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Locating Longitudinal Respondents After a 50-Year Hiatus

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Many longitudinal and follow-up studies face a common challenge: locating study participants. This study examines the extent to which a geographically dispersed subsample of participants can be relocated after 37 to 51 years of noncontact. Relying mostly on commercially available databases and administrative records, the 2011–12 Project Talent Follow-up Pilot Study (PTPS12) located nearly 85 percent of the original sample members, many of whom had not participated in the study since 1960. This study uses data collected in the base year to examine which subpopulations were the hardest to find after this extended hiatus. The results indicate that females were located at significantly lower rates than males. As expected, sample members with lower cognitive abilities were among the hardest-to-reach subpopulations. We next evaluate the extent to which biases introduced during the tracking phase can be minimized by using the multivariate chi-square automatic interaction detection (CHAID) technique to calculate tracking loss adjustments. Unlike a 1995 study that found that these adjustments reduced statistical biases among its sample of located females, our results suggest that statistical adjustments were not as effective in PTPS12, where many participants had not been contacted in nearly 50 years and the tracking rates varied so greatly across subgroups.

Key words: Respondent tracking; attrition bias; panel reengagement.

1. Introduction

While most longitudinal studies, sometimes also called panel or follow-up studies, are prospectively planned and have a definitive end date, there has been a recent resurgence in reconstituting "dormant" longitudinal or even cross-sectional studies (e.g., Haggerty et al. 2008; Hampson et al. 2001; Hauser 2005; Kimmel and Miller 2008; Ortiz and Godinez Ballon 2007). One reason for this resurgence is the higher costs associated with conducting new longitudinal studies relative to repurposing or continuing preexisting ones. Recent advances in technology provide relatively inexpensive methods for relocating sample

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members after an unplanned length of noncontact. These advances – which include the compilation of information into low-cost commercial databases – have led social scientists to consider how existing data sources and samples can be reutilized. Researchers use these studies to broaden their understanding of complex causal relationships and social phenomena throughout the life span.

The feasibility of reconstituting a study lies first and foremost in the successful location (or relocation, tracing, or tracking; these terms are used interchangeably) of study sample members. It becomes particularly difficult to relocate such persons after a long period of noncontact. Successful location depends on several factors, such as the length of time since last contact, the amount of information available to locate sample members, and the budget and resources available for locating activities.

In addition, individual characteristics are known to affect tracking success. Age, lifestyle, socioeconomic status (SES), employment situation, family circumstances, geographic region, and urbanicity (i.e., urban, rural, suburban) play a role in a person's mobility and as a result can affect how difficult it is to locate someone after a long period of noncontact. Other behaviors and characteristics affect the extent to which individuals are "politically, socially, or economically engaged in their new community" (Couper and Ofstedal 2009, p. 187). Lower levels of engagement decrease the likelihood that individuals will be accessible through the lower-cost commercial databases. (See Becker et al. 2012 for a discussion of contemporary low-cost and high-cost tracking databases and methods.)

These systematic differences are problematic for two reasons. First, studies with high proportions of hard-to-find individuals must be prepared to devote more time, effort, and resources to tracking activities. Second, and perhaps more problematic, is the type of bias that results when the individual behaviors and characteristics correlated with tracking propensity are also correlated with the outcomes of interest.

This article contributes to the limited but growing research on locating study sample members after a long period of noncontact (e.g., Call et al. 1982; Clarridge et al. 1978; Haggerty et al. 2008; Hampson et al. 2001; Hauser 2005; Kimmel and Miller 2008; Masson et al. 2013; Meehan et al. 2009; Ortiz and Godinez Ballon 2007; Strawn et al. 2007) by evaluating the use of widely available and used locating methods. Specifically, this study used commercial databases, which consolidate information from a variety of sources such as credit histories, voting records, property records, and voluntary registries such as the National Change of Address Register, to locate sample members. Because of the tracking methods employed, the results of this study are of practical use to a wide variety of other studies – large or small, national or regional, longitudinal or cross-sectional.

This article focuses specifically on locating the original participants of a study conducted in the United States (U.S.). Though not necessarily different from the mobility rates and frequencies for residents of other countries, the combination of Americans' geographic dispersion and mobility makes them difficult to locate in general, and particularly difficult to locate after a long period of time. If anything, this study presents a worst-case scenario for applying scalable tracking methods to other longitudinal studies worldwide. The U.S. lacks population registers common in Scandinavia and spans a large geographic area. Americans are relatively mobile. According to a recent report by the

U.S. Census Bureau (Ren 2011) approximately 50 percent of American residents age 55 and older resided in a state other than their state of birth in 2010, and data from the 2011 American Community Survey suggest that U.S. residents move as many as eleven times in a lifetime, with the majority of moves occurring between the ages of 18 and 45.

2. Background

Published research on locating survey sample members after a long period of noncontact is limited, but not new. The Wisconsin Longitudinal Study (WLS) was one of the first surveys that attempted to do so. In 1975, researchers used information from printed telephone directories, high schools, post offices, military locator services, employers/licensing associations, college alumni associations, parents, neighbors, siblings, and high school classmates to successfully locate 97 percent of a 10,317-person subsample of the original sample. The sample members, all around 35 years of age, had not been contacted in 10 to 17 years (Hauser 2005). Most sample members were located through their parents. WLS's next locating effort, conducted in 1992, used the then newly developed technologies of CD-ROM-based telephone and address directories, online credit agency databases, and high school reunion booklets to locate respondents, as well as their parents, siblings, classmates, and neighbors. Again, the effort achieved a 97 percent location rate (Hauser 2005).

Beginning in 1998, Hampson et al. (2001) sought to find and recontact nearly 2,000 sample members last surveyed in elementary school during the years 1959 through 1967 – with no contact in the intervening 32 to 40 years. Moreover, the study was not originally designed as a longitudinal study. Relying on the limited baseline participant information that was available, Hampson and colleagues located 75 percent of sample members by searching through printed and CD-ROM-based telephone and address directories, newspaper announcements of sample member milestone events (e.g., weddings, children's births), high school websites, Department of Education records, and Internet databases, to name a few.

Similarly, after 35 years of noncontact, the Mexican American Study Project located 79 percent of its original 1,000-plus household sample members between 18 and over 50 years old last contacted in 1965 and 1966 (Ortiz and Godinez Ballon 2007). The Mexican American Study Project also was not planned as a longitudinal study. Like Hampson and colleagues, Ortiz and Ballon employed a mix of old and new locating strategies, including manual searches of printed telephone directories and public records and computerized searches of "people-finder" databases, property and voter registration records, and the Internet database Missing Links (one of the first such people-finder databases on the Internet).

Each of these studies included relatively homogeneous samples in specific places with limited geographic dispersion, which can make tracking participants both easier and more cost efficient. The WLS was a study of twelfth graders attending high school in Wisconsin in 1957. The Hampson et al. (2001) relocating effort was limited to persons who were initially assessed as elementary students attending school on one of two Hawaiian Islands. Ortiz and Godinez Ballon (2007) focused on finding Mexican Americans in Los Angeles, California, and San Antonio, Texas.

As summarized by Calderwood (2012), studies such as these have two advantages over studies that attempt to recontact sample members of large-scale, national studies. First, they can make better use of social networks of friends, siblings, and neighbors, because there is a greater likelihood that those individuals will also be in the study. Second, greater geographic specificity means it is more feasible to use "localized" methods. By contacting local post offices, governmental offices, and other community groups, these studies have greater success in locating and promoting continued study participation.

Though some national studies have attempted to locate sample members after a long hiatus, only a few have published comprehensive, empirical information about the results of their efforts (see Couper and Ofstedal 2009). After over ten years of noncontact, the Longitudinal Study of American Youth (LSAY) located nearly 94 percent of a nationally representative sample of persons aged 32 to 35 who were first contacted when in seventh or 10th grade in 1987 (Kimmel and Miller 2008). The Midlife Development in the United States (MIDUS) study began in 1995 with over 7,000 individuals aged 25 to 74 in the U.S. In 2004–06, staff located approximately 90 percent of its sample members (Ryff et al. 2006). The Longitudinal Study of Adult Learning (LSAL) tracked on average 90 percent of its participants when the lag between interviews was one year (Waves 1 through 3); tracking rates dropped to 86 to 87 percent when the lag between contact was extended to two years in Waves 4 and 5 (Strawn et al. 2007). The National Longitudinal Study of Adolescent Health (Add Health) began in 1994 as a longitudinal study of adolescents aged 11 to 18. The study located 87 percent of the original sample in the unplanned third wave of data collection. Participants had not been contacted in 5 to 8 years. The study improved its locating rate to 92 percent in the fourth wave six years later. Meehan et al. (2009) attributed this improvement to both the reduced mobility of the sample members – who were between 24 and 32 years of age at Wave 4 – as well as improvements in tracking planning and implementation.

As noted by Couper and Ofstedal (2009), few studies have explored the factors that affect location propensity or have used multivariate approaches to model the tracking process. Most studies on attrition in longitudinal studies have focused on *total attrition* – the loss of sample members owing to both nonlocation and nonresponse. Only a few have disentangled nonlocation from noncooperation (e.g., Cotter et al. 2002; Hauser 2005; Radler and Ryff 2010). Across these studies, there are very few commonalities in the populations under study, study designs, length of time between waves, variables available for analysis, and analytical approaches. What have we learned? Certain subgroups are more difficult and expensive to find because they require more complex tracking steps: females, minorities, and individuals with lower educational attainment, higher rates of financial instability, and criminal behavior or substance abuse (Andresen et al. 2008; Cotter et al. 2005; Cottler et al. 1996; Haggerty et al. 2008; Iannacchione 2003; Jessor and Jessor 1977; Passetti et al. 2000; Ribisl et al. 1996; Stouthamer-Loeber and van Kammen 1995).

Our review found only one study (Iannacchione 2003) that researched statistical methods for reducing tracking-related biases. Using the National Health Interview Survey (NHIS), Iannacchione used sequential logistic regression models to first explore the factors related to location propensity and next compute tracking-related weighting adjustments. The NHIS wave under examination had a locating rate of 95 percent. The study found that these adjustments ultimately preserved the "location-adjusted weighted means" among females in the study. However, we do not know if this method could be applied as effectively to studies with a lower locating rates, because they may be unable to locate a sufficient number of key groups to allow for weighting adjustments or do not have the data to allow for such adjustments.

This study contributes to the existing research on locating sample members after a long period of noncontact. It extends what is currently known by examining a longer period of noncontact – 37 to 51 years – and by investigating the effectiveness of applying a weighted adjustment to minimize tracking-related biases in such a study. Three research questions are addressed:

1. To what extent can geographically dispersed sample members of a national study be located after a very long hiatus using tracking methods that rely primarily on lower-cost commercial databases?
2. Using relatively low-cost methods to locate sample members after a lengthy hiatus, which subpopulations are the hardest to find?
3. To what extent can biases introduced through tracking failure be minimized by employing statistical tracking-loss adjustments?

3. Study Design and Methods

3.1. *Sample and Dataset*

We review findings from a 2011–12 follow-up of a subsample of participants of the Project Talent longitudinal study, which began as a nationally representative sample of high school students in 1960. After three rounds of data collection, the study went on hiatus in 1974. In 2011, researchers with the American Institutes for Research (AIR), the University of Michigan's Survey Research Center (SRC), and the University of Michigan's Health and Retirement Study (HRS) began planning a follow-up study of the original Project Talent participants.

The large-scale pilot test was designed to gauge the feasibility of locating and persuading participants of the original 1960 study to participate in a follow-up 50 years after the initial base-year survey. A subsample of 4,879 participants was randomly selected from a ten percent random subsample of the original 1960 schools. This two-stage sample design eased the operational burden of cleaning contact information that was originally captured by some of the earliest optical scanning machines developed in the 1960s and 1970s. In addition, the sample design allowed for the possibility of using schools and classmates, who began holding their 50-year class reunions in 2010, to locate sampled individuals. Most individuals sampled for the 2011–12 Project Talent Follow-up Pilot Study (PTPS12) were between 67 and 70 years old when tracking activities began.

3.2. *Study Design and Tracking Methods*

The follow-up began in June 2011 with a tracking phase. Information available in the Project Talent historical records was used to identify sample members' most recent addresses. These records contain much of the information needed for locating activities, though most of it is outdated: first, middle, and last names as of 1960; updated names and addresses through 1978; date of birth; and 1960 school name and location. The records also include Social Security Numbers (SSNs), which were collected in the year 1 and 5 follow-ups and are available for approximately 50 percent of Project Talent sample members. In addition, AIR began compiling more current contact information through outreach activities – including attendance of class reunions and participant registration through the Project Talent Website (http://projecttalent.org) – in 2010. Contact information collected through these outreach efforts was available for approximately five percent of sampled individuals at the start of the tracking phase.

The pilot study used a tiered approach for its retrospective tracking activities – an approach used by large-scale, national longitudinal studies such as Add Health and the Beginning Postsecondary Students Longitudinal Study (BPS) (see Meehan et al. 2009 and Wine et al. 2011, respectively). Two tracking methods were used to locate pilot study sample members: batch tracking and interactive tracking. *Batch tracking* refers to automated processes in which tracking vendors use client-provided inputs (e.g., first name, last name, date of birth) and hard logic algorithms to identify potential matches across multiple databases and return current contact information for those matches. Because these services process numerous cases at one time, they provide researchers with relatively quick access to address confirmations or updates at a low per-case cost and low operational burden. However, cases not matched in batch tracking will require additional effort before they can be located.

This pilot study used commercially available batch tracking services provided by LexisNexis to obtain recent telephone numbers, addresses, and vital status information on every sample member. Given the age of the target population, an important part of the tracking activities involved determining a person's vital status. Thus, the PTPS12 batch-tracking protocol ascertained sample members' vital status by also matching cases to the Social Security Administration's Death Master File (DMF) and the National Center for Health Statistics' National Death Index (NDI), which at the time of this study contained U.S. death record information for the years 1979 through 2009. Cases not located through batch tracking were sent to *interactive tracking,* where a trained staff member in SRC's centralized data collection unit reviewed each case on an individual basis and took a variety of steps to locate the sample 1 member using both free and proprietary web-based databases. SRC also carried out telephone verification for a small group of cases for which multiple recent addresses were found, conflicting information was received, or there was uncertainty that the correct person was located. Given the additional labor and costs associated with interactive tracking, only those cases not located through batch tracking were followed up using this method.

Finally, contact information obtained passively through ongoing, study-wide outreach activities was utilized as necessary. The ongoing outreach activities (which included attending or sending information to 50-year class reunions, sending press releases to local media outlets, and developing a participant registration page on the study's website) were not part of the formal pilot study tracking protocols and were completely independent of the PTPS12 batch and interactive tracking efforts. This approach relies largely on voluntary submission or active engagement on the part of the sample member. However, the pilot study made use of the information collected through the outreach activities, particularly where it allowed for contact with otherwise unlocated sample members. The tracking activities employed for the pilot study are summarized in Table 1.

Table 1. 2011–12 Project Talent Follow-up Pilot Study (PTPS12) tracking activities

Tracking activity	Pilot test sample	Information collected (source): Vital status	Information collected (source): Addresses and/or telephones
Batch tracking	All pilot sample members	LexisNexis; Death Master File; National Death Index	LexisNexis; National Change of Address registry
Interactive tracking	Pilot sample members not found in batch tracking	Consolidated, proprietary tracking databases; web searches; telephone verification of participant identity and/or address	
Informal tracking	Nontargeted	Class lists, contacts	Reunions, class lists, web sign-ups, requests for 1960 test scores, contacts

3.3. Measures and Analysis Methods

The present article appraises the success of the tiered approach and lower-cost tracking methods used in PTPS12, which could be applied to other studies in the U.S. and elsewhere. Research question 1 uses this pilot study to assess the extent to which members of a geographically dispersed sample can be located after a very long hiatus. Based on the results from previous small-scale feasibility studies conducted for Project Talent, we expected that the tracking phase would identify twelve percent of the pilot sample as deceased and locate addresses for 74 percent of the pilot sample, for a combined tracking rate of 86 percent.

Research question 2 considers which subpopulations are the hardest to find. Because data collected in the base year (1960) were available for all cases sampled for PTPS12, base-year data were used to examine the characteristics associated with tracking success, which is defined as the identification of a sample member's current address or vital status. Previous studies of nonresponse in Project Talent follow-ups have shown that sample members in certain subgroups – particularly those in the lower quintiles for cognitive ability and family SES relative to their peers, as well as minorities and students attending high-minority schools – were less likely to have participated in at least one of the follow-ups, when key information like SSNs and name changes would have been captured (Flanagan and Cooley 1966; Orr 1963; Rossi et al. 1976). Therefore, these variables are not only indicators of subgroups who may be systematically more difficult to locate simply because the records contain less information for tracking, but are also associated with individual characteristics (e.g., educational attainment, financial instability) known from other studies to be related to lower tracking propensities. We hypothesized that the same subgroups would be difficult to locate in 2011. In addition, other studies on aging (e.g., Gale et al. 2012; Anstey et al. 2001; Ritchie and Bates 2013; Wilson et al. 2009; and Crowe et al. 2013) have shown that early life health, SES, personality, and cognitive indicators are often correlated with key aging outcomes, such as health, cognitive function, and well-being. Therefore, these variables provide good indicators of potential biases in survey estimates that may be introduced during the tracking phase of the present study.

The analyses focused on 17 measures of sample characteristics, including sex, family SES, academic performance, cognitive aptitude, three measures of early life health (health in past three years; health in first ten years; number of days sick in bed in past year), and ten measures of personality (sociability; social sensitivity; impulsiveness; vigor; calmness; tidiness; culture; leadership; self-confidence; and mature personality). The SES measure reflects students' reporting and perceptions of their family environment (e.g., number of books in home, number of rooms in home, student-reported financial well-being). Cognitive aptitude was measured using the general academic aptitude variable, a weighted composite that combines results from three informational tests (mathematics and vocabulary I and II) and six cognitive aptitude/ability tests (English, reading comprehension, creativity, abstract reasoning, and mathematics I and II). For more information on these and other measures, see Wise et al. (1979).

One shortcoming of this dataset is that individual measures of race/ethnicity were not captured in the baseline data collection in 1960. In lieu of individual measures, we included a categorical school-level measure reflecting the minority composition of each sample member's 1960 school. Given that individual mobility and the stability of social networks over time vary by environmental factors, we also included four control variables reflecting 1960 school and regional attributes: population size of the surrounding community in 1960, Census region, school type (i.e., private versus public), and building type (junior high school versus senior high school). We also included a categorical measure of the 1960 grade cohort to control for the inherent selection bias related to school attrition, as well as to the length of time between the 1960 collection and subsequent follow-ups, which varied by grade cohort. We expected to find that even after controlling for individual characteristics such as sex, family SES, and school attributes, individuals with lower cognitive scores relative to their peers would be more difficult to find. We also anticipated that individuals with certain personality characteristics (e.g., those who were less mature, more impulsive, and less calm) when measured as adolescents would be more mobile and also less tied to local communities and therefore more difficult to locate.

Finally, research question 3 investigates the extent to which nonresponse adjustment techniques can be used and applied separately to the tracking phase to reduce attrition biases introduced solely as a result of tracking loss. A multivariate chi-square automatic interaction detection (CHAID) technique (see Kass 1980), the same method used by Iannacchione (2003), was used to calculate the tracking adjustment weighting classes. The CHAID algorithm was used to identify the variables that were the most significant predictors of being located (the dependent variable) by calculating the chi-square measure of association between the dependent and each independent variable and then using this information to successively partition the sample into subsets that are homogeneous in terms of tracking status. The predictor variable with the highest significance level for the chi-square test was used to split the sample into groups. This process was repeated for each of the predictor variables until there were no further logical splits or until there were too few observations for further splitting. The result is a tree-like structure that groups observations in the dataset into cells (or nodes) that have the greatest discrimination with respect to response status. For the purpose of this CHAID analysis, only variables having a Bonferroni-adjusted p value of less than or equal to .05 were eligible for segmentation and cells were required to have at least 50 observations. The last partitions define the tracking adjustment weighting cells to calculate the tracking adjustment factor given by each weighting cell (i):

$$TAF_i = \frac{WLC_i + WNLC_i}{WLC_i},$$

where

The *tracking adjustment factor* (TAF_i) is the weighted ratio of the total sampled individuals to the total located individuals for cell i, and
The *weighted located count* (WLC_i) is the base-weighted located count for cell i and the *weighted nonlocated count* ($WNLC_i$) is the base-weighted not located count for cell i.

The final *tracking adjusted weight* is the product of the TAF and the PTPS12 base weight. The base weight is the product of the student-level 1960 Project Talent base weight and the probability of selection for the PTPS12 sample.

The CHAID algorithm used the same candidate variables used as predictor and control variables in the logistic regression analysis. In addition, the CHAID algorithm included four additional categorical variables that were either of substantive interest to the study or were believed to be related to location propensity: 1960 school size, proximity to largest cities as of the 1950 census, 1960 self-reported number of doctor visits in the past year, and a flag indicating if an SSN was provided in one of the previous Project Talent follow-ups.

4. Results

4.1. Tracking Rates

At the end of the tracking phase, the project team had identified 14.7 percent of the pilot sample members as deceased and found updated address information for 71.5 percent of the pilot sample members – yielding an initial locating rate of 86.2 percent. These rates are in line with the expected locating rates for this study. The initial locating rate is nearly ten percentage points higher than the locating rates reported by Hampson et al. (2001) and Ortiz and Godinez Ballon (2007), who faced a similar challenge of locating participants after an extended hiatus but with little geographic dispersion. However, this locating rate is between three and nine percentage points lower than those reported by LSAY, MIDUS, LSAL, and Add Health, which used similar tracking methods, but with only two to ten years of elapsed time since the last contact.

Approximately 71 percent of sample members were located at the batch-tracking stage: about 87 percent of all decedents and 82 percent of all located, presumed living sample members were found at this tracking stage. Interactive tracking increased the overall tracking rate by nearly 14 percentage points. Fewer than two percent of all cases were located through other means (e.g., outreach activities), or had multiple tracking sources and could not be categorized.

Survey materials were mailed to all presumed surviving cases for whom an address was found ($n = 3{,}462$). To evaluate the accuracy of the address information obtained during the tracking phase, we measured the extent to which we were able to verify that the correct person was located for the 3,462 mailing cases. A case was considered to be verified if the name, school, and date of birth collected for a located individual as part of the tracking and data collection activities matched the corresponding information available in the study's historical files. About 71 percent of the contacted individuals either returned a survey or were verified to be the correct person through some type of direct contact logged in the Project Talent participant database. Only about two percent of the mailing cases were classified as erroneous matches because there was some indication that tracking had obtained either the wrong address (e.g., an outdated address) or had located the wrong person, and interviewers were unable to find the correct address during the data collection period. About one percent of the mailed cases were later identified as deceased. The analysis was unable to verify that the correct person was located for the remaining 26 percent of the mailing cases. At the end of data collection (and after these changes had been accounted for), 84.8 percent of the sample had been located: 15.5 percent as deceased, 50.3 percent as located with an address and verified, and 19.0 percent as located with an address and not verified. About 15.2 percent of the sample was not located.

4.2. Identification of Hard-to-Find Subpopulations

We used a multivariate logistic regression model to compare the individuals who were not located (15.2 percent) to those who were located (84.8 percent) on a subset of variables available from the 1960 baseline data collection. As shown in Table 2 below, 22 predictor and control variables – covering student characteristics, cognitive aptitude and personality, as well as school and regional attributes – were used in the analysis. All continuous measures were categorized into quintiles. Those in the middle three quintiles were combined and used as the referent group in the logistic regression.

Analyses of tracking propensity consistently showed that sex was the single biggest predictor of tracking success, such that male respondents were 3.6 times more likely to be located than females. This is partially due to the substantial number of sampled females with no SSN and no new (e.g., married) last name in the historical records (39.0 percent of all sampled females). Because SSN is a unique identifier that rarely changes over the course of a person's life, it is particularly helpful for locating people whose names have changed. For example, locating rates for females with an SSN or married name available were comparable to those for males (males: 92.0 percent; females with SSN or married name: 94.3 percent), whereas the average locating rate for females for whom no SSN or married name were available was 52.7 percent.

Differences like this could suggest that the mechanisms underlying locating propensity operate differently for males and females. This is due in part or in whole to name changes. For example, certain types of females may have been more likely to get married right after high school. Name changes, as well as the increased likelihood of housing and banking records being in their partners' names rather than their own, make tracking these females successively more difficult relative to males or females who did not get married or change their names shortly after high school. Males are generally easier to find regardless of their marital status or age at first marriage, because by comparison men rarely change their names.

To investigate this further, we analyzed males and females separately. Such an approach can be used to answer the following question: Within a given subpopulation (i.e., males or females), what characteristics are associated with tracking failure? To control for the unobserved heterogeneity across models, we report the predicted probabilities obtained from the separate logistic regression models (see Mood 2010). Table 2 presents the predicted probabilities and *p* values for the significant results from the multivariate analyses of tracking failure for males and females separately (complete results are reported in the Appendix).

For males, the analysis indicated that the parameters associated with six of the 22 variables examined were significantly associated with tracking propensity ($p < .05$ for the Wald chi-square test for parameters): 1960 family SES, percent minority for the school attended in 1960, general academic aptitude, and three personality measures (impulsivity, tidiness, and leadership). We confirmed our suspicion that males scoring in the top quintile for the impulsivity measure were harder to locate than those scoring in the middle quintiles. The regression showed that we were also less likely to locate males who scored in the bottom quintiles for tidiness and leadership (relative to those in the middle or top quintiles). The predicted probabilities were highest for males who attended a school in which minorities

Table 2. Predicted probability estimates of tracking failure for significant predictors from multivariate logistic regression model, by selected 1960 variables

	Males		Females	
Selected characteristics (1960)	Predicted probability	p value	Predicted probability	p value
Grade in 1960: 9th/10th vs. 11th/12th grade	0.80	.0877	0.81	.0005
Family SES: Bottom quintile vs. higher quintiles	0.80	.0256	0.81	.0052
General academic aptitude: Bottom quintile vs. middle quintiles	0.82	.0435	0.86	$<.0001$
General academic aptitude: Top quintile vs. middle quintiles	0.66	.1562	0.62	.0002
Sociability: Bottom quintile vs. middle quintiles	0.73	.9219	0.79	.0477
Impulsivity: Bottom quintile vs. middle quintiles	0.82	.0179	0.72	.4671
Tidiness: Bottom quintile vs. middle quintiles	0.84	.0096	0.75	.5564
Leadership: Bottom quintile vs. middle quintiles	0.75	.0383	0.75	.5058
Self-confidence: Bottom quintile vs. all higher quintiles[1]	0.67	.1576	0.68	.0266
Percent minority in school: (50–79%) vs. 0–49%	0.95	.0465	0.63	.0585
Census region: Mid-Atlantic, South Atlantic, or Mountain regions vs. all other regions	0.78	.1794	0.79	.0153
Population size of surrounding community: Under 5,000 vs. 1.5 million or more	0.69	.6683	0.64	.0384
Population size of surrounding community: 5,000–249,999 vs. 1.5 million or more	0.83	.2874	0.64	.0170
Population size of surrounding community: 250,000 vs. 1.49 million or more	0.89	.0951	0.63	.0192

[1] The parameter estimates indicated that those in the bottom and top quintiles for the psychological measure of self-confidence were tracked at higher rates than were those in the middle three quintiles, although the difference was only significant for those in the bottom quintile.

Note: Only significant results are reported from the multivariate logistic regression. Regression models were run separately for males and females. In addition, the models included the following categorical measures: health in past three years; health in first ten years; number days sick in bed in past year; class rank; personality (creativity, social sensitivity, vigor, calmness, culture, mature personality); school type and building type (junior high school or senior high school).

made up 50–79 percent of the student body. It is interesting to note that the predicted probabilities of tracking failure for males attending high-minority schools (80–100 percent of the school body) were lower than the predicted probabilities for those attending schools where minorities constituted 50–79 percent of the student body, and that there was no significant difference in tracking propensity for males attending high-minority schools relative to males who attended a school with 0–49 percent minorities ($p = .11$). We also confirmed that even after controlling for other individual characteristics, males with lower cognitive scores relative to their peers would be more difficult to find. As Table 2 shows, we were significantly less likely to locate males scoring in the bottom quintile for the composite measures of general academic aptitude (relative to those in the middle or top quintiles).

As expected, the patterns associated with tracking failure were quite different for females, with one notable similarity. Consistent with the findings for males and our expectations, we were significantly less likely to locate females scoring in the bottom quintile for the composite measure of general academic aptitude (relative to those in the middle or top quintiles). In addition, there were significant differences in tracking propensity for parameters associated with grade cohort in 1960, family SES quintile, and self-confidence as well as Census region and population size of the surrounding community for the school attended in 1960. The tracking efforts employed for this pilot study were significantly less likely to locate females from the 9th- or 10th-grade cohorts or those in the bottom quintile for the family SES measure. Finally, the analysis suggested that there was a U-shaped relationship between self-confidence and tracking propensity, such that those in the bottom and top quintiles of the self-confidence measure were tracked at higher rates relative to those in the middle three quintiles. However, the difference was only significant for those in the bottom quintile.

There were also significant regional differences. We were significantly less likely to locate females who attended schools in very large urban communities. Tracking propensities for those in the Mid-Atlantic, South Atlantic, or Mountain regions in 1960 were also lower relative to females from other regions.

4.3. Implementation of Tracking-loss Adjustments

To assess the extent to which biases introduced through tracking failure can be minimized by employing tracking-loss adjustments, we first created a tracking-loss adjustment using the CHAID algorithm. We then computed the weighted estimates and percent relative bias before and after the tracking loss adjustment and compared the estimates for a selected subset of the base-year variables available for all of the cases sampled for the pilot study. The percent relative bias is the estimated bias divided by the estimates produced after the analysis is restricted to include only those who were located. We also computed the estimated bias, which is the difference between all those who were sampled for PTPS12 and the subset that were located. A t-test was used to determine whether these differences were statistically significant. Estimates from PTPS12 sample that are significantly different ($p < .05$) from those located in PTPS12 estimate suggest that a potential for tracking bias may be present.

Table 3 shows the results for five of the 41 variables selected for this analysis. The nontracking adjustment was able to reduce the significant tracking loss bias for the estimated proportion of individuals whose family SES in 1960 was in the bottom quintile, but not for the estimated proportion of individuals who had missing data for this variable. The adjustment reduced the tracking loss bias for the variables measuring health until age ten, general academic aptitude, and impulsivity; however, the t-tests indicate that even after this adjustment, these estimates remain significantly biased.

5. Discussion

The Project Talent pilot study was used to evaluate the use of relatively low-cost methods to locate and obtain cooperation from a large, national follow-up of longitudinal study sample members after an extended hiatus. Though the age of the target population and the extended hiatus of 37 to 51 years may limit the generalizability of these results to other studies, the study offered a unique opportunity to explore correlates related to tracking success. In addition, we were able to use the base-year measures to examine the use of statistical adjustments of tracking-related biases.

This study confirmed our expectations that even without expensive in-person tracking activities we would be able to locate a relatively high proportion of sample members (85 percent). As might be expected, the tracking rate for this study was slightly lower than those obtained in similar studies of less geographically dispersed sample members, which are able to apply more localized tracking methods (e.g., Hampson et al. 2001; Ortiz and Godinez Ballon 2007), as well as those obtained in large, national studies using similar tracking methods, but with shorter periods of noncontact (e.g., LSAY, MIDUS, LSAL, and Add Health). AIR recently applied the same tiered tracking protocol used in this study to a geographically dispersed group of minorities who participated in an aquatic science program as undergraduate and graduate students between 1990 and 2011. Though many of the participants had not been involved with the program in as many as 22 years, 93.4 percent were located (Sandoval and Stone 2013).

However, the results presented here suggest that even with relatively high tracking rates, certain subpopulations may be systematically harder to find (research question 2). We confirmed that even after controlling for individual characteristics such as sex, family SES, and school attributes, individuals with lower cognitive scores relative to their peers would be more difficult to find and that certain personality characteristics are associated with higher rates of tracking failure. Our findings suggest that males who scored low on the tidiness measure in 1960 tend to be harder to find – perhaps because these males are less likely to update their addresses with creditors, voluntary registers, or other databases after moves or to engage in other behaviors that may leave traces to their new address and make them easier to locate.

Contrary to our expectations, this study also found that males who scored lower on the impulsivity measure (i.e., those who were less impulsive) were actually harder to locate than those who scored in the middle quintiles. We are not sure why this may be, but one explanation could be that less impulsive males exhibit more deliberate purchasing behavior (e.g., saving and then purchasing), particularly when purchasing expensive items such as cars or electronics. As a result, these less impulsive males may be less likely to open lines of credit, and hence will have less information in consolidated tracking databases.

Table 3. Comparison of base weighted estimates for the pilot study population and population located during the tracking phase for the 2011–12 Project Talent Follow-up Pilot Study, before and after nontracking weighting adjustments, for key sample characteristics measured in 1960

Selected sample characteristics (1960)	Before nontracking adjustment (base weights only)				After nontracking adjustment and base weights		
	Estimated percent for pilot sample[1]	Estimated percent for located[2]	Estimated bias	Percent relative bias	Estimated percent for located[2]	Estimated bias	Percent relative bias
Sex (1960)							
Male	48.8	49.2	0.5	0.01	46.2	−2.5	−0.05
Female	51.2	50.8	−0.5	−0.01	53.8	2.5	0.05
Family SES							
Missing	2.4	1.4	−1.0	−0.72*	1.4	−0.9	−0.66*
Bottom 20%	19.6	15.0	−4.6	−0.31*	15.7	−3.9	−0.25
Middle 60%	58.3	60.1	1.8	0.03	59.6	1.3	0.02
Top 20%	19.7	23.6	3.8	0.16	23.3	3.6	0.15
Usual health before age ten							
Missing	9.2	6.0	−3.2	−0.53*	6.2	−3.0	−0.47*
Very poor or poor	4.8	4.8	0.0	−0.01	5.0	0.1	0.03
Good or average	29.6	28.1	−1.5	−0.05	28.1	−1.5	−0.05
Very good or excellent	56.4	61.1	4.7	0.08*	60.8	4.3	0.07*
General academic aptitude							
Missing	12.7	10.3	−2.4	−0.23	10.2	−2.5	−0.24
Q1	19.1	11.2	−8.0	−0.71*	11.5	−7.6	−0.66*
Q2	18.2	16.2	−2.0	−0.12	16.7	−1.5	−0.09
Q3	17.8	19.2	1.4	0.07	19.5	1.7	0.09
Q4	16.8	21.2	4.4	0.21*	21.3	4.5	0.21*
Q5	15.4	22.0	6.6	0.30*	20.8	5.4	0.26*
Impulsivity							
Missing	1.2	0.6	−0.6	−0.94*	0.6	−0.6	−0.95*
Q1	29.9	29.7	−0.1	0.00	29.5	−0.4	−0.01
Q2	15.7	16.0	0.3	0.02	16.2	0.5	0.03
Q3	22.7	22.7	0.1	0.00	23.0	0.4	0.02

Table 3. Continued

Selected sample characteristics (1960)	Before nontracking adjustment (base weights only)				After nontracking adjustment and base weights		
	Estimated percent for pilot sample[1]	Estimated percent for located[2]	Estimated bias	Percent relative bias	Estimated percent for located[2]	Estimated bias	Percent relative bias
Q4	14.5	14.1	−0.5	−0.03	13.8	−0.7	−0.05
Q5	16.0	16.8	0.8	0.05	16.8	0.8	0.05

[1] All cases sampled for the 2011–12 Project Talent Follow-up Pilot Study.

[2] Located includes only those who were located during the tracking phase.

Note: An asterisk (*) indicates where there is a statistically significant difference at the $p = 0.05$ level between the estimates for the full pilot study sample and the estimates produced after the analysis is restricted to include only those who were located. The percent relative bias is the estimated bias divided by the estimates produced after the analysis is restricted to include only those who were located.

Another unexpected finding was that among females, those scoring in the middle quintiles of the self-confidence measure were located at significantly lower rates relative to those scoring in the bottom quintile (those who were less self-confident). One possible explanation is that females who were less confident in high school were also less likely to relocate after completing high school. This reduced mobility would make them easier to find.

Regardless, these findings clearly support existing concerns that certain groups are located at disproportionately low rates that, if left uncorrected, could bias the survey results. For example, the pilot study was significantly less successful at locating females as well as males and females scoring in the bottom quintile of the cognitive measure of general academic aptitude. This is of particular concern because lower cognitive ability is also associated with different decision-making processes, different risk factors, and higher mortality rates. As a result, these individuals are often of particular interest for longitudinal studies that focus on health, financial, psychosocial, and general well-being outcomes throughout the life course.

Like Iannacchione (2003), we applied a tracking-loss adjustment to evaluate the extent to which such a statistical adjustment could be used to reduce biases introduced as a result of systematic differences in tracking propensity across subgroups (research question 3). The tracking weighting adjustment reduced, but did not remove, all significant biases. Our findings suggest that where differential tracking rates are expected to vary greatly across subgroups (e.g., where the amount and quality of information needed for tracking may be uneven across subgroups), studies attempting to locate individuals after a long hiatus should not rely solely on statistical adjustments to reduce and remove biases. Rather, researchers should identify the hardest-to-locate subgroups and use this information to develop a sample design and tracking protocol that can improve the representation and statistical efficiency of the resulting study. This could include the stratification of samples using variables that are expected to be correlated with tracking propensity and the outcomes of interest to ensure that a sufficient number of individuals from key subgroups will be located and can be used for tracking-loss adjustments.

Studies should also reflect on whether shifting study resources into the development and implementation of more extensive, tailored tracking protocols – methods that would simply be too costly to implement for the full sample – can be applied on a smaller scale for historically underlocated subgroups. For example, it seems likely that individuals with certain personality or cognitive characteristics may be more isolated or lead elusive lives that make them more difficult to locate using methods that rely on consolidated tracking databases. Tracking plans may want to include protocols for contacting local government offices (e.g., marriage bureaus or city halls), or even classmates and siblings, in order to find hard-to-find sample members. Such work would be most effective if implemented early in the tracking phase, as these individuals will likely take more time and resources (i.e., tracking steps) to locate. Longitudinal studies, including those that have been revived after an extended hiatus, should make good use of their existing data and consider using key measures and indicators to prioritize cases with lower tracking propensities to receive longer and more intensive tracking methods.

Appendix

Appendix. Percentage of persons not found during tracking and predicted probability estimates of tracking failure, from multivariate logistic regression model, by selected 1960 variables

	Males				Females			
Selected characteristics (1960)	Number	Percent not found	Predicted probability (PP)	95% confidence interval for PP	Number	Percent not found	Predicted probability (PP)	95% confidence interval for PP
Grade cohort								
9–10	1,328	9.3	0.80	(0.72, 0.87)	1,329	25.9	0.81***	(0.76, 0.86)
11–12	1,049	6.4	–	–	1,173	17.6	–	–
Socioeconomic status								
Low SES	452	10.8	0.80	(0.72, 0.88)	492	31.1	0.81**	(0.75, 0.86)
Not low SES	1,850	7.0	–	–	1,963	19.7	–	–
Missing	75	17.3	0.99*	(0.77, 1.00)	47	25.5	0.78	(0.61, 0.98)
Health in last three years								
Very poor or poor	49	10.2	0.78	(0.61, 0.97)	56	28.6	0.76	(0.65, 0.9)
Good or average	525	7.0	0.70	(0.63, 0.79)	729	23.9	0.74	(0.69, 0.79)
Very good or excellent	1,517	7.4	–	–	1,557	20.4	–	–
Missing	286	12.6	0.93	(0.63, 1.00)	160	27.5	0.81	(0.61, 0.99)
Health in first 10 years								
Very poor or poor	102	7.8	0.74	(0.61, 0.91)	131	19.8	0.70	(0.63, 0.8)
Good or average	682	6.6	0.69	(0.63, 0.77)	774	23.3	0.73	(0.69, 0.78)
Very good or excellent	1,300	7.9	–	–	1,433	20.9	–	–
Missing	293	11.9	0.61	(0.52, 0.9)	164	27.4	0.68	(0.57, 0.91)
Number of days sick in bed in past year								
None	655	8.1	–	–	523	20.8	–	–
1–2	887	7.2	0.70	(0.64, 0.78)	906	20.1	0.75	(0.69, 0.81)
3 or more	565	7.3	0.70	(0.63, 0.79)	922	23.8	0.77	(0.72, 0.84)
Missing	270	12.2	0.64	(0.53, 0.9)	151	27.2	0.71	(0.57, 0.96)
Class rank								
Bottom 20%	407	9.6	0.77	(0.69, 0.87)	284	24.3	0.72	(0.66, 0.78)
Middle 60%	1,498	7.5	–	–	1,588	23.2	–	–
Top 20%	374	7.5	0.75	(0.66, 0.85)	559	17.2	0.71	(0.66, 0.76)

Appendix. Continued

Selected characteristics (1960)	Males				Females			
	Number	Percent not found	Predicted probability (PP)	95% confidence interval for PP	Number	Percent not found	Predicted probability (PP)	95% confidence interval for PP
Missing	98	12.2	0.62	(0.54, 0.83)	71	23.9	0.70	(0.59, 0.88)
General academic aptitude								
Bottom 20%	456	12.7	0.82*	(0.73, 0.91)	407	35.4	0.86	(0.79, 0.91)
Middle 60%	1,206	7.2	–	–	1,358	21.2	–	–
Top 20%	407	4.2	0.66	(0.59, 0.76)	444	11.5	0.62***	(0.59, 0.67)
Missing	308	9.4	0.76	(0.66, 0.87)	293	23.2	0.73	(0.67, 0.80)
Sociability								
Bottom 20%	778	9.0	0.73	(0.67, 0.82)	503	25.8	0.79*	(0.73, 0.85)
Middle 60%	1,266	7.5	–	–	1,381	21.4	–	–
Top 20%	297	6.7	0.76	(0.66, 0.88)	590	19.5	0.72	(0.67, 0.77)
Missing[1]	36	16.7	0.84	(0.64, 0.99)	28	35.7	0.84	(0.66, 0.98)
Social sensitivity[1]								
Bottom 20%	745	8.7	0.72	(0.65, 0.81)	387	23.5	0.71	(0.66, 0.77)
Middle 60%	1,427	7.6	–	–	1,681	22.5	–	–
Top 20%	169	7.1	0.78	(0.65, 0.92)	406	17.5	0.72	(0.66, 0.78)
Impulsivity[1]								
Bottom 20%	1,116	9.4	0.82*	(0.75, 0.90)	1,117	21.3	0.72	(0.68, 0.76)
Middle 60%	874	6.3	–	–	947	21.8	–	–
Top 20%	351	7.1	0.76	(0.67, 0.87)	410	23.7	0.76	(0.7, 0.82)
Vigor[1]								
Bottom 20%	468	9.0	0.76	(0.68, 0.85)	553	22.6	0.72	(0.67, 0.78)
Middle 60%	1,627	8.0	–	–	1,676	22.3	–	–
Top 20%	246	5.3	0.69	(0.6, 0.81)	245	17.6	0.71	(0.65, 0.78)
Calmness[1]								
Bottom 20%	810	9.9	0.78	(0.71, 0.87)	721	24.3	0.75	(0.7, 0.81)
Middle 60%	1,300	7.2	–	–	1,421	22.0	–	–
Top 20%	231	4.8	0.69	(0.6, 0.83)	332	16.3	0.71	(0.65, 0.78)

Appendix. Continued

Selected characteristics (1960)	Males: Number	Males: Percent not found	Males: Predicted probability (PP)	Males: 95% confidence interval for PP	Females: Number	Females: Percent not found	Females: Predicted probability (PP)	Females: 95% confidence interval for PP
Tidiness[1]								
Bottom 20%	844	10.0	0.84**	(0.76, 0.92)	495	23.6	0.75	(0.69, 0.81)
Middle 60%	1,222	7.0	–	–	1,440	22.4	–	–
Top 20%	275	5.5	0.69	(0.63, 0.76)	539	18.9	0.73	(0.68, 0.79)
Culture[1]								
Bottom 20%	937	8.2	0.81	(0.69, 0.93)	444	23.6	0.72	(0.67, 0.78)
Middle 60%	1,159	7.6	–	–	1,459	22.4	–	–
Top 20%	245	8.2	0.66	(0.61, 0.73)	571	19.1	0.74	(0.69, 0.80)
Leadership[1]								
Bottom 20%	913	6.8	0.75*	(0.66, 0.85)	842	22.8	0.75	(0.70, 0.80)
Middle 60%	1,036	8.9	–	–	1,134	21.8	–	–
Top 20%	392	7.9	0.68	(0.63, 0.75)	498	20.5	0.73	(0.68, 0.79)
Self-confidence[1]								
Bottom 20%	702	7.8	0.67	(0.6, 0.77)	714	20.3	0.68*	(0.65, 0.72)
Middle 60% and top 20%	1,639	7.9	–	–	1,323	22.5	–	–
Mature personality[1]								
Bottom 20%	612	8.8	0.70	(0.63, 0.78)	483	21.7	0.69	(0.64, 0.74)
Middle 60%	1,416	8.0	–	–	1,547	23.4	–	–
Top 20%	313	5.8	0.69	(0.61, 0.82)	444	16.7	0.71	(0.66, 0.78)
School type								
Public	2,163	8.3	0.90	(0.68, 1.00)	2,209	22.1	0.76	(0.60, 0.96)
Private	214	5.1	–	–	293	21.2	–	–
Building type								
Not junior high school	2,111	7.5	–	–	2,245	21.6	–	–
Junior high school	266	12.0	0.73	(0.65, 0.84)	257	25.7	0.71	(0.65, 0.78)

Appendix. Continued

Selected characteristics (1960)	Males: Number	Males: Percent not found	Males: Predicted probability (PP)	Males: 95% confidence interval for PP	Females: Number	Females: Percent not found	Females: Predicted probability (PP)	Females: 95% confidence interval for PP
Percent minority in school								
0–49 percent	2,055	7.3	–	–	2,071	21.4	–	–
50–79 percent	27	22.2	0.95*	(0.73, 1.00)	78	23.1	0.63	(0.57, 0.74)
80–100 percent	279	12.5	0.78	(0.68, 0.88)	336	26.2	0.70	(0.65, 0.76)
Missing	16	6.3	0.70	(0.53, 1.00)	17	11.8	0.60	(0.52, 0.87)
Census region (school)								
Mid-Atlantic, South Atlantic, Mountain	890	10.2	0.78	(0.71, 0.86)	1,004	25.4	0.79*	(0.74, 0.84)
Other region	1,487	6.7	–	–	1,498	19.8	–	–
Population size of surrounding community								
Rural	262	7.3	0.77	(0.62, 0.95)	239	26.8	0.66	(0.60, 0.76)
Under 5,000	259	4.6	0.69	(0.57, 0.9)	280	19.6	0.64*	(0.58, 0.73)
5,000–249,999	1,155	8.7	0.83	(0.67, 0.97)	1,188	21.3	0.64*	(0.59, 0.71)
250,000–1,499,999	323	10.5	0.89	(0.71, 0.99)	337	19.6	0.63*	(0.58, 0.71)
1,500,000 or more	109	7.3	–	–	140	30.7	–	–
Not classified	269	6.7	0.92	(0.68, 1.00)	318	22.0	0.71	(0.58, 0.93)

Odds ratio notes: Adjusted odds ratio that person will not be located based on multivariate logistic regression adjusting for the other factors shown in the table.

[1] $N = 36$ observations were missing data for all 10 of the personality measures under examination. As a result, only one of the parameters associated with these variables could be estimated, since the corresponding parameters associated with the remaining variables would be perfectly correlated. The odds ratio estimate for the "Missing" parameter is reported only for the "sociability" variable. The redundant parameters for the remaining personality variables (social sensitivity, impulsivity, vigor, calmness, tidiness, culture, leadership, self-confidence, and mature personality) have been removed from the table. The number and percent not found are not reported for these variables; therefore, the estimates will not sum to totals.

— indicates reference group.

*** $p < .001$, ** $p < .01$, * $p < .05$.

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