources) to map occupations from the 1970 COC into the 1980 COC. We tested this procedure by double coding class using the 1980 COC and the 1970 COC in the three years (1988-1990) in which the GSS has both. The results were acceptable at the very high level of aggregation adopted here. We compared the results from this approach with those obtained

using several other mappings and were unable to secure results superior to those reported here.

[13] In some cases, researchers group EGP IIIb with EGP IIIa, instead of grouping it with EGP VIIa, as we do here. We aggregated EGP IIIb with EGP VIIa because their average income in 2010 were quite similar. The averages in 2010 for EGP IIIa, EGP IIIb, and EGP VIIa are $71,140, $48,677, and $51,877 respectively.

[14] The NPM tables are generated by dropping any cell in which the respondent or at least one parent is in the professional-managerial class. That is, a cell is dropped from the father-only tables if either the respondent or the father is in the professional-managerial class, and a cell is dropped from the two-parent tables if the respondent or either parent is in the professional-managerial class.

[15] In the PM-1 tables, respondents are classified into only two categories, fathers into three (with the additional category of "non-resident parent"), and mothers into four (with yet another additional category of "out of labor force"). The two-parent class scheme has eight categories in its PM-1 form: (a) PM, PM; (b) PM, NPM; (c) NPM, NPM; (d) PM, NR; (e) PM, OLF; (f) NPM, NR; (g) NPM, OLF; and (h) NR, OLF.

[16] In these PM-2 tables, the two-parent class scheme includes just two categories: (a) at least one professional-managerial parent; and (b) neither parent is in the professional-managerial class.

[17] We have also carried out analyses within the 2x2 tables formed by contrasting the PM and non-PM categories (and excluding the "non-resident" and "out of labor force" categories). The results from these analyses are similar to those presented and hence will not be reported here.

[18] The likelihood-ratio tests upon which we rely are tests of restrictions and hence are not directional. Because developing and implementing the right test are difficult endeavors, we have not done so here.

[19] These are chi-square tests of the difference in G^2 between a saturated model and a model in which the ratio between the log odds ratios in the 1990s and the 2000s is the same for men and women.

References

Aaronson, David and Bhashkar Mazumder. 2008. "Intergenerational Economic Mobility in the U.S., 1940 to 2000." *Journal of Human Resources* 43(1):139-72.

Andrews, Dan and Andrew Leigh. 2009. "More Inequality, Less Social Mobility." *Applied Economics Letters* 16(15):1489–92.

Atkinson, Anthony B., Thomas Piketty, and Emmanuel Saez. 2011. "Top Incomes in the Long Run of History." *Journal of Economic Literature* 49(1):3-71.

Beller, Emily. 2009. "Bringing Intergenerational Social Mobility Research Into the Twenty-First Century: Why Mothers Matter." *American Sociological Review* 74(4):507-28.

Beller, Emily and Michael Hout. 2006. "Intergenerational Social Mobility: The United States in Comparative Perspective." *The Future of Children* 16(2):19-36.

Bowles, Samuel, Herbert Gintis, and Melissa Osborne. 2001. "The Determinants of Earnings: A Behavioral Approach." *Journal of Economic Literature* 39(4):1137-76.

Bloome, Deirdre and Bruce Western. 2011. "Cohort Change and Racial Differences in Educational and Income Mobility." *Social Forces* 90(2): 375-95.

Bourdieu, Pierre and Jean-Claude Passeron. 1977. *Reproduction in Education, Society, and Culture.* London: Sage Publications.

Breen, Richard, ed. 2004. *Social Mobility in Europe*. Oxford: Oxford University Press.

------. 2010a. "Educational Expansion and Social Mobility in the 20th Century." *Social Forces* 89(2):365-88.

------. 2010b. "Social Mobility and Equality of Opportunity." *The Economic and Social Review* 41(4):413-28.

Breen, Richard and Jan O. Jonsson. 2007. "Explaining Change in Social Fluidity: Educational Equalization and Educational Expansion in Twentieth-Century Sweden." *American Journal of Sociology* 112(6):1775-1810.

Breen, Richard, Ruud Luijkx, Walter Müller, and Reinhard Pollak. 2009. "Nonpersistent Inequality in Educational Attainment: Evidence from Eight European Countries." *American Journal of Sociology* 114(5):1475-1521.

Burtless, Gary T. and Christopher Jencks. 2003. “American Inequality and its Consequences.” Pp. 61-108 in *Agenda for the Nation*, edited by Henry J. Aaron, James M. Lindsay, and Pietro S. Nivola. Washington, DC: Brookings Institution Press**.**

Corak, Miles. 2013. “Inequality from Generation to Generation: The United States in Comparison.” Pp. 107-26 in *Economics of Inequality, Poverty and Discrimination in the 21st Century,* Volume I, edited by Robert S. Rycroft. Santa Barbara, CA: ABC-Clio Publishers (also http://milescorak.files.wordpress.com/2012/01/inequality-from-generation-to-generation-the-united-states-in-comparison-v3.pdf).

Corcoran, Sean and William N. Evans. 2010. “Income Inequality, the Median Voter, and the Support for Public Education.” NBER Working Paper No. 16097.

Davis, James A., Tom W. Smith, and Peter H. Marsden. 2010. *General Social Surveys 1972-2008.* Chicago, IL: National Opinion Research Center.

DeParle, Jason. 2012. “Harder for Americans to Rise from Lower Rungs.” *The New York Times*, January 4 (http://www.nytimes.com/2012/01/05/us/harder-for-americans-to-rise-from-lower-rungs.html).

Duncan, Greg J., Ariel Kalil, Kjetil Telle, and Kathleen M. Ziol-Guest. 2012. “Increasing Inequality in Parent Incomes and Children’s Completed Schooling: Correlation or Causation?” Presented at the Income, Inequality, and Educational Success: New Evidence about Socioeconomic Status and Educational Outcomes Conference, May 15-16, Stanford University.

Durlauf, Steven N. 1996. “A Theory of Persistent Income Inequality.” *Journal of Economic Growth* 1(1):75–93.

The Economist. 2010. “Upper Bound.” (http://www.economist.com/node/15908469.)

Erikson, Robert and John H. Goldthorpe. 1992. *The Constant Flux: A Study of Class Mobility in Industrial Societies*. Oxford: Clarendon Press.

Fichtenbaum, Rudy and Hushang Shahidi. 1988. “Truncation Bias and the Measurement of Income Inequality.” *Journal of Business and Economic Statistics* 6(3):335-37.

Foroohar, Rana. 2011. “What Ever Happened To Upward Mobility?” *Time Magazine*, November 14 (http://www.time.com/time/magazine/article/0,9171,2098584,00.html).

Franke-Ruta, Garance. 2012. “Class Now Trumps Race as the Great Divide in America.” *The Atlantic*, June 30 (http://www.theatlantic.com/politics/archive/2012/06/robert-putnam-class-now-trumps-race-as-the-great-divide-in-america/259256/).

Gamoran, Adam. 2001. “American Schooling and Educational Inequality: A Forecast for the 21st Century.” *Sociology of Education* 74:135-153.

Goldin, Claudia and Lawrence Katz. 1997. "Why the United States Led in Education: Lessons from Secondary School Expansion, 1910 to 1940." NBER Working Paper 6144.

Goodman, Leo. 1979. “Multiplicative Models of the Analysis of Mobility Tables and Other Kinds of Mixed-Classification Tables.” *American Journal of Sociology* 84(4):804-819.

Grusky, David B. and Erin Cumberworth. 2010. “A National Protocol for Measuring Intergenerational Mobility?” Presented at the National Academy of Science Workshop on Advancing Social Science Theory: The Importance of Common Metrics, February 25-26.

------. 2013. “Economic Inequality in the United States: An Occupy-Inspired Primer.” Pp. 13-42 in *Occupy the Future*, edited by David B. Grusky, Douglas McAdam, Robert Reich, and Debra Satz. Cambridge, MA: MIT Press.

Hall, Peter A. and David Soskice, eds. 2001. *Varieties of Capitalism: The Institutional Foundations of Comparative Advantage*. Oxford: Oxford University Press.

Harding, David J., Christopher Jencks, Leonard M. Lopoo, and Susan E. Mayer. 2005. “The Changing Effect of Family Background on the Incomes of American Adults.” Pp. 100-44 in *Unequal Chances: Family Background and Economic Success*, edited by Samuel Bowles, Herbert Gintis, and Melissa Osborne Groves. New York: Russell Sage Foundation.

Harrison, Bennett and Barry Bluestone. 1988. *The Great U-Turn: Corporate Restructuring and the Polarizing of America*. New York: Basic Books.

Hauser, Robert M. 1998. “Intergenerational Economic Mobility in the United States: Measures, Differentials, and Trends.” Center for Demography and Ecology Working Paper 98-12. Updated 2010.

Hertz, Tom. 2007. “Trends in the Intergenerational Elasticity of Family Income in the United States.” *Industrial Relations* 46(1):22-50.

Hertzler, J.O. 1952. “Some Tendencies Toward a Closed Class System in the United States.” *Social Forces* 30(3): 313-23.

Hout, Michael. 1988. “More Universalism, Less Structural Mobility: The American Occupational Structure in the 1980s.” *American Journal of Sociology* 93(6): 1358-1400.

Hout, Michael and Daniel P. Dohan. 1995. “Two Paths to Equality of Educational Opportunity:

Sweden and the United States Compared." Pp. 121-146 in *Equality of Educational Opportunity in Sweden: Historical and Comparative Perspectives*, edited by Robert Erikson and Janne Jonsson. Boulder, CO: Westview Press.

Hout, Michael and Alexander Janus. 2011. "Educational Mobility in the United States since the 1930s." Pp. 165-186 in *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*, edited by Greg J. Duncan and Richard J. Murnane. New York: Russell Sage Foundation.

Hout, Michael, Adrian E. Raftery, and Eleanor O. Bell. 1993. "Making the Grade: Educational Stratification in the United States, 1925–89. Pp. 25-49 in *Persistent Inequality: Changing Educational Attainment in Thirteen Countries*, edited by Yossi Shavit and Hans-Peter Blossfield. Boulder, CO: Westview Press.

Jackson, Michelle, Ruud Luijkx, Reinhard Pollak, Louis-André Vallet, and Herman G. van de Werfhorst. 2008. "Educational Fields of Study and the Intergenerational Mobility Process in Comparative Perspective." *International Journal of Comparative Sociology* 49(4-5):369-88.

Jäntti, Markus, Bernt Bratsberg, Knut Røed, Oddbjøorn Raaum, Robin Naylor, Eva Österbacka, Anders Björklund, and Tor Eriksson. 2006. "American Exceptionalism in a New Light: A Comparison of Intergenerational Earnings Mobility in the Nordic Countries, the United Kingdom, and the United States." IZA Discussion Paper No. 1938.

Kaushal, Neeraj, Katherine Magnuson, and Jane Waldfogel. 2011. "How is Family Income Related to Investments in Children's Learning?" Pp. 187-206 in *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*, edited by Greg J. Duncan and Richard J. Murnane. New York: Russell Sage Foundation.

Kim, ChangHwan and Arthur Sakamoto. 2008. "The Rise of Intra-Occupational Wage Inequality in the United States, 1983 to 2002." *American Sociological Review* 73(1):129-57.

Kornrich, Sabino and Frank Furstenberg. 2013. "Investing in Children: Changes in Parental Spending on Children, 1972 to 2007." *Demography* 50(1):1-23.

Krueger, Alan. 2012. "The Rise and Consequences of Inequality in the United States." Presented to the Center for American Progress, January 12, Washington, DC (www.americanprogress.org/events/2012/01/pdf/krueger.pdf).

Lareau, Annette. 2003. *Unequal Childhoods: Class, Race, and Family Life.* Berkeley, CA: University of California Press.

Lee, Chul-In and Gary Solon. 2009. "Trends in Intergenerational Income Mobility." *Review of Economics and Statistics* 91(4):766-72.

Levine, David I. and Bhashkar Mazumder. 2007. “The Growing Importance of Family: Evidence from Brothers’ Earnings.” *Industrial Relations* 46(1):7-21.

Mayer, Susan. 1997. *What Money Can’t Buy: Family Income and Children's Life Chances*. Cambridge, MA: Harvard University Press.

Mayer, Susan. 2001. “How Did the Increase in Economic Inequality between 1970 and 1990 Affect Children’s Educational Attainment?” *American Journal of Sociology* 107(1):1–32.

Mayer, Susan and Leonard Lopoo. 2004. “What do Trends in the Intergenerational Economic Mobility of Sons and Daughters in the United States Mean?” Pp. 90-121 in *Generational Income Mobility in North America and Europe*, edited by Miles Corak. Cambridge, MA: Cambridge University Press.

------. 2005. “Has the Intergenerational Transmission of Economic Status Changed?” *The Journal of Human Resources* 40(1):169-85

Mayo, Deborah G. and Aris Spanos. 2006. "Severe Testing as a Basic Concept in a Neyman–Pearson Philosophy of Induction." *British Journal for the Philosophy of Science* 57(2):323-357.

Mazumder, Bhashkar. 2012. “Is Intergenerational Economic Mobility Lower Now Than In the Past?” Federal Reserve Bank of Chicago Essays on Issues Number 297.

Morgan, Stephen L. and Youngjoo Cha. 2007. “Rent and the Evolution of Inequality in Late Industrial United States.” *American Behavioral Scientist* 50(5):677-701.

Morgan, Stephen L. and Young-Mi Kim. 2006. "Inequality of Conditions and Intergenerational Mobility: Changing Patterns of Educational Attainment in the United States." Pp. 165-94 in *Mobility and Inequality: Frontiers of Research from Sociology and Economics*, edited by Stephen L. Morgan, David B. Grusky, and Gary S. Fields. Stanford, CA: Stanford University Press.

Morgan, Stephen L. and Mark W. McKerrow. 2004. “Social Class, Rent Destruction, and the Earnings of Black and White Men, 1982-2000.” *Research in Social Stratification and Mobility* 21:215-251.

Mouw, Ted and Arne Kalleberg. 2010. “Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s.” *American Sociological Review* 75(3):402-31.

OECD (Organisation for Economic Co-operation and Development). 2010. “A Family Affair: Intergenerational Social Mobility across OECD Countries.” Pp. 181-98 in *Economic Policy Reforms: Going for Growth*. Paris: OECD Publishing.

Pfeffer, Fabian T. 2008. "Persistent Inequality in Educational Attainment and Its Institutional Context." *European Sociological Review* 24(5):543-565.

Pollak, Reinhard, David B. Grusky, Jan O. Jonsson, and Matthew Di Carlo. 2011. “Recent Trends in Social Mobility in the United States. A New Approach to Modeling Trend in Big Class, Gradational, and Microclass Reproduction.” Stanford Center on Poverty and Inequality Working Paper.

Reardon, Sean F. 2011. “The Widening Academic Achievement Gap Between the Rich and the Poor: New Evidence and Possible Explanations.” Pp. 91-116 in *Whither Opportunity? Rising Inequality, Schools, and Children’s Life Chances*, edited by Greg J. Duncan and Richard J. Murnane. New York: Russell Sage Foundation.

Roemer, John. 1998. *Equality of Opportunity*. Cambridge, MA: Harvard University Press.

------. 2004. “Equal Opportunity and Intergenerational Mobility: Going Beyond Intergenerational Income Transition Matrices.” Pp.48-57 in *Generational Income Mobility in North America and Europe*, edited by Miles Corak. Cambridge, MA: Cambridge University Press.

------. 2012. “On Several Approaches to Equality of Opportunity.” *Economics and Philosophy* 28(Special Issue 02):165-200

Roksa, Josipa, Eric Grodsky, Richard Arum, and Adam Gamoran. 2007. “Changes in Higher Education and Social Stratification in the United States.” Pp. 165-191 in *Stratification in Higher Education: A Comparative Study*, edited by Yossi Shavit, Richard Arum, and Adam Gamoran. Stanford, CA: Stanford University Press.

Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. *Integrated Public Use Microdata Series: Version 5.0* [Machine-readable database]. Minneapolis, MN: University of Minnesota.

Shavit, Yossi and Hans-Peter Blossfield, eds. 1993. *Persistent Inequality: Changing Educational Attainment in Thirteen Countries*. Boulder, CO: Westview Press.

Shavit, Yossi, Meir Yaish, and Eyal Bar-Haim. 2007. “The Persistence of Persistent Inequality.” Pp. 1-21 in *Origin to Destination: Trends and Mechanisms in Social Stratification Research*, edited by Stefani Scherer, Reinhard Pollak, Gunnar Otte, and Markus Gangl. Chicago, IL: The University of Chicago Press.

Sibley, Elbridge. 1942. “Some Demographic Clues to Stratification.” *American Sociological Review* 7(3): 322-30.

Swift, Adam. 2005. “Justice, Luck, and the Family: The Intergenerational Transmission of Economic Advantage from a Normative Perspective.” Pp. 256-76 in *Unequal Chances:*

Family Background and Economic Success, edited by Samuel Bowles, Herbert Gintis, and Melissa Osborne Groves. New York: Russell Sage Foundation.

Tawney, Richard Henry. 1930. *Equality.* London: G. Allen and Unwin.

Torche, Florencia. 2011. "Is a College Degree Still the Great Equalizer? Intergenerational Mobility across Levels of Schooling in the United States." *American Journal of Sociology* 117(3):763-807.

------. 2013. "Education and the Intergenerational Transmission of Advantage in the US." New York University Working Paper.

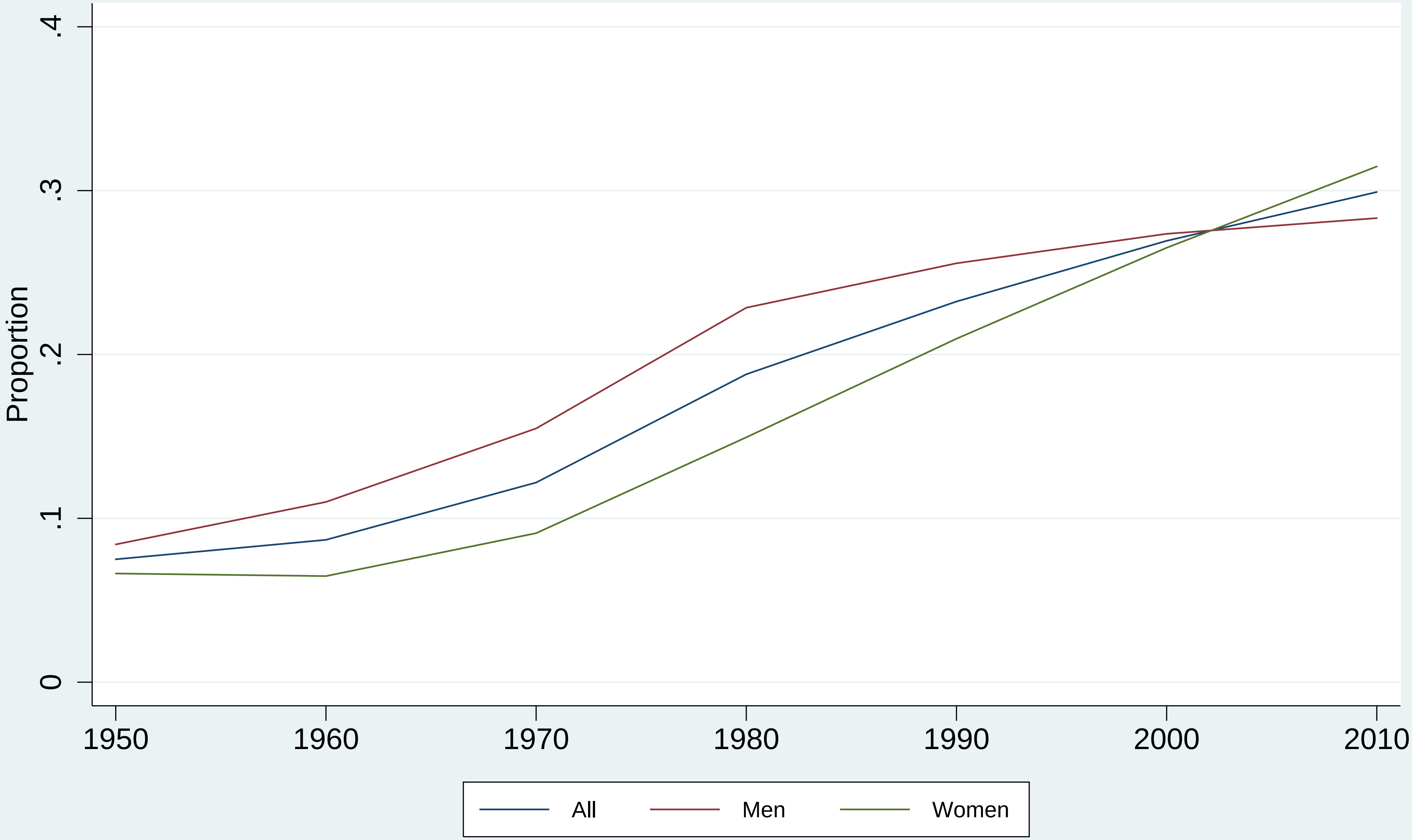
Vallet, Louis-André. 2001. "Forty Years of Social Mobility in France: Change in Social Fluidity in the Light of Recent Models." *Revue Française de Sociologie*, 42(Supplement):5-64.

-------. "Change in Intergenerational Class Mobility in France from the 1970s to the 1990s and its Explanation: An Analysis Following the CASMIN approach." Pp. 115-148 in *Social Mobility in Europe*, edited by Richard Breen. Oxford: Oxford University Press.

Weeden, Kim, Young-Mi Kim, Matthew Di Carlo, and David Grusky. 2007. "Social Class and Earnings Inequality." *American Behavioral Scientist* 50(5):702-36.

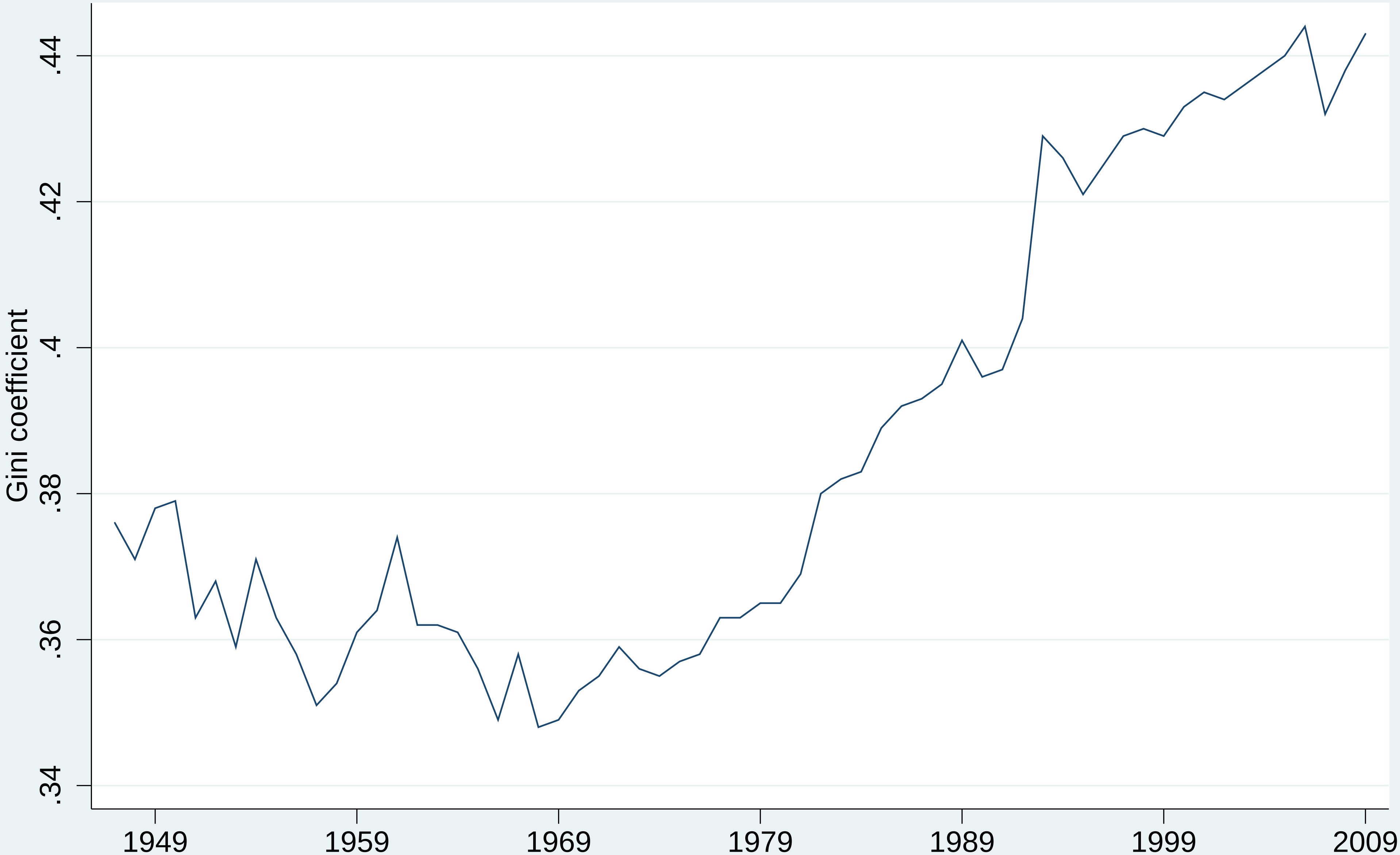
Xie, Yie. 1992. "The Log-Multiplicative Layer Effect Model for Comparing Mobility Tables." *American Sociological Review* 57(3):380-95.

Figure 1: Proportion of 25−60 Year Olds with a BA or More, 1949−2009



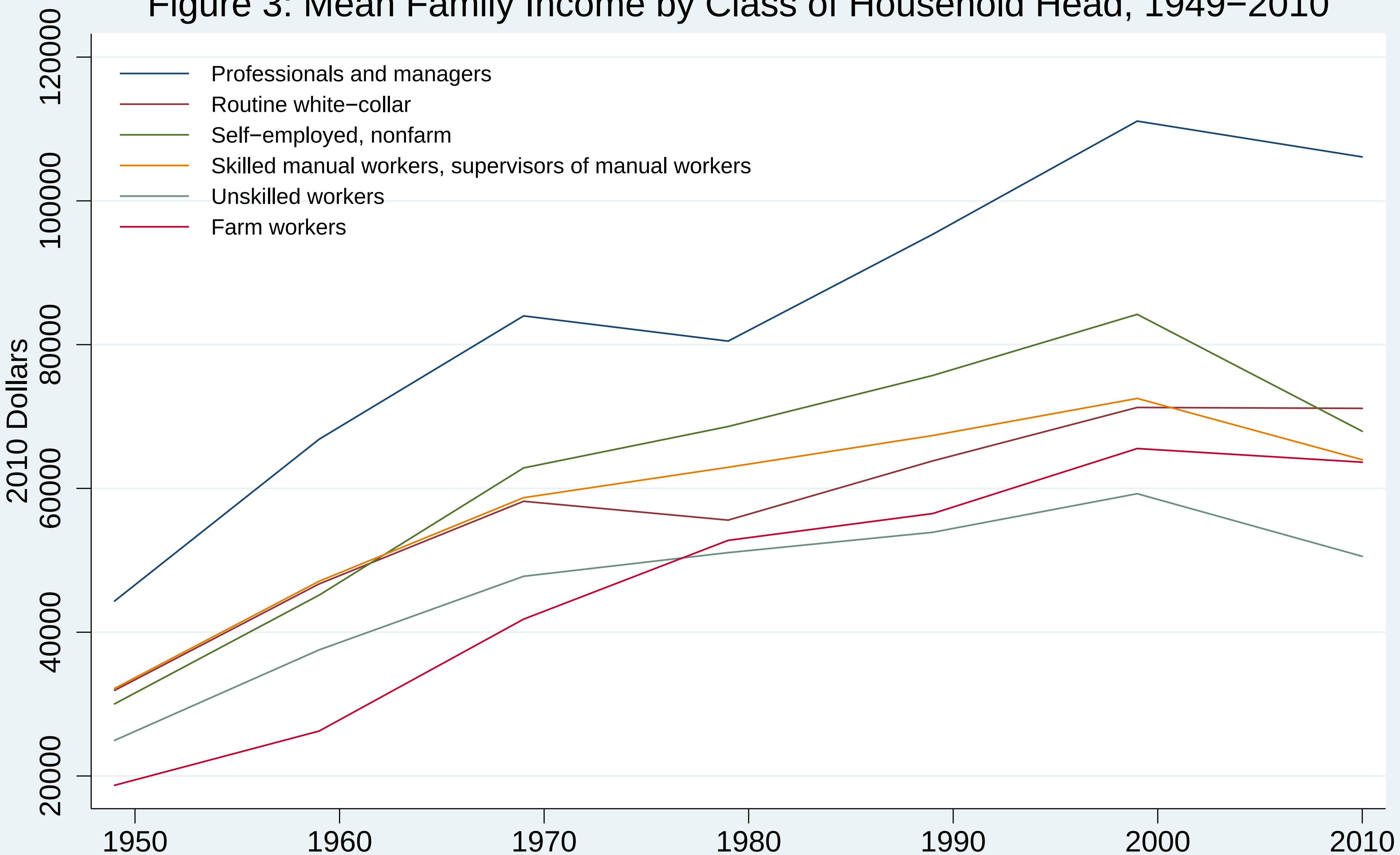
Source: Authors' analysis of data from Census of Population 1950−2000, and American Community Survey 2010, Integrated Public Use Microdata Series (Ruggles et al., 2010).

Figure 2: Family Income Inequality, 1947−2009



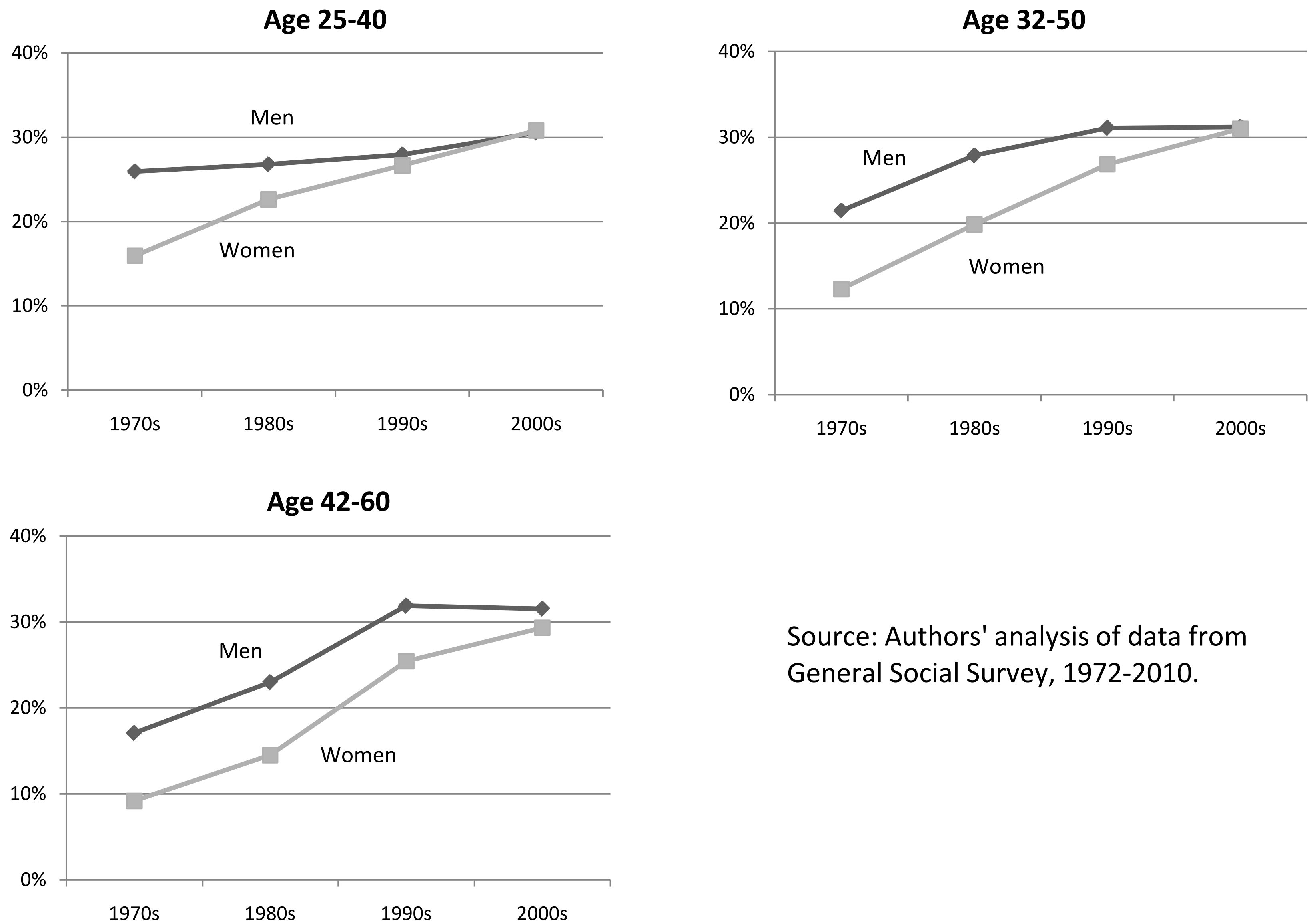
Source: Census Bureau’s Historical Income Tables for Families, Table F−4 (Gini Ratios for Families, by Race and Hispanic Origin of Householder: 1947 to 2010).

Figure 3: Mean Family Income by Class of Household Head, 1949−2010



Source: Authors' analysis of data from Census of Population 1950−2000, and American Community Survey 2011, Integrated Public Use Microdata Series (Ruggles et al., 2010).

Figure 4. Percent with a Bachelor's degree or more



Source: Authors' analysis of data from General Social Survey, 1972-2010.

Figure 5a: Unidiff Parameter Phi, Men Ages 25-40 (Reference Period:1990s)

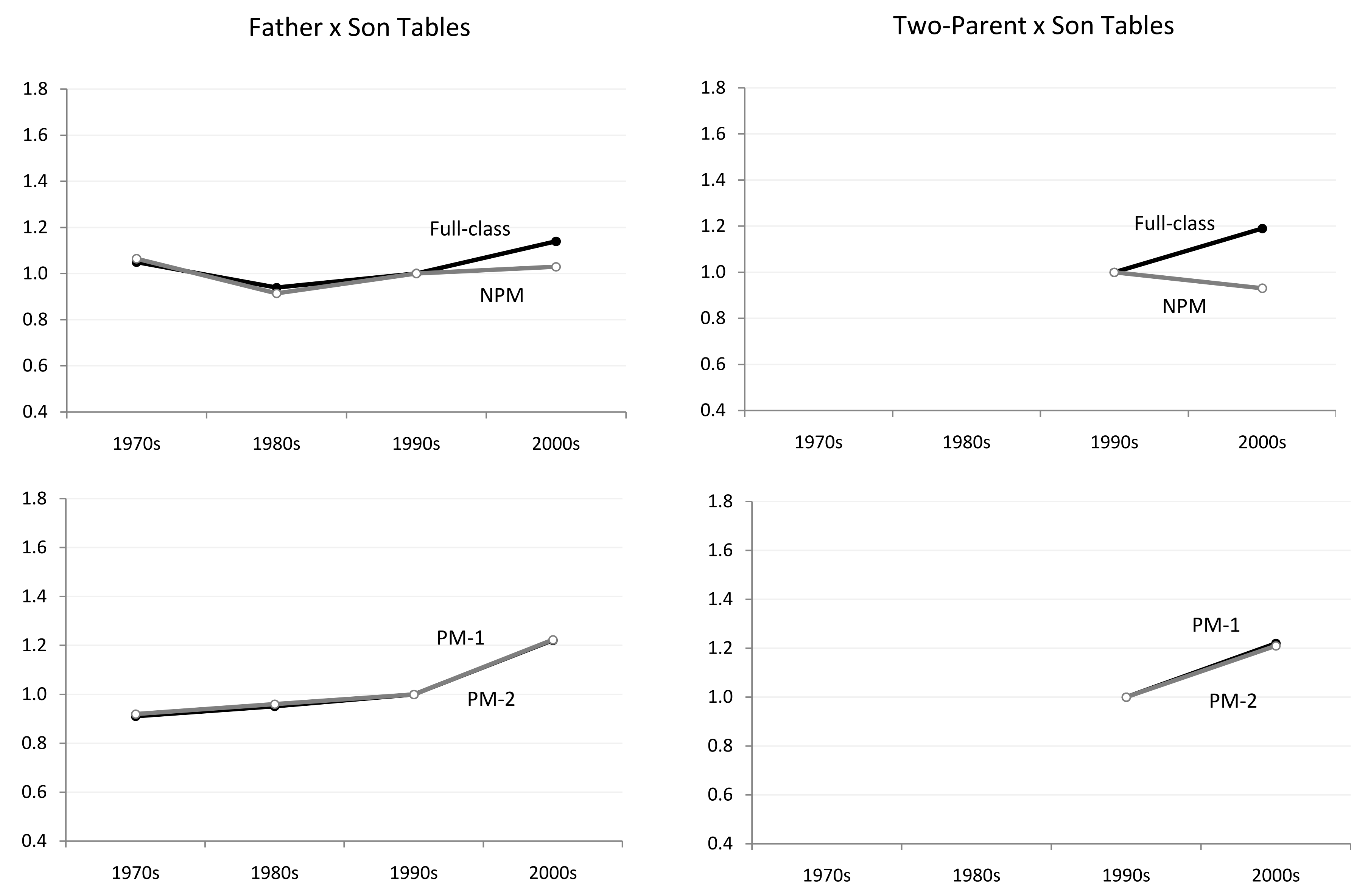


Figure 5b: Unidiff Parameter Phi, Women Ages 25-40 (Reference Period:1990s)

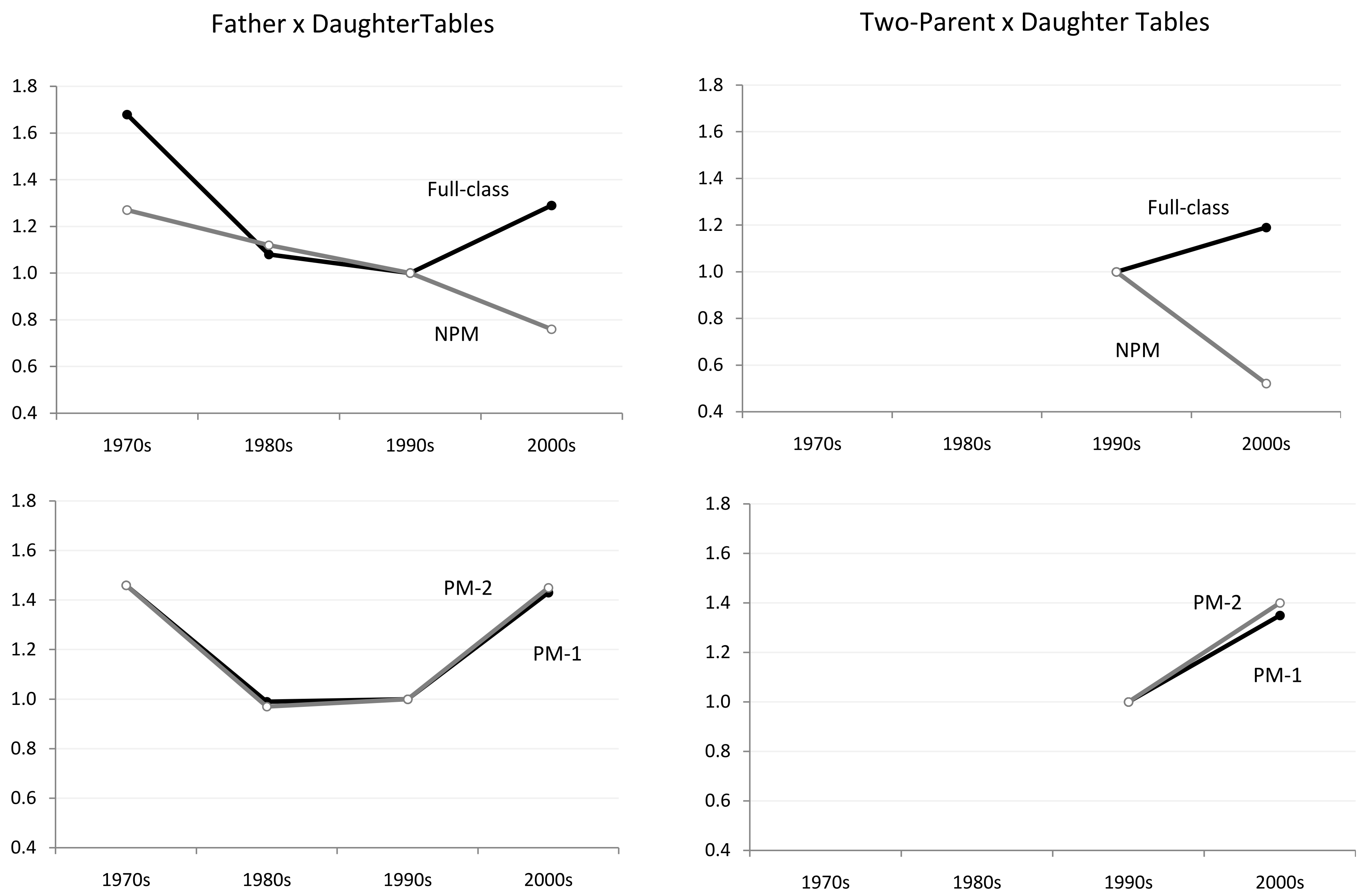


Figure 5c: Unidiff Parameter Phi, Men Ages 32-50 (Reference Period:1990s)

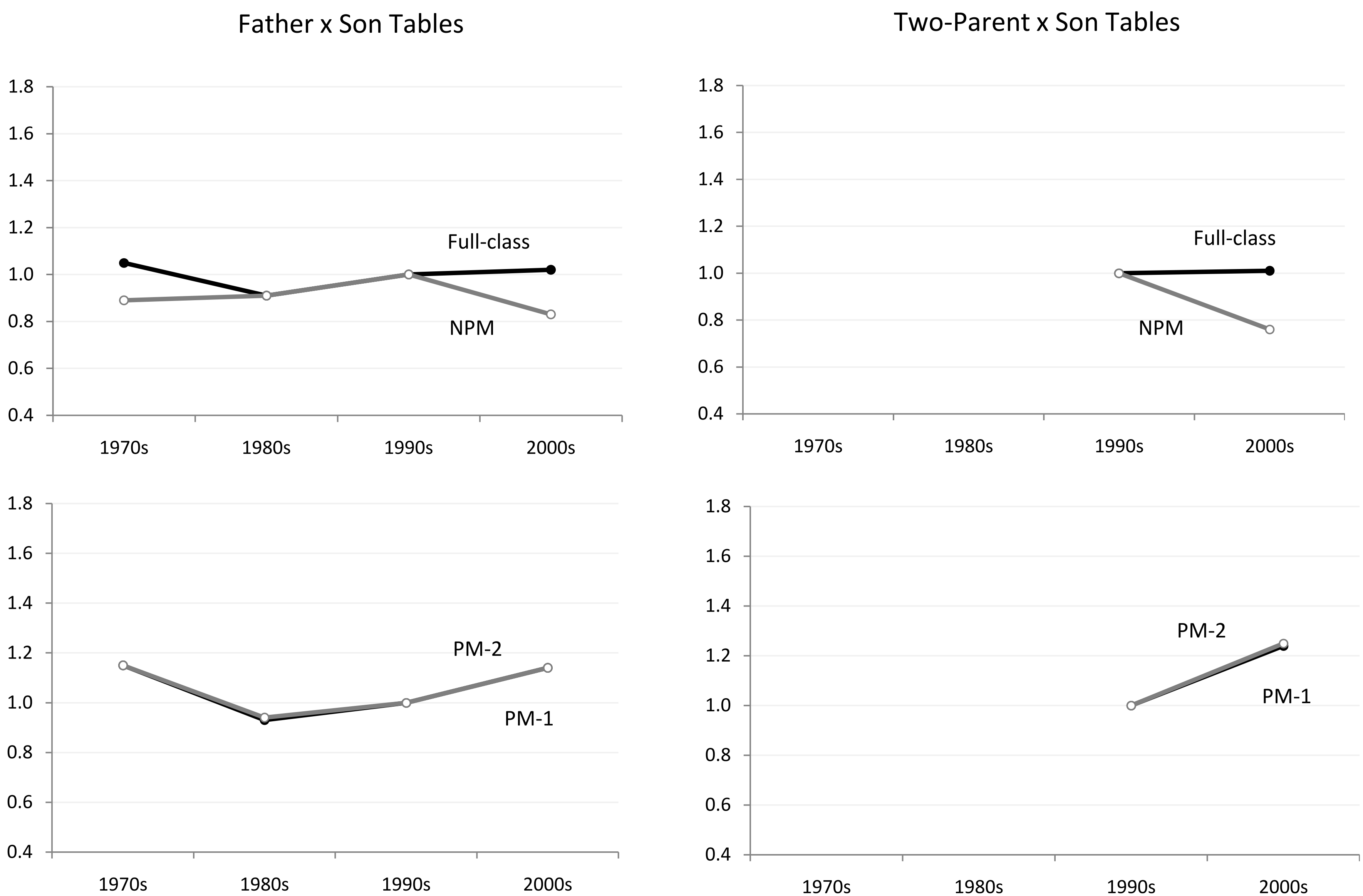


Figure 5d: Unidiff Parameter Phi, Women Ages 32-50 (Reference Period:1990s)

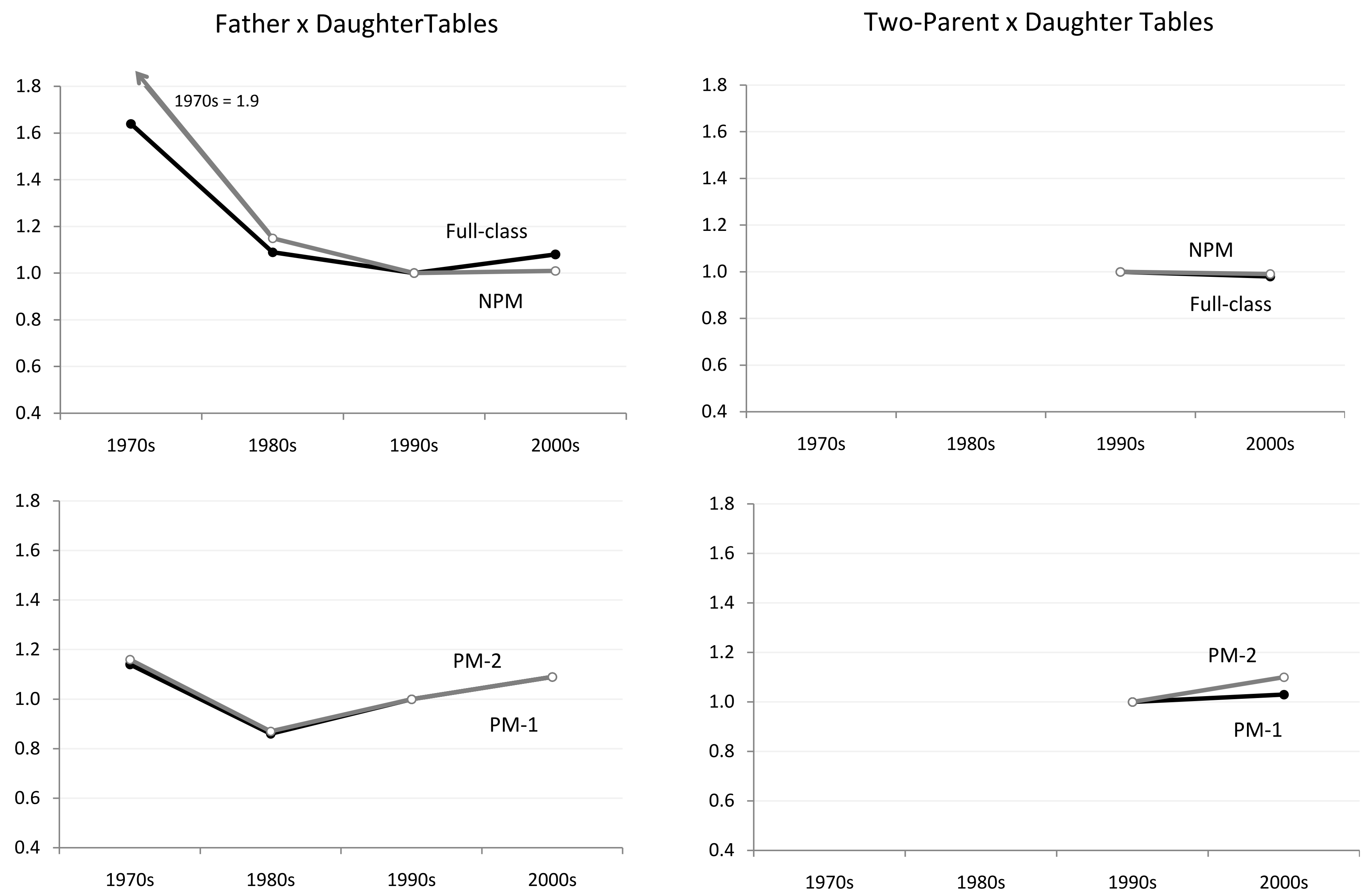


Figure 5e: Unidiff Parameter Phi, Men Ages 42-60 (Reference Period:1990s)

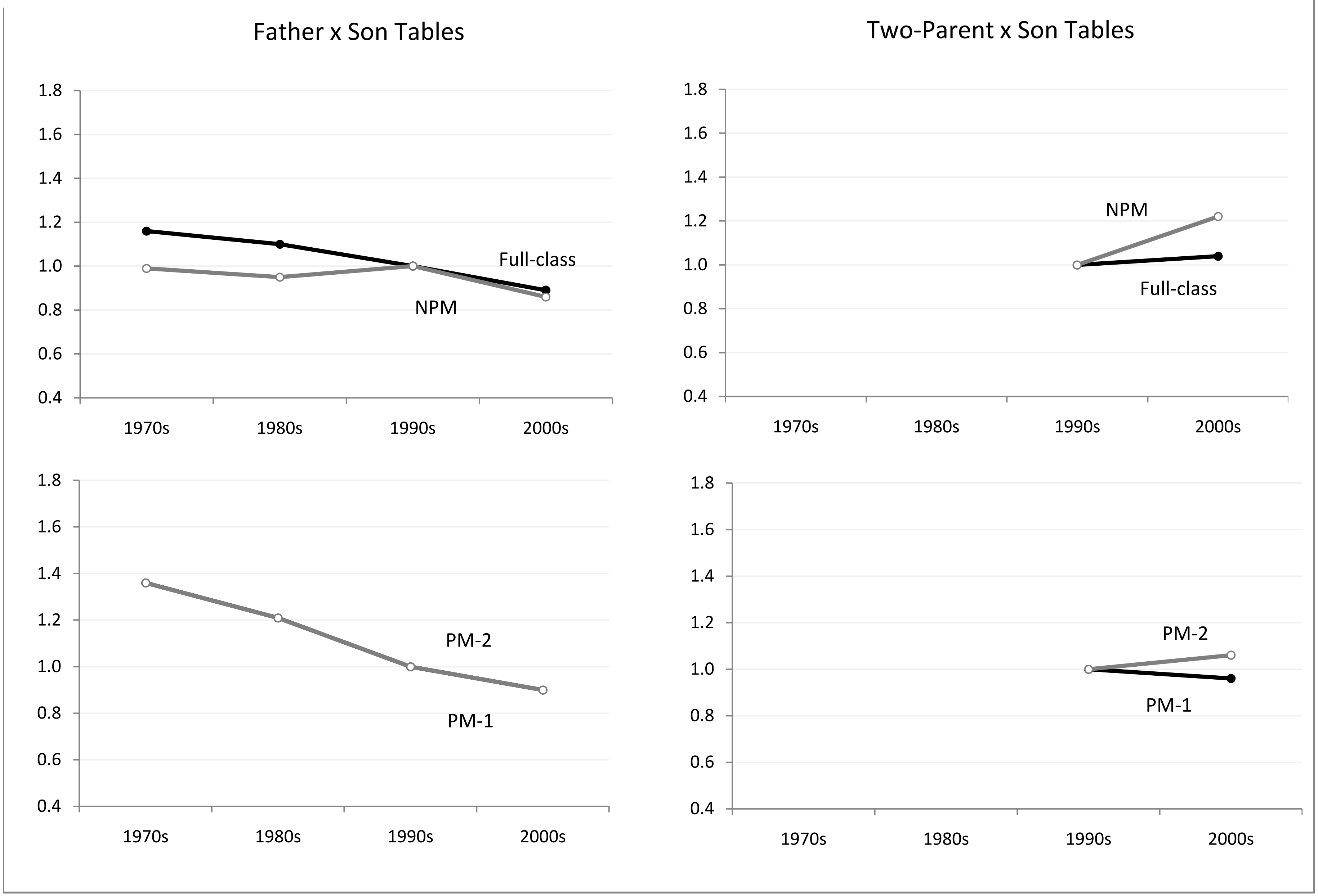


Figure 5f: Unidiff Parameter Phi, Women Ages 42-60 (Reference Period:1990s)

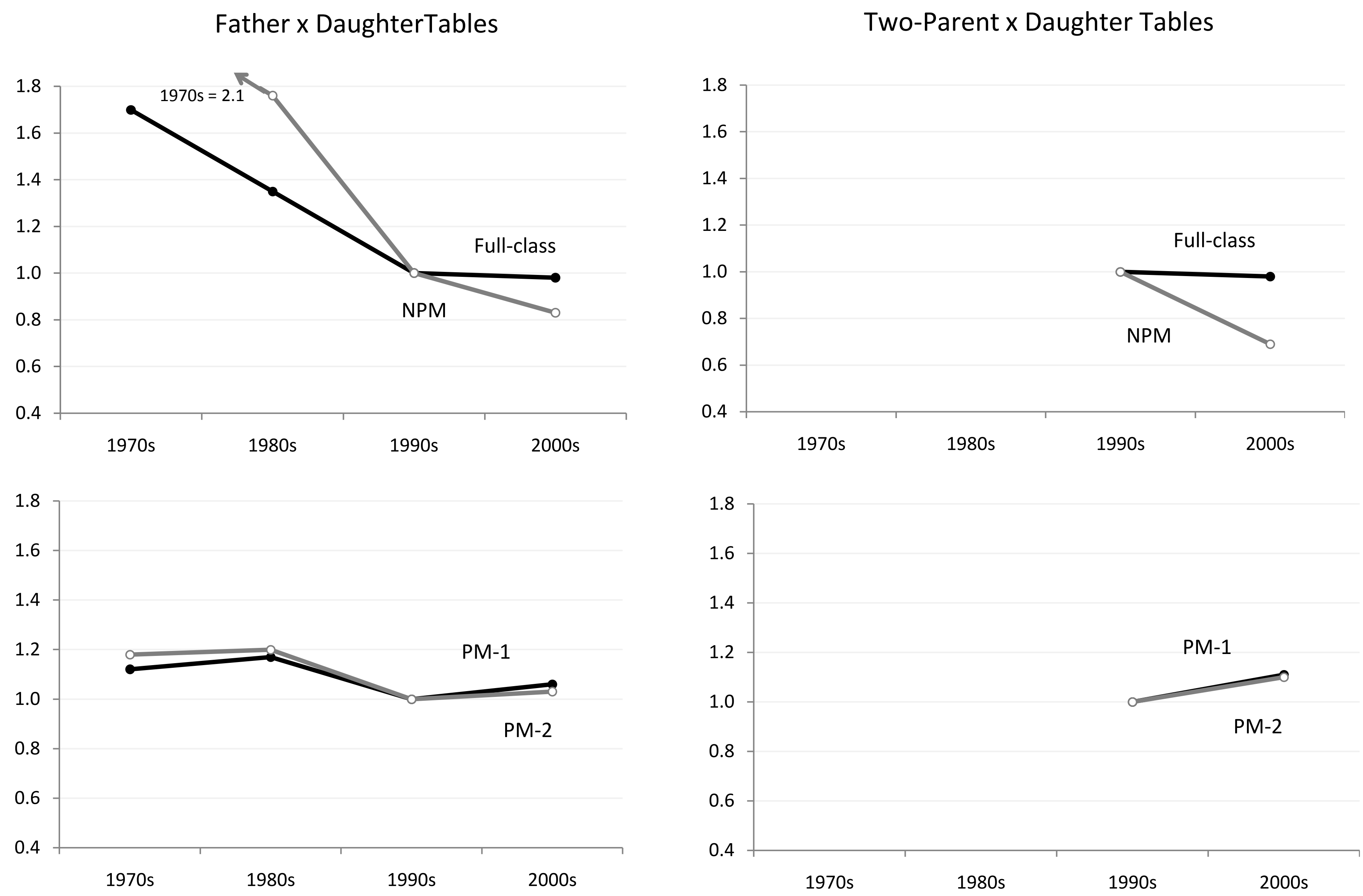


Figure A1. Birth cohort, years when aged 16-18, and ages and years observed of respondents in the three age groups studied

Cohort	Year at			1970s										1980s										1990s										2000s									
	16	17	18	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
1911	1927	1928	1929	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99
1912	1928	1929	1930	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98
1913	1929	1930	1931	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97
1914	1930	1931	1932	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96
1915	1931	1932	1933	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95
1916	1932	1933	1934	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94
1917	1933	1934	1935	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93
1918	1934	1935	1936	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92
1919	1935	1936	1937	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91
1920	1936	1937	1938	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90
1921	1937	1938	1939	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89
1922	1938	1939	1940	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88
1923	1939	1940	1941	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87
1924	1940	1941	1942	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86
1925	1941	1942	1943	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85
1926	1942	1943	1944	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84
1927	1943	1944	1945	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83
1928	1944	1945	1946	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82
1929	1945	1946	1947	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81
1930	1946	1947	1948	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80
1931	1947	1948	1949	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79
1932	1948	1949	1950	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78
1933	1949	1950	1951	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77
1934	1950	1951	1952	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76
1935	1951	1952	1953	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75
1936	1952	1953	1954	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74
1937	1953	1954	1955	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73
1938	1954	1955	1956	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72
1939	1955	1956	1957	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71
1940	1956	1957	1958	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70
1941	1957	1958	1959	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69
1942	1958	1959	1960	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68
1943	1959	1960	1961	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67
1944	1960	1961	1962	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66
1945	1961	1962	1963	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65
1946	1962	1963	1964	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64
1947	1963	1964	1965	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63
1948	1964	1965	1966	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62
1949	1965	1966	1967	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61
1950	1966	1967	1968	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
1951	1967	1968	1969	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59
1952	1968	1969	1970	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58
1953	1969	1970	1971	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57
1954	1970	1971	1972	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56
1955	1971	1972	1973	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55
1956	1972	1973	1974	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54
1957	1973	1974	1975	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53
1958	1974	1975	1976	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52
1959	1975	1976	1977	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51
1960	1976	1977	1978	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
1961	1977	1978	1979	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49
1962	1978	1979	1980	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
1963	1979	1980	1981	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47
1964	1980	1981	1982	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46
1965	1981	1982	1983	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
1966	1982	1983	1984	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44
1967	1983	1984	1985	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43
1968	1984	1985	1986	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42
1969	1985	1986	1987	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41
1970	1986	1987	1988	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1971	1987	1988	1989		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39
1972	1988	1989	1990			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
1973	1989	1990	1991				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37
1974	1990	1991	1992					1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
1975	1991	1992	1993						1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
1976	1992	1993	1994							1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1977	1993	1994	1995								1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1978	1994	1995	1996									1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1979	1995	1996	1997										1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1980	1996	1997	1998											1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1981	1997	1998	1999												1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1982	1998	1999	2000													1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1983	1999	2000	2001														1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1984	2000	2001	2002															1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1985	2001	2002	2003																1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25

Respondent ages 25-40   Respondents ages 32-50   Respondents ages 42-60

Notes:

GSS data not collected in 1971, 1979, 1981, 1992, 1995, 1997, 1999, 2001, 2003, 2005, 2007 and 2009.

Information needed to establish mother's class only available starting in 1994.

Table 1: Sample descriptives (unweighted proportions)

Variables	1970s	1980s	1990s	2000s	Variables	1990s	2000s
Female	0.53	0.55	0.55	0.54	*Two-parent class**		
					Prof/manager, Prof/manager	0.07	0.09
Age 25-40	0.51	0.57	0.52	0.45	Prof/manager, rout. white collar	0.05	0.05
Age 32-50	0.51	0.54	0.61	0.56	Prof/manager, self-employed	0.02	0.02
Age 42-60	0.46	0.40	0.45	0.52	Prof/manager, skilled/supervisor	0.02	0.03
					Prof/manager, unskilled	0.05	0.06
Respondent's class					Prof/manager, farm	0.01	0.00
Professional/manager	0.28	0.34	0.39	0.43	Prof/manager, non-resident parent	0.03	0.04
Routine white collar	0.20	0.17	0.14	0.12	Prof/manager, out of labor force	0.08	0.07
Self-employed	0.06	0.07	0.07	0.06	Rout. white collar, rout. white collar	0.01	0.01
Skilled/supervisor	0.12	0.11	0.11	0.10	Rout. white collar, self-employed	0.02	0.01
Unskilled	0.35	0.31	0.29	0.29	Rout. white collar, skilled/supervisor	0.02	0.03
					Rout. white collar, unskilled	0.03	0.03
Father's class					Rout. white collar, farm	0.00	0.00
Professional/manager	0.14	0.19	0.23	0.25	Rout. white collar, Non-resident parent	0.02	0.03
Routine white collar	0.04	0.04	0.05	0.03	Rout. white collar, out of labor force	0.02	0.01
Self-employed	0.12	0.12	0.10	0.10	Self-employed, self-employed	0.01	0.01
Skilled/supervisor	0.17	0.16	0.16	0.16	Self-employed, skilled/supervisor	0.01	0.01
Unskilled	0.26	0.24	0.22	0.23	Self-employed, unskilled	0.02	0.02
Farm	0.16	0.11	0.08	0.06	Self-employed, farm	0.00	0.00
Non-resident parent	0.12	0.13	0.15	0.18	Self-employed, non-resident parent	0.01	0.01
					Self-employed, out of labor force	0.04	0.04
					Skilled/supervisor, skilled/supervisor	0.01	0.01
					Skilled/supervisor, unskilled	0.06	0.07
					Skilled/supervisor, farm	0.00	0.00
					Skilled/supervisor, non-resident parent	0.01	0.02
					Skilled/supervisor, out of labor force	0.06	0.04
					Unskilled, unskilled	0.09	0.08
					Unskilled, farm	0.02	0.01
					Unskilled, non-resident parent	0.07	0.07
					Unskilled, out of labor force	0.07	0.06
					Farm, farm	0.00	0.00
					Farm, non-resident parent	0.01	0.00
					Farm, out of labor force	0.04	0.03
					Non-resident parent, out of labor force	0.03	0.02
Sample size	6,854	7,902	9,221	7,422	Sample size	9,221	7,422

* Mother's class is only available starting in 1994.

Table 2: Expanded class schemas

Full class schema, Respondent		
	1	Professionals/Managers
	2	Routine white collar
	3	Self-Employed
	4	Skilled/Supervisor
	5	Unskilled
Full class schema, Father		
	1	Professionals/Managers
	2	Routine white collar
	3	Self-Employed
	4	Skilled/Supervisor
	5	Unskilled
	6	Farm
	7	Non-Resident parent
Full class schema, Mother (available from 1994 on)		
	1	Professionals/Managers
	2	Routine white collar
	3	Self-Employed
	4	Skilled/Supervisor
	5	Unskilled
	6	Farm
	7	Non-Resident parent
	8	Out of Labor Force

Notes:

1. For respondents not living with their fathers at age 16, the occupation of a father substitute—that is, a step-father, male relative, or other male adult with whom they were living – was often reported. In these cases the information for the father-substitute was used to determine the class of the “father.” In the case of respondents not living with any male adult, the corresponding origin has been coded as “non-resident father.” The same rules were used in constructing mothers’ expanded class.
2. In models with father and mother class combined, equivalent combinations of father’s and mother’s classes are coded the same (see text for an example). The combinations “Farm, Self-Employed” and “Non-resident parent, Non-resident parent” were dropped to avoid zero marginal totals.

Table 3a. Results of fitting log-linear models to father x respondent full-class mobility tables

Four periods (1970s, 1980s, 1990s, 2000s)

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	7333	96	829.7	0.00	-24.7	14	
CA	7333	72	88.5	0.09	-552.3	3.7	
Unidiff	7333	69	85.2	0.09	-528.9	3.5	0.352
Women 25-40							
CI	8855	96	720.70	0.00	-151.8	11.4	
CA	8855	72	88.80	0.09	-565.6	3.5	
Unidiff	8855	69	67.00	0.55	-560.1	2.7	0.000
Men 32-50							
CI	8046	96	968.1	0.00	104.8	14.4	
CA	8046	72	82.9	0.18	-564.5	3.6	
Unidiff	8046	69	81.0	0.15	-539.5	3.5	0.593
Women 32-50							
CI	9491	96	776.40	0.00	-102.8	11.4	
CA	9491	72	125.40	0.00	-534.0	4.2	
Unidiff	9491	69	104.30	0.00	-527.6	3.8	0.000
Men 42-60							
CI	6565	96	860.3	0.00	16.6	14.7	
CA	6565	72	100.8	0.01	-532.0	4.5	
Unidiff	6565	69	94.8	0.02	-511.7	4.2	0.109
Women 42-60							
CI	7736	96	685.90	0.00	-173.6	12.2	
CA	7736	72	136.40	0.00	-508.2	4.7	
Unidiff	7736	69	113.10	0.00	-504.7	4.1	0.000

Two periods (1990s, 2000s)

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3670	48	444.9	0	50.9	14.5	
CA	3670	24	28.3	0.25	-168.7	3	
Unidiff	3670	23	26.9	0.26	-161.8	2.9	0.242
Women 25-40							
CI	4479	48	346.9	0	-56.7	11.2	
CA	4479	24	36	0.05	-165.8	3.1	
Unidiff	4479	23	31.4	0.11	-162	2.9	0.032
Men 32-50							
CI	4445	48	559.9	0	156.7	15	
CA	4445	24	15	0.92	-186.6	2.1	
Unidiff	4445	23	14.8	0.9	-178.4	2	0.631
Women 32-50							
CI	5310	48	385.8	0	-25.9	10.4	
CA	5310	24	44.2	0.01	-161.7	3.2	
Unidiff	5310	23	43.7	0.01	-153.6	3.1	0.497
Men 42-60							
CI	3623	48	449.4	0	56	14.8	
CA	3623	24	30.4	0.17	-166.3	3.5	
Unidiff	3623	23	29.3	0.17	-159.2	3.4	0.306
Women 42-60							
CI	4346	48	293.4	0	-108.7	10.5	
CA	4346	24	28.6	0.24	-172.5	2.7	
Unidiff	4346	23	28.6	0.19	-164.1	2.7	0.975

Notes:

1. CI=Conditional independence model; CA=Constant association model.

2. "P diff" is the p-value from a chi-square test of the difference in G^2 between the constant association and unidiff models.

Table 3b. Results of fitting log-linear models to father x respondent NPM mobility tables

Four periods (1970s, 1980s, 1990s, 2000s)

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3947	60	273.3	0.00	-223.5	9.6	
CA	3947	45	54.2	0.16	-318.4	3.7	
Unidiff	3947	42	53.5	0.11	-294.3	3.6	0.870
Women 25-40							
CI	4668	60	147.60	0.00	-359.3	6.5	
CA	4668	45	46.10	0.43	-334.1	3.1	
Unidiff	4668	42	44.30	0.37	-310.5	3	0.617
Men 32-50							
CI	4368	60	311.4	0.00	-191.5	9.6	
CA	4368	45	38.5	0.74	-338.7	3.5	
Unidiff	4368	42	37.2	0.68	-314.8	3.3	0.730
Women 32-50							
CI	5121	60	194.70	0.00	-317.8	6.9	
CA	5121	45	61.50	0.05	-322.9	4	
Unidiff	5121	42	52.60	0.13	-306.1	3.6	0.031
Men 42-60							
CI	3788	60	334.6	0.00	-159.7	10.7	
CA	3788	45	59.1	0.08	-311.7	4.5	
Unidiff	3788	42	58.2	0.05	-287.8	4.4	0.839
Women 42-60							
CI	4450	60	234.70	0.00	-269.3	8.3	
CA	4450	45	78.80	0.00	-299.2	4.8	
Unidiff	4450	42	64.20	0.02	-288.7	3.4	0.002

Two periods (1990s, 2000s)

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	1884	30	135.3	0	-90.9	9.4	
CA	1884	15	16.3	0.37	-96.9	2.6	
Unidiff	1884	14	16.2	0.3	-89.3	2.6	0.960
Women 25-40							
CI	2117	30	60.4	0	-169.3	5.9	
CA	2117	15	18.4	0.24	-96.4	3.2	
Unidiff	2117	14	18.3	0.19	-88.9	3	0.701
Men 32-50							
CI	2240	30	158.8	0	-72.6	9.5	
CA	2240	15	11.2	0.73	-104.5	2.8	
Unidiff	2240	14	10.4	0.73	-97.6	2.5	0.352
Women 32-50							
CI	2504	30	68.6	0	-166.2	5.1	
CA	2504	15	12.7	0.62	-104.7	2.4	
Unidiff	2504	14	12.5	0.56	-97	2.4	0.671
Men 42-60							
CI	1891	30	172.7	0	-53.6	10.9	
CA	1891	15	17	0.32	-96.2	3.5	
Unidiff	1891	14	16	0.31	-89.6	3.6	0.330
Women 42-60							
CI	2096	30	71.6	0	-157.8	5.4	
CA	2096	15	13.2	0.59	-101.6	2.7	
Unidiff	2096	14	13.1	0.52	-94	2.7	0.824

Notes: 1. CI=Conditional independence model; CA=Constant association model.

2. "P diff" is the p-value from a chi-square test of the difference in G^2 between the constant association and unidiff models.

Table 3c. Results of fitting log-linear models to father x respondent PM-1 mobility tables

Four periods (1970s, 1980s, 1990s, 2000s)

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	7333	8	392.9	0.00	321.7	9.5	
CA	7333	6	6.2	0.40	-47.2	1.1	
Unidiff	7333	3	1.6	0.66	-25.1	0.4	0.205
Women 25-40							
CI	8855	8	332.50	0.00	259.8	7.7	
CA	8855	6	13.70	0.03	-40.8	1.6	
Unidiff	8855	3	2.80	0.42	-24.5	0.6	0.012
Men 32-50							
CI	8046	8	460.0	0.00	388.1	9.5	
CA	8046	6	12.4	0.05	-41.5	1.4	
Unidiff	8046	3	9.5	0.02	-17.5	0.8	0.402
Women 32-50							
CI	9491	8	310.90	0.00	237.7	6.9	
CA	9491	6	9.10	0.17	-45.8	1	
Unidiff	9491	3	6.20	0.10	-21.2	0.8	0.411
Men 42-60							
CI	6565	8	305.0	0.00	234.7	7.8	
CA	6565	6	10.9	0.09	-41.9	1.3	
Unidiff	6565	3	3.8	0.29	-22.6	0.6	0.069
Women 42-60							
CI	7736	8	222.70	0.00	151.1	5.9	
CA	7736	6	13.40	0.04	-40.3	1.4	
Unidiff	7736	3	12.70	0.01	-14.1	1.2	0.875

Two periods (1990s, 2000s)

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3670	4	246.6	0	213.8	11.2	
CA	3670	2	2.8	0.25	-13.6	1.1	
Unidiff	3670	1	0.5	0.49	-7.7	0.4	0.128
Women 25-40							
CI	4479	4	186.6	0	152.9	8.6	
CA	4479	2	6.4	0.04	-10.5	1.5	
Unidiff	4479	1	0.7	0.39	-7.7	0.5	0.018
Men 32-50							
CI	4445	4	301.2	0	267.6	11.2	
CA	4445	2	1.8	0.41	-15	0.7	
Unidiff	4445	1	0.6	0.45	-7.8	0.4	0.276
Women 32-50							
CI	5310	4	207.6	0	173.3	8.1	
CA	5310	2	1	0.62	-16.2	0.5	
Unidiff	5310	1	0.6	0.45	-8	0.4	0.526
Men 42-60							
CI	3623	4	161.7	0	129	8.6	
CA	3623	2	0.8	0.66	-15.6	0.7	
Unidiff	3623	1	0.4	0.55	-7.8	0.3	0.497
Women 42-60							
CI	4346	4	139.7	0	106.2	6.8	
CA	4346	2	2.2	0.34	-14.6	0.7	
Unidiff	4346	1	1.9	0.17	-6.5	0.8	0.603

Notes:

1. CI=Conditional independence model; CA=Constant association model.

2. “P diff” is the p-value from a chi-square test of the difference in G^2 between the constant association and unidiff models.

Table 3d. Results of fitting log-linear models to father x respondent PM-2 mobility tables

Four periods (1970s, 1980s, 1990s, 2000s)

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	7333	4	390.7	0	355.1	9.5	
CA	7333	3	4.4	0.22	-22.3	0.8	
Unidiff	7333	0	0	n/a	0	0	0.222
Women 25-40							
CI	8855	4	327.7	0	291.3	7.7	
CA	8855	3	11.9	0.01	-15.4	1.4	
Unidiff	8855	0	0	n/a	0	0	0.008
Men 32-50							
CI	8046	4	450.4	0	414.4	9.4	
CA	8046	3	2.8	0.42	-24.2	0.7	
Unidiff	8046	0	0	n/a	0	0	0.420
Women 32-50							
CI	9491	4	302.9	0	266.3	6.9	
CA	9491	3	2.7	0.44	-24.8	0.5	
Unidiff	9491	0	0	n/a	0	0	0.441
Men 42-60							
CI	6565	4	301.2	0	266.1	7.8	
CA	6565	3	7.1	0.07	-19.3	1.1	
Unidiff	6565	0	0	n/a	0	0	0.069
Women 42-60							
CI	7736	4	207.3	0	171.5	5.8	
CA	7736	3	1.3	0.73	-25.6	0.4	
Unidiff	7736	0	0	n/a	0	0	0.728

Two periods (1990s, 2000s)

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3670	2	244.7	0	228.3	11.2	
CA	3670	1	2.4	0.12	-5.8	1.1	
Unidiff	3670	0	0	n/a	0	0	0.121
Women 25-40							
CI	4479	2	185.2	0	168.4	8.6	
CA	4479	1	6	0.01	-2.4	1.5	
Unidiff	4479	0	0	n/a	0	0	0.014
Men 32-50							
CI	4445	2	299.6	0	282.8	11.2	
CA	4445	1	1.2	0.27	-7.2	0.7	
Unidiff	4445	0	0	n/a	0	0	0.272
Women 32-50							
CI	5310	2	200.9	0	183.7	8.1	
CA	5310	1	0.3	0.57	-8.3	0.3	
Unidiff	5310	0	0	n/a	0	0	0.568
Men 42-60							
CI	3623	2	160.9	0	144.5	8.6	
CA	3623	1	0.4	0.51	-7.8	0.4	
Unidiff	3623	0	0	n/a	0	0	0.508
Women 42-60							
CI	4346	2	126.1	0	109.3	6.8	
CA	4346	1	0	0.86	-8.3	0.1	
Unidiff	4346	0	0	n/a	0	0	0.861

Notes:

1. CI=Conditional independence model; CA=Constant association model.

2. "P diff" is the p-value from a chi-square test of the difference in G^2 between the constant association and unidiff models.

Table 3e. Results of fitting log-linear models to two-parent x respondent full-class and NPM mobility tables (1990s, 2000s)

Full-class

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3125	256	721.9	0.00	-1338.2	19.6	
CA	3125	128	166.1	0.01	-863.9	7.3	
Unidiff	3125	127	163.5	0.02	-858.5	7.4	0.108
Women 25-40							
CI	3796	256	667.10	0.00	-1442.8	16.8	
CA	3796	128	147.30	0.12	-907.7	6.4	
Unidiff	3796	127	145.00	0.13	-901.7	6.1	0.130
Men 32-50							
CI	3836	256	818.3	0.00	-1294.3	18.9	
CA	3836	128	150.7	0.08	-905.6	6.5	
Unidiff	3836	127	150.8	0.07	-897.3	6.5	1.000
Women 32-50							
CI	4549	256	779.10	0.00	-1377.1	16.5	
CA	4549	128	152.00	0.07	-926.1	6.1	
Unidiff	4549	127	151.80	0.07	-917.8	6.1	0.723
Men 42-60							
CI	3205	256	683.2	0.00	-1383.4	18.7	
CA	3205	128	122.8	0.61	-910.5	6.1	
Unidiff	3205	127	122.6	0.59	-902.6	6.1	0.727
Women 42-60							
CI	3831	256	639.30	0.00	-1472.9	15.4	
CA	3831	128	134.50	0.33	-921.6	5.6	
Unidiff	3831	127	134.60	0.31	-913.3	5.6	1.000

NPM

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	1365	144	247.7	0.00	-791.8	14.5	
CA	1365	72	87.5	0.10	-432.3	7.3	
Unidiff	1365	71	87.6	0.09	-425.0	7.2	1.000
Women 25-40							
CI	1504	144	216.10	0.00	-837.4	12	
CA	1504	72	82.70	0.18	-444.1	7.6	
Unidiff	1504	71	79.20	0.24	-440.2	6.6	0.062
Men 32-50							
CI	1719	144	296.0	0.00	-776.8	14.3	
CA	1719	72	85.9	0.13	-450.5	7.5	
Unidiff	1719	71	83.6	0.14	-445.3	7.1	0.133
Women 32-50							
CI	1894	144	234.90	0.00	-851.8	11.3	
CA	1894	72	73.70	0.42	-469.6	5.6	
Unidiff	1894	71	73.60	0.39	-462.2	5.6	0.776
Men 42-60							
CI	1522	144	278.3	0.00	-776.9	15	
CA	1522	72	62.9	0.77	-464.7	6.5	
Unidiff	1522	71	61.8	0.77	-458.5	6.3	0.288
Women 42-60							
CI	1677	144	231.60	0.00	-837.6	11	
CA	1677	72	79.90	0.25	-454.7	6.4	
Unidiff	1677	71	78.20	0.26	-449.0	6.3	0.191

Notes:

1. CI=Conditional independence model; CA=Constant association model.

2. “P diff” is the p-value from a chi-square test of the difference in G^2 between the constant association and unidiff models.

Table 3f. Results of fitting log-linear models to two-parent x respondent PM-1 and PM-2 mobility tables (1990s, 2000s)

PM-1

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3129	14	266.3	0.00	153.7	12.8	
CA	3129	7	6.0	0.55	-50.4	1.5	
Unidiff	3129	6	3.5	0.74	-44.8	1.2	0.117
Women 25-40							
CI	3800	14	201.40	0.00	86.0	9.7	
CA	3800	7	12.90	0.07	-44.8	2.3	
Unidiff	3800	6	9.10	0.17	-40.3	1.9	0.052
Men 32-50							
CI	3839	14	291.6	0.00	176.1	12.1	
CA	3839	7	7.1	0.42	-50.7	1.5	
Unidiff	3839	6	4.1	0.66	-45.4	1.0	0.087
Women 32-50							
CI	4556	14	302.30	0.00	184.4	10.2	
CA	4556	7	17.40	0.02	-41.6	2.7	
Unidiff	4556	6	17.30	0.01	-33.2	2.7	0.830
Men 42-60							
CI	3208	14	159.4	0.00	46.4	9.4	
CA	3208	7	4.6	0.71	-51.9	1.2	
Unidiff	3208	6	4.5	0.61	-43.9	1.3	0.826
Women 42-60							
CI	3837	14	221.30	0.00	105.8	9.1	
CA	3837	7	3.50	0.84	-54.3	1.3	
Unidiff	3837	6	3.00	0.81	-46.5	1.1	0.491

PM-2

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3129	2	229.2	0	213.1	12.8	
CA	3129	1	2	0.16	-6.1	1.2	
Unidiff	3129	0	0	n/a	0	0	0.161
Women 25-40							
CI	3800	2	158	0	141.5	9.7	
CA	3800	1	4.3	0.04	-4	1.6	
Unidiff	3800	0	0	n/a	0	0	0.039
Men 32-50							
CI	3839	2	256.2	0	239.7	12.1	
CA	3839	1	3.1	0.08	-5.2	1.3	
Unidiff	3839	0	0	n/a	0	0	0.079
Women 32-50							
CI	4556	2	218.9	0	202	10.2	
CA	4556	1	0.5	0.48	-7.9	0.5	
Unidiff	4556	0	0	n/a	0	0	0.479
Men 42-60							
CI	3208	2	139.5	0	123.4	9.4	
CA	3208	1	0.1	0.72	-7.9	0.3	
Unidiff	3208	0	0	n/a	0	0	0.715
Women 42-60							
CI	3837	2	157.7	0	141.2	9.1	
CA	3837	1	0.3	0.57	-7.9	0.4	
Unidiff	3837	0	0	n/a	0	0	0.569

Notes:

1. CI=Conditional independence model; CA=Constant association model.

2. "P diff" is the p-value from a chi-square test of the difference in G^2 between the constant association and unidiff models.

Table 3g. Results of fitting log-linear models to father x respondent mobility tables (1970s, 1980s)

Full-class

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3663	48	383.8	0	-10	13.6	
CA	3663	24	29.8	0.19	-167.1	3.1	
Unidiff	3663	23	28.7	0.19	-160	3	0.292
Women 25-40							
CI	4376	48	373.9	0	-28.5	11.6	
CA	4376	24	30.6	0.17	-170.6	3	
Unidiff	4376	23	16.7	0.82	-176.1	1.8	0.000
Men 32-50							
CI	3601	48	409	0	15.9	13.6	
CA	3601	24	40.5	0.02	-156	4.1	
Unidiff	3601	23	39.6	0.02	-148.7	4	0.343
Women 32-50							
CI	4181	48	389.4	0	-10.9	12.6	
CA	4181	24	34	0.09	-166.1	3.3	
Unidiff	4181	23	22.9	0.46	-168.8	2.5	0.001
Men 42-60							
CI	2942	48	409	0	25.6	14.7	
CA	2942	24	19.7	0.71	-171.9	3.1	
Unidiff	2942	23	19.1	0.7	-164.6	2.9	0.413
Women 42-60							
CI	3390	48	387.6	0	-2.6	14.2	
CA	3390	24	33.2	0.1	-161.9	3.5	
Unidiff	3390	23	28.5	0.2	-158.5	3.2	0.030

PM-2

Model	N	df	G^2	p	BIC	DI	P diff
Men 25-40							
CI	3663	2	144.4	0	128	7.6	
CA	3663	1	0.1	0.8	-8.1	0.2	
Unidiff	3663	0	0	n/a	0	0	0.803
Women 25-40							
CI	4376	2	142.4	0	125.7	6.7	
CA	4376	1	5.8	0.02	-2.6	1.4	
Unidiff	4376	0	0	n/a	0	0	0.016
Men 32-50							
CI	3601	2	152.3	0	135.9	7.3	
CA	3601	1	1.4	0.24	-6.8	0.7	
Unidiff	3601	0	0	n/a	0	0	0.238
Women 32-50							
CI	4181	2	102.8	0	86.1	5.3	
CA	4181	1	2.1	0.15	-6.2	0.8	
Unidiff	4181	0	0	n/a	0	0	0.148
Men 42-60							
CI	2942	2	139.9	0	124	6.8	
CA	2942	1	0.5	0.49	-7.5	0.4	
Unidiff	2942	0	0	n/a	0	0	0.486
Women 42-60							
CI	3390	2	81.7	0	65.4	4.6	
CA	3390	1	0	0.93	-8.1	0	
Unidiff	3390	0	0	n/a	0	0	0.933

Notes:

1. CI=Conditional independence model; CA=Constant association model.

2. “P diff” is the p-value from a chi-square test of the difference in G^2 between the constant association and unidiff models.

Table 4. Unidiff Parameter Phi

	Sons				Daughters			
	1970s	1980s	1990s	2000s	1970s	1980s	1990s	2000s
Respondent Ages 25-40								
Father, all periods, full-class	1.05	0.94	1.00	1.14	1.68	1.08	1.00	1.29
Father, all periods, NPM	1.06	0.91	1.00	1.03	1.27	1.12	1.00	0.76
Father, all periods, PM-1	0.91	0.95	1.00	1.22	1.46	0.99	1.00	1.43
Father, all periods, PM-2	0.92	0.96	1.00	1.22	1.46	0.97	1.00	1.45
Father, 1970s-1980s, full-class	1.00	0.89			1.00	0.65		
Father, 1970s-1980s, NPM	1.00	0.85			1.00	0.88		
Father, 1970s-1980s, PM-1	1.00	1.05			1.00	0.68		
Father, 1970s-1980s, PM-2	1.00	1.04			1.00	0.67		
Father, 1990s-2000s, full-class			1.00	1.13			1.00	1.31
Father, 1990s-2000s, NPM			1.00	0.99			1.00	0.85
Father, 1990s-2000s, PM-1			1.00	1.22			1.00	1.43
Father, 1990s-2000s, PM-2			1.00	1.22			1.00	1.45
Two-parent, 1990s-2000s, full-class			1.00	1.19			1.00	1.19
Two-parent, 1990s-2000s, NPM			1.00	0.93			1.00	0.52
Two-parent, 1990s-2000s, PM-1			1.00	1.22			1.00	1.35
Two-parent, 1990s-2000s, PM-2			1.00	1.21			1.00	1.40
Respondent Ages 32-50								
Father, all periods, full-class	1.05	0.91	1.00	1.02	1.64	1.09	1.00	1.08
Father, all periods, NPM	0.89	0.91	1.00	0.83	1.88	1.15	1.00	1.01
Father, all periods, PM-1	1.15	0.93	1.00	1.14	1.14	0.86	1.00	1.09
Father, all periods, PM-2	1.15	0.94	1.00	1.14	1.16	0.87	1.00	1.09
Father, 1970s-1980s, full-class	1.00	0.90			1.00	0.68		
Father, 1970s-1980s, NPM	1.00	1.01			1.00	0.65		
Father, 1970s-1980s, PM-1	1.00	0.84			1.00	0.76		
Father, 1970s-1980s, PM-2	1.00	0.82			1.00	0.75		
Father, 1990s-2000s, full-class			1.00	1.04			1.00	1.09
Father, 1990s-2000s, NPM			1.00	0.85			1.00	1.13
Father, 1990s-2000s, PM-1			1.00	1.14			1.00	1.09
Father, 1990s-2000s, PM-2			1.00	1.14			1.00	1.09
Two-parent, 1990s-2000s, full-class			1.00	1.01			1.00	0.98
Two-parent, 1990s-2000s, NPM			1.00	0.76			1.00	0.99
Two-parent, 1990s-2000s, PM-1			1.00	1.24			1.00	1.03
Two-parent, 1990s-2000s, PM-2			1.00	1.25			1.00	1.10

Respondent Ages 42-60

Father, all periods, full-class	1.16	1.10	1.00	0.89	1.70	1.35	1.00	0.98
Father, all periods, NPM	0.99	0.95	1.00	0.86	2.12	1.76	1.00	0.83
Father, all periods, PM-1	1.36	1.21	1.00	0.90	1.12	1.17	1.00	1.06
Father, all periods, PM-2	1.36	1.21	1.00	0.90	1.18	1.20	1.00	1.03
Father, 1970s-1980s, full-class	1.00	0.91			1.00	0.77		
Father, 1970s-1980s, NPM	1.00	0.93			1.00	0.82		
Father, 1970s-1980s, PM-1	1.00	0.90			1.00	1.00		
Father, 1970s-1980s, PM-2	1.00	0.89			1.00	1.02		
Father, 1990s-2000s, full-class			1.00	0.90			1.00	1.00
Father, 1990s-2000s, NPM			1.00	0.84			1.00	0.94
Father, 1990s-2000s, PM-1			1.00	0.90			1.00	1.10
Father, 1990s-2000s, PM-2			1.00	0.90			1.00	1.03
Two-parent, 1990s-2000s, full-class			1.00	1.04			1.00	0.98
Two-parent, 1990s-2000s, NPM			1.00	1.22			1.00	0.69
Two-parent, 1990s-2000s, PM-1			1.00	0.96			1.00	1.11
Two-parent, 1990s-2000s, PM-2			1.00	1.06			1.00	1.10

Table 5. One-sided tests for changes in log odds ratio in PM-2 models

	Men						Women					
	Father				Two-parent		Father				Two-parent	
	1990s-2000s		*1970s-1980s*		*1990s-2000s*		*1990s-2000s*		*1970s-1980s*		*1990s-2000s*	
	Percent change	*p* value	Percent change	*p* value	Percent change	*p* value	Percent change	*p* value	Percent change	*p* value	Percent change	*p* value
Age 25-40	22%	0.061	4%	0.598	21%	0.081	45%	0.007	-34%	0.008	40%	0.020
Age 32-50	14%	0.136	-18%	0.119	25%	0.040	9%	0.284	-24%	0.074	10%	0.239
Age 42-60	-10%	0.746	-11%	0.243	7%	0.358	3%	0.430	2%	0.533	10%	0.284

Notes:

1. Percent change refers to the change of the log odds ratio in the PM-2 models, from the 1990s to the 2000s or from the 1970s to the 1980s.
2. The null hypothesis for the 1990s-2000s one-sided tests is that that the change in the log odds ratio between the 1990s and the 2000s is smaller or equal to zero. The null hypothesis for the 1970s-1980s tests is that the change in the log odds ratio between the 1970s and the 1980s is greater than or equal to zero. See Appendix for description and derivation of the test.

Table 6. Testable Hypotheses about Trend in Origin-Destination Association for the Youngest Age Group (Ages 25-40)

Name	*Description*	*Results*
1. Convexity	The origin-destination association is convex towards the time axis	Supported
2. Accelerating change	The origin-destination association either (a) increases more or falls less between the 1990s and the 2000s than in prior periods, or (b) falls during the decades up to the 1990s but increases after the 1990s	Supported
3. Initial gender-specific change	The decline in association between the 1970s and 1980s is more prominent for women than for men	Supported
4. Recent gender-neutral change	The trend in association is the same for women and men between the 1990s and 2000s	Point estimates are inconsistent with hypothesis, but null hypothesis of equality of change is not rejected
5. Simple income	The trends are similar across the FC, NPM, and PM tables	Not supported
6. Top income	The trends are more prominent within the PM tables	Supported