Small Area Population Estimates for 2011 through 2020

Prepared for the Massachusetts Department of Public Health's Bureau of Environmental Health

Prepared by

UMass Donahue Institute
Economic and Public Policy Research
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Background

The Massachusetts Department of Public Health's Bureau of Environmental Health (MA DPH) publishes disease rates and other health-related incidence rates for specific populations at small-level geographies, including the city, town, and even neighborhood level. To calculate these rates, small-level geography population data (including population by age, sex, race, ethnicity, and geography) are needed on an annual basis.[1] These population data serve as the denominators when calculating health-related incidence rates. While the Census Bureau enumerates population by age, sex, race, and ethnicity at a very fine level of geography—the census block—it does so only every ten years. In the years following the census, or "post-censal" years, the Census Bureau's Population Estimates Program (PEP) produces annual estimates of the population down to the town level; however, they break out age, sex, race, and ethnicity only at the county level and higher. Researchers needing detailed population estimates for any sub-county geography must find another source.

Populations at small levels of geography and small sub-populations, such as specific age/sex cohorts, are notoriously difficult to estimate accurately. Baker et al., 2013 note:

> As in previous studies, the overall magnitude of errors for tract-level… estimates is much larger than observed for larger geographic groupings such as counties or states; moreover, the large differences observed between mean and median percentage errors for both absolute and algebraic values speaks to the ubiquitous presence of outlying values in sets of demographic estimates for small areas. (932-936)

They report mean absolute percent errors of 83% to 92% overall for male and female 5-year cohorts, respectively, in a 2010 tract-level estimates test.

Relying on these potentially inaccurate small area estimates to produce specific incidence rates will likely produce unreasonable rates and unrealistic findings. Given this knowledge, epidemiologists need to know not only the estimated population for a given place and time, but also the estimated error associated with the estimate. Considering both the estimate and its full range of values—including its error, or confidence intervals—allows researchers to assess where a rate may be significant or reliable and where it will not.

To meet the MA DPH project needs, UMDI has produced small area population estimates by age, sex, race, and ethnicity at both the town and census tract levels for the years 2011 through 2020.[2] Age cohorts include 5-year age groups from 0-4 through 80-84, plus an 85+ group. Estimates by single year of age are also produced for ages 0-20. Race groups in the estimates conform to the "Race Alone" plus "Two or More Races" categories from the Census Bureau's county-level *Annual Estimates of the*

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[1] "Ethnicity" in this report refers to Hispanic or non-Hispanic origin.

[2] Tract-level estimates conform to Census 2010 tract boundaries. Estimates for years 2011 through 2015 are controlled to the latest, June 2016 release of the U.S. Census Bureau's *Annual Estimates of the Resident Population by Sex, Race, and Hispanic Origin Population Estimates for Massachusetts Counties, 2010-201.* Estimates 2016-2020 are uncontrolled, to be later controlled to county estimates to be released by the Census Bureau in future years.

Resident Population by Sex, Race, and Hispanic Origin Population Estimates, and each age/sex/race cohort is also broken down by Hispanic or Non-Hispanic origin.[3] Finally, UMDI has produced error ranges by age and cohort size, which are incorporated into the estimates as low-to-high values for each cohort estimate, making each a range-of-values rather than a single-value estimate.

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[3] The "Race Alone" categories include: White, Black or African American, Asian, American Indian and Alaska Native, Asian, and Native Hawaiian and Other Pacific Islander.

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Method Overview

To produce small area population estimates for the purposes of this project, UMDI developed a modified Hamilton-Perry method. The Hamilton-Perry model is a simplified version of the cohort-component method of estimating population change. In general, a cohort-component model considers basic components of population change, including birth, death, and migration for a specific cohort and geography. It takes the starting, or base, population for the cohort, ages it forward and adds or subtracts births, deaths, and migration to create a future estimate. These components of change are often expressed as cohort-specific rates—for example, birth rates by age and race of mother, death rates by age and sex, etc.—which are then applied back to the appropriate cohort population in the base year to model the future population. Rates can be held constant, increased, or decreased depending on the assumptions that a particular model makes.

Smith, Tayman, and Swanson explain:

> Hamilton and Perry (1962) proposed the use of cohort-change ratios as a short-cut way to apply the cohort-component method… The major difference [in the Hamilton-Perry model] is that it treats mortality and migration as a single unit rather than separately. In addition, the fertility component is often simplified by using child-woman ratios rather than ASBRs [age-specific birth rates]... The Hamilton-Perry method projects population by age and sex using cohort-change ratios (CCRs) based on data from two consecutive censuses. (176-177)

More specifically, the model creates a ratio between a specific cohort population (by age, sex, geography, and sometimes additional variations such as race) for age a in year y to its corresponding cohort age $a\text{-}10$ in year $y\text{-}10$. The ratio is then applied to the corresponding base population to create a forecast of the cohort population ten years later. In this way, each individual group is aged up by ten years over a ten-year period and is also increased or decreased by the effects of mortality and migration experienced over the same period.

Because it relies solely on decennial census count data, which is available at a very detailed level, the Hamilton-Perry method is particularly well suited for estimating small geographies and specific sub-populations. Smith, Tayman, and Swanson explain:

> Large data requirements preclude the use of some forms of the cohort-component method at some levels of geography. Although seldom a problem for states and large counties, the lack of data presents a formidable challenge for small counties and subcounty areas. Birth and death data are routinely available for counties but not for most subcounty areas. Migration data are an even greater problem. ACS [American Community Survey] migration data are quite limited, especially at the subcounty level. Although PUMS [Public Use Microdata Sample] files provide detailed migration information, they are often based on a small sample size and are available only for places with at least 100,000 residents. IRS migration data are not tabulated below the county level and do not provide breakdowns of demographic characteristics. Because of these

data problems, the Hamilton-Perry method is often the best cohort-component model to use for subcounty projections. (181-182)

While in Massachusetts birth and death data by age and sex are available at the sub-county level, they are not available by tract. Additionally, direct measures of migration are not available by any means at the sub-county level in Massachusetts. Researchers who have tested the use of vital statistics data that has been geocoded by street address have found that method to be unreliable (Baker et al., 2012).

While the Hamilton-Perry method assumes that the cohort-change ratios observed between recent censuses will carry forward into the future, the UMDI model modifies this assumption by incorporating current, and sometimes unanticipated, changes in population by age, sex, race, and ethnicity. In our method, we control the town- and tract-level estimates produced by the cohort-change ratio method to the most recent, annual county-level estimates of age/sex/race/ethnicity populations produced by the Census Bureau.[4] In this way, if a particular race group begins to grow in an area at a rate higher than what past censuses would have predicted, or if migration within a particular age group suddenly changes in a region, this change will be picked up by the estimates and distributed to the sub-county geographies. While the UMDI model still assumes that the *sub-county* distribution of population by age/sex/race/etc. is the same as that indicated by the Hamilton-Perry forecast, the total populations by age, sex, race, and ethnicity updated for each county.

For their annual county-level estimates, the Census Bureau uses administrative records data to capture birth and death counts at the county level and uses IRS, Medicare enrollment, and American Community Survey data to capture recent county-to-county and international migration. While these data can lag by two years, they are still effective in capturing trends that have emerged since the last census count. For instance, they can reflect increased migration to and from specific counties or changes in overall birth rates since the last census. In assessing the accuracy of their post-censal county estimates, the Census Bureau reported a high level of accuracy in accounting for population change between 2000-2010, reporting an average absolute difference of 3.1 percent between the population estimates and the actual Census 2010 count across all counties.[5] The Census Bureau now also uses a records-matching method to assign characteristics such as race and age to their annual estimates, matching IRS records to Census 2010 household responses wherever possible to capitalize further on the integration of current administrative data and to improve the accuracy of their estimates.

While the Hamilton-Perry method is considered a standard model for population forecasting, for the purposes of this product UMDI tested and applied various modifications to maximize performance for Massachusetts geographies. Our primary tests included analyzing 10-year versus 20-year cohort-change ratios (CCRs); customized child-to-woman-ratios; and the application of CCR caps. We performed additional testing when faced with specific processing choices, as described in the *Detailed Methodology* section of this report.

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[4] U.S. Census Bureau's *Annual Estimates of the Resident Population by Sex, Race, and Hispanic Origin Population Estimates for Massachusetts Counties.*

[5] Methodology for the United States Population Estimates: Vintage 2015. *Nation, States, Counties, and Puerto Rico – April 1, 2010 to July 1, 2015* (1) *https://www.census.gov/popest/methodology/2015-natstcopr-meth.pdf.*

In the testing process, UMDI applied each model variation to create 2010 population estimates and compared them to Census 2010 population counts.[6] The differences between the estimated and actual 2010 populations-by-cohort were recorded as errors, mean absolute percent errors (MAPEs), and weighted absolute percent errors (WAPEs). Lower MAPEs or WAPEs indicate a smaller average absolute difference between the resulting 2010 estimate and the actual 2010 Census data; therefore, model variations with lower MAPEs or WAPEs were considered the better performers. As previously noted, the evaluation based on historic performance assumes that the model will perform similarly in the 2010-2020 period as it did in the 2000-2010 period.

As a result of our model testing, we made the following three decisions for our final model: 1) to use a 10-year cohort-change ratio (2000-2010) over a 20-year (1990-2010); 2) to use a modified child-to-woman ratio for estimating children aged 0-9; and 3) to use capped CCR values for small cohort groups. These decisions are described in more detail in the *Model Testing and Modifications* section of this report.

Note on Assumptions and Special Cases

It is important to note that the Hamilton-Perry method, like all estimation methods, relies on particular assumptions—the prime assumption being that future population trends will resemble trends observed in the past. UMDI's modification of the Hamilton-Perry also includes a number of other assumptions that are described in the methods section of this report. These assumptions should be carefully considered by researchers using or evaluating the resulting population estimates. Where feasible, UMDI tested which of the various candidate models and assumptions performed best in predicting historic population counts. However, even these analyses rely on the assumption that the performance of the model in the current decade will be like that of the past decade.

It is also critical to note that while we make an attempt to reduce the effect of outlier events in our model, and account for them in our confidence intervals, when working with small-level geographies there are inevitably a number of special or extreme cases of population change that can and do occur. Some of these are past events that are picked up and perpetuated by our model, and some are current events over which our model has no predictive power.

For example, in the *Detailed Methodology* section of this report, we describe a special adjustment we make for the Town of Lincoln, which was subject to a Census 2010 count that did not reflect the true population trend in that geography. While Lincoln is one special case about which we have direct and detailed knowledge, it should be noted that there are likely many other special cases around the state which our model does not account for. Especially at the tract level, an off-trend change occurring from one census to the next can significantly exaggerate population in one direction or another. We attempt to minimize the effect of special cases by adding CCR caps, as described in the *Model Testing and Modifications* section of this report. We also capture the effect of the unusual situations that have occurred in the past in the error ranges and confidence intervals assigned to our estimates, to the extent

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[6] This testing method assumes that future estimates errors for each method will be the same as historic estimates errors for each model variation, however past performance is our best evaluation tool given the unavailability of current, precise cohort-level data.

that the present decade is similar to the last in terms of numbers and magnitude of special cases. Nonetheless it is worth noting that there exist a number of typical "special case" geographies that researchers should be sensitive to when evaluating the accuracy of estimates at a refined level. These include:

- Geographies in which student housing or enrollment changes significantly from one census to the next or since 2010. For example, an all-male college or dormitory becomes co-ed; a large new residence hall is built; or a graduate studies program is added to an undergraduate campus. In our model results, for example, there exist a number of Suffolk County tracts in which cohorts aged 20 through 30 show tremendous percentage increases from 2010 to 2020, based on accelerated building in the 2000-2010 period. Only additional, localized research can determine whether the same level of concentrated growth continued into the present decade or not.
- Geographies in which an assisted living or nursing home residence or some other large group quarters facilities is opened or closed from one census to the next or post-Census 2010.[7]
- Geographies that have undergone major new construction or demolition of residential housing that is out-of-trend with the usual historical or regional (county) construction.
- Geographies that include concentrations of shifting seasonal or international workers, such as the Cape and Islands region.
- Geographies for which post-census count corrections have been made. In these cases, changes are approved by the Census Bureau for total population change but no revisions are made to the detailed Summary File data used in our estimates model, which is required for age/sex/race/ethnicity distributions.

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[7] UMDI tracks changes in large group quarters facilities around the state on an annual basis. DPH researchers may consult with UMDI to determine whether a specific geography in their analysis may be experiencing facility-related changes that affect the accuracy of their estimates.

Model Testing and Modifications

Ten-Year Cohort-Change Ratio

In a cohort-component projections model, past trends of migration, births, and deaths are used to predict future trends. A key factor in the model is the length of the historic period that is used to inform the rates that are applied going forward. A 10-year CCR captures the rates of change that occurred between only the two most recent censuses—in this case, the 2000-2010 period. A 20-year CCR averages two decades' worth of change—in this case the 1990-2000 and 2000-2010 periods. Longer-term projections may go back even further in an effort to predict future trends. A compelling argument for using a 10-year CCR is that it represents the most recent period of birth, death, and migration trends. In theory, the near future is more likely to resemble the recent past than the distant past. If the 10- and 20-year CCR perform similarly, the 10-year model would be preferable for this reason. On the other hand, it could be argued that a 20-year CCR may be preferable because it can better encompass cyclical change over long periods of time and because it can average out irregularities due to one-time drastic changes that would more heavily influence rates in a short-term CCR.

To test the 10-year versus 20-year CCR model, UMDI ran both variations and compared the results to actual Census 2010 counts. First, UMDI created 2010 age/sex estimates based on a historical 1990-2000 CCR applied to the Census 2000 base to test the 10-year CCR. Next, UMDI created another set of 2010 estimates using a 20-year CCR—1980-1990 averaged with 1990-2000 ratios—applied to the Census 2000 base. The differences between the resulting cohort estimates and the Census 2010 counts were expressed as absolute values and absolute percent differences, which were averaged together to create MAPEs for each cohort or group of cohorts evaluated. We evaluated the 10 and 20-year results in terms of how accurately they predicted town totals, populations by age group, and population by cohort size. The results of these model comparisons are outlined in the following sections, which discuss the resulting population estimate totals by town; error by sex; error by age group; and error by cohort size and age.

Town Totals

For total town populations, the performance of the two models was very close (Figure 1). While we had reasoned that a longer time frame might improve performance in very small towns by averaging out short-term irregularities, the difference was not as great as anticipated. The 20-year CCR model performed better in the ten Massachusetts towns with populations under 500 people in the base year 2000 and just slightly better than the 10-year CCR model in the 98 towns with populations between 500 and 5,000. However, in most cities and towns (and especially in larger places), the 10-year model performed best. Overall, the 10-year CCR model performed better in 182 towns (54%), while the 20-year CCR performed better in 169 towns (46%). Table A-1 in Appendix A of this report shows the mean absolute percent errors by town size in the 10-year versus 20-year CCR estimates test.

Figure 1. Average absolute percent error by town population size for 10-year CCR versus 20-year CCR estimates
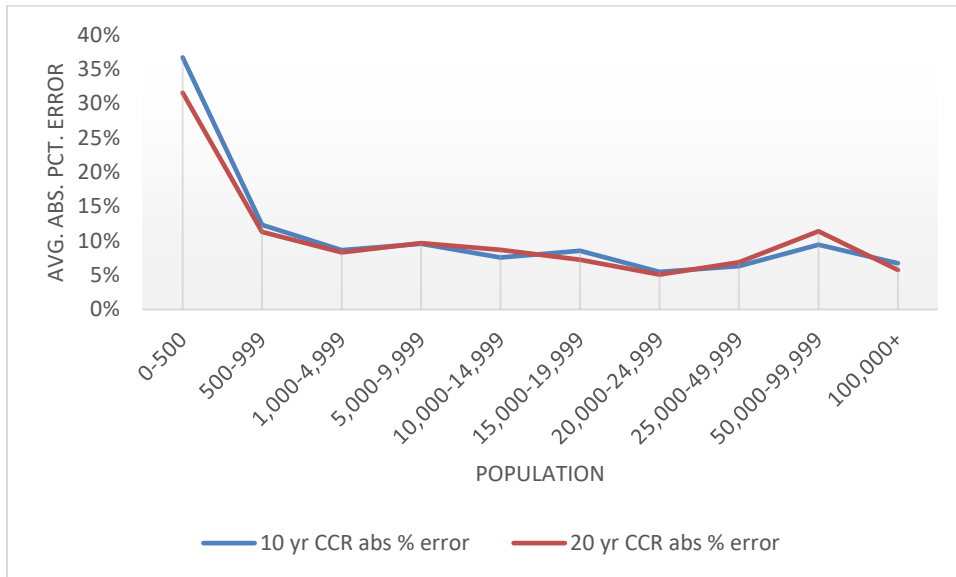
Male and Female Error

For testing by age group and cohort size, we estimated male and female cohorts separately but grouped their errors together in the evaluation. Before grouping these errors together, however, we first performed tests to ascertain that there was no significant difference in the performance of one gender over another. In a test of age/sex/town estimates using a 10-year CCR, we compared the MAPEs for the male and female populations by age group (Figure 2).

Figure 2. **Male versus female MAPE by age group, 10-year CCR estimates**
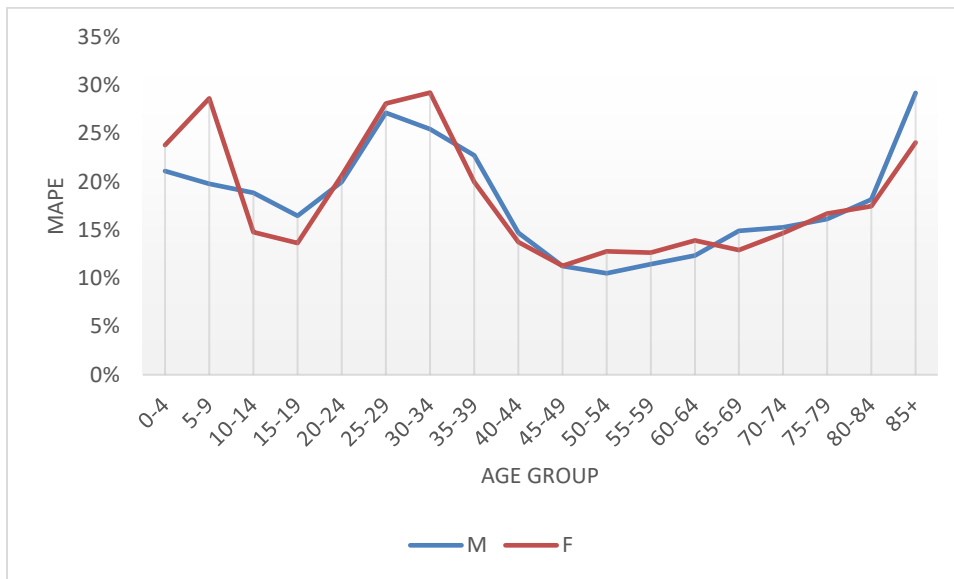
While the evaluation by MAPE shows differences between male and female absolute errors, we reasoned that this is likely due to differences in cohort size by age between the sexes. An evaluation of the WAPEs showed that differences were negligible after accounting for cohort size (Figure 3). Table A-2 in Appendix A of this report shows MAPEs and WAPEs by age group for males and females in a 10-year CCR estimate test.

Figure 3. Male versus female WAPE by age group, 10-year CCR estimates

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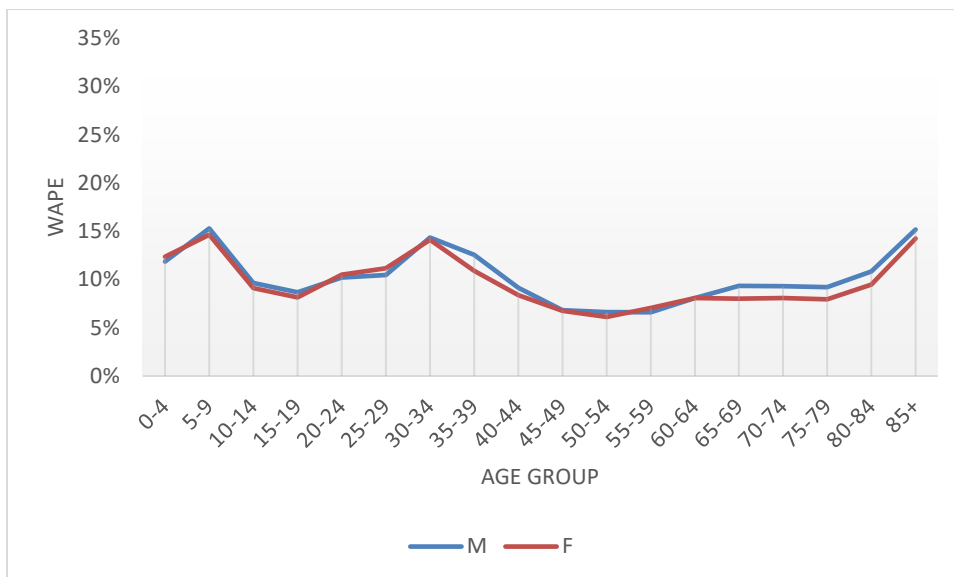
Finally, at the town level, we conducted T-tests by sex (total) and by sex/age group.[8] Testing once again showed that the difference between error in the male and female populations was not significant in any age group in our model.

Error by Age Group

The performance of the 10-year and 20-year CCR models was also tested by age group. UMDI found that the 20-year CCR performed better in many of the less mobile age groups, including the elderly and middle-aged, while the 10-year CCR performed significantly better for more mobile populations, including those aged 20-34 (Figure 4). Table A-3 in Appendix A of this report displays the MAPEs and WAPEs by age group for the 10- and 20-year CCR estimates, with the MAPEs graphed in Figure 4.

Figure 4. 10-Year CCR versus 20-year CCR MAPE by age group
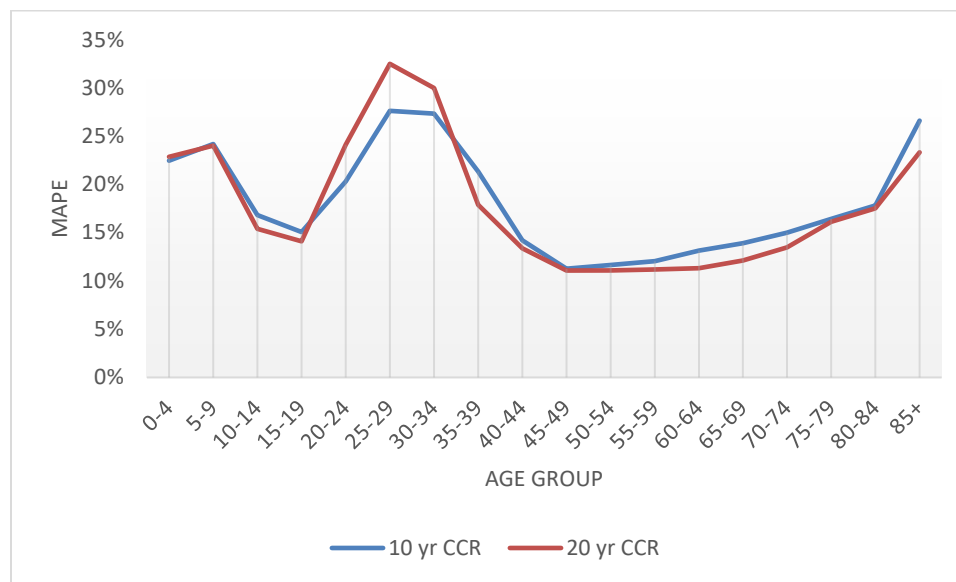
As a point of reference, Figure 5 shows mobility by age in the United States, utilizing data from the American Community Survey 2014 5-year estimates. The group called "all movers" include those that moved within the same county or from another county, state, or country within the 12 months preceding the survey. "Out-of-county and beyond" movers exclude the in-county movers. The graph shows movers by age group as a percentage of their total age group. The "all movers" category most closely corresponds to the tract- and town-level estimates produced in the UMDI model. While the age groups in this graph do not correspond exactly to the CCR MAPE age groups discussed above, the overall trend is apparent; mobility is highest among people aged 18-34.

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[8] Assuming unequal variances alpha/significance at 0.05.

Figure 5. Percent movers by age group, United States, 2010-2014
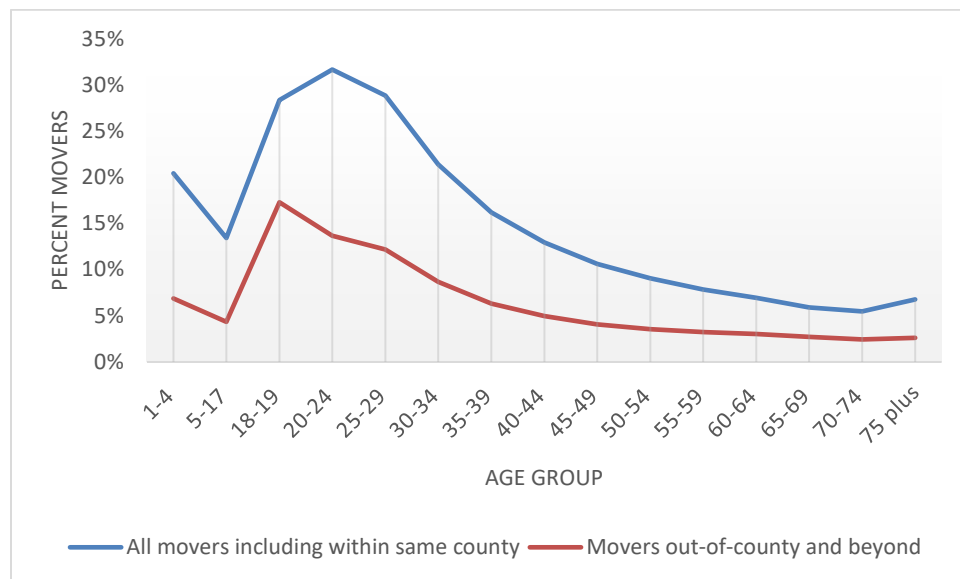
The MAPEs comparison by age group also shows that some age groups perform much better than others in the Hamilton-Perry model—whether using a 10- or 20-year CCR. Highly mobile groups in their 20s and 30s are the hardest to predict, as evidenced by their higher MAPEs. Migration is especially difficult to predict in population forecasting models because it is largely affected by economic changes that occur outside of the demographic model. While birth and death rates by age change slowly over time and are thus easier to predict, migration is the most variable component of change.

The populations of children and the very elderly are also difficult to predict in this model. The performance of the model in predicting population of children aged 0-9—who tend to follow the migration trends of their parents—may be improved with an adjustment to the child-to-woman ratio. For elders over the age of 70, the poor performance is most likely tied to their small cohort sizes within individual towns. For very small cohorts, nominally small changes result in large percent errors. The use of CCR "ceilings," which will be discussed in a later section of this report, improve the error range for these elderly cohorts and for small groups in general.

Error by Cohort Size and Age

The results of our 10-year versus 20-year CCR estimates test demonstrated the importance of cohort size and age-group in determining error. Once we determined that the 10-year CCR method performed better than the 20-year method in most places and for most age groups, we ran a preliminary assessment of error by age and cohort size combined, and this assessment led to additional modifications to the model. For example, because the smallest cohort groups were performing worst, we tested the use of CCR "ceilings" to minimize the error generated by a model for these small groups. Additionally, because the 0-4 and 5-9 age groups showed very large errors relative to their cohort sizes, we tested and applied modifications to the standard child-to-woman ratios used in the model.

Table A-4 in Appendix A displays the mean percent errors by age and cohort size generated by a 10-year CCR model run at the age/sex/town level.[9] These preliminary observations were critical in informing our later decisions on how to assign error rates.

Child-to-Woman Ratio Modification

To estimate future populations of children aged 0-9, Smith, Tayman, and Swanson explain that:

> Hamilton and Perry (1962) used the most recent age-specific birth rates held constant over the projection interval. This procedure is valid, of course, but it requires data on births by age of mother; these data are not always available, especially for subcounty areas. We prefer a simpler approach that does not require any data beyond that available in the decennial census. This approach uses two child-woman ratios (CWRs) from the most recent census and applies them to the projected female population in the appropriate age groups. (177)

Smith, Tayman, and Swanson recommend using the ratio of 0-4 year-olds to women aged 15-44 to estimate the future population of 0-4 year olds, and they use the ratio of 5-9 year-olds to women aged 20-49 to estimate the future population of 5-9 year-olds. However, UMDI modifies this model, using the age ranges of 20-44 and 30-49 for women to estimate the population of 0-4 and 5-9 year-olds respectively.[10] We do this because current data shows that women in Massachusetts tend to have children at older ages than the U.S. average. In Table 1 below, data from the American Community Survey shows Massachusetts rates of birth by age-group compared to average rates in the U.S.[11]

Table 1. Massachusetts and U.S. birth rates by age group

Rate per 1,000 women	United States		Massachusetts	
	Estimate	Margin of Error	Estimate	Margin of Error
15 to 19 years	21	+/-1	10	+/-1
20 to 34 years	95	+/-1	75	+/-2
35 to 50 years	25	+/-1	31	+/-1
Women 15 to 50 years	54	+/-1	46	+/-1

To determine the ideal maternal age ranges for our model ratios, we tested all plausible variations of the female denominator age-range (variations of all age cohorts within the natural fertility range) and selected the ranges that performed best in terms of lowest absolute percent errors. The tested variations all used 10-year CCR age/sex estimates compared to Census 2010 counts at the town and tract levels.

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[9] Cohort size was assigned by size in the base population year, which is 2000 in the test model.

[10] Because the change-ratio incorporates not only births but also migration of young children in a ten-year period, there is a rationale behind using not only and older, but also a different span, in terms of number of years, for the females used as denominators in the age 5-9 ratio compared to the 0-4 ratio.

[11] Source U.S. Census Bureau, 2010-2014 American Community Survey 5-Year Estimates, S1301: FERTILITY.

Table 2 and Figure 6 display the MAPEs and WAPEs by cohort size for the population ages 0-4 and 5-9, comparing the results generated by the standard child-to-woman ratios and the modified ratios used in the UMDI model in a town-level estimates comparison. UMDI also conducted testing for both college and non-college towns and for cohorts at the tract level.[12] The final modified child-to-woman ratio performed best overall in all scenarios we tested.

Table 2. Mean absolute percent error by cohort size for ages 0-4 and 5-9 estimates using standard and modified child-to-woman ratios

SIZE (2000)	Std. 0-4	Mod. 0-4	Std. 5-9	Mod. 5-9
0-99	34.7%	34.6%	58.9%	68.1%
100-199	24.8%	21.8%	18.8%	16.4%
200-499	19.3%	16.3%	14.1%	13.4%
500-999	17.3%	15.5%	13.4%	13.5%
1,000-1,999	13.7%	13.3%	12.7%	11.4%
2,000-3,999	7.2%	8.1%	15.4%	11.9%
4,000-9,999	3.1%	5.6%	15.2%	6.9%
All Sizes	22.5%	20.8%	24.2%	25.4%
Weighted Abs. % Error	12.1%	11.9%	15.0%	13.1%
Standard:	female denominators, ages 15-44 and 20-49			
Modified:	female denominators, ages 20-44 and 30-49			

Figure 6. Mean absolute percent error by cohort size for ages 0-4 and 5-9 estimates using standard and modified child-to-woman ratios

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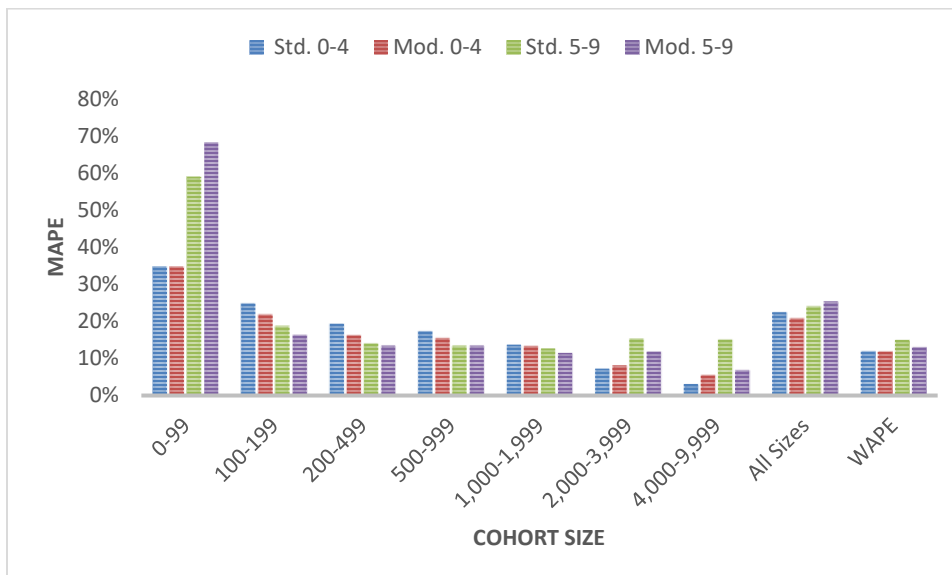
[12] Variations were tested for both "college towns" and "non-college" towns as defined by percent of female population aged 15 and over enrolled in college or graduate school. The age-ranges we decided upon performed best in both cases.

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Cohort-Change Ratio Caps

An additional adjustment to the Hamilton-Perry model is the use of CCR caps for very small cohorts in the UMDI model. In the case of small cohorts, minor changes in population may result in large percentage increases—or large change ratios in the context of a Hamilton-Perry method. For example, a cohort population of 2 persons aging forward and increasing to 12 persons from 2000 to 2010 would yield a change ratio of 12 ÷ 2, or 6. Applying the CCR of 6 to the 2010 base population of 12 would now suggest that the future cohort population would increase to 72. While unusual or erratic population jumps do sometimes occur—and are accounted for in our estimated error ranges—they do not necessarily need to be perpetuated forward by the model. Unreasonable increases that occur solely as the by-product of a ratio method should be limited, which can be achieved by applying caps to the ratios themselves.

To decide where to cap the CCRs, UMDI examined the frequency of actual 2000-2010 CCR values by cohort size and noted the values at which most CCRs naturally occur and at which level they are outliers. Figures A-1 through A-4 in the Appendix to this report show example distributions of the CCRs that are calculated between Census 2000 and Census 2010, displayed by size of cohort. As with the child-to-woman ratio adjustment, we also conducted scenario testing of various CCR cap values applied to different cohort sizes to see which adjustment brought our 2010 estimates closest to the Census 2010 actuals. We determined that a reasonable cap—one that minimizes error in our projections—is the CCR value "1" for cohort groups including fewer than 25 people and "2" for groups under 100 people. In our example of 2 persons increasing to 12, the effect of a CCR cap of "1" would mean that the group of 12 ages forward to a population of 12 again, not 72. For larger groups, a cohort of 30 people that aged into 90 people over ten years (indicating a CCR of "3") would be allowed to age up to 60 people using a CCR cap of "2," but no higher. While the larger CCR cap of "2" still allows for significant growth, both caps mitigate the possibility of "runaway" cohorts that may grow into unreasonably large groups in small places. Table A-5 in the Appendix displays the MAPEs by age and cohort size before and after the CCR caps are applied in the model for cohort groups between 0 and 99 population size.

Because the resulting cohort estimates are ultimately controlled to current age/sex/race/ethnicity estimates at the county level, rapid changes in one age or ethnic group are still permitted in the model. For example, if an unprecedented number of young people aged 20-24 moved into Suffolk County, the UMDI estimates for the 20-24 cohort would be controlled to that new county total, with the sub-county proportions of our estimates model applied to the new and perhaps unanticipated cohort population total. Likewise, if a particular race group increases at an unprecedented rate in a region of the state, the sub-county (town- or tract-level) estimates will sum to meet the new population total or likewise decrease in the case of a declining age or race group. In this way, the caps moderate the level of growth or decline but still ultimately allow for extreme increase within a sub-population should it actually occur. Tables A-6 and A-7 in the Appendix to this report summarize the MAPEs by age-group and cohort size for all age/size observations at the town and tract level, respectively, after both the CCR caps and the adjusted CTW ratios are applied.[13] We describe our complete method in more detail in the *Detailed Methodology* section of this report.

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[13] Note that age/size groups that had no observations in the 2010 dataset are assigned proxy errors of the next smaller-sized group of the same age. There were five of these age/sex groups at the tract level and six at the town level. See also Appendix tables.

Detailed Methodology

As described in the *Method Overview* section of this report, the UMDI *Small Area Population Estimates for 2011 through 2020* are the product of a modified Hamilton-Perry model that uses Census 2000-2010 10-year CCRs with customized child-to-woman ratios and CCR limits or "caps."

The implementation of our final model includes the following processing steps:

1. Obtaining, structuring, and normalizing 1990, 2000, and 2010 census data;
2. Re-assigning census "Some other race" population data to defined racial categories;
3. Calculating CCRs and child-to-woman ratios;
4. Applying ratios and caps to the modified Census 2010 base population to create "uncontrolled" 2020 estimates;
5. Distributing estimates over single years from 2011 to 2020;
6. Controlling sub-county estimates to current county-level estimates by age/sex/race/ethnicity released by the Census Bureau for years 2011-2015
7. Distributing 5-year age group estimates to single years of age for ages 0-20;
8. Assigning error and confidence intervals; and
9. Distributing error and confidence intervals over single years 2011-2020.

The above production methods themselves involve a number of detailed processing steps and assumptions, which we describe in more detail below.

1) Obtaining, structuring, and normalizing 1990, 2000, and 2010 census data

While the geographies and categories counted in the decennial census can change over time, our 2020 estimates model requires data from the 1990, 2000, and 2010 Censuses to be normalized to Census 2010 geography. Although city and town boundaries in Massachusetts have not changed during the time period used in our model, census tract boundaries are revised every ten years. Therefore, a first step in our production method is to normalize census data from 1990 through 2010. This step is necessary because for each 2010 cohort population, we create a CCR based on a corresponding 2000 cohort population. In order to calculate and apply the proper ratio, the two associated groups must correspond precisely in terms of their geography, age groups, and race and ethnic categories.

Corresponding 1990 Census data is also required in our method for the purpose of creating historic errors associated with each cohort estimate. To create error ranges, we run the estimates model to create 2010 age/sex estimates for comparison against 2010 Census counts. The difference between the estimates and the actual counts form the basis of our confidence interval assignments. This "historic" model requires data from the 1990 Census normalized to 2000 and 2010 census data; that is, the data must be standardized across geographic boundaries. For the purpose of evaluating error rates by age,

sex, and race, we also had to normalize race data across the censuses, even though race was ultimately not used in the assignment of error.

UMDI downloaded U.S. Census Summary File 1 (SF1) data for 1990, 2000, and 2010 from the National Historical Geographic Information System (NHGIS), which provides online access to aggregate census data and GIS-compatible boundary files for United States geographies.[14]

To normalize age/sex/race/ethnicity data from 2000 tract geography to 2010 tract geography for the purposes of calculating 2000-2010 CCRs, we utilize time series data from NHGIS that has already been normalized. NHGIS explains their methods as follows:

> To reaggregate 2000 block data to 2010 census units, NHGIS first allocates census counts from 2000 census blocks to 2010 census blocks and then sums the reallocated counts for all 2010 blocks that lie within each target 2010 unit. Where a 2000 block intersects multiple 2010 units, NHGIS interpolates from the 2000 block data to estimate how the 2000 block characteristics are distributed among the intersecting 2010 blocks… No distinctions are made for different subgroups of population or housing. In effect, the model assumes that, *within each 2000 block*, the Black population's spatial distribution is proportionally the same as the White population's, and the distribution of owner-occupied housing is proportionally the same as renter-occupied housing's, etc. This assumption of consistent within-block distributions across subgroups is one source of error in the interpolation model, but it greatly simplifies the model and ensures that all interpolated subtotals will correctly sum to totals.[15]

For the purpose of creating historic error ranges, we normalize data from 1990 through 2010 using the Census Bureau's tract relationship files.[16] We did not use the NHGIS time-series data in this case because in their time-series products they match 1990 and 2000 data by tract name only, even if the geography associated with the name has changed, has been split up into additional tracts, or has incorporated additional area—all of which happen from one census to the another. The Census Bureau's tract relationship files for 1990 to 2000, in contrast, distribute 1990 population according to the percentage of the 1990 block (a sub-geography of a census tract) that falls within the 2000 block, and then sums block populations to the new tract. This method, like NHGIS' 2000-to-2010 method, also assumes that the age/sex/race/ethnicity distribution of the redistributed block population is the same as the distribution for the block population as a whole; however, it is possible that the portion of a block that "moved" actually contained a higher concentration of a particular age or race group than the block overall.

In the Census Bureau's 2000-2010 tract relationship files, the method is more refined than in the 1990-2000 series. For this series, the population data associated with each individual housing unit record is re-allocated (actually geocoded) according to where the housing unit fell within the new boundary. The re-allocated population in this relationship file is not, however, broken out by age, sex, or race. So while total population values will be very accurate, the assumption integrated into our method is that the

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[14] Minnesota Population Center. *National Historical Geographic Information System: Version 2.0*. Minneapolis, MN: University of Minnesota 2011. http://www.nhgis.org.

[15] https://nhgis.org/documentation/time-series/2000-blocks-to-2010-geog

[16] Available for download at: https://www.census.gov/geo/maps-data/data/relationship.html

age/sex/race/ethnicity distribution of the re-allocated population is the same as the age/sex/race/ethnicity distribution of the original geography.[17]

It should be noted that the error ranges that we generate for each age/sex cohort do capture the error introduced by the distribution assumptions embedded in the tract normalization process because these same assumptions are made when generating the 2010 estimates used to assign error. Also, because the 2000-2010 relationship files are more precise than the 1990-2000 relationship files, the historic error associated with the model, which is generated using the 1990-2000 ratios, is likely to be higher than the actual error in the current estimates, which use 2000-2010 ratios. That is, our assigned error ranges are conservative and probably somewhat higher than the actual error.

To normalize race and ethnicity data from 1990 to 2000, we collapse the Census 2000 categories "Asian Alone" and "Native Hawaiian and other Pacific Island alone" into the 1990 "Asian or Pacific Islander" category. Because 1990 age/sex/race data is not available by ethnic breakdown, we are limited in our ability to examine historic error rates by race broken out by ethnicity. We produced historic errors for age/sex/race categories only, combining both Hispanic and Non-Hispanic together, including: total White, Black, American Indian/Alaskan Native, Asian or Pacific Islander, and Other. "Two or more races" was also not a category in the 1990 Census; therefore, this group is also left out of historic error testing. Ultimately, for the five race groups for which we were able to generate error rates in our testing, we did not determine that race alone was a reliable cause of error, the more significant determinants of performance being cohort size and age-group. Therefore, in the final application of the 1990-2000 ratios to the error range assignment, a direct correspondence between these sub-groups was not needed.

In processing census data, we exclude from our working data set the ".99" water tracts from the 1990 Census, which include only persons living off-shore on civilian or military ships. According to the Census Bureau, "These crews-of-vessels census tracts/BNAs [block numbering areas] refer to the water near the piers, docks, or onshore facilities associated with the ships; they do not represent any land area or any specific area of water."[18]

Finally, we adjust population in our model for the Town of Lincoln and for the census tract in Lincoln that represents the Hanscom Air Force Base.[19] We do this because Lincoln was counted in Census 2010 with a significantly reduced population—as much as 21% of the town and 55% of the tract population by our estimates—because a large number of the housing units at the military base were demolished just prior to the 2010 count and then replaced in 2011. Using the temporarily diminished population in 2010 as a base for calculation ratios and projecting future estimates produces very unreasonable results.

Instead in our model we substitute 2000 population for 2010, reasoning that population housed at a military base is similar to population in other group quarters, such as college dormitories and nursing homes, and does not necessarily age or migrate at the same rate as the household population, but is

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[17] Also note that because the Census tract relationship files include percentage values that are rounded to two decimal points, the "normalized" 1990 and 2000 data will no longer sum exactly to the original SF1 data, however these differences are minor and inconsequential for our purposes.

[18] See Chapter 10 of the U.S. Census Bureau's Geographic Areas Reference Manual (GARM), 1994 for additional information at: https://www.census.gov/geo/reference/garm.html. We provide a list of the ".99" tracts in Appendix A, Table A-8.

[19] Census 2010 tract 3601.00 in Middlesex County

rather a "revolving door" population in terms of age breakdown.[20] Although this substitution introduces the assumption that the count and characteristics of Lincoln population in 2010 were the same as that of 2000, we believe that overall, this processing decision produces a much more realistic estimate for that area than the unadjusted Census 2010 count.

2) Re-assigning "Some other race" in the 2000 and 2010 SF1 census data (tract and town)

Having normalized data across census years, we then re-assign the "Some other race" population counted in the Census 2000 and 2010 Summary File data to the six race categories comprising the post-Census 2010 county-level age/sex/race/ethnicity estimates.[21] We do this because "Some other race" is not technically a race category recognized by the Office of Management and Budget (OMB), but rather a survey response category. UMDI consulted Population Division staff at the U.S. Census Bureau who confirmed that for our purposes this category was better left out. More critically for our purposes, re-assigning the "Some other race" category also allows our model to correspond fully to the county-level age/sex/race/ethnicity population estimates by county that the Census Bureau updates on an annual basis.[22] Finally, inconsistencies in "Some other race" reporting from census to census were causing large errors in model testing, the highest among all race groups tested, indicating instability in this reporting category from census to census.

We re-assign the "Some other race" populations by age/sex/geography to the six major race categories using percentage allocations created from the Census Bureau's Modified Race Summary Files. The Census Bureau produces these correspondence files for both 2000 and 2010 at the age/sex/race/county level.[23] Our method assumes that each sub-county geography's race reassignment percentages are the same as the parent county's reassignment percentage. Regarding this assumption, Census Bureau staff advised that within a state the reassignment will not vary much by geography and that the even finer county-level files should be sufficient barring any unusual circumstances.

To apply the modified race files, we compare each age/sex/race/ethnicity population in the Census SF1 county file to the age/sex/race/ethnicity population in the corresponding modified county file, in which all "Some other race" populations have been re-assigned, and calculate a ratio between the two. We then apply each age/sex/race/ethnicity/county-specific ratio to the corresponding age/sex/race/ethnicity cohorts within each county. Because processing these ratios within Stata includes some decimal rounding, there is some difference between the final "modified" race totals and the original SF1 race totals, however these differences due to rounding average less than one person total per town.[24]

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[20] Also assuming that the mission of the base does not significantly change, which would lead to a base change in workforce and population.

[21] U.S. Census Bureau's *Annual Estimates of the Resident Population by Sex, Race, and Hispanic Origin Population Estimates for Massachusetts Counties*. "Race Alone" categories include: White, Black or African American, Asian, American Indian and Alaska Native, Asian, and Native Hawaiian and Other Pacific Islander.

[22] Ibid

[23] The Modified Race Data Summary Files and related documentation are available for download at: https://www.census.gov/popest/research/modified.html

[24] In our Stata processing files, we store data in "doubles" format, which rounds to about 16 decimals on average, depending on varying circumstances.

3) Calculating cohort-change ratios and child-to-woman ratios

Once 2000 and 2010 data has been normalized and re-assigned, we can now calculate the 2000 to 2010 CCRs for population age 10 and over and child-to-woman ratios (CTWs) for the population aged 0-9. The CCR method accounts for the aging of each individual cohort from one census to the next and creates a ratio between a specific cohort population (by age, sex, geography and sometimes additional variations such as race) age $_a$ in year $_y$ to its corresponding cohort aged $_{a-10}$ in year $_{y-10}$. For 2000 to 2010 CCRs, this is expressed as:

$$CCR_{age\ a} = \frac{Population\ 2010_{age\ a}}{Population\ 2000_{age\ a-10}}$$

For example, the CCR for a 25-29-year-old cohort would be calculated as:

$$CCR_{age25-29} = \frac{Population\ 2010_{age\ 25-29}}{Population\ 2000_{age\ 15-19}}$$

Note that for the 85-plus population, the CCR takes the sum of the population aged 75 and over as its denominator.

The child-to-woman ratios are calculated as follows in our model, with children aged 0-4 calculated as a ratio of the female population aged 20-44 and children aged 5-9 calculated as a ratio of the population aged 30-49:

$$CTW_{age0-4} = \frac{Population\ 2010_{age\ 0-4}}{Population\ 2010_{age\ 20-44}}$$

$$CTW_{age5-9} = \frac{Population\ 2010_{age\ 5-9}}{Population\ 2010_{age\ 30-49}}$$

For all age groups, the resulting cohort-specific ratio is then applied to the corresponding base population (the Census 2010 population in our model) in order to estimate the population 10 years later (2020 in this case). At both the town and tract geographic levels, we calculate geographically-specific CCRs and CTWs in two ways for each geography: ratios for each age/sex cohort (including all races and ethnicities combined) and ratios for each age/sex/race/ethnicity cohort (where each age/sex/race/ethnicity cohort is treated separately). As described in the *Model Testing and Modifications* section of this report, before we integrate the resulting CCRs into our model, we cap them at "1" for cohort groups including fewer than 25 people and "2" for groups under 100 people.

4) Applying ratios and caps to the modified Census 2010 base population to create "uncontrolled" 2020 estimates

The next step in the estimation model is to apply the 2000-2010 CCR and CTW ratios to the 2010 Census base population to create 2020 estimates. At both the town and tract levels, we apply the geographically-specific CCRs and CTWs for each age/sex cohort and also for each age/sex/race/ethnicity cohort to their corresponding 2010 base population. In this way, we produce estimates by age and sex as well as by age, sex, race, and ethnicity. We then control the age/sex/race/ethnicity estimates to the age/sex estimates for each geography, meaning that cohort *totals* are generated by the age/sex CCR estimates while race and ethnicity *distributions* within each age/sex cohort are determined by the age/sex/race/ethnicity CCR estimates.

In determining how to best distribute population estimates to specific race and ethnicity groups, we first ran three test versions of our historic model. In all three tests, we applied 1990-2000 CCRs to the Census 2000 base to generate 2010 estimates, which we then compared to actual census counts. Estimates for this test were created at the tract level for each age, sex, race group, combining both Hispanic and non-Hispanic for each race, and with errors for both sexes combined in our MAPEs evaluation.[25] The tested variations included the following:

1. In one test we generated specific age/sex/race/ethnicity CCRs for each census tract to create age/sex/race/ethnicity estimates and compared these (uncontrolled) to the Census 2010 counts by age, sex, race, and ethnicity.
2. In another variation, we generated age/sex/race/ethnicity CCRs and estimates but then controlled these back to the age/sex estimates generated by age/sex CCRs.
3. Finally, we tested a "shift-share" approach. In the shift-share version, we looked at the percentage point shift in each race group's share of each age/sex/geography cohort from 1990 to 2000 and applied the same shift to the 2010 population. For example, among all males age 0-4 in Amherst, if 10% were non-Hispanic Asian in 1990 and 12% were non-Hispanic Asian in 2000, we calculated that 14% would be non-Hispanic Asian in 2010, and applied this 14% share to the 0-4 male population estimated for Amherst in 2010.

Of these three race-distribution models, the one that yielded the lowest MAPEs was the age/sex/race/ethnicity-CCR estimate controlled back to the age/sex-CCR estimate.

Tables A-9, A-10, and A-11 in Appendix A of this report show the MAPEs generated by the three model variations, respectively, by race, cohort size, and age group. Table 3 summarizes these results below. With the lowest average MAPEs highlighted in bold, it shows that while the uncontrolled variation works somewhat better for Black and American Indian/Alaskan Native cohorts, the average difference is small compared to the improvements that the controlled model makes to both Asian and Some Other Race cohorts. When MAPEs for all race/size/age estimates are compared, the controlled version again has a lower MAPE overall.

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[25] Race by Hispanic origin is not available in the 1990 Census data required for this test.

Table 3. Average MAPE of all age/cohort-size categories

race	Average MAPE		
	controlled	uncontrolled	shift-share
White	**32%**	**32%**	35%
Black	43%	**42%**	57%
Native	84%	**83%**	104%
Asian	**52%**	57%	74%
Other	**57%**	59%	296%
All	**46%**	48%	99%

In our tests, the shift-share method performed much worse than both of the other variations. As Table 3 above indicates, MAPEs generated in the shift-share method come in much higher across all race groups tested, and especially in the "Other" category. The poor performance in Some Other Race in particular is likely due to the shifting and inconsistent response rate for that category from census to census, as technically it is a response category and not a race, therefore highly dependent on respondents' interpretation of the census survey's race response options.

5) Distribute age/sex and age/sex/race/ethnicity estimates to single years 2011-2020

The application of our model to Census 2010 base populations produces CCR estimates for the year 2020. A next step is to distribute the resulting estimates to the single years from 2011 through 2020. Population change is not necessarily linear; it can accelerate or decelerate over time depending on numerous factors, including changes in localized migration due to economic or other development at the local level. However, because our model cannot account for the factors that may cause uneven change in one place or cohort from year to year, we simply create a linear interpolation for each age/sex/race/ethnicity/geography cohort from 2010 to 2020. The formula for this, as applied to each cohort, is:

$$Population\ year\ y = \left(\frac{Population\ 2020 - Population\ 2010}{10}\right) \times (y - 2010)$$

While this method makes the assumption that change is evenly distributed through the projection period, toggling our estimates results to the year-by-year county-level estimates, as described below, may help to ameliorate the effect of this assumption on our annual estimates.[26]

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[26] Because the annual, intercensal estimates produced by the Census Bureau are themselves estimates that use a combination of year-by-year component data adjusted to two census-count endpoints, we have no means of quantifying the effect of the control to the county on error, having no accurate count to measure them against.

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6) Control the 2011 to 2020 age/sex/race/ethnicity estimates by tract and by town to the county-level age/sex/race/ethnicity annual post-census estimates

As described in the *Method Overview* section of this report, we control the sub-county (tract- and town-level) age/sex/race/ethnicity estimates to the county-level age/sex/race/ethnicity estimates produced by the Census Bureau on an annual basis.[27] To do this, we simply sum the age/sex/race/ethnicity/geography cohort estimates produced thus far in our model to county totals, and calculate each sub-county (town or tract) cohort's share of the corresponding county cohort. These shares are then applied to the Census Bureau's current county-level estimates to produce a new "controlled" estimate for each cohort for each year. At the time of this report, estimates for 2011 through 2015 have been controlled and estimates from 2016 through 2020 are uncontrolled. For this reason, a review of the entire estimates time-series will show a break in series from 2015 to 2016. In general, places that have been growing more quickly this decade than what the last decade would have anticipated will show a drop from 2015 to 2016, while places that have been growing more slowly than anticipated will show the opposite. Once future years are also controlled, the time-series will trend will be smoother. Note that when 2016 and subsequent vintages of the Census Bureau estimates are released and incorporated into the model as controls, all years in the time-series, from 2011 to date, will be updated again, as with each new release the Census Bureau makes revisions to previous years in the post-censual series.

7) Distributing 5-year age-group estimates and errors to single years of age for ages 0-20

One of the last steps in our method is to calculate estimates for single-year-of-age cohorts for ages 0 through 20. Because we found that the CCRs and CTWs generated for larger cohort groups generally perform better than smaller groups, we controlled our single-year estimates to the estimates we had produced for the 5-year age-group cohorts 0-4 through 20-24. Table A-12 in Appendix A to this report displays the MAPEs by single-year of age generated using single-year-of-age CCRs by sex at the town-level. Table A-13 displays how these single-year CCRs compare to 5-year age-group CCRs when averaged together into the corresponding 5-year cohort groups. While the very smallest cohort groups, those totaling under 25 persons, show better performance using a single-year CCR model, most other cohort-size groups perform best using the 5-year CCR grouping.

We distributed the 5-year groups into single-years-of-age using a constant-share ratio method. For each geography (tract or town), we took the share of each single-year-of-age sex/race/ethnicity cohort within its 5-year age group in 2010 and applied it to the 5-year age/sex/race/ethnicity estimates for 2011-2020. This constant share method ensures that if a particular geography has a distinct single-year distribution within a 5-year cohort, such as a large share of 18 and 19 year-olds within the 15-19 group within a college town, the proportion is preserved moving forward.

Other than these types of localized single-year shares, which are preserved in our method, we have no theoretical basis for assuming how, or even that, shares of a single age within its 5-year group will shift from decade to decade. These shifts can and do occur, but their exact causes are not predictable by a

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[27] Annual Estimates of the Resident Population by Sex, Race, and Hispanic Origin for the United States, States, and Counties: April 1, 2010 to July 1, 2015. Source: U.S. Census Bureau, Population Division. Release Date: June 2016.

model like ours, based on historic trends. To support this assumption, we reviewed the time series of single-year age distributions within 5-year groups in Massachusetts from 1980 through 2010. The table below shows the percent of each single-year within its 5-year cohort, by decade, from 1980 through 2010, along with the 10-year percentage point shift. Percentages remain fairly even, especially from 2000 to 2010. However, even when they do shift more significantly, the direction of the shift is not consistent from decade to decade; it may increase over one decade and decrease over the next. This directional change underscores the unpredictability of the shift-in-share. Again, for this reason, we assume a constant share, based on the most recent census in 2010.

Table 4. Single year of age as percent of 5-year age group and 10-year percentage point shift

Age	Single year of age as percent of 5-year age group				10-Year Percentage Point Shift		
	1980	1990	2000	2010	1980-1990	1990-2000	2000-2010
< 1 year	21%	18%	20%	19%	-3%	2%	0%
1 year	20%	22%	20%	20%	2%	-2%	0%
2 years	20%	21%	20%	20%	1%	-1%	0%
3 years	19%	20%	20%	20%	0%	0%	0%
4 years	20%	20%	21%	20%	0%	1%	0%
5 years	18%	21%	19%	20%	3%	-2%	0%
6 years	18%	20%	19%	20%	2%	-1%	0%
7 years	20%	20%	20%	20%	0%	0%	0%
8 years	21%	19%	20%	20%	-2%	1%	0%
9 years	24%	20%	21%	20%	-4%	1%	0%
10 years	20%	21%	21%	20%	2%	0%	-1%
11 years	19%	20%	20%	20%	1%	0%	0%
12 years	20%	20%	20%	20%	0%	0%	0%
13 years	20%	19%	19%	20%	-1%	0%	1%
14 years	21%	19%	19%	21%	-2%	0%	1%
15 years	19%	17%	20%	18%	-2%	3%	-1%
16 years	19%	17%	19%	19%	-2%	2%	0%
17 years	19%	18%	19%	19%	-1%	1%	0%
18 years	21%	22%	21%	21%	1%	-1%	1%
19 years	22%	26%	22%	22%	4%	-4%	1%

8) Assigning error and confidence intervals

A key component of the UMDI estimates series for small geographies is the range of error associated with each estimate. Because detailed estimates at fine levels of geography are prone to large estimation error, we need a measure of how accurate, or inaccurate, a specific estimate is to better understand its utility. To produce error ranges for the estimates, we run "historic" versions of the model, using 1990 and 2000 data to produce age/sex estimates for 2010 at the town and tract level and then compare

these to the actual Census 2010 counts. The mean percent errors (MPEs) and standard deviations generated in this historic run are then used to adjust our estimates and to assign specific confidence intervals for each value.

The assumption in our error assignment method—and one of the major assumptions in our model—is that the model performance will be the same from 2010 to 2020 as it was from 2000 to 2010. In actuality, a number of factors may affect the model performance from one period to another. These include both changes in migration, fertility, and death-by-age trends from one decade to the next as well as differences in the accuracy of the actual census counts from 1990 to 2000 to 2010. Because our model incorporates a control back to current county estimates, which are based on recent administrative records data including recent IRS-based migration rates and recent birth and death data by county, we believe that our current estimates will perform better than the historic estimates we use to assign error. However, the extent of this improvement is unquantified and is reliant also upon the strength of the county estimates themselves.

In our error assignment, we also preserve the directional bias of the error associated with the historic model, such that if our model tended to over- or under-predict particular age groups, this directionality is also captured in our MPEs and confidence intervals. As above, the likelihood of the directional bias is based on the assumption that the model will perform the same this decade as it did in the last. So, if our method under-predicted the population of 0-4 year olds in 2010, we assume that it will under-predict them again in 2020, and we adjust our estimate accordingly, based on our historic MPE. In our output, we refer to the estimates that account for the historic MPEs and standard deviations as our "adjusted estimates," and our upper and lower bound estimates—our "CI lower" and "CI upper" values are likewise a product of the historically-based MPEs and standard deviations.

As a check against the historic, directional assumptions that we make in our adjusted estimate, we also provide in our output a "CCR estimate" value. This value represents the pure model output value that has not been adjusted by historical error. In cases where a researcher does not want to assume that the model will perform similarly in this decade as compared to last, in terms of under- or overestimating a particular group, the unadjusted "CCR estimate" may be a better denominator in rates calculation.

As described in the *Model Testing and Modifications* section of this report, testing revealed that age and cohort size were significant determinants of error within the cohort-change model. We also reviewed historic estimates errors by race to understand whether race should also be a factor in assigning error to future estimates. Our review showed that many of the smaller race groups, such as American Indian or Alaskan Native, displayed greater errors than the total population by age/size cohort. However, a multivariate regression analysis that included cohort size, age, and race did not distinguish race alone as a reliable cause of error. A second deterrent to assigning historic error based on race is a practical one. Since the "Two or more" races category did not exist in 1990, and since Hispanic and non-Hispanic populations were not broken out by race at the tract level in the 1990 Census, we are unable to determine historical rates of error by race and ethnicity for all groups in our model. Finally, race reporting is subjective and self-reported and may have a tendency to shift from decade to decade, unlike age or size of cohort.[28] So for those groups for which we can calculate errors, we are unable to

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[28] Testing by the U.S. Census Bureau, for example, shows that many respondents who would be categorized by the Bureau as White and Hispanic sometimes report as "Some other race" due to an unclear understanding of how the Bureau distinguishes race and ethnicity as separate categories. Ten years later, education efforts or a revised questionnaire may lead this same

determine which are true errors and are due to shifting self-categorizations. For these reasons, ultimately in our model we assign historically-based error to cohorts on the basis of their age and cohort size alone.

In our error assignment, we take the mean percent errors and standard deviations for the 18 age groups by 10 size categories. [29] As mentioned in the *Background* section of our report, we group male and female error together in same age/size groups. We calculate one set of errors for age/size groups at the town level, and another for age/size groups at the tract-level. For each estimate value, we assign the corresponding historic age/size MPE and standard deviation. Next, using the following formula for sample standard deviation, we calculate 95% confidence intervals of percent error for each age/size category (using the number of cohorts in each category to determine the t-value) and output the values as upper and lower confidence intervals around the estimate, where $\bar{x}$ = mean, x = individual observation, t = t-value, and n = sample size.

$$\left(\bar{x} - t^* \sqrt{\frac{\sum(x - \bar{x})^2}{(n-1)}} \quad , \quad \bar{x} + t^* \sqrt{\frac{\sum(x - \bar{x})^2}{(n-1)}} \right)$$

9) Distributing error and confidence intervals over single years 2011-2020

Our historic model estimates provide us with the historic error associated with a 10-year CCR estimate (in this case a 2010 estimate based on 2000) that we then apply to our 2020 output. Since we create estimates by single year in the entire 2010-2020 series, we also need to distribute this 10-year error across the single year estimates. To do this, we assume that the 10-year error will be evenly distributed across the 10-year period. In reality, growth or decline in a particular geography may start slowly at the start of a decade and then accelerate, or it may start off strong and then taper off, or even change sporadically. In the absence of definitive information, we assume even change over the ten-year period.

To do this, we start with zero error in our base year 2010, assign the full 10-year error by age/size to the 2020 estimate, and interpolate the error over the interim years. In this method, the first year estimate (2011) will entail 1/10th of the full error, the second year (2012) will entail 2/10th, and so on until the full 10-year error is reached in 2020. In all years, the age/size assignment is based on the cohort size in the base year 2010. The assumption that every 5-year age/sex/race cohort's error will increase or decrease linearly over the 10-year period also causes the standard deviation to be evenly distributed over the 10-year period. As a result, the confidence interval bounds will linearly expand by fractions of 10. Formulaically this works out to the following:

$$percent\ Error\ year\ y = \left(\frac{Error\ 2020}{10} \right) \times (y - 2010)$$

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respondent to now report as "White" instead of other. In other example, in some censuses respondents may be more likely to consider their multi-racial origins and choose "Two or more" for race while in other years they may decide to report just one.
[29] While errors are calculated for 18 five-year age categories, single-year age cohorts are assigned the same errors as the 5-year cohort groups to which they belong. See Table A-14 in Appendix A of this report for size categories used in error assignment.

The last step is to take the annual mean percent error, the standard deviation, and the upper and lower confidence interval bounds and multiply them by the adjusted annual estimates to calculate the upper and lower population estimates that the adjusted estimate 95% likely to fall between. In our final output, these upper and lower bounds are labelled as simply "ci upper" and "ci lower" estimates, which are equidistant in value from the "adjusted estimate" value for that year.

Detailed Processing Steps

Note that we include as a companion product for DPH use the Stata "do-files" that contain the step-by-step code used to execute the estimates model. Instructions are also provided on how to update county controls for 2016 and subsequent vintage releases of the Census Bureau's annual estimates.

Appendix A

Table A-1. Mean absolute percent error by town size (2000) in 10-year versus 20-year CCR estimates test. Estimates produced for 2010 by age/sex/town and measured against Census 2010 town totals.

Town Size (2000)	Number of Observations	Mean Absolute Percent Error	
		10-year CCR	20-year CCR
0-500	10	36.7%	31.6%
500-999	20	12.3%	11.3%
1,000-4,999	78	8.6%	8.3%
5,000-9,999	70	9.6%	9.7%
10,000-14,999	52	7.6%	8.7%
15,000-19,999	29	8.6%	7.2%
20,000-24,999	21	5.5%	5.1%
25,000-49,999	48	6.3%	6.9%
50,000-99,999	18	9.4%	11.4%
100,000+	5	6.7%	5.8%

Table A-2. Mean absolute percent error and weighted absolute percent error for males versus females by age group. 10-year CCR estimates for 2010 produced by age/sex/town and measured against Census 2010 values.

Age Group	MAPE, 10-Year CCR estimates		WAPE, 10-Year CCR estimates	
	Male	Female	Male	Female
0-4	21.1%	23.8%	11.9%	12.4%
5-9	19.8%	28.6%	15.3%	14.6%
10-14	18.9%	14.8%	9.7%	9.1%
15-19	16.5%	13.7%	8.7%	8.2%
20-24	20.0%	20.7%	10.2%	10.5%
25-29	27.2%	28.1%	10.5%	11.2%
30-34	25.5%	29.2%	14.4%	14.1%
35-39	22.7%	20.0%	12.6%	10.9%
40-44	14.7%	13.7%	9.2%	8.4%
45-49	11.3%	11.3%	6.8%	6.7%
50-54	10.5%	12.8%	6.6%	6.1%
55-59	11.5%	12.7%	6.6%	7.1%
60-64	12.4%	13.9%	8.1%	8.1%
65-69	14.9%	12.9%	9.4%	8.0%
70-74	15.3%	14.7%	9.3%	8.1%
75-79	16.1%	16.7%	9.2%	8.0%
80-84	18.2%	17.5%	10.8%	9.5%
85+	29.2%	24.1%	15.2%	14.3%

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Table A-3. Mean absolute percent errors and weighted absolute percent errors by age group in 10-year versus 20-year CCR estimates test. Estimates produced for 2010 at age-group/sex/town level and measured against Census 2010 values. Male and female errors combined in MAPEs summary.

Age Group	MAPE		WAPE	
	10-year CCR	20-year CCR	10-year CCR	20-year CCR
0-4	22.5%	22.9%	12.1%	12.7%
5-9	24.2%	24.0%	15.0%	16.1%
10-14	16.8%	15.4%	9.4%	8.6%
15-19	15.1%	14.1%	8.4%	7.4%
20-24	20.3%	24.1%	10.4%	12.7%
25-29	27.6%	32.5%	10.8%	16.5%
30-34	27.4%	30.0%	14.2%	15.3%
35-39	21.4%	17.9%	11.7%	10.9%
40-44	14.2%	13.4%	8.8%	9.5%
45-49	11.3%	11.1%	6.8%	7.5%
50-54	11.7%	11.1%	6.4%	6.3%
55-59	12.1%	11.2%	6.8%	6.5%
60-64	13.1%	11.3%	8.1%	7.8%
65-69	13.9%	12.1%	8.6%	8.1%
70-74	15.0%	13.5%	8.6%	8.5%
75-79	16.4%	16.2%	8.5%	9.0%
80-84	17.8%	17.5%	10.0%	11.2%
85+	26.6%	23.3%	14.5%	13.5%
All ages	18.2%	17.9%	9.7%	10.4%

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Table A-4. Mean absolute percent error and number of observations by age group and cohort size (in 2000). Estimates produced for 2010 at age-group/sex/town level and measured against Census 2010 values. Male and female errors combined in MAPEs summary. Note that these estimates do not incorporate the child-to-woman-ratio adjustments or CCR caps applied after subsequent testing.

MAPES by Age and Cohort Size																			
Cohort size	Avg. All	0-4	5-9	10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84	85+
0-99	32%	35%	59%	38%	31%	32%	51%	48%	45%	27%	22%	25%	22%	20%	22%	24%	26%	24%	33%
100-199	16%	25%	19%	14%	15%	14%	22%	27%	20%	16%	14%	11%	13%	11%	10%	11%	11%	12%	18%
200-499	13%	19%	14%	13%	10%	15%	19%	22%	17%	14%	11%	11%	9%	11%	11%	9%	9%	10%	17%
500-999	11%	17%	13%	10%	9%	14%	13%	21%	17%	9%	6%	6%	7%	7%	8%	8%	6%	7%	12%
1,000-1,999	9%	14%	13%	9%	9%	14%	10%	16%	12%	8%	6%	6%	6%	7%	8%	6%	6%	3%	7%
2,000-3,999	7%	7%	15%	7%	9%	10%	11%	13%	9%	7%	6%	4%	3%	2%	2%	4%	3%	5%	6%
4,000-9,999	6%	3%	15%	5%	5%	8%	8%	10%	9%	9%	4%	1%		1%	2%	7%	8%	7%	5%
10,000-19,999	8%	5%	33%	7%						4%	3%	1%	1%						
20,000+	3%				3%	3%	2%	2%	7%										
Number of Observations by Age and Cohort Size																			
Cohort size	n	0-4	5-9	10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84	85+
0-99	3874	181	153	147	158	240	225	169	141	130	124	139	168	227	258	272	318	390	434
100-199	1915	85	80	79	108	124	119	92	75	70	79	86	127	149	139	139	130	121	113
200-499	3228	197	197	194	214	181	171	182	161	175	209	212	206	193	178	172	155	133	98
500-999	2115	136	164	175	129	75	96	140	165	172	153	157	138	88	89	82	70	44	42
1,000-1,999	1067	74	82	83	64	45	51	71	109	108	104	83	46	39	33	30	22	11	12
2,000-3,999	328	23	18	17	21	23	25	34	43	41	27	20	15	4	3	5	5	2	2
4,000-9,999	85	4	6	5	6	12	13	12	6	4	4	3	0	2	2	2	2	1	1
10,000-19,999	14	2	2	2	0	0	0	0	0	2	2	2	2	0	0	0	0	0	0
20,000+	10	0	0	0	2	2	2	2	2	0	0	0	0	0	0	0	0	0	0

Figures A1-A4. Example distributions of age/sex CCRs by cohort size, based on town-level data from Census 2000 and Census 2010

CCRs for cohort sizes 50-74
n= 838

CCRs for cohort sizes 75-99
n= 626
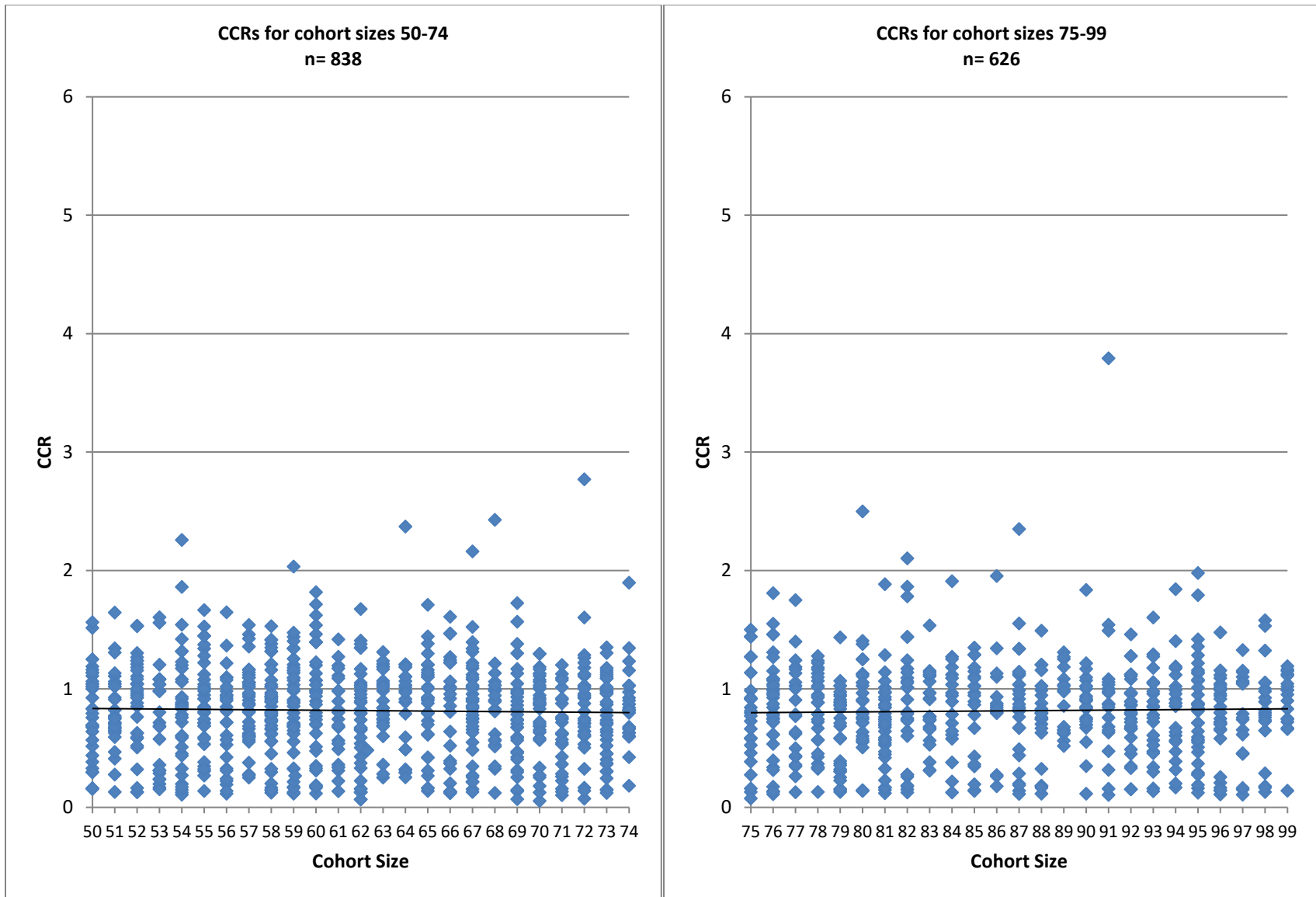
Table A-5. Mean absolute percent error by age group and cohort size (in 2000) with and without CCR caps applied in model. Estimates produced at age-group/sex/town level measured against Census 2010 values. Male and female errors combined in MAPEs summary. Note that these estimates incorporate child-to-woman-ratio adjustments determined through previous tests.

Estimates Series	Cohort Size	0-4	5-9	10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84	85+
MAPES without CCR Caps	0_24	58%	103%	49%	57%	47%	91%	81%	89%	54%	47%	65%	31%	30%	33%	37%	41%	31%	46%
	25_49	28%	27%	31%	29%	28%	37%	51%	49%	24%	22%	22%	21%	18%	20%	21%	20%	21%	20%
	50_99	21%	18%	19%	17%	22%	26%	24%	26%	20%	15%	15%	17%	14%	13%	15%	14%	16%	22%
MAPES with CCR Caps	0_24	44%	50%	38%	40%	45%	64%	37%	47%	33%	36%	34%	28%	20%	22%	33%	40%	31%	46%
	25_49	26%	26%	30%	29%	28%	37%	46%	45%	24%	23%	22%	21%	19%	20%	21%	20%	21%	20%
	50_99	20%	18%	18%	17%	22%	26%	23%	25%	20%	15%	15%	17%	14%	13%	15%	14%	16%	22%
Percent Difference: With Caps to without Caps	0_24	-14%	-52%	-11%	-17%	-2%	-27%	-44%	-41%	-20%	-12%	-31%	-3%	-10%	-11%	-4%	-1%	-1%	0%
	25_49	-2%	-1%	-1%	0%	0%	0%	-5%	-5%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%
	50_99	0%	0%	0%	0%	0%	0%	-1%	-1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Number of Observations by Age/Size Cohort	0_24	59	37	30	39	77	74	43	25	22	20	21	39	68	87	95	123	170	214
	25_49	60	55	48	44	81	66	59	46	31	34	41	63	71	75	70	66	87	114
	50_99	62	61	69	75	82	85	67	70	77	70	77	66	88	96	107	129	133	106

Table A-6. Mean absolute percent error by age group and cohort size (in 2000) with CCR caps and adjusted CTW applied. Estimates produced for 2010 at age-group/sex/town level and measured against Census 2010 values. Male and female errors combined in MAPEs summary.
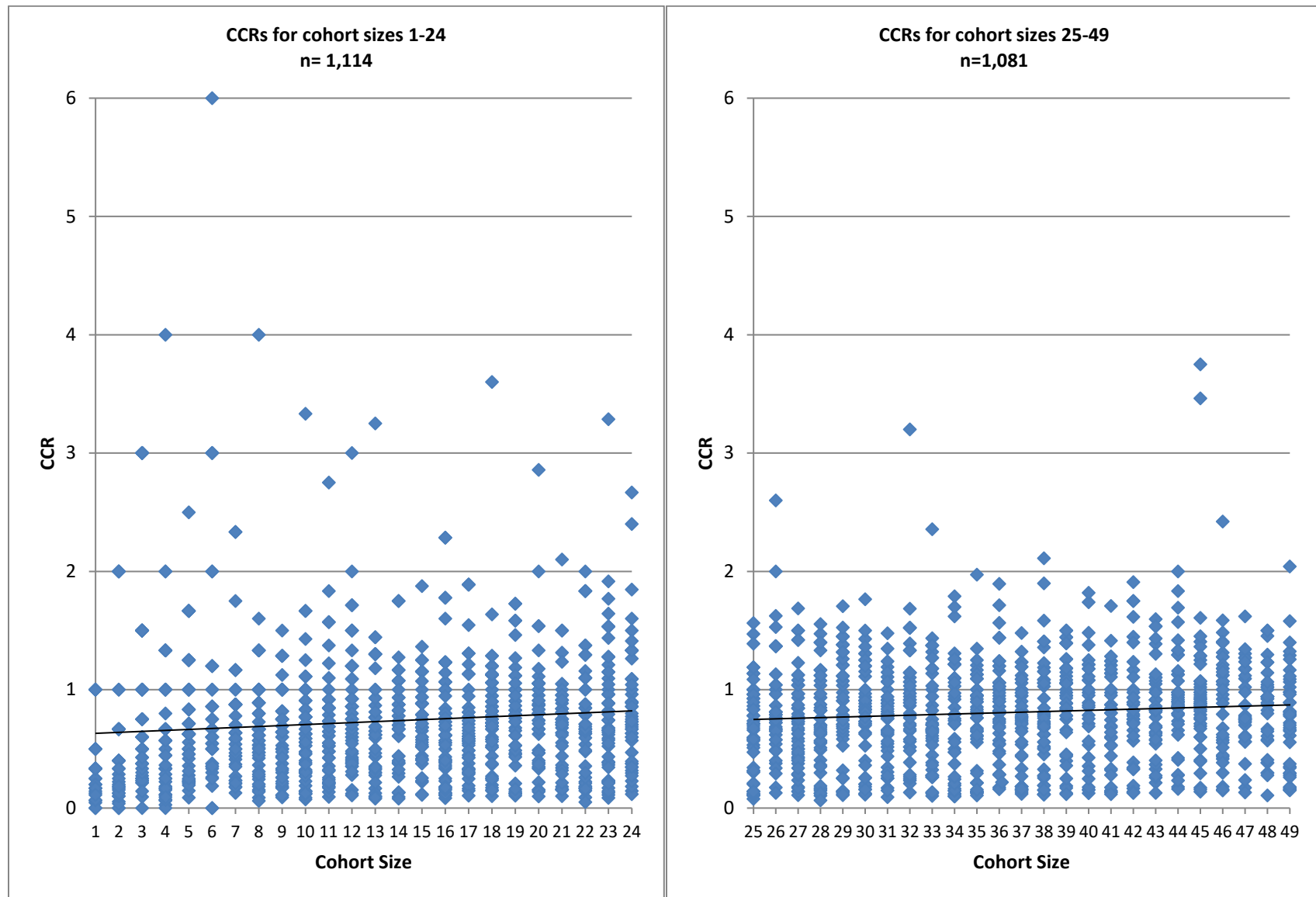
Cohort Size	Avg. All	0-4	5-9	10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84	85+
								MAPES by Age and Cohort Size											
0_24	38%	44%	50%	38%	40%	45%	64%	37%	47%	33%	36%	34%	28%	20%	22%	33%	40%	31%	46%
25_49	27%	26%	26%	30%	29%	28%	37%	46%	45%	24%	23%	22%	21%	19%	20%	21%	20%	21%	20%
50_99	18%	20%	18%	18%	17%	22%	26%	23%	25%	20%	15%	15%	17%	14%	13%	15%	14%	16%	22%
100_199	15%	22%	16%	14%	15%	14%	22%	27%	20%	16%	14%	11%	14%	11%	10%	11%	11%	12%	18%
200_499	13%	16%	13%	13%	10%	16%	19%	22%	17%	14%	11%	11%	9%	11%	11%	9%	9%	10%	17%
500_999	11%	16%	13%	10%	9%	14%	13%	21%	18%	10%	6%	6%	7%	7%	8%	8%	6%	7%	12%
1000_1999	9%	13%	11%	9%	9%	14%	10%	16%	12%	8%	6%	6%	6%	7%	8%	6%	6%	3%	7%
2000_9999	7%	8%	11%	6%	8%	10%	10%	12%	9%	8%	6%	4%	3%	2%	2%	5%	5%	6%	6%
10000+	3%	4%	23%	7%	3%	3%	2%	2%	7%	4%	3%	1%	1%	2%	2%	5%	5%	6%	6%
								Number of Observations by Age and Cohort Size											
Cohort Size	Total n	0-4	5-9	10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84	85+
0_24	1243	59	37	30	39	77	74	43	25	22	20	21	39	68	87	95	123	170	214
25_49	1111	60	55	48	44	81	66	59	46	31	34	41	63	71	75	70	66	87	114
50_99	1520	62	61	69	75	82	85	67	70	77	70	77	66	88	96	107	129	133	106
100_199	1917	85	80	79	108	124	120	93	75	70	79	86	127	149	139	139	130	121	113
200_499	3222	197	197	194	214	181	169	180	160	174	209	212	206	193	178	172	155	133	98
500_999	2119	136	164	175	129	75	97	141	166	173	153	157	138	88	89	82	70	44	42
1000_1999	1067	74	82	83	64	45	51	71	109	108	104	83	46	39	33	30	22	11	12
2000_9999	413	27	24	22	27	35	38	46	49	45	31	23	15	6	5	7	7	3	3
10000+	24	2	2	2	2	2	2	2	2	2	2	2	2	0	0	0	0	0	0

Note that age/size groups that included zero observations in the 2010 dataset are assigned proxy errors of the next smaller-sized group of the same age.

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Table A-7. Mean absolute percent error by age group and cohort size (in 2000) with CCR caps and adjusted CTW applied. Estimates produced for 2010 at age-group/sex/tract level and measured against Census 2010 values. Male and female errors combined in MAPEs summary.

Cohort Size	Avg. All	0-4	5-9	10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84	85+
							MAPEs by Age and Cohort Size												
0_29	46%	45%	55%	49%	75%	47%	41%	51%	49%	45%	41%	62%	39%	37%	36%	41%	38%	38%	40%
30_49	31%	31%	50%	37%	28%	26%	31%	31%	34%	52%	39%	34%	22%	21%	22%	25%	24%	22%	29%
50_74	24%	25%	34%	28%	22%	22%	29%	39%	31%	25%	24%	22%	17%	15%	15%	17%	18%	19%	36%
75_99	22%	28%	31%	22%	19%	22%	26%	30%	26%	23%	20%	17%	13%	12%	13%	15%	15%	17%	43%
100_124	20%	20%	21%	20%	16%	19%	26%	30%	26%	20%	16%	14%	13%	13%	15%	13%	15%	24%	47%
125_149	20%	19%	18%	18%	16%	22%	23%	25%	21%	16%	13%	12%	13%	13%	14%	14%	16%	29%	55%
150_174	21%	19%	19%	16%	17%	22%	23%	25%	20%	14%	13%	12%	12%	14%	20%	16%	14%	31%	73%
175_199	18%	19%	16%	15%	17%	24%	25%	24%	17%	15%	11%	11%	10%	10%	24%	15%	16%	10%	48%
200_299	20%	22%	17%	15%	21%	31%	26%	24%	17%	13%	11%	10%	9%	6%	13%	13%	30%	14%	68%
300+	21%	43%	18%	18%	50%	43%	33%	25%	23%	15%	9%	8%	9%	6%	13%	13%	24%	14%	65%

Cohort Size	Total n	0-4	5-9	10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84	85+
							Number of Observations by Age and Cohort Size												
0_29	5453	127	161	169	102	92	79	56	57	64	74	84	138	207	312	387	591	1130	1623
30_49	5145	156	121	105	151	249	139	38	34	50	89	117	253	472	548	575	651	806	591
50_74	7494	308	246	240	307	497	368	182	133	160	229	302	506	760	814	754	763	589	336
75_99	7357	424	328	346	436	544	430	311	242	244	303	409	580	666	621	579	483	239	172
100_124	6793	489	442	382	512	497	424	387	313	321	393	453	515	444	376	371	271	110	93
125_149	5668	438	397	439	463	351	400	407	375	378	381	386	413	279	177	174	107	47	56
150_174	4498	369	363	372	373	233	303	379	365	377	391	367	273	92	71	70	56	18	26
175_199	3272	234	306	287	218	134	221	337	325	324	324	302	158	19	21	21	16	2	23
200_299	6056	365	503	551	300	184	439	704	854	811	678	497	110	7	6	15	7	5	20
300+	1292	36	79	55	84	165	143	145	248	217	84	29	0	0	0	0	1	0	6

Note that age/size groups that included zero observations in the 2010 dataset are assigned proxy errors of the next smaller-sized group of the same age.

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Table A-8. List of ".99 water tracts" and associated population excluded from 1990 data in historic error calculations.

County Name	County Code	Tract Name	1990 Population
Barnstable	1	Tract 149.99	106
Bristol	5	Tract 6442.99	21
Bristol	5	Tract 6518.99	154
Essex	9	Tract 2215.99	0
Suffolk	25	Tract 305.99	401
Suffolk	25	Tract 408.99	170
Suffolk	25	Tract 605.99	21
Suffolk	25	Tract 606.99	18

Table A-9. Controlled age/sex/race estimates MAPEs by race, size of cohort, and age group. Estimates produced for 2010 at the tract level and measured against Census 2010 values. Male and female errors combined in MAPEs summary.

cohort size	n	00_04	05_09	10_14	15_19	20_24	25_29	30_34	35_39	40_44	45_49	50_54	55_59	60_64	65_69	70_74	75_79	80_84	85+
White																			
0-24	6608	54%	55%	61%	60%	53%	64%	85%	64%	68%	57%	69%	51%	45%	46%	53%	49%	46%	43%
25-49	7574	35%	34%	36%	37%	32%	39%	39%	38%	34%	33%	29%	24%	25%	25%	30%	28%	25%	29%
50-99	15819	26%	29%	28%	26%	27%	31%	32%	29%	28%	24%	22%	18%	17%	16%	18%	18%	21%	39%
100-199	17804	21%	21%	19%	20%	28%	29%	25%	22%	17%	15%	13%	13%	14%	17%	15%	16%	23%	52%
200-499	5148	30%	17%	16%	31%	47%	32%	25%	20%	15%	11%	10%	9%	N/A	14%	13%	N/A	N/A	N/A
500-999	67	N/A	N/A	N/A	39%	47%	35%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1000-1999	7	N/A	N/A	N/A	N/A	34%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2000-3999	1	N/A	N/A	N/A	81%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Black																			
0-24	49751	72%	69%	74%	69%	72%	75%	73%	70%	71%	69%	63%	64%	68%	68%	69%	69%	72%	86%
25-49	1901	52%	54%	45%	41%	54%	54%	80%	62%	48%	28%	27%	31%	26%	24%	30%	25%	N/A	N/A
50-99	916	36%	33%	33%	47%	51%	46%	45%	39%	27%	28%	22%	18%	20%	17%	20%	N/A	N/A	N/A
100-199	411	26%	28%	25%	30%	31%	39%	39%	42%	26%	19%	15%	14%	4%	N/A	N/A	N/A	N/A	N/A
200-499	49	N/A	16%	31%	17%	N/A	N/A	N/A	24%	6%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
American Indian or Alaskan Native																			
0-24	53028	86%	86%	84%	86%	88%	88%	86%	83%	81%	82%	80%	80%	81%	82%	84%	83%	85%	84%
Asian or Pacific Islander																			
0-24	51207	71%	67%	72%	71%	74%	75%	74%	72%	72%	62%	60%	57%	61%	63%	67%	70%	68%	85%
25-49	1307	75%	42%	47%	58%	52%	67%	57%	56%	44%	26%	27%	40%	25%	22%	33%	13%	3%	9%
50-99	415	42%	24%	25%	55%	70%	59%	65%	40%	28%	30%	25%	12%	8%	9%	N/A	72%	N/A	N/A
100-199	86	88%	22%	N/A	78%	79%	97%	57%	82%	39%	39%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
200-499	13	N/A	N/A	N/A	N/A	63%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Other																			
0-24	50612	74%	68%	72%	70%	75%	90%	110%	74%	72%	69%	68%	70%	75%	76%	77%	76%	85%	100%
25-49	1601	42%	34%	41%	34%	50%	47%	50%	70%	49%	37%	35%	39%	48%	N/A	N/A	N/A	N/A	N/A
50-99	695	49%	30%	44%	48%	51%	50%	91%	36%	26%	35%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
100-199	115	45%	20%	20%	36%	52%	52%	45%	21%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
200-499	5	N/A	N/A	N/A	84%	94%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table A-10. Uncontrolled age/sex/race estimates MAPEs by race, size of cohort, and age group. Estimates produced for 2010 at the tract level and measured against Census 2010 values. Male and female errors combined in MAPEs summary.

cohort size	n	00_04	05_09	10_14	15_19	20_24	25_29	30_34	35_39	40_44	45_49	50_54	55_59	60_64	65_69	70_74	75_79	80_84	85+
								White											
0-24	6608	54%	53%	59%	58%	54%	64%	83%	63%	67%	56%	63%	50%	44%	45%	51%	47%	44%	43%
25-49	7574	34%	33%	34%	34%	29%	36%	41%	36%	33%	31%	28%	22%	23%	23%	29%	28%	25%	29%
50-99	15819	25%	28%	26%	23%	24%	29%	32%	28%	26%	22%	20%	17%	16%	16%	18%	18%	20%	40%
100-199	17804	20%	21%	17%	18%	23%	25%	24%	21%	16%	14%	12%	12%	14%	16%	14%	15%	23%	53%
200-499	5148	28%	17%	15%	31%	46%	29%	24%	18%	14%	10%	10%	9%	N/A	14%	12%	N/A	N/A	N/A
500-999	67	N/A	N/A	N/A	133%	59%	41%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1000-1999	7	N/A	N/A	N/A	N/A	35%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2000-3999	1	N/A	N/A	N/A	61%	35%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
								Black											
0-24	49751	72%	69%	73%	68%	71%	72%	73%	69%	70%	68%	62%	63%	67%	67%	69%	69%	73%	90%
25-49	1901	44%	53%	43%	42%	46%	45%	64%	56%	44%	27%	28%	28%	24%	27%	29%	25%	N/A	N/A
50-99	916	37%	36%	33%	43%	46%	40%	45%	38%	29%	29%	23%	17%	20%	18%	22%	N/A	N/A	N/A
100-199	411	30%	31%	25%	30%	28%	35%	42%	51%	25%	24%	16%	15%	4%	N/A	N/A	N/A	N/A	N/A
200-499	49	N/A	18%	27%	16%	N/A	N/A	N/A	26%	12%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
								American Indian or Alaskan Native											
0-24	53028	85%	86%	83%	84%	85%	85%	85%	82%	80%	81%	79%	79%	80%	81%	84%	83%	85%	84%
								Asian or Pacific Islander											
0-24	51207	70%	67%	70%	69%	73%	74%	74%	73%	72%	61%	59%	57%	60%	63%	67%	71%	69%	90%
25-49	1307	71%	43%	45%	44%	57%	68%	62%	57%	46%	27%	27%	24%	23%	30%	39%	19%	5%	10%
50-99	415	53%	31%	28%	53%	71%	59%	66%	60%	38%	25%	21%	15%	10%	16%	N/A	84%	N/A	N/A
100-199	86	154%	13%	N/A	65%	62%	153%	130%	152%	80%	55%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
200-499	13	N/A	N/A	N/A	N/A	58%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
								Other											
0-24	50612	73%	68%	70%	69%	73%	96%	107%	72%	71%	68%	67%	70%	74%	76%	78%	78%	87%	108%
25-49	1601	38%	33%	37%	33%	51%	45%	47%	63%	46%	35%	32%	37%	56%	N/A	N/A	N/A	N/A	N/A
50-99	695	54%	30%	47%	50%	51%	47%	87%	38%	35%	46%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
100-199	115	62%	30%	28%	41%	53%	68%	63%	44%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
200-499	5	N/A	N/A	N/A	94%	97%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table A-11. Shift-share age/sex/race estimates MAPEs by y race, size of cohort, and age group. Estimates produced for 2010 at the tract level and measured against Census 2010 values. Male and female errors combined in MAPEs summary.

cohort size	n	00_04	05_09	10_14	15_19	20_24	25_29	30_34	35_39	40_44	45_49	50_54	55_59	60_64	65_69	70_74	75_79	80_84	85+
							White Persons												
0-24	6608	69%	65%	72%	67%	68%	80%	81%	82%	72%	68%	83%	64%	57%	56%	59%	56%	50%	45%
25-49	7574	43%	40%	44%	40%	32%	40%	54%	45%	38%	38%	34%	27%	25%	25%	30%	30%	25%	29%
50-99	15819	29%	34%	30%	27%	25%	29%	34%	29%	28%	24%	23%	18%	16%	16%	18%	18%	20%	40%
100-199	17804	21%	22%	18%	17%	23%	25%	26%	22%	17%	14%	13%	13%	14%	16%	15%	16%	23%	53%
200-499	5148	28%	17%	15%	30%	40%	27%	24%	19%	14%	11%	10%	9%	N/A	13%	13%	N/A	N/A	N/A
500-999	67	N/A	N/A	N/A	30%	36%	42%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1000-1999	7	N/A	N/A	N/A	N/A	46%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
2000-3999	1	N/A	N/A	N/A	84%	35%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
							Black Persons												
0-24	49751	89%	83%	96%	88%	101%	88%	86%	86%	93%	90%	90%	97%	114%	104%	91%	89%	98%	102%
25-49	1901	72%	68%	66%	101%	99%	145%	180%	95%	64%	40%	35%	47%	39%	34%	36%	31%	N/A	N/A
50-99	916	39%	31%	38%	46%	57%	54%	58%	47%	37%	33%	26%	23%	22%	19%	22%	N/A	N/A	N/A
100-199	411	24%	28%	23%	26%	36%	37%	37%	40%	25%	18%	19%	16%	6%	N/A	N/A	N/A	N/A	N/A
200-499	49	N/A	19%	23%	18%	N/A	N/A	N/A	15%	6%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
						American Indian or Alaskan Native Persons													
0-24	53028	104%	92%	103%	110%	113%	107%	101%	89%	98%	106%	109%	112%	115%	104%	95%	96%	108%	101%
						Asian or Pacific Islander Persons													
0-24	51207	94%	80%	95%	112%	130%	109%	85%	76%	80%	91%	95%	98%	117%	105%	87%	88%	96%	101%
25-49	1307	108%	51%	75%	108%	96%	144%	59%	54%	42%	50%	58%	115%	37%	50%	31%	20%	5%	9%
50-99	415	50%	23%	44%	66%	63%	120%	169%	25%	30%	85%	85%	10%	8%	75%	N/A	69%	N/A	N/A
100-199	86	87%	21%	N/A	181%	85%	133%	62%	44%	37%	45%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
200-499	13	N/A	N/A	N/A	N/A	39%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
							Other Persons												
0-24	50612	91%	88%	101%	107%	110%	93%	84%	85%	83%	87%	92%	99%	114%	105%	93%	90%	100%	108%
25-49	1601	61%	44%	63%	101%	94%	112%	66%	88%	53%	47%	49%	44%	67%	N/A	N/A	N/A	N/A	N/A
50-99	695	62%	39%	54%	730%	593%	85%	113%	51%	29%	36%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
100-199	115	48%	21%	21%	2698%	4936%	50%	39%	32%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
200-499	5	N/A	N/A	N/A	1302%	1526%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table A-12. MAPEs of single-year-of-age CCR estimates by cohort size and by single year of age 0-19. Estimates produced at town-level for 2010 and compared to 2010 Census.

Cohort Size	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0-24	33%	33%	37%	26%	30%	29%	23%	24%	26%	25%	26%	26%	23%	19%	26%	27%	24%	22%	25%	29%
25-49	30%	33%	26%	30%	22%	23%	22%	24%	27%	25%	28%	26%	28%	24%	19%	34%	22%	29%	26%	29%
50-99	36%	33%	31%	35%	29%	23%	26%	32%	36%	31%	23%	33%	22%	28%	21%	23%	19%	22%	22%	41%
100-199	25%	31%	32%	28%	29%	22%	24%	26%	31%	30%	26%	24%	24%	20%	22%	30%	22%	24%	33%	39%
200-499	28%	28%	30%	30%	26%	21%	24%	25%	32%	25%	31%	25%	25%	20%	20%	24%	26%	24%	25%	31%
500-999	35%	57%	24%	35%	80%	34%	105%	46%	33%	30%	43%	33%	28%	22%	55%	54%	23%	24%	28%	45%
1000-1999	6%	14%	29%	28%	27%	17%	15%	38%	37%	36%	14%	24%	15%	26%	17%	33%	38%	18%	18%	38%
2000-3999	15%	37%	8%	9%	10%	11%	20%	21%	28%	27%	35%	16%	26%	5%	7%	12%	16%	3%	N/A	10%
4000-9999	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	10%	54%
10000-19999	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
20000+	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table A-13. Averaged single-years MAPEs and 5-year MAPEs by 5-year age-group. Estimates produced at town-level for 2010 and compared to 2010 Census.

Cohort Size	Single years MAPEs averaged into 5-year groups					5-Year age group MAPEs				
	0-4	5-9	10-14	15-19	Average all ages	0-4	5-9	10-14	15-19	Average all ages
0-24	32%	25%	24%	25%	27%	44%	50%	38%	40%	43%
25-49	28%	24%	25%	28%	26%	26%	26%	30%	29%	28%
50-99	33%	30%	25%	25%	28%	20%	18%	18%	17%	18%
100-199	29%	26%	23%	30%	27%	22%	16%	14%	15%	17%
200-499	28%	26%	24%	26%	26%	16%	13%	13%	10%	13%
500-999	46%	50%	36%	35%	42%	16%	13%	10%	9%	12%
1000-1999	21%	29%	19%	29%	24%	13%	11%	9%	9%	11%
2000-3999	16%	21%	18%	10%	16%	8%	12%	7%	9%	9%
4000-9999	N/A	N/A	10%	32%	21%	6%	7%	5%	5%	6%
10000-19999	N/A	N/A	N/A	N/A	N/A	4%	23%	7%	N/A	11%
20000+	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	3%	3%
average all sizes	29%	29%	23%	27%	27%	18%	19%	15%	15%	17%

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Table A-14. Cohort-size categories used in error assignment.

Tract Level	Town Level
0-29	0-24
30-49	25-49
50-74	50-99
75-99	100-199
100-124	200-499
125-149	500-999
150-174	1,000-1,999
175-199	2,000-9,999
200-299	10,000+
300+	

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The UMass Donahue Institute (UMDI) is the public service outreach and economic development unit of the University of Massachusetts President's Office. Established in 1971, the UMDI coordinates multi-campus initiatives that link UMass, other public and private higher education, and other external resources with the needs of government agencies, corporations, and nonprofit organizations. UMDI provides significant economic and public policy analysis, organizational development, training, education, financial management education, research, and evaluation to federal and state agencies, nonprofits, industry associations, and corporations. UMDI draws on its unique position within higher education to serve as a bridge between theory, innovation, and real-world applications.

The Economic and Public Policy Research (EPPR) group is a leading provider of applied research, helping clients make more informed decisions about strategic economic and public policy issues. EPPR produces in-depth economic impact and industry studies that help clients build credibility, gain visibility, educate constituents, and plan economic development initiatives. EPPR is known for providing unbiased economic analysis on state-level economic policy issues in Massachusetts and beyond, and has completed a number of industry studies on IT, defense industries, telecommunications, health care, and transportation. Their trademark publication is called MassBenchmarks, an economic journal that presents timely information concerning the performance of and prospects for the Massachusetts economy, including economic analyses of key industries that make up the economic base of the state.

UMDI also serves as the Commonwealth's official partner with the U.S. Census Bureau for Massachusetts, and EPPR is home to both the Massachusetts State Data Center and the Population Estimates Program.

The Population Estimates Program (PEP) is the formal mechanism through which the Commonwealth helps ensure accurate U.S. Census estimates and counts. As the state's liaison to the U.S. Census Bureau's Federal-State Cooperative for Population Estimates, PEP supplies critical data updates for Massachusetts that are incorporated into the official U.S. Census annual population estimates. PEP also produces independent population estimates and a public-use series of population projections for all Massachusetts municipalities.

The State Data Center (SDC) Program is a cooperative program between the states and the U.S. Census Bureau to make data available locally to the public through a network of state agencies, universities, libraries, and regional and local governments. The SDC program's mission is to provide easy and efficient access to all U.S. Census Bureau data and information through a wide network of affiliate agencies in each state. The SDCs are official sources of demographic, economic, and social statistics produced by the U. S. Census Bureau. The SDC also provides training and technical assistance in accessing and using Census Bureau data. The Massachusetts SDC maintains its own network of affiliates which it relies on to provide local knowledge and expertise.

Works Cited

Baker et al. 2013
A Comparative Evaluation of Error and Bias in Census Tract-Level Age/Sex-Specific Population Estimates: Component I (Net-Migration) vs Component III (Hamilton–Perry)
Jack Baker, Adelamar Alcantara, Xiaomin Ruan, Kendra Watkins, Srini Vasan
Received: 2 July 2012 / Accepted: 8 July 2013 / Published online: 3 August 2013
Springer Science+Business Media Dordrecht 2013

Baker et al. 2012
Baker, J., Alcantara, A., Ruan, X. M., & Watkins, K. The impact of incomplete geocoding on small area population estimates. Journal of Population Research, 29, 91–112. 2012.
Hamilton, C., & Perry, J. (1962). A short method for projecting population by age from one decennial census to another. Social Forces, 41(2), 163–170.

Smith, Tayman, and Swanson
A Practitioner's Guide to State and Local Population Projections, Stanley K. Smith, Jeff Tayman, David A. Swanson, THE SPRINGER SERIES ON DEMOGRAPHIC METHODS AND POPULATION ANALYSIS. Series Editor KENNETH C. LAND
Duke University, Springer Science+Business Media, Dordrecht 2013