Population Projections by Demographic Details: A Multi-Layered Approach

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ABSTRACT

In this paper, we develop a straightforward, flexible approach to projecting total population, as well as detailed population projections by age, sex, and race and by age, sex, and Hispanic origin. The approach is a top-down, layered approach that relies on multiple methods. Having implemented the approach to produce detailed population projections for the state of Virginia and its 134 localities, the current research explores its applicability to producing population projections across the 50 states and Washington, D.C. for 2020-2040.

INTRODUCTION

As many state agencies are developing their own post-2010 projections, the most common approach to producing detailed population projections is the cohort-component method, a theoretically intuitive but cumbersome procedure.

A review of the empirical literature and the practices among states reveals little consensus on the most appropriate projection methodology (Smith, Tayman, and Swanson 2001). While the most commonly employed method for projecting population at the national, state, and sub-state level is the cohort component method (cf. Egan-Robertson, Harrier, and Wells 2008), though others have used time series methods, structural models, or a combination of methodologies. Evaluations of the accuracy of various methods across a 20-year horizon reveal that, with the exception of the poor performance of exponential trend models, nearly all approaches to total population projections produce similar results with respect to measures of error (Smith and Sincich 1992). In addition, in most states that produce projections with detailed population characteristics, the cohort-component method is used; few have employed or evaluated an alternative, the Hamilton and Perry method (1962).

The lack of consensus--and inherent uncertainty of the future---means practical considerations should prevail in the choice of methodology. In this paper, we develop a straightforward, flexible approach to projecting total population, as well as detailed population projections by age, sex, and race, and by age, sex, and Hispanic origin. This approach is a top-down, layered approach that relies on multiple methods. Having implemented this approach to produce detailed population projections for the state of Virginia and its 134 localities, the current research explores its applicability to producing population projections across the 50 states and Washington, D.C., for 2020-2040.

CRITERIA

Three criteria shaped our approach: parsimony, universal applicability, and state specificity. The method is elegant, requiring fewer input data and fewer assumptions than cohort component, and the procedures are easy to implement. The approach is generalizable to all equivalent geographical units. And, the method incorporates state-level demographic accounting to the greatest extent possible to reflect the influence of existing state trends on future population.

Because detailed projections, broken down by age, race, ethnicity, and sex, are prone to larger errors, we begin by projecting total population. Total population is the most commonly used component of population projections. Because these tend to be more stable and accurate than subpopulation totals, we use the projected total population as a control total for more detailed projections. The second priority in our approach was to develop accurate age projections. Age projections are frequently used to assess the future demand for education, healthcare, housing, and many other goods and services. Third, race and ethnicity are projected within each age group. Finally, sex is projected for each age-race and age-ethnicity group.

DATA AND METHODS

Data

We use state total population counts from the decennial census from 1950-2010 to develop total population projections. We use detailed state-level age breakdowns from 1990, 2000, and 2010; state-level age-race and age-Hispanic origin breakdowns from 2000 and 2010; and state-level sex breakdowns from 2010 to project detailed population characteristics.

Methods

(1) Total Population

Future population is modeled as a function of past population. Using Census population data from 1950 through 2010, the total population in each state is regressed on the prior three decades' population counts.[1] Having opted for an over-time model-approach, the two dominant choices revolved around (1) how to deal with state heterogeneity – the potentially different patterns across states – in a unified framework, and (2) the appropriate lag structure for a model.

No model of over-time change is going to apply equally well to a set of units as diverse as the fifty states (and Washington D.C.). We begin with the observation that the census counts of the states over time comprise panel data, and adopt traditional panel data approaches for dealing with unit heterogeneity – mixed effects or multilevel models.[2] The multilevel model allows us to retain state-specific estimates while borrowing strength across observations in all states. As a consequence, we can estimate a model with relatively few time points (Maas and Hox 2005). We do not assume that each state follows the same trajectory, that is, that they are governed by the

[1] We assessed the model using on various ranges of data, as well, incorporating data from 1900 to present.
[2] This family of models is also widely known as hierarchical models or random effects models.

same relationship between past and present. Rather, coefficients are allowed to vary across states; these random effects, written as additional error terms, u_{0i} and u_{1i}, capture how much each state's coefficients deviate from the nation-wide effect.

The usefulness of the model depends heavily on adequately representing the dynamics in the series. The model chosen for total population projections was the best performing model based on an evaluation of multiple lag lengths and multiple transformations of the dependent variable, including population counts, differencing, and growth rates. We evaluated these alternatives with reference to time series diagnostics (the augmented Dickey-Fuller (ADF) tests for unit roots (Said and Dickey 1984; Hamilton 1994)[3]), model fit criteria such as the Bayesian Information Criteria (BIC),[4] and out-of-sample forecasting accuracy.[5]

After extensive testing and evaluation, we selected an autoregressive mixed-effects model in which future population is modeled as a function of three lags of past population (AR3):

$$Y_{ti} = \beta_{0i} + \beta_{1i}Y_{(t-1)i} + \beta_{2i}Y_{(t-2)i} + \beta_{3i}Y_{(t-3)i} + \varepsilon_{ti}$$
$$\beta_{0i} = \beta_0 + u_{0i}$$
$$\beta_{1i} = \beta_1 + u_{1i}$$
$$\beta_{2i} = \beta_2 + u_{2i}$$
$$\beta_{3i} = \beta_3 + u_{3i}$$

Where Y is the population level, or count, t indexes time (Census decade) and i indexes the 50 states and Washington D.C. The βs are parameters to be estimated, and the ε and μ are random effects. The auto-regressive part of the model implies that past population predicts future population; the mixed-effects element implies that there are differences in the relationship between the past and future across localities.

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[3] The augmented Dickey-Fuller procedure tests for the presence of a unit root, but can incorporate a trend term to test for trend-stationarity as well as multiple lags to represent a more complex error process.

For a simple AR(1) model, $y_t = \rho_{t-1} + \varepsilon_t$, a unit root is present if $\rho = 1$. Such a model is non-stationary. The Dickey-Fuller test is implemented by regressing the first-difference of y on the lag of y along with, if desired, a deterministic time trend. That is, $\Delta y_t = \alpha_0 + \delta y_{t-1} + \gamma t + \varepsilon_t$. The test for a unit root is equivalent to a test of whether $\delta = 0$.

The augmented Dickey-Fuller test is used to test for a unit root in higher order autoregressive models. The procedure is like that of the Dickey-Fuller test but with an autoregressive process of lag order p: $\Delta y_t = \alpha_0 + \delta y_{t-1} + \gamma t + \theta_1 \Delta y_{t-1} + \cdots + \theta_{p-1}\Delta y_{t-p+1} + \varepsilon_t$. Typically, the lag structure is selected by beginning with a relatively high number of lags and successively eliminating each lag. The lag structure that produces the lowest information criteria (Akaike information criteria, AIC, or Bayesian information criteria, BIC), or the lowest number of lags that produces significant coefficients is selected.

[4] The Bayesian, or Schwarz, information criteria is a measure of the relative goodness of fit of a model, and is generally used to compare among a finite set of models. Related to the Akaike information criteria, the BIC is based on the likelihood function but introduces a penalty for additional parameters in a model to discourage overfitting. The model with the lowest BIC is preferred, though the BIC cannot be meaningfully compared across models with different dependent variables.

[5] Details are available from the authors upon request.

Out-of-sample validation

In addition to model fit criterion, we evaluated the AR(3) model performance over 10-, 20-, and 30-year projections horizons by comparing projected state population counts with observed census counts in 1990, 2000, and 2010. We used mean absolute percent error (MAPE) as a measure of overall error, and mean algebraic percent error (MALPE) as a measure of bias. Both MAPE and MALPE are regularly used as measures of forecast accuracy (e.g., Smith and Sincich 1992; Tayman, Smith, and Lin 2007).

Table 1. Out-of-Sample Forecast Errors for 10-, 20-, and 30-year State Projections with AR(3) Model

Data/Launch Year	Horizon (Years)	Projection Year	MALPE	MAPE
1950-2000	10	2010	0.84	2.41
1950-1990	10	2000	-4.27	7.01
1950-1990	20	2010	-4.28	10.2
1950-1980	10	1990	3.27	5.44
1950-1980	20	2000	1.06	7.86
1950-1980	30	2010	1.72	10.38

Consistent with other forecast evaluations, the accuracy of the model varies with the base data, launch year, and horizon (Keilman 2008; Smith and Tayman 2003; Tayman, Smith, and Lin 2007). Accuracy declines with horizon length, reflecting the increasing uncertainty associated with making long-range projections. Overall, the AR(3) model shows no bias and performs very well.

(2) Age

The Hamilton-Perry method is a reduced form of the cohort-component method that requires less detailed data and captures the major components of population change (births, deaths, and migration) in a general way (Hamilton and Perry 1962). Research has shown that the Hamilton-Perry method is an accurate methodology for projecting population characteristics (Smith and Tayman 2003). In our implementation, birth rates in the prior decade are measured by a *child-population ratio* (CPR) in which the child population (0-4 and 5-9) is divided by the population of child-bearing age. For example, the CPR for children 0 to 4 is

$$CPR_{0-4} = \frac{Pop\,_{0-4}^{2010}}{Pop_{15-44}^{2010}}$$

Deaths and migration are jointly captured in *cohort-change ratios* (CCR), that is, the ratio of total population in age group $a+10$ in the launch year (2010) divided by the total population of age group a in the base year (2000)

$$CCR_a = \frac{Pop\ _{a+10}^{2010}}{Pop_a^{2000}}$$

For example, the CCR for the 25 to 29 year-old age group would be calculated as

$$CCR_{25-29} = \frac{Pop\ _{35-39}^{2010}}{Pop_{25-29}^{2000}}$$

CCRs greater than 1 indicate population growth due to net migration that outweighs deaths, whereas CCRs less than 1 indicate population loss due to deaths, out-migration, or a combination of the two. The population is projected forward by multiplying the current population at age *a* by the CCR for that age group. The young population (ages 0 to 9) is then projected by multiplying the CPR by the projected population of childbearing age.

For the 2020-2040 projections by age, the following procedure was developed:

1) CCRs and CPRs were calculated for each state for 1990-2000 and 2000-2010 and averaged together. This helps smooth decade-to-decade variability that might result in unreasonable future projections if projected forward 30 years.
2) The averaged CCRs and CPRs were applied to the 2010 base population to project 2020, to the projected 2020 population to project 2030, and to the projected 2030 population to project 2040.
3) The age projections are controlled to the state total population projection developed in the AR(3) model.

(3) Race and Ethnicity

The Hamilton-Perry method was also used to project age groups by race (white, black, Asian, and other) and Hispanic origin (Hispanic and non-Hispanic), albeit with different implementation. We first considered using state-specific age-race/ethnicity CCRs. However, preliminary analyses of detailed population projections revealed substantial shifts toward the end of the projection horizon that were inconsistent with historical trends. This was largely due to high cohort-change ratios for Asian, other, and Hispanic groups, compared to more stable CCRs for white, black, and non-Hispanic residents. The high CCRs for these groups reflected high immigration among an initially smaller population; changes in the way that individuals are able to identify themselves on the Census form; social changes that increase the prevalence of multi-racial individuals; and increasing individual willingness to identify and claim “other race” on Census forms.

To address these issues, we developed an approach to implementing the Hamilton-Perry method to project the proportion of each racial and ethnic group within each age group:

1) Used national-level age-race/ethnicity-specific CCRs (based on 2000 to 2010) and CPRs (held constant to 2010) to project each state.[6]

2) Adjusted CCRs for Asian and other race and Hispanic groups downwards to reflect growing population base and slowing of immigration. For each age-race and age-ethnicity grouping we slowly tamped their CCR towards that of white or non-Hispanic groups to reflect convergence in the net effects of mortality and migration over time. For Asian, other, and Hispanic projections at each age group

   a. Their CCR was averaged with the CCR for white (or non-Hispanic) Americans ($CCR_{2020proj} = [2*CCR_{2010}+CCR_{white2010}]/3$) and applied to the 2010 base population to project 2020.

   b. The averaged CCR was again averaged with the CCR for white (or non-Hispanic) Americans (2/3 and 1/3 again) and applied to the projected 2020 population to project 2030. This CCR averaging procedure was repeated again to project the 2030 projected population to 2040.

3) For each projection year, the population proportion of race *r* at age *a* for each state was determined by

$$\frac{\boldsymbol{r_a}}{(white_a + \ black_a + Asian_a + other_a)}$$

   while the population proportion of ethnic group *e* at age *a* for each state was determined by

$$\frac{\boldsymbol{e_a}}{(nonHispanic_a + \ Hispanic_a)}$$

4) The race/ethnicity proportion was raked to the state-specific age distribution.

(4) Sex

Our methodology holds the sex ratio for all subgroups constant to the total population's age-specific sex ratio within each state. Since sex ratios are historically stable, this enables states with unique sex structures (a high proportion of prisons, military barracks, etc.) to retain their local characteristics.

$$Prop_{i-a-s} = \frac{N_{i-a-s}^{2010}}{N_{i-a}^{2010}}$$

In the above equation, *i* indexes state, *a* indexes age group, and *s* indexes sex.

[6] We did not use average of 1990-2000 for two reasons: 1) Change in Census form means that other race CCRs will be highly skewed between 1990 and 2000; 2) Concerns about rapidly changing, initially small populations are magnified when using 1990 to 2000, when the immigration wave began.

Producing Detailed Characteristics

The final distribution of detailed population characteristics is calculated by the following:

$$N_{ti-a-r-s} = Y_{ti} \times Prop_{i-a} \times Prop_{i-a-r} \times Prop_{i-a-s}$$

Where the number of individuals in a given age group *a* of race or ethnic group *r* and sex *s* living in state *i* at time *t* are equal to the projected total population Y of state *i* (from AR(3) model, step (1)), times the proportion within that age group (step (2), HP model), the proportion of the race or ethnic group within that age group (step (3), HP model), and the proportion of the sex within that age group (step (4), 2010 ratio).

National Projections

National projections are equal to the sum of the projections for each of the 50 states and the District of Columbia.

RESULTS

Projecting 2020, 2030, and 2040 by age, sex, and race, and by age, sex, and ethnicity for all 50 states and the District of Columbia, and summing these results to produce national totals produces far more detail than can reasonably be presented in this paper. We focus on the presentation of descriptive statistics for 2020-2040 at the national level. **Appendix 1** contains forecasts of total population for 2020, 2030, and 2040 for each of the 50 states and the District of Columbia.

Table 2. Observed and Projected Characteristics, U.S., 2010-2040

	2010 Census	Projections		
		2020	**2030**	**2040**
Total Population	308,745,538	337,979,529	370,164,485	405,021,914
Age				
Under 15	19.8%	19.3%	19.2%	19.2%
15 to 24	14.1%	13.3%	13.2%	13.2%
25 to 64	53.0%	51.7%	49.3%	49.5%
65 to 84	11.3%	14.1%	16.8%	16.0%
Over 85	1.8%	1.5%	1.6%	2.0%
Median Age	37.2	37.6	38.2	38.2
Race				
White	72.4%	69.6%	66.8%	63.9%
Black	12.6%	12.9%	13.2%	13.4%
Asian	4.8%	5.6%	6.2%	6.5%
Other	10.2%	11.9%	13.8%	16.2%
Hispanic	16.3%	20.2%	24.2%	28.2%

Table 2 shows projected total population and projected characteristics at the national level for 2020 through 2040. Total population is projected to grow steadily, at a projected growth rate of about 9.5% each decade. The proportion of the total population at younger ages (under 15) is projected to decrease slightly, while the proportion at ages 65 and above will increase significantly starting in 2020, due to the aging of the Baby Boomers.

Racial and ethnic diversity are projected to continue to increase nationally, with growing proportions of Hispanic and of Asian and other race populations. These projections reflect population growth due to both childbearing and continued immigration.

Comparison to U.S. Census Bureau and United Nations Projections

Both the U.S. Census Bureau and the United Nations recently released long-range population projections utilizing the standard cohort-component approach. The U.S. Census Bureau's are limited to the United States and use time series methods to project the components of change and corresponding population by age, sex, race, and Hispanic origin through 2050 (U.S. Census Bureau 2012). The U.N. used probabilistic projections of fertility (a Bayesian hierarchical model) to produce population projections by age for 196 countries through 2100 (UN-DESA 2011).

Total Population

Table 3 shows the projected U.S. total population for 2020, 2030, and 2040 under the AR(3) model developed in this paper, the U.S. Census Bureau's cohort-component approach, and the U.N.'s cohort-component approach. The U.N. and U.S. Census Bureau projections track closely for all three time points. The persistent 2,000,000 difference in projections most likely reflects the discrepancy between 2010 data: the U.N. projected the U.S. population at 310 million, whereas the actual 2010 census count was 308 million.

Table 3. U.S. Total Population Projections by Source, 2020-2040

	2020	**2030**	**2040**
AR(3)	337,979,529	370,164,485	405,021,914
U.S. Census Bureau	333,896,000	358,471,000	380,016,000
U.N.	336,683,000	360,581,000	382,075,000

Both the Census Bureau and the U.N. project steadily declining growth rates in the coming decades, dropping from 8% between 2010-2020 to 6% between 2030-2040. In contrast, the AR(3) model projects a relatively stable growth rate of about 9.5% for each decade. Consequently, when compared to the Census Bureau and U.N. numbers, the AR(3) total population projections are fairly close for 2020, and then begin to diverge over time.

Age Structure

Figure 1 shows the projected population proportion under 15 according to the Hamilton-Perry method employed in our approach (HP), the U.S. Census Bureau (CB), and the U.N. (UN) population projections. These proportions are quite close, though the Hamilton-Perry projections developed in this paper project a relatively constant population proportion under 15 (on average, 19.3%), while both the Census Bureau and U.N. projections project a steadily declining population proportion at young ages. The declining proportion at young ages is predominantly due to the growing proportions of the population at older ages, shown in Figure 2.

Figure 1. Projected Population Proportion Under 15 by Methodology, 2020-2040

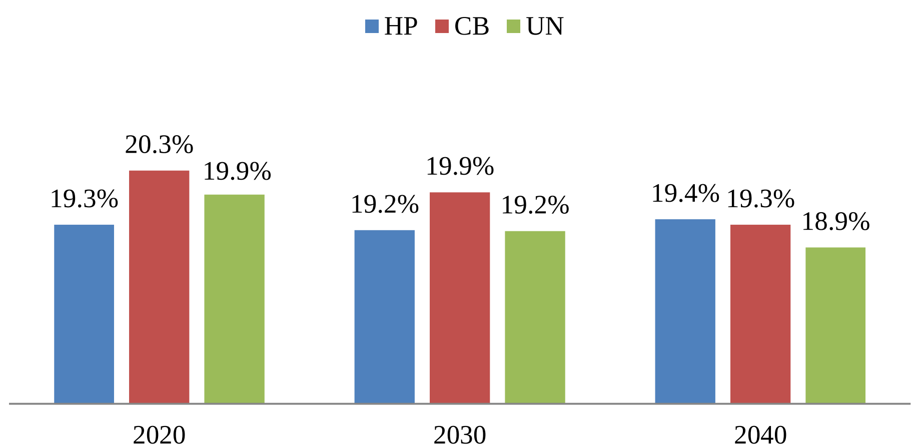
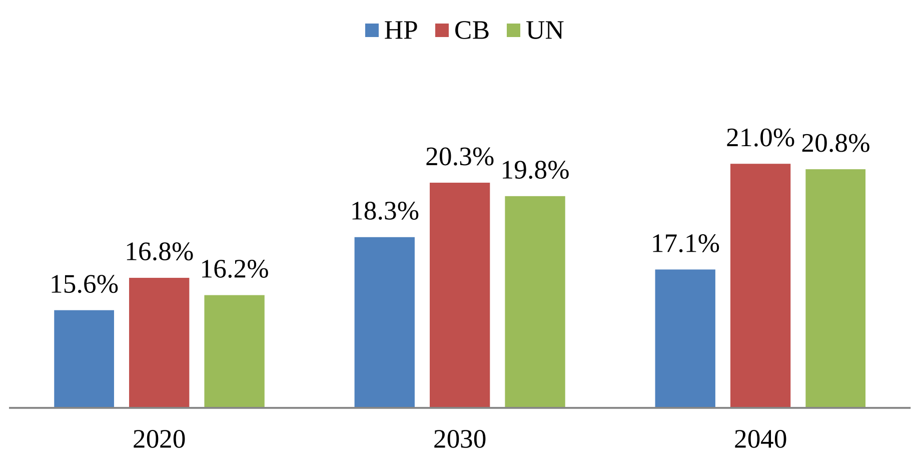


Figure 2. Projected Population Proportion Over 65 by Methodology, 2020-2040

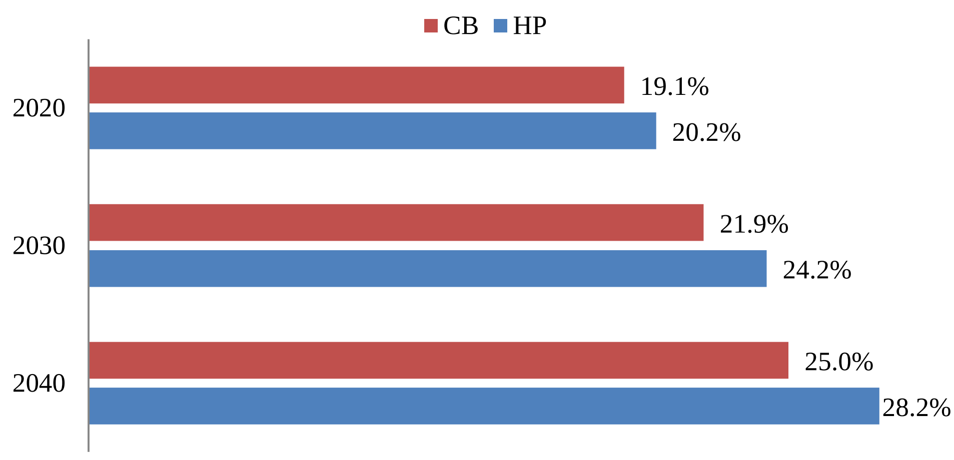


All three projections scenarios project increasing proportions of adults 65 and older in the United States. The Hamilton-Perry method used here projects continued immigration for working-age individuals at higher levels than projected in the cohort-component models employed by the U.S. Census Bureau and the U.N., and it does not extrapolate regarding improvements in life expectancy and mortality declines. As a result, the proportion of older adults under the H-P method peaks out in 2030 with the last of the Baby Boom cohort, and then declines slightly in 2040, in contrast to the continued increase in adults 65 and older in the other models.

Ethnicity

The U.S. Census Bureau produces its projections with race and ethnicity crossed (white, non-Hispanic; black, non-Hispanic; etc.) so specific comparisons by race are limited. Figure 3 shows the projected population proportion Hispanic under the Census Bureau (CB) projections and the Hamilton-Perry (HP) projections. In both projections scenarios, the population proportion Hispanic increases steadily between 2020 and 2040. The two methods are very close in 2020. The slightly higher population proportions Hispanic in 2030 and 2040 in the Hamilton-Perry projections again most likely reflect continued higher levels of migration assumed in the H-P approach than in the cohort-component methodology employed by the Census Bureau.

Figure 3. Projected Proportion Hispanic by Methodology, 2020-2040



DISCUSSION/CONCLUSIONS

We hope this research encourages applied demographers, planners, and other data users to think more broadly about projections, their inherent uncertainty, and their usability. Our approach is a probabilistic total population projection with deterministic characteristics. It has the following characteristics:

1. Prioritizes the most important component with the highest level of accuracy, total population. Next, age distribution is often critical for future planning. After this, population details by race, ethnicity, and sex may be desirable, but are more prone to social/measurement fluctuation, particularly in racial and ethnic identification.

2. Consequently, it layers the most accurate information and uses it as a control total for less accurate information.
3. Allows for the retention of state or local-specificity to the greatest extent possible.

The layered approach implements the most effective method for each aspect of the projections and the model-based approach offers multiple benefits.

The autoregressive mixed-effects model we employ here holds substantial promise for researchers interested in expanding this approach. The flexibility of the model and the relative simplicity of estimation allow the testing of many alternative assumptions, such as multiple lag structures and multiple transformations of the dependent variable, in a relatively brief time. The multilevel model can accommodate additional complexity in the form of additional random effects, such as the inclusion of spatial lags. Additional covariates could be added to the model, like non-time-varying covariates representing long-standing state characteristics though to affect population. Time-varying covariates could be added as well, like state GDP, unemployment, housing stock, so long as the researcher is prepared to forecast these inputs.

Similarly, the Hamilton-Perry approach can be easily manipulated to test the effect of varying assumptions, such as declining mortality at older ages and lowered fertility rates, on long-term trends in population composition.

Finally, projections are meant to paint a ballpark picture of what the future *might* hold, rather than carving out numerous detailed tiny cells with unknown accuracy. A comparison with the population projections recently released by the U.S. Census Bureau and the United Nations shows that the methodology developed here produces national population totals, age structure, and ethnic breakdown that are quite similar, particularly for shorter-range projections of 10 or 20 years. With increasing demands for detailed data production, this approach may work well for projections producers who wish to develop detailed, short-range projections.

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Appendix 1. Observed and Projected Total Population, States, 2010-2040

State	2010 Census	Projections		
		2020	**2030**	**2040**
Alabama	4,779,736	5,063,010	5,344,109	5,631,240
Alaska	710,231	807,768	908,083	1,007,569
Arizona	6,392,017	7,838,769	9,556,768	11,558,644
Arkansas	2,915,918	3,063,981	3,199,806	3,344,352
California	37,253,956	41,225,964	45,394,776	49,511,716
Colorado	5,029,196	5,754,161	6,561,624	7,444,989
Connecticut	3,574,097	3,791,290	4,001,783	4,193,111
Delaware	897,934	996,539	1,091,878	1,188,365
District of Columbia	601,723	611,618	609,235	606,302
Florida	18,801,310	22,292,758	26,310,824	30,767,300
Georgia	9,687,653	11,407,810	13,477,429	15,932,734
Hawaii	1,360,301	1,508,604	1,651,536	1,793,336
Idaho	1,567,582	1,743,841	1,901,224	2,067,764
Illinois	12,830,632	13,214,281	13,625,826	14,011,325
Indiana	6,483,802	6,819,620	7,138,444	7,445,297
Iowa	3,046,355	3,120,119	3,184,968	3,251,831
Kansas	2,853,118	2,999,622	3,145,552	3,291,771
Kentucky	4,339,367	4,559,315	4,768,093	4,983,525
Louisiana	4,533,372	4,725,753	4,957,351	5,168,018
Maine	1,328,361	1,400,635	1,476,237	1,550,052
Maryland	5,773,552	6,252,371	6,720,727	7,171,419
Massachusetts	6,547,629	6,788,833	7,045,072	7,288,405
Michigan	9,883,640	10,078,204	10,382,446	10,634,796
Minnesota	5,303,925	5,661,565	6,035,216	6,419,457
Mississippi	2,967,297	3,062,460	3,167,959	3,278,352
Missouri	5,988,927	6,313,716	6,633,987	6,963,034
Montana	989,415	1,057,125	1,122,032	1,188,491
Nebraska	1,826,341	1,908,363	1,984,255	2,062,172
Nevada	2,700,551	3,297,777	3,940,937	4,671,394
New Hampshire	1,316,470	1,429,691	1,556,031	1,681,726
New Jersey	8,791,894	9,174,874	9,560,118	9,910,012
New Mexico	2,059,179	2,280,993	2,507,412	2,738,504
New York	19,378,102	19,780,808	20,205,132	20,584,586
North Carolina	9,535,483	11,063,087	12,807,800	14,844,307
North Dakota	672,591	691,785	705,133	718,392
Ohio	11,536,504	11,822,135	12,127,654	12,380,847
Oklahoma	3,751,351	3,986,235	4,208,416	4,437,472
Oregon	3,831,074	4,209,593	4,601,805	5,002,050
Pennsylvania	12,702,379	13,049,097	13,359,257	13,654,876

Appendix 1. Observed and Projected Total Population, States, 2010-2040 (continued)

State	2010 Census	Projections		
		2020	2030	2040
Rhode Island	1,052,567	1,096,698	1,154,679	1,210,842
South Carolina	4,625,364	5,152,439	5,676,951	6,238,921
South Dakota	814,180	851,068	882,550	915,338
Tennessee	6,346,105	6,934,312	7,550,122	8,207,164
Texas	25,145,561	30,233,340	36,317,932	43,572,640
Utah	2,763,885	3,191,506	3,614,587	4,070,568
Vermont	625,741	664,071	710,842	757,062
Virginia	8,001,024	8,933,032	9,906,608	10,933,777
Washington	6,724,540	7,582,515	8,513,320	9,504,881
West Virginia	1,852,994	1,864,454	1,864,355	1,865,440
Wisconsin	5,686,986	6,000,200	6,322,054	6,640,505
Wyoming	563,626	621,732	673,556	725,247