

Methodology for Constructing Mother, Father and Couple Weights for Core Telephone Survey Wave 5

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1 Overview

The Fragile Families and Child Well-being Study is an on-going panel study that follows a 1998-1999 birth cohort of about 3,600 children born to unwed parents, and 1,100 children born to married parents from 20 large US cities in fifteen states. The study places particular emphasis on how parental resources in the form of parental presence or absence, time, and money influence children under the age of five. Results from the study will provide insight into the ways in which public policies that have an impact on parental resources, such as, welfare programs, child support enforcement, and child care subsidies affect neglect. The target population for the Fragile Family (FF) studies is: live births (ultimate sampling unit) occurring in large cities, by mothers who plan to keep the child, can identify the still-living father, and speak English or Spanish.

Respondents of the Fragile Families Baseline survey were located and screened for eligibility for inclusion in the succeeding waves of the core survey and collaborative studies of the core survey. The survey administration process allows all still eligible respondents of the Baseline survey to participate in any follow-up surveys of the Fragile Families Study. As such, eligible respondents who could not participate in a prior wave of the follow-up survey, because of reasons other than permanent refusal, may still participate in the current or future wave of the follow-up survey.

Carlson (2008) constructed the weights for wave 1 to wave 4. Here we construct the weights for wave 5, including mother, father and couple weights. There are city-level weights and national weights. The birth weights for individual FF city-level were developed to provide users of the mother baseline survey data with final survey weights for analyses within individual cities, where the weights are consistent with total population counts of births in the corresponding large U.S. cities based on the Centers for Disease Control and Prevention (CDC) data. The national-level weights are the final survey weights attached to individual births for analyses that pool records for the 16 national-sample cities within the sample. The analysis generalizes to births occurring in the 77 large cities defined as the FF population. The weights were raked to total (population) birth counts in the 77 cities based on CDC data. The national-level weights have two sets: one based on all 16 of the

national-sample cities in the sample, with all 77 cities as the population being targeted, and the other based on only 15 cities (City X is excluded) in the sample, with all 77 cities as the population being targeted. Table 1 summarizes the weights that are constructed.

Table 1: Weighting variable names for Fragile Families Year 9 follow-up core survey.

	Basic weight	Replicate weights
National Level	m5natwt	m5natwt_rep1-m5natwt_rep26
	f5natwt	f5natwt_rep1-f5natwt_rep26
	c5natwt	c5natwt_rep1-c5natwt_rep26
National Level (without City X)	m5natwtx	m5natwtx_rep1-m5natwtx_rep23
	f5natwtx	f5natwtx_rep1-f5natwtx_rep23
	c5natwtx	c5natwtx_rep1-c5natwtx_rep23
City Level	m5citywt	m5citywt_rep1-m5citywt_rep72
	f5citywt	f5citywt_rep1-f5citywt_rep72
	c5citywt	c5citywt_rep1-c5citywt_rep72

2 Mother weighting

wave 4 weight as anchor The wave 4 weight serves as the anchor for wave 5 weight. Because there is no subsampling at the various follow-ups, we concern ourselves mainly with nonresponse adjustments and re-raking to the wave 4 totals.

eligible population A case was ineligible at follow-up only if the child associated with the sampled birth died. While no survey was completed (or only a few questions of the survey were answered), we would still consider these cases part of the target population. The situations without responses—cases in which the child was adopted, neither parent had custody of the child, or one of the parents died—were a type of outcome. These cases were considered to be completes without survey data for weighting purposes. The flag *cm5samp* indicates whether some or all of a questionnaire was completed, among those considered to be part of the eligible completes within the sample. All other final dispositions were considered to be eligible non-completes, sub-classified as located or un-located. In summary, the eligible samples are divided into eligible complete and eligible noncomplete groups, and eligible noncompetes are subdivided into located and un-located.

If a previous round of the survey indicated ineligibility (child deceased or duplicate), then the current round was classified as ineligible, regardless of the current disposition code. The flag *cm5mint* indicates eligible complete cases with survey data. The samples we consider include cases that are eligible complete with survey data, mother died, adopted or neither parent has legal custody, refusal, could not locate, other nonresponse and assigned weights in wave 4.

Table 2: Sample classification

Eligible	located	response (with mom weight)	-7 NA (with survey data) 1 Mother died 3 Adopted/Neither parent has legal custody
		nonresponse	5 Refusal 7 Other non-response
	unlocated		6 Could Not Locate
Ineligible			2 Child died 4 Other Ineligible

In short, each follow-up weight starts with the final poststratified wave 4 mother weight (national, national without City X, or city, as appropriate). If the units were not assigned wave 4 weights, we check wave 3, wave 2 and wave 1 sequentially. That is, we work on the cases with weights, even though some cases are ineligible. The summary of the inclusion criteria for nonresponse adjustment is: *cm5mint* has *yes* value, mother died and adopted or neither parent has legal custody; The inclusion criterial for raking adjustment is: *cm5mint* has *yes* value, mother died, adopted or neither parent has legal custody, Child died or Other Ineligible.

2.1 National weighting

We collect the sample dispositions based on the flag *cm5samp* and determine the cases that should be included in wave 5. We start with mother national weights at wave 4 for these cases. If these units were not assigned wave 4 weights, we move on to incorporate the weights in previous waves sequentially. This results in sample size 3404 (3100 located and 304 unlocated cases). The sample size of eligible completes is 2623 (with survey data—*cm5mint* has *yes* value, mother died and adopted or neither parent has legal custody).

2.1.1 Nonresponse Adjustment

two stage adjustment More intuitively for the weighting adjustment, the eligible samples are divided into located and un-located, and the located samples have completes and non-completes. We use located samples to adjust for unallocated and then located completes for located non-completes. We adjust the weights of the eligible completes to account for those of the eligible non-completes in these two stages.

1. First we adjust for un-locatability; that is, we adjust the initial weights for all the eligible located cases upward to account for those of the eligible un-located cases (*cm5samp*=“6 Could Not Locate ” ; 3100 located and 304 unallocated).
2. Then we adjust for nonresponse among the located; that is, these adjusted weights for the eligible located completes are further adjusted upward to account for those of

the eligible located non-completes (cm5samp=“5 Refusal” & “7 Other non-response”; 2623 responded and 477 non-responded).

For each adjustment, we build a logistic regression with the indicator — located and response, respectively — being the outcome variable. We select a set of covariates as candidates for these models among the baseline and wave 4 survey variables, which are available for both respondents and nonrespondents in the wave 5 follow-up survey. We did a preliminary selection by excluding the variables with more than 20% item missingness, more than 11 possible values ¹. The list of variables from the baseline and wave 4 is in Appendix A. We filled in the missing items by random draws from the corresponding observed frequency distributions ². The predictors after dummy coding are used as covariates. We developed two separate unweighted logistic regression models using lasso (Friedman *et al.* , 2010) for regularization to predict the two types of nonresponse. We use the predicted propensity scores for weighting adjustment.

weighting cells—response propensity stratification Inverse propensity score weights are often highly variable and trimming is necessary to control the large uncertainty. Little (1986) proposed a response propensity stratification method, which forms adjustment cells based on the estimated response propensities. Specifically, the estimated response propensities are first ordered; respondents and nonrespondents with similar estimated response propensities are grouped to form adjustment cells; and the respondents in each cell are weighted by the inverse of observed response rate in that cell. Since the estimated response propensities are used only for the purpose of forming adjustment cells, the response propensity stratification method relies less on correct specification of the response propensity regression model. Furthermore, the large weighting adjustments due to small estimated response propensities can be avoided by placing appropriate cut points in forming adjustment cells. Rosenbaum & Rubin (1983) suggested that five adjustment cells may provide the most effective bias reduction. Common approach is to define the adjustment cells using the deciles or quintiles of the distribution of the estimated response propensities.

We used the predicted propensity scores to form deciles for the national weights, and quintiles within city for the city-level weights. We used these deciles to form the weighting cells for the nonresponse adjustments. Therefore, each weighting cell comprises sample members who have similar response propensities. Once the cells are formed, the two sets of adjustments are made separately for each of the two national weights and the city weight. For example, the summary for adjustment number of the national weights is

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.013	1.072	1.122	1.298	1.298	4.141

¹we did not include the continuous variables here, but we included city as a covariate. We will use dummy coding the regression to recode these categorical variables. Only using categorical variables helps implement the R package *glmnet*.

²More work is doing for more sophisticated imputation of large scale categorical variables, using the algorithms developed by Si (2012) and Si & Reiter (2013).

2.1.2 Poststratification

Note that the ineligible sample members were excluded from these nonresponse adjustments and simply retained their initial weight from wave 4. After the nonresponse adjustment, we bring back the ineligible weights in (cm5samp=“2 Child died” or “4 Other Ineligible”). We eliminate the cases who were not assigned weights from the first four waves.

We rake the weights to their wave 4 totals. From Carlson (2008), the raking variables include mother’s age, education, ethnicity and marital status. We find the frequency of the variables “msn”, “edun”, “ethn” and “agen” as in the collected dataset below. These four variables are used to rake national weights. To obtain the external information for the calibration of wave 5 national weights, we use wave 4 national weights to obtain the weighted frequency distributions of these 4 variables: msn, edun, ethn and agen, which are treated as the golden standard.

Table 3: Frequency of the mother’s demographic information used for raking national weights; FF–Fragile Families samples; POP–weighted frequency in wave 4.

MSN:		married	unmarried	NA		
FF		827	2615	1456		
POP		680817.7	450215.0			

EDUN:	<8th grade	Some HS	HS or equiv	Some College	College+	NA
FF	193	972	1026	852	399	1456
POP	113127.7	211968.1	338151.4	214318.9	253466.5	

ETHN:	white, non-hispanic	black, non-hispanic	hispanic	other	NA
FF	1020	845	1430	147	1456
POP	353197.81	429932.34	254690.94	93211.53	

AGEN:	<18	18-19	20-24	25-29	30-34	35-30	40+	NA
FF	108	514	1262	757	487	239	75	1456
POP	53430	89690	283532	294845	252185	128291	29059	

We implement the raking process utilizing commands from the R package *survey* (Lumley, 2013). The complex survey design of the FF studies involves cluster sampling and requires corresponding specification when defining the survey subject. We find the variable “natpsu” representing the primary sampling unit (PSU) and “natstratum” representing the strata structure, with the following frequency distributions.

```
table(All$natpsu,useNA="always")
  1   4   5   6   8   9  10  11  13  14  15  16  17  18  19  20
302 327 342 337 331 325 348 297  99 102 134 100 101 100 100  99
9901 9902 9903 9906 9907 9908 9909 9910 9925 9926 9944 9945 9946 9947 <NA>
  99 130  97  72 108  71  36  51 121 206 120 124  61  21 109
table(All$natstratum,useNA="always")
111 999 9902 9903 9907 9912 <NA>
1501 1943 326 338 327 326 109
```

Hence we define the survey object with the one stage cluster sampling, nested stratified sampling and without replacement. We use the summation of the wave 4 national weights to approximate the population size and incorporate it for the finite population correction factor. Then we rake the nonresponse-adjusted weights to their baseline totals, trim any outlier weights, and rake the weights. After raking based on the four variables listed above, the summary of weights is

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.757	25.940	100.300	425.000	353.600	13780.000

There are some extremely large weights (95% percentile: 1840; 99% percentile: 5727). We trim the large weights to remove the outliers. Carlson (2008) set the trim value as mean plus four standard deviations for each type of weights by marital status. The summaries of the finalized weights of the first four waves are as below (msn=1: married; msn=2: unmarried).

```
summary(All$m1natwt[All$msn==1])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
 3.35  94.50  263.60  823.20  900.00 7543.00  1428
summary(All$m1natwt[All$msn==2])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
 1.487  17.560  56.440  172.300  188.900 2464.000  1428
summary(All$m2natwt[All$msn==1])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
 3.745  97.370  289.800  902.900 1049.000 8058.000  1501
summary(All$m2natwt[All$msn==2])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
 1.32  18.74  60.02  190.30  195.20 2243.00  1677
summary(All$m3natwt[All$msn==1])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
 4.12  97.75  286.40  915.10  994.60 8427.00  1511
summary(All$m3natwt[All$msn==2])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
 1.352  19.410  62.460  196.800  194.000 2393.000  1755
summary(All$m4natwt[All$msn==1])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
 4.849  88.660  279.500  935.200 1055.000 8005.000  1527
summary(All$m4natwt[All$msn==2])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.   NA's
 1.712  19.840  65.660  197.600  208.300 2215.000  1765
```

The values of standard deviation of the weights in the first four waves for married families are 1372.128, 1498.603, 1517.131 and 1554.853; for unmarried families are 298.2256, 323.8694, 342.8304 and 330.9030. The weights are still highly variable and have extreme values after their trimming.

We choose a different trimming rule to achieve better control of the extreme weights by marital status. We set the 97.5% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level.³ Then we re-rake the weights to match the wave 4 totals. The summaries are as below.

```
summary(weights(All.rake_t_n)[data_rake$msn==1])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 49.09 140.30 354.40 981.60 1065.00 5411.00
summary(weights(All.rake_t_n)[data_rake$msn==2])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 45.02  64.08 113.90 249.50 263.10 1463.00
```

Table 4: Summary of national sample mother weights.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
wave 1	1.49	21.45	82.19	328.70	290.30	7543.00	1456
wave 2	1.32	23.43	90.49	362.50	328.20	8058.00	1778
wave 3	1.35	24.07	94.23	373.00	327.60	8427.00	1866
wave 4	1.71	24.26	96.75	376.30	329.80	8005.00	1892
wave 5	45.02	69.20	143.60	425.00	396.90	5411.00	2237

2.1.3 Variance Estimation

Replicate weights The FF study used a multistage complex sample design, and there is no available or appropriate variance estimation formula. When the data files do not contain the geographic identifiers needed to construct the strata and primary sampling unit (PSU) variables, replication procedures with the creation of a set of replicate weights can be utilized for variance estimation. There are several different methods for creating replicate weights. The basic idea is to randomly exclude some samples, re-weight the remaining to account for those excluded, calculate a new weighted estimate based on the remaining subsample, and then calculate the variance across a series of these subsamples. We use the Jackknife schemes for stratified designs in the R package *survey*. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time. These subsamples were selected so that no case could appear in more than one excluded random group.

³The R command for trimming is subject to the error message: “Error: evaluation nested too deeply: infinite recursion / options(expressions=)? Error during wrapup: evaluation nested too deeply: infinite recursion / options(expressions=)?”. If it happens, we suggest rerunning the command or changing for different trimming rules.

Then the replicate weights for those remaining in the subsamples are adjusted by raking with the same variables described in Section 2.1.2 on mothers’ demographics to match the known total. For trimming on each replicate weights, we set the 97.5% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. This resulted trimming values are different across the 26 replicate weights. The trimmed weights are calibrated by raking with the same factors again to match the totals in wave 4.

2.2 National weighting—exclude City X

Another set of national weights is based on 15 cities, excluding City X, which make the random national samples. The reason for excluding City X is that different questionnaire was used in City X from the remaining 15 cities. We start from the same disposition codes for the samples and the wave 4 national weights—*m4natwt_x*, where the letter *x* is added to distinguish from the national weights constructed as above. If these units were not assigned wave 4 weights, we move on to incorporate the weights in previous waves sequentially. The eligible sample size is 3080 (2808 located and 272 un-located cases). The sample size of eligible completes is 2389 (with survey data—*cm5mint* has *yes* value, mother died and adopted or neither parent has legal custody).

Then we implement the two-stage nonresponse adjustment and build the two sequential logistic regression with the same predictors in Appendix A. We use the predicted response propensity scores to construct the weighting cells, and the inverse of response rates inside weighting cells are the nonresponse adjustment weighting factors. We bring the ineligible cases back in. We calibrate the weights with the same raking procedure and variables in Section 2.1.2. The wave 4 weight *m4natwt_x* is the anchor. We set the 97.5% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. Then we re-rake the weights to match the wave 4 totals. The summaries are as below in Table 5. Finally, we construct the replicate weights for variance estimate, following the same procedure in Section 2.1.3. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time. For trimming on each replicate weights, we set the 97.5% quantile of weights after raking for unmarried families as their upper truncation level and 97.5% quantile of weights for married families as their upper truncation level. This resulted trimming values are different across the 23 replicate weights. The trimmed weights are calibrated by raking with the same factors again to match the totals in wave 4.

2.3 City weighting

We start from the wave 4 city weight *m4citywt* and work on 3595 cases in wave 5 to construct city specific weights. For the two-stage nonresponse adjustment, we use the same predictors as in Appendix A. Note that “city” indicator is a predictor in the two regression models. When constructing the weighting cells by poststratification of the predicted response propensity scores, we do this city by city. That is, we form the quintiles within city, and

Table 5: Summary of national sample mother weights (without City X).

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
wave 1	1.53	27.71	96.71	363.10	332.40	7810.00	1782
wave 2	1.37	28.96	110.30	400.60	363.90	8450.00	2075
wave 3	1.40	30.31	111.50	412.50	381.50	8824.00	2156
wave 4	1.78	30.60	113.30	416.40	387.40	8329.00	2182
wave 5	47.07	77.83	163.80	466.40	454.80	5525.00	2473

the weighting cells differ by response rates and city. The inverse values of the response rates inside weighting cells are the weighting adjustment factors for nonresponse.

Next we bring the ineligible cases back in. We calibrate the city weights to match the city total counts. For each city, we post-stratify the weights by mother’s demographic information: marital status, education, ethnicity and age. The constructed raking variables for city weights are different from those for the national weights. We implement the poststratification city by city. For the frequency of the variables “ms”, “edu”, “eth” and “age” in the sample, we realize that they were used to rake city weights, some of which have different levels from those used for the national weights. However, the coding construction for “edu”, “eth” and “age” is different by city. For example, level 1 for age represents younger than 18 in Richmond, however, it denotes younger than 20 in Indianapolis. So we cannot use these variables as consistent raking factors. To avoid zero counts in the joint frequency cells between these demographic variables and city, we collapse their categories starting from the original questions (*cm1age*, *m1i1*, *m1h3*, *m1h3a*). Here is the frequency distribution.

Table 6: Frequency of the mother’s demographic information by used for raking city weights; FF–Fragile Families samples.

	MS:	married	unmarried	NA	
	FF	1155	3634	109	
EDU:	< HS	HS or equiv	Some College	College+	NA
FF	1679	1214	1240	656	109
ETH:	white, non-hispanic	black, non-hispanic	other	NA	
FF	998	2257	1534	109	
AGE:	≤19	20-24	25-34	35+	NA
FF	841	1724	1777	447	109

We set the 95% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. Then we re-rake the city weights to match the wave 4 city totals. The summaries are as below in Table 7. Finally, we construct the replicate weights for variance estimate, following the same procedure in Section 2.1.3. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time.

The variables “citypsu” and “citystratum” indicator the PSU and strata structure for the city weights, where hospitals are the PSU. The replicate city weights are raked to match the wave 4 total counts.

Table 7: Summary of mother city weights.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
wave 1	1.00	12.08	26.62	72.70	59.18	2924.00	109
wave 2	1.08	13.05	29.23	80.48	63.97	3345.00	576
wave 3	1.23	13.68	29.83	82.50	64.49	3973.00	680
wave 4	1.08	13.31	30.75	83.47	64.06	4927.00	735
wave 5	26.82	40.95	58.76	95.10	94.46	830.90	1249

2.3.1 Checking

- The sum of the follow-up weight should be equal to the sum of the comparable baseline weight
- We cross that classification with the eligibility status, locatability status, and completion status, and then check whether the weight is appropriately missing or has a positive value.
- The city weights should all have a positive value if the case is (1) eligible and located and complete, or (2) ineligible and non-complete.
- For the national weights (including and excluding City X), the same rules apply, except for: For national weights including City X, those from the four cities that not part of the national sample will have zero weights. For national weights excluding City X, those from those four cities plus City X will have zero weights.
- Check the summary statistics of the ratio between the follow-up weight and its comparable baseline weight (for the city-specific weight, this is done separately by city) to see if there are any extreme values.

3 Father weighting

wave 4 weight as anchor The mother weights are created to make the sample of births representative of the eligible births occurring in large cities of US during the study period. All the father weights (baseline and follow-up) would match the total mother baseline weights, which represents the population of births. Since the father weights at wave 1-4 are available, the wave 4 father weight serves as the anchor for wave 5 father weight. Because

there is no subsampling at the various follow-ups, we concern ourselves mainly with nonresponse adjustments and re-raking to the wave 4 totals. The raking variables are on mothers' demographics, the same as those for the mother weights.

eligible population A case was ineligible at follow-up only if the child associated with the sampled birth died. The flag *cf5samp* indicates whether some or all of a questionnaire was completed, among those considered to be part of the eligible completes within the sample. All other final dispositions were considered to be eligible non-completes, sub-classified as located or un-located. In summary, the samples are divided into eligible complete and eligible noncomplete groups, and eligible noncompetes are subdivided into located and un-located.

If a previous round of the survey indicated ineligibility (child deceased or duplicate), then the current round was classified as ineligible, regardless of the current disposition code. The samples we consider include cases that are eligible complete with survey data, mother died, adopted or neither parent has legal custody, refusal, could not locate, other nonresponse and assigned weights in wave 4.

In short, each follow-up weight starts with the final poststratified wave 4 father weight (national, national without City X, or city, as appropriate). If the units were not assigned wave 4 weights, we check wave 3, wave 2 and wave 1 sequentially. That is, we work on the cases with weights, even though some cases are ineligible.

3.1 National weighting

We collect the sample dispositions based on the flag *cf5samp* and determine the cases that should be included in wave 5. We start with father national weights at wave 4 for these cases. If these units were not assigned wave 4 weights, we move on to incorporate the weights in previous waves sequentially. This results in sample size 3030 (2687 located and 343 un-located cases). The sample size of eligible completes is 2014 (with survey data, father died and adopted or neither parent has legal custody).

3.1.1 Nonresponse Adjustment

two stage adjustment More intuitively for the weighting adjustment, the eligible samples are divided into located and un-located, and the located samples have completes and non-completes. We use located samples to adjust for unallocated and then located completes for located non-completes. We adjust the weights of the eligible completes to account for those of the eligible non-completes in these two stages.

1. First we adjust for un-locatability; that is, we adjust the initial weights for all the eligible located cases upward to account for those of the eligible un-located cases (*cf5samp*="6 Could Not Locate").
2. Then we adjust for nonresponse among the located; that is, these adjusted weights for the eligible located completes are further adjusted upward to account for those of the eligible located non-completes (*cf5samp*="5 Refusal" & "7 Other non-response").

For each adjustment, we build a logistic regression with the indicator — located and response, respectively — being the outcome variable. We use the predictors in Appendix A. We filled in the missing items by random draws from the corresponding observed frequency distributions . The predictors after dummy coding are used as covariates. We developed two separate unweighted logistic regression models using lasso (Friedman *et al.* , 2010) for regularization to predict the two types of nonresponse. We use the predicted propensity scores for weighting adjustment.

weighting cells—response propensity stratification We used the predicted propensity scores to form deciles for the national weights, and quintiles within city for the city-level weights. We used these deciles to form the weighting cells for the nonresponse adjustments. Therefore, each weighting cell comprises sample members who have similar response propensities. Once the cells are formed, the two sets of adjustments are made separately for each of the two national weights and the city weight. For example, the summary for adjustment number of the national weights is

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.031	1.111	1.218	1.504	1.547	7.061

3.1.2 Poststratification

Note that the ineligible sample members were excluded from these nonresponse adjustments and simply retained their initial weight from wave 4. After the nonresponse adjustment, we bring back the ineligible weights in (cf5samp=“2 Child died” or “4 Other Ineligible”). We eliminate the cases who were not assigned weights from the first four waves. We rake the weights to their wave 4 totals. The raking variables include mother’s age, education, ethnicity and marital status.

To obtain the external information for the calibration of wave 5 national weights, We use wave 4 national weights to obtain the weighted frequency distributions of these 4 variables: msn, edun, ethn and agen, which are treated as the golden standard. The variable “natpsu” representing the primary sampling unit (PSU) and “natstratum” representing the strata structure. Hence we define the survey object with the one stage cluster sampling, nested stratified sampling and without replacement. We use the summation of the wave 4 national weights to approximate the population size and incorporate it for the finite population correction factor. Then we rake the nonresponse-adjusted weights to their baseline totals, trim any outlier weights, and re-rake the weights.

We set the 95% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. Then we re-rake the weights to match the wave 4 totals. The summaries are as below.

```
summary(weights(All.rake_t_n)[data_rake$msn==1])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
97.44 197.70  438.50 1070.00 1221.00 5425.00
```

```
summary(weights(All.rake_t_n)[data_rake$msn==2])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
94.44 114.60 167.80 317.50 381.00 1260.00
```

Table 8: Summary of national sample father weights.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
wave 1	2.02	28.37	109.10	415.00	376.70	8623.00	2172
wave 2	1.55	28.50	106.30	435.50	368.70	10160.00	2440
wave 3	1.38	30.60	117.00	458.70	405.00	10340.00	2502
wave 4	1.62	28.26	113.20	469.50	414.30	10630.00	2539
wave 5	94.44	122.00	208.20	530.90	536.50	5425.00	2812

3.1.3 Variance Estimation

Replicate weights We use the Jackknife schemes for stratified designs in the R package *survey*. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time. These subsamples were selected so that no case could appear in more than one excluded random group.

Then the replicate weights for those remaining in the subsamples are adjusted by raking with the same variables described in Section 2.1.2 on mothers' demographics to match the known total. For trimming on each replicate weights, we set the 97.5% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. This resulted trimming values are different across the 26 replicate weights. The trimmed weights are calibrated by raking with the same factors again to match the totals in wave 4.

3.2 National weighting—exclude City X

Another set of national weights is based on 15 cities, excluding City X, which make the random national samples. The reason for excluding City X is that different questionnaire was used in City X from the remaining 15 cities. We start from the same disposition codes for the samples and the wave 4 national weights—*f4natwt_x*, where the letter *x* is added to distinguish from the national weights constructed as above. If these units were not assigned wave 4 weights, we move on to incorporate the weights in previous waves sequentially. The eligible sample size is 2746 (2449 located and 297 un-located cases). The sample size of eligible completes is 1843 (with survey data, father died and adopted or neither parent has legal custody).

Then we implement the two-stage nonresponse adjustment and build the two sequential logistic regression with the same predictors in Appendix A. We use the predicted response propensity scores to construct the weighting cells, and the inverse of response rates inside

weighting cells are the nonresponse adjustment weighting factors. We calibrate the weights with the same raking procedure and variables in Section 2.1.2. The wave 4 weight $f4natwtx$ is the anchor. We set the 95% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. Then we re-rake the weights to match the wave 4 totals. The summaries are as below in Table 9. Finally, we construct the replicate weights for variance estimate, following the same procedure in Section 3.1.3. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time. For trimming on each replicate weights, we set the 92.5% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. This resulted trimming values are different across the 23 replicate weights. The trimmed weights are calibrated by raking with the same factors again to match the totals in wave 4.

Table 9: Summary of national sample father weights (without City X).

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
wave 1	2.10	36.12	132.70	458.20	434.80	9029.00	2429
wave 2	1.60	34.79	125.40	479.40	424.80	10660.00	2667
wave 3	1.43	36.56	139.30	503.30	459.30	10680.00	2714
wave 4	1.69	33.98	136.60	518.30	482.50	11140.00	2762
wave 5	101.10	132.90	237.40	579.60	575.70	5697.00	2988

3.3 City weighting

We start from the wave 4 city weight $f4citywt$ and work on 2760 cases to construct city specific weights. For the two-stage nonresponse adjustment, we use the same predictors as in Appendix A. Note that “city” indicator is a predictor in the two regression models. When constructing the weighting cells by poststratification of the predicted response propensity scores, we do this by city. That is, we form the quintiles within city, and the weighting cells differ by response rates and city. The inverse values of the response rates inside weighting cells are the weighting adjustment factors for nonresponse.

Next we calibrate the city weights to match the city total counts. For each city, we post-stratify the weights by mother’s demographic information: marital status, education, ethnicity and age, the same raking variables for mother city weights.

We set the 95% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. Then we re-rake the city weights to match the wave 4 totals. The summaries are as below in Table 10. Finally, we construct the replicate weights for variance estimate, following the same procedure in Section 2.1.3. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time.

The variables “citypsu” and “citystratum” indicator the PSU and strata structure for the city weights, where hospitals are the PSU.

Table 10: Summary of father city weights.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
wave 1	1.17	15.83	35.69	92.94	74.66	3673.00	1156
wave 2	1.25	14.50	34.86	98.38	79.28	4307.00	1523
wave 3	1.32	16.75	36.92	100.40	76.55	5158.00	1563
wave 4	1.32	17.12	37.85	104.30	78.01	6780.00	1650
wave 5	36.48	54.21	77.98	118.30	123.40	840.80	2037

4 Couple weighting

wave 4 weight as anchor All the couple weights (baseline and follow-up) would match the total mother baseline weights, which represents the population of births. The baseline couple weights are the same as the baseline father weights. Since the couple weights at wave 1-4 are available, the wave 4 couple weight serves as the anchor for wave 5 couple weight. Because there is no subsampling at the various follow-ups, we concern ourselves mainly with nonresponse adjustments and re-raking to the wave 4 totals. The raking variables are on mothers’ demographics, the same as those for the mother weights.

eligible population A case was ineligible at follow-up only if the child associated with the sampled birth died. The flag *cm5samp* and *cf5samp* indicate whether some or all of a questionnaire was completed, among those considered to be part of the eligible completes within the sample. All other final dispositions were considered to be eligible non-completes, sub-classified as located or un-located. In summary, the samples are divided into eligible complete and eligible noncomplete groups, and eligible noncompetes are subdivided into located and un-located. The final dispositions of the couples are affected by both the mother and father disposition codes. If either member of the couple was classified as “ineligible”, then the couple was classified as “ineligible”. If both members of the couple were classified as “eligible completes”, the couple was classified as “eligible”. To be classified as “eligible non-complete un-located”, both members of the couple had to be un-located. Otherwise, the couple was classified as “eligible non-complete”.

If a previous round of the survey indicated ineligibility (child deceased or duplicate), then the current round was classified as ineligible, regardless of the current disposition code. The samples we consider include cases that are eligible complete with survey data, mother or father died, adopted or neither parent has legal custody, refusal, could not locate, other nonresponse and assigned weights in wave 4.

In short, each follow-up couple weight starts with the final poststratified wave 4 couple weight (national, national without City X, or city, as appropriate). If the units were not

assigned wave 4 weights, we check wave 3, wave 2 and wave 1 sequentially. Note that wave 1 couple weight is the sample as the baseline father weight. That is, we work on the cases with weights, even though some cases are ineligible.

4.1 National weighting

We collect the sample dispositions based on the *flagcm5samp* and *cf5samp*, and determine the cases that should be included in wave 5. We start with couple national weights at wave 4 for these cases. If these units were not assigned wave 4 weights, we move on to incorporate the weights in previous waves sequentially.

This results in sample size 2987 (2816 located and 171 un-located cases). The sample size of eligible completes is 2014 (with survey data, father died and adopted or neither parent has legal custody).

4.1.1 Nonresponse Adjustment

two stage adjustment More intuitively for the weighting adjustment, the eligible samples are divided into located and un-located, and the located samples have completes and non-completes. We use located samples to adjust for unallocated and then located completes for located non-completes. We adjust the weights of the eligible completes to account for those of the eligible non-completes in these two stages.

1. First we adjust for un-locatability; that is, we adjust the initial weights for all the eligible located cases upward to account for those of the eligible un-located cases.
2. Then we adjust for nonresponse among the located; that is, these adjusted weights for the eligible located completes are further adjusted upward to account for those of the eligible located non-completes.

For each adjustment, we build a logistic regression with the indicator — located and response, respectively — being the outcome variable. We use the predictors in Appendix A. We filled in the missing items by random draws from the corresponding observed frequency distributions. The predictors after dummy coding are used as covariates. We developed two separate unweighted logistic regression models using lasso (Friedman *et al.*, 2010) for regularization to predict the two types of nonresponse. We use the predicted propensity scores for weighting adjustment.

weighting cells—response propensity stratification We used the predicted propensity scores to form deciles for the national weights, and quintiles within city for the city-level weights. We used these deciles to form the weighting cells for the nonresponse adjustments. Therefore, each weighting cell comprises sample members who have similar response propensities. Once the cells are formed, the two sets of adjustments are made separately for each of the two national weights and the city weight. For example, the summary for adjustment number of the national weights is

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.048	1.115	1.240	1.484	1.484	5.632

4.1.2 Poststratification

Note that the ineligible sample members were excluded from these nonresponse adjustments and simply retained their initial weight from wave 4. After the nonresponse adjustment, we bring back the ineligible weights in (*cm5samp* or *cf5samp*: “2 Child died” or “4 Other Ineligible”). We eliminate the cases who were not assigned weights from the first four waves. We rake the couple weights to their wave 4 totals. The raking variables include mother’s age, education, ethnicity and marital status.

To obtain the external information for the calibration of wave 5 national weights, We use wave 4 national weights to obtain the weighted frequency distributions of these 4 variables: *msn*, *edun*, *ethn* and *agen*, which are treated as the golden standard. The variable “*natpsu*” representing the primary sampling unit (PSU) and “*natstratum*” representing the strata structure. Hence we define the survey object with the one stage cluster sampling, nested stratified sampling and without replacement. We use the summation of the wave 4 national weights to approximate the population size and incorporate it for the finite population correction factor. Then we rake the nonresponse-adjusted weights to their baseline totals, trim any outlier weights, and re-rake the weights.

We set the 95% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. Then we re-rake the weights to match the wave 4 totals. The summaries are as below.

```
summary(weights(All.rake_t_n)[data_rake$msn==1])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
88.81 196.80 419.10 1070.00 1256.00 5496.00
summary(weights(All.rake_t_n)[data_rake$msn==2])
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
86.84 107.00 162.60 301.90 343.20 1220.00
```

Table 11: Summary of national sample couple weights.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA’s
wave 1	2.02	28.37	109.10	415.00	376.70	8623.00	2172
wave 2	1.50	28.73	109.40	455.20	393.70	10230.00	2549
wave 3	1.34	32.46	123.10	484.80	423.10	11150.00	2678
wave 4	1.81	32.07	127.10	503.00	433.80	10430.00	2770
wave 5	86.84	115.20	199.10	515.80	495.30	5496.00	2823

4.1.3 Variance Estimation

Replicate weights We use the Jackknife schemes for stratified designs in the R package *survey*. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time. These subsamples were selected so that no case could appear in more than one excluded random group.

Then the replicate weights for those remaining in the subsamples are adjusted by raking with the same variables described in Section 2.1.2 on mothers' demographics to match the known total. For trimming on each replicate weights, we set the 97.5% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. This resulted trimming values are different across the 26 replicate weights. The trimmed weights are calibrated by raking with the same factors again to match the totals in wave 4.

4.2 National weighting—exclude City X

Another set of national weights is based on 15 cities, excluding City X, which make the random national samples. The reason for excluding City X is that different questionnaire was used in City X from the remaining 15 cities. We start from the same disposition codes for the samples and the wave 4 national weights—*c4natwt_x*, where the letter *x* is added to distinguish from the national weights constructed as above. If these units were not assigned wave 4 weights, we move on to incorporate the weights in previous waves sequentially.

The eligible sample size is 2706 (2554 located and 152 un-located cases). The sample size of eligible completes is 1837 (with survey data, parent died and adopted or neither parent has legal custody).

Then we implement the two-stage nonresponse adjustment and build the two sequential logistic regression with the same predictors in Appendix A. We use the predicted response propensity scores to construct the weighting cells, and the inverse of response rates inside weighting cells are the nonresponse adjustment weighting factors. We calibrate the weights with the same raking procedure and variables in Section 2.1.2. The wave 4 weight *c4natwt_x* is the anchor. We set the 97.5% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. Then we re-rake the weights to match the wave 4 totals. The summaries are as below in Table 12. Finally, we construct the replicate weights for variance estimate, following the same procedure in Section 2.1.3. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time. For trimming on each replicate weights, we set the 92.5% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. This resulted trimming values are different across the 23 replicate weights. The trimmed weights are calibrated by raking with the same factors again to match the totals in wave 4.

Table 12: Summary of national sample couple weights (without City X).

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
wave 1	2.10	36.12	132.70	458.20	434.80	9029.00	2429
wave 2	1.57	35.89	129.70	501.40	466.00	10640.00	2767
wave 3	1.38	38.78	145.20	532.60	472.70	11580.00	2878
wave 4	1.87	38.40	147.20	556.60	498.30	11070.00	2975
wave 5	75.56	110.10	207.40	565.10	536.30	5841.00	3004

4.3 City weighting

We start from the wave 4 city weight $c_4citywt$ and work on 2794 cases to construct city specific weights. For the two-stage nonresponse adjustment, we use the same predictors as in Appendix A. Note that “city” indicator is a predictor in the two regression models. When constructing the weighting cells by poststratification of the predicted response propensity scores, we do this by city. That is, we form the quintiles within city, and the weighting cells differ by response rates and city. The inverse values of the response rates inside weighting cells are the weighting adjustment factors for nonresponse.

Next we calibrate the city weights to match the city total counts. For each city, we post-stratify the weights by mother’s demographic information: marital status, education, ethnicity and age, the same raking variables for mother city weights.

We set the 95% quantile of weights after raking for unmarried families as their upper truncation level and 95% quantile of weights for married families as their upper truncation level. Then we re-rake the city weights to match the wave 4 totals. The summaries are as below in Table 13. Finally, we construct the replicate weights for variance estimate, following the same procedure in Section 2.1.3. The number of sets of replicate weights is equal to the number of PSUs, where the random subsamples exclude one PSU at each time. The variables “citypsu” and “citystratum” indicator the PSU and strata structure for the city weights, where hospitals are the PSU.

Table 13: Summary of couple city weights.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
wave 1	1.17	15.83	35.69	92.94	74.66	3673.00	1156
wave 2	1.34	15.27	36.22	103.00	78.75	3474.00	1680
wave 3	1.25	17.22	37.45	105.60	79.84	5172.00	1805
wave 4	1.33	17.65	39.84	110.80	84.78	5577.00	1962
wave 5	33.65	50.55	71.05	112.80	118.00	780.40	2016

A Predictor list for propensity score prediction

[1]	"m1a3"	"m1a4"	"m1a7"	"m1a8"	"m1a9"
[8]	"m1a13"	"m1a15"	"cm1bsex"	"cm1lbw"	"cm1numb"
[15]	"m1b26"	"m1b27"	"m1b28"	"cm1relf"	"cm1marf"
[22]	"m1c1b"	"m1c1c"	"m1c1d"	"m1c1e"	"m1c1f"
[29]	"m1c3a"	"m1c3b"	"m1c4a"	"m1c4b"	"m1c5a"
[36]	"m1c7"	"m1d1a"	"m1d1b"	"m1d1c"	"m1d1d"
[43]	"m1d2a"	"m1d2b"	"m1d2c"	"m1d2d"	"m1d2e"
[50]	"m1d3a"	"m1d3b"	"m1d3c"	"m1d3d"	"m1d3e"
[57]	"m1e1b1"	"m1e1c1"	"m1e1e1"	"m1e2"	"m1e3a"
[64]	"m1e4a"	"m1e4b"	"m1e4c"	"cm1gdad"	"cm1gmom"
[71]	"m1f4"	"m1f5"	"m1f6"	"m1f12"	"m1f13"
[78]	"m1g1"	"m1g2"	"m1g3"	"m1g4"	"m1g5"
[85]	"m1h3"	"m1h3a"	"cm1edu"	"cm1ethrace"	"m1i1"
[92]	"m1i3"	"m1i4"	"m1i4a"	"m1i6"	"m1i7"
[99]	"m1i10"	"m1j1a"	"m1j1b"	"m1j1c"	"m1j1d"
[106]	"m1j5"	"cm1hhimp"	"cm1povca"	"m1l3"	"m1l4"
[113]	"m1l7"	"m1l8"	"m1l9"	"m1l10"	"m1l11"
[120]	"m1l14"	"m1l15"	"m1l16"	"m1l17"	"m1l20"
[127]	"m4a4"	"m4a8c"	"m4a12e"	"m4a16"	"cm4relf"
[134]	"m4b0"	"m4b1"	"m4b2"	"m4b2a"	"m4b2b"
[141]	"m4b4a3"	"m4b4a4"	"m4b4a5"	"m4b4a6"	"m4b4a7"
[148]	"m4b6a"	"m4b6b"	"m4b6c"	"m4b6d"	"m4b7"
[155]	"m4c7"	"m4c8"	"m4c11"	"m4c27"	"m4c33"
[162]	"m4d4a"	"m4d5"	"m4d8"	"m4d10"	"m4e1"
[169]	"m4f2b1"	"m4f3"	"cm4gdad"	"cm4gmom"	"m4h1"
[176]	"m4h2"	"m4h3"	"m4h4"	"m4h5"	"m4h6"
[183]	"m4i0l"	"m4i0m1"	"m4i0m2"	"m4i0m3"	"m4i0m4"
[190]	"m4i0n2"	"m4i0n3"	"m4i0n5"	"m4i0o"	"m4i0p"
[197]	"m4i7b"	"m4i7c"	"m4i7d"	"m4i7e"	"m4i7f"
[204]	"m4i8a2"	"m4i8a3"	"m4i9"	"m4i15"	"m4i18d"
[211]	"m4i23a"	"m4i23b"	"m4i23c"	"m4i23d"	"m4i23e"
[218]	"m4i23h"	"m4i23i"	"m4i23j"	"m4i23k"	"m4i23l"
[225]	"m4i23p1"	"m4i23p2"	"m4i23p3"	"m4i23p5"	"m4i24"
[232]	"m4j1"	"m4j2"	"m4j2b"	"m4j2c"	"m4j3"
[239]	"m4j20"	"m4j22a"	"m4j22b"	"m4j22c"	"m4j22d"
[246]	"m4j22g"	"m4j22i"	"m4j22j"	"m4j24a"	"m4j25a1"
[253]	"m4j25b2"	"m4j25b3"	"m4j25b4"	"m4j25c"	
	"cm4md_case_con"	"cm4md_case_lib"	"m4r1"		
[260]	"m4r2"	"m4r3"	"m4k1"	"m4k3"	"m4k3b"
[267]	"m4k11"	"m4k12"	"m4k14a1"	"m4k14a2"	"m4k14a3"
[274]	"m4k15"	"m4k24a"	"m4k25a"	"m4k26a"	"m4l2"

[281] "cm4povca" "cm4tele" "cm4span" "city" "hospital"

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