Population Forecast Errors: A Primer for Planners

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Abstract

Projections of future populations are integral to many planning applications, yet are often poorly understood. This analysis focuses on the implications of the choices planners make when they construct projections. Specifically, it examines the impact of length of base period, analyzes the error structure of projection techniques for counties in the aggregate and by size and growth rates, investigates the role of averaging, and compares the performance of trend extrapolation and cohort–component methods. The article concludes by discussing forecast complexity, data quality, the role of assumptions, and other considerations of forecasting in a planning context.

Keywords: Population projections; model specification; forecast accuracy; averaging techniques; trend extrapolation; complexity.

Introduction

Calculations of future populations are used extensively in urban and land use planning; for economic development initiatives; for infrastructure, transportation, and health services planning; for water demand assessments; for natural resource management and protection; among other applications. According to Myers (2001, 384), "planning analysts regard population statistics as integral to virtually all aspects of planning," yet he laments that the demographic approach has been underutilized by the discipline. This is unfortunate, because planners are in a unique position to shape the future (Isserman 1985; Myers and Kitsuse 2000).

Predicting future population change involves the application of demographic methods by which a population is projected or forecasted. Demographic convention considers *projections* to be conditional statements about the future, which reflect the outcome of particular assumptions, and which are always correct unless there was an error in their calculation, while *forecasts* are unconditional statements that reflect what the analyst believes most likely to happen in the future (Isserman 1984; Shryock and Siegel 1976). The terms *projection* and *forecast* are used interchangeably in this article because, as Keyfitz (1972, 353) noted, "a demographer makes a projection, and his reader uses it as a forecast."

Planners and other practitioners that produce population forecasts are faced with making decisions regarding the choice of methods, input data, assumptions, treatment of special populations, etcetera. The evaluation criteria discussed in this paper are targeted at both producers and users to provide a better understanding of what matters for small area projections of total population. In particular, the study pursues three primary objectives. The first is to investigate the relationship between the length of the projection horizon and the base period with regard to forecast accuracy. The second is to analyze forecast errors for commonly-used horizon lengths, first for all counties, and then by population size and growth categories. The third is to examine forecast error by forecast technique, comparing individual trend models to various averages, and cohort-component models to trend extrapolation techniques. The paper concludes with a discussion of the evaluation criteria analyzed in this study, as well as data quality and related issues that also affect forecast outcomes.

Criteria for Evaluating Population Projections

Population projections can be evaluated on many grounds. Smith, Tayman, and Swanson (2001), in their review of the literature, list in this regard provision of necessary detail, face validity, plausibility, costs of production, timeliness, ease of application and explanation, usefulness as an analytical tool, political acceptability, and forecast accuracy. Depending on the situation, producers and users place different emphases on the importance of these criteria, but for many forecast accuracy is paramount (Mentzer and Kahn 1995; Yokum and Armstrong 1995). Because planning decisions and funding allocations are often tied to calculations of future populations, it is critical to pay attention to forecast accuracy.

For planners, though, accuracy is not everything (Sawicki 1989). Forecasting in planning practice often contains an inherent conflict between pure or analytic forecasts on the one hand, and normative or advocacy forecasts on the other hand (Isserman 2007; Wachs 1989). Accuracy is of less interest for advocacy forecasts, for "if some political purpose was being served by making a forecast, that forecast need not really be correct in order for it to have its intended effect" (Wachs 2001, 369). Taken to the extreme, "planners on the dark side are busy not with getting forecasts right and following the AICP Code of Ethics but with getting projects funded and built. And accurate forecasts are often not an effective means for achieving this objective.

Indeed, accurate forecasts may be counterproductive, whereas biased forecasts may be effective in competing for funds and securing the go-ahead for construction" (Flyvbjerg, Skamris Holm, and Buhl 2005, 142).

This analysis is not concerned with the 'dark side' of forecasting. Rather, it presumes that the planner wants to achieve a reasonable forecast and would like to know what the likely forecast error will be. For that purpose, the study focuses on typical forecast errors that can be expected with commonly applied techniques for short to medium horizons for small areas. Previous studies that evaluated forecast errors were limited in space and/or time (see e.g. Isserman 1977; Murdock, Leistritz, Hamm, Hwang, and Parpia 1984; Smith 1987; Smith and Sincich 1991; Tayman 1996a; Tayman, Schafer, and Carter 1998). In particular, there is a paucity of sub-state population projection evaluations that involve more than a few decades, and which are nationally representative. Research that evaluates forecast accuracy for small areas is needed in order to improve projection models and assumptions (Wilson and Rees 2005). The present analysis investigates forecast errors for all counties in the United States that had comparable data available for the entire 20th century, thus greatly enhancing the ability to make generalizations about the findings.

Data and Techniques

This study uses population data for counties and county equivalents in the United States (excluding Alaska and Hawaii) from the decennial censuses spanning the period 1900–2000. To ensure the comparability of the data, following Forstall (1996), the analysis was limited to those counties that did not experience significant boundary changes between 1900 and 2000. This resulted in a total number of 2,482 counties, which amounts to 79.0% of all counties in Census

2000. In a companion study the sample used in this analysis was found to be representative of the nation at large. It produced similar results by projection technique and by horizon length compared to a sample covering 94.8% of all counties in Census 2000 for the sub-period 1930–2000 for which the data were available for the larger sample (Rayer 2004).

[Figure 1 about here.]

Figure 1 displays a map of the continental United States that shows the counties that were excluded from the analysis, because their boundaries have changed significantly since 1900. As the map illustrates, the excluded areas are mostly in the Mountain States; western North and South Dakota; Oklahoma; along the Gulf Coast; and in parts of Florida, Georgia, South Carolina, and Virginia. Also shown are average forecast errors for the 2,482 counties left in the analysis. These will be discussed below in the section on accuracy by length of projection horizon, population size, and growth rate.

Following Smith, Tayman, and Swanson (2001), the following terminology is used to describe population forecasts:

1) Base year: the year of the earliest population size used to make a forecast.

2) Launch year: the year of the latest population size used to make a forecast.

3) Target year: the year for which population size is forecasted.

4) Base period: the interval between the base year and launch year.

5) Forecast horizon: the interval between the launch year and target year.

For example, if data from 1960 and 1980 were used to forecast population in 1990, then 1960 would be the base year, 1980 would be the launch year, 1990 would be the target year, 1960–1980 would be the base period, and 1980–1990 would be the forecast horizon.

Covering census data for the entire 20th century, the analysis involves 63 projection horizon / base period / target year combinations. For each of these, a total of five commonly used trend extrapolation techniques were applied: linear (LIN), share-of-growth (SHR), shift-share (SFT), exponential (EXP), and constant-share (COS). A description of these techniques can be found in Appendix A. From these techniques two averages were calculated: one comprising all five techniques (AV5), and one excluding the highest and lowest projection (AV3), the latter representing a "trimmed" mean.

Forecasts from these techniques are analyzed with respect to their error structures. The study examines forecast accuracy in two ways: in terms of *precision* and with respect to *bias*. *Precision* refers to the average percent difference between projections and actual census counts, ignoring whether projections are too high or low; *bias* indicates whether projections are too high or low by focusing on algebraic errors where positive and negative values offset each other. With regard to precision, the most popular error measure in population forecasting is the *mean absolute percent error* or MAPE (see e.g. Ahlburg 1995; Isserman 1977; Smith 1987; Smith and Sincich 1988, 1992). It is calculated as follows:

$$MAPE = \Sigma\ |PE_t|\ /\ n, \quad PE_t = [(F_t - A_t)\ /\ A_t] * 100$$

where PE represents the percent error, t the target year, F the population forecast, A the actual population, and n the number of areas. Projections that are completely precise result in a MAPE of zero. The MAPE has no upper limit – the larger the MAPE, the lower the precision of the projections. For projection bias, the *mean algebraic percent error* (MALPE) can be calculated analogously to the MAPE, though using algebraic rather than absolute percent errors. Negative values on the MALPE indicate a tendency for projections to be too low, while positive values indicate a tendency for projections to be too high. Being arithmetic means, the MAPE and

MALPE are susceptible to outliers, but for practical purposes simple summary measures such as the MAPE and MALPE are sufficient to describe the error distribution of population forecasts (Rayer 2007).

Accuracy by Base Period Length

When preparing population forecasts, one of the first decisions a practitioner has to make is which base data to include. For trend extrapolation techniques, this means specifying the length of the base period. Unfortunately, few studies have addressed this issue (analyses at the state level include Beaumont and Isserman 1987, and Smith and Sincich 1990). A general recommendation is that the length of the base period should correspond to that of the forecast horizon (Alho and Spencer 1997; Murdock, Hamm, Voss, Fannin, and Pecotte 1991).

This study revisits the relationship between the length of the base period and that of the forecast horizon with respect to both precision and bias. Because the data set covers the entire 20th century, significantly more base period / forecast horizon / target year combinations are investigated at a lower level of geography than in previous studies. Tables 1a and 1b show MAPEs and MALPEs by projection horizon, base period, and trend extrapolation technique for the 1960 to 2000 target years. This part of the analysis was restricted to those years to ensure that each projection horizon / base period combination includes the same number of target years (n=5). In addition to the 10, 20, and 30 year base period results, the fourth row of each panel also includes data for a 10–30 year base period average to determine whether averaging can be beneficial when it comes to choosing among base periods.

[Table 1 about here.]

The data in Table 1a suggest that the length of the base period has only a limited impact on forecast precision. The exponential method and AV5 are exceptions; here, outliers greatly influence the longer-term projections, and increasing the length of the base period beyond ten years improves precision markedly. For most techniques and projection horizons, 20 year base periods show lower MAPEs than either 10 or 30 year base periods. In most instances calculating an average projection from the three different base periods further improves precision. This makes sense intuitively, because population change patterns fluctuate over time and – given that the future is essentially unknowable – rather than trying to determine which period fits best, using the average change from several periods in the recent past often works well.

With respect to forecast bias, Smith and Sincich (1990) found no consistent relationship between the MALPE and the length of the base period, which Beaumont and Isserman (1987) concluded as well. The results for this study (Table 1b) also show no clear pattern. While for 10 and 20 year horizons bias tends to increase with lengthening base periods, the opposite seems to be the case for 30 year horizons. When looked at for individual target years, the launch year had a much greater impact on bias than the length of the base period or the length of the projection horizon. For example, for ten year horizons all projections with a 1990 launch year came out too low, all projections with a 1980 launch year were too high, and all projections with a 1970 launch year were too low (data not shown). Thus, projection bias is primarily determined by launch year and remains by and large unknowable in advance.

Although this analysis detected only minor variations in forecast precision with respect to base period length, this does not mean that planners need not pay attention to this issue. Only base periods of at least 10 years were considered here. Smith and Sincich (1990) found that shorter base periods were associated with larger errors, especially for longer forecast horizons.

Furthermore, for areas with particular past population change patterns, and for specific trend models, certain base periods can be more appropriate than others. The sensitivity of the exponential method is one example. A case could also be made for differentially weighting past population changes, e.g. weighting more recent changes more heavily. These are all decisions the population forecaster needs to make, and which should be based on professional knowledge. Isserman (2007) describes a case study for Harrison County, West Virginia, that illustrates how an analysis of demographic and economic trends encountered over the base period can be incorporated into a forecasting model.

Accuracy by Length of Projection Horizon, Population Size, and Growth Rate

Having examined the impact of base period length on projection accuracy, the focus now shifts to a discussion of county-level errors by forecast horizon. Starting first with the MAPEs for the all county total reported in Table 1a, one can see how precision declines with increasing projection horizons. This is a well established finding in the literature (see e.g. Keyfitz 1981; Smith and Sincich 1992; Stoto 1983). In general, for most projection methods the relationship between precision and the length of the horizon is linear or nearly linear (Smith and Sincich 1991). This is reflected in Table 1a, where the MAPEs increase steadily by about 10% to 14% each decade, depending on the method used. In contrast to precision, previous research has found no consistent relationship between bias and the length of the forecast horizon (Smith and Sincich 1991). The data in Table 1b appear to suggest otherwise, showing increasing bias with lengthening horizons. However, the apparent increase in the MALPE for longer horizons is really due to the lower precision of the longer-range projections.

Following the analysis of forecast accuracy for all counties, the study now turns to an investigation by demographic characteristic. Both population size and rate of growth have been found to be important and consistent determinants of projection precision, while results have been mixed with respect to bias. In general, when measured in percentage terms, projections made for larger places tend to be more precise than those for smaller places, and projections made for slow to moderately growing places tend to be more precise than those for fast growing or declining places. With respect to bias, areas that declined over the base period tend to be under-projected, while forecasts for areas that grew rapidly often turn out too high. Population size was generally not found to be related to bias (Isserman 1977; Murdock, Leistritz, Hamm, Hwang, and Parpia 1984; Smith 1987; Smith and Sincich 1988; Tayman 1996a; Tayman, Schafer, and Carter 1998; White 1954).

In actual forecasting situations, an area's growth rate over the projection horizon is unknown, as is its population size for the target year. Therefore, in this study, the rate of growth or decline refers to the per decade percentage change over the base period, and population size is measured at the launch year. The analysis distinguishes among six growth-rate categories and six size categories. Table 2 reports forecast errors by the rate of population growth, while Table 3 focuses on population size.

[Table 2 about here.]

To keep the discussion of forecast errors by demographic characteristics concise, the following analysis was restricted to 20 year horizons and 20 year base periods. Twenty year base period projections were chosen because, as the data in Table 1a have demonstrated, there was some improvement in precision over 10 year base periods. One could have also picked the 10–30 year average, which would have resulted in a further slight improvement in accuracy, but this would have entailed fewer projections to analyze. The pattern in the results for 10 and 30 year horizons were similar to those reported here for twenty year horizons, though the levels of precision were higher and lower, respectively. In contrast to Table 1, which was limited to the 1960–2000 target years, the data in the following tables use the entire data set, covering all target years from 1940 to 2000.

Table 2a reports MAPEs by the per decade rate of population change observed over the base period. The results confirm the well-known u-shaped form of the relationship between forecast precision and population growth (Isserman 1977; Murdock, Leistritz, Hamm, Hwang, and Parpia 1984; Smith 1987; Tayman 1996a): irrespective of technique, errors are largest for counties at both ends of the growth spectrum – those that experienced significant declines and those that grew rapidly. While all extrapolation techniques follow this basic pattern, there are noticeable differences among the methods. For counties that are declining rapidly, shift-share shows the highest and exponential the lowest errors. At the other end of the growth spectrum, constant-share and linear perform best and exponential worst. Interestingly, while constant-share is generally associated with low precision (Table 1a), for counties with high growth rates this technique proves very competitive. The two averages perform well throughout, apart from AV5 becoming influenced by the high MAPEs of the exponential method for high growth counties. For counties in the middle of the growth spectrum, all techniques provide similar levels of forecast precision; only shift-share and constant-share at times show elevated MAPEs.

These performance differentials can be used when deciding among methods to choose for areas with particular past growth characteristics. For example, areas that have grown rapidly should not be projected using the exponential method, while this method would work well for areas that have declined in population. Results from the performance of the individual trend models by growth rate will be applied later in the analysis in the calculation of composite averages.

Before moving on to the discussion of projection bias by population growth, it is instructive to look again at Figure 1, which shows the geographic pattern of forecast precision. While both population size and rate of growth impact forecast precision, the focus for now is on growth rates. The map illustrates how counties that experienced rapid and/or unpredictable population change are associated with low forecast precision. Examples include high growth areas of the South and West, and energy dependent boom-bust counties mostly in the Mountain States, Texas, and Appalachia. In contrast, the smallest forecast errors are achieved in counties in the Midwest and Northeast that have experienced relatively modest population growth throughout the 20th century.

Table 2b displays MALPEs by growth rate. For all techniques the relationship between the county characteristic and projection bias varies in a consistent fashion, following a stepwise pattern in which bias either increases or decreases along the growth spectrum. With the exception of constant-share, there is a tendency to under-project the target population for counties that experienced population declines over the base period, while counties that grew are likely to have projections that turn out too high. This supports the notion that population change patterns moderate over time, i.e. regress towards the mean (Beaumont and Isserman 1987; Smith 1987). It is an important finding that should be considered when producing population forecasts using trend extrapolation techniques. Moreover, it also affects other projection methods such as cohort-component and structural models through the assumptions made for the various variables in the model.

[Table 3 about here.]

In addition to population growth, the size of the population of an area being projected has been found to affect forecast error. The precision of the projections improves the larger the county (Table 3a), corroborating previous findings. For most methods and projection horizons, the MAPEs decrease consistently from the smallest to the largest counties, with the largest reduction in error recorded for the two smallest size categories. For some trend methods, and especially the exponential technique, the MAPEs increase again for the largest counties. This apparent anomaly can be explained by the confounding influence of population growth; i.e., the higher MAPEs for the largest size category are due to the fact that these counties experienced higher growth rates, on average, than counties in the next smaller size category over the base period, and not to population size effects as such (data not shown). The interaction between population size and rate of growth with respect to forecast precision can also be detected in Figure 1. Many of the counties with high forecast errors – especially in the West – experienced both rapid population change and entered the 20th century with small populations.

Finally, with respect to forecast bias, previous studies found either no consistent relationship between size and bias (Murdock, Leistritz, Hamm, Hwang, and Parpia 1984; Smith and Sincich 1988) or a spurious relationship that went away when controlled for differences in rates of growth (Smith 1987; Tayman, Schafer, and Carter 1998). In this analysis, population size appears to influence whether projections turn out too high or too low (Table 3b), but this is due to the confounding impact of population growth. To test for spuriousness, forecast errors by population size were analyzed within various growth categories (data not shown). When the rate of population growth was taken into account, projection bias did not vary much by population size.

The Role of Averaging

While averaging techniques have been advocated for forecasts in various fields (see e.g. Armstrong 2001; Clemen 1989; Makridakis, Andersen, Carbone, Fildes, Hibon, Lewandowski, Newton, Parzen, and Winkler 1982; Makridakis, Wheelwright, and Hyndman 1998; Webby and O'Conner 1996), they are surprisingly rare in population projections. In this study, averages were employed with respect to base period length and by extrapolation technique, which resulted in competitive projections, both in terms of precision and bias. So far, averaging was restricted to an overall average (of all base periods, or all extrapolation techniques) and a trimmed version that excluded the techniques that produced the highest and the lowest projection. But as the analysis by growth rate has exposed, some extrapolation methods performed better for fast growing areas, while others were more suitable for areas with declining populations, and this information can be used to develop more customized averages. In this section of the paper, four targeted averages are examined, which were constructed based on the performance of the individual trend techniques by growth rate as reported in Table 2. This is analogous to the "composite" approach advocated by Isserman (1977). Smith and Shahidullah (1995) applied this process for census tracts and found that excluding the exponential method for fast growing and shift-share for slow growing and declining places produced more accurate projections than a simple average.

[Table 4 about here.]

Composite or customized averages can be inclusive or exclusive. C1 and C2 in Table 4 include two different sets of techniques that performed well for particular growth categories, while C3 and C4 exclude techniques that performed not as well (see notes at the bottom of Table 4 for the specific extrapolation techniques that were used in the composites). Looking first at precision, one can see that C1 and C2 exhibit the lowest MAPEs for all projection horizons, with the improvement most pronounced for longer horizons. C3 and C4 show somewhat higher MAPEs, but perform well with respect to bias, especially C3.

Judging from these results, which projection technique should a population forecaster choose? For short horizons, most techniques provide similar results, with shift-share and constant-share showing somewhat larger errors. For longer horizons, C1 is the most precise of the techniques, but it is also more biased than AV3 and the other composite averages. The inclusive composite techniques were easy to define for counties with declining populations, where the exponential technique showed the lowest MAPEs and MALPEs throughout. On the other hand, for the fastest growing counties, linear and constant-share were the most precise, but their MALPEs were quite different, which is reflected when comparing C1 to C2. More surprising is why C3 and C4 do not perform better than AV3 given that the composites specifically exclude the techniques that were associated with the lowest precision for the particular growth categories rather than leaving out simply the highest and lowest projection. Excluding one or more individual techniques associated with larger errors may not produce the expected result because, while more biased and/or less precise by themselves, these techniques often counterbalance the projections from the other methods, which is particularly true for the exponential and constant-share methods. From this, it appears as if the inclusive composites work better than those that exclude certain techniques, but further refinements could be attempted. Yet whatever the exact specification, the benefits of averaging are sufficiently established to encourage planners to more seriously consider these tools when projecting future populations.

Trend Extrapolations vs. Cohort-Component Models

This analysis of population projection accuracy utilized an unprecedented dataset with respect to space and time. Previous long-term evaluations of forecast accuracy have been at the national or state level (Beaumont and Isserman 1987; Smith and Sincich 1988, 1990, 1991, 1992; White 1954). Yet in planning practice, projections are most needed for counties or smaller areas where previous evaluations have focused on shorter time periods (Isserman 1977; Murdock, Leistritz, Hamm, Hwang, and Parpia 1984; Smith 1987; Smith and Shahidullah 1995; Tayman 1996a; Tayman, Schafer, and Carter 1998). The results reported here largely support the conclusions of the earlier studies, which is an important finding, because the temporal and geographical scope of this study alleviates concerns regarding the ability to generalize the results reached in the earlier analyses. However, to do so, it was necessary to focus on trend extrapolation techniques, because it would have been impossible to create cohort-component models or other more complex projection techniques for such a large number of counties and so many time periods.

There have been numerous studies that have shown that complex models are no more accurate than simple trend extrapolations for projections of total population (Ascher 1978; Isserman 1977; Long 1995; Murdock, Leistritz, Hamm, Hwang, and Parpia 1984; Smith and Sincich 1992; Stoto 1983), a conclusion that has been reached in other fields of forecasting as well (Makridakis 1986; Makridakis and Hibon 1979; Mahmoud 1984). Nonetheless, simple trend extrapolation models are not always held in high regard among population forecasters, and the cohort-component method, in which fertility, mortality, and migration are projected separately, has become the de-facto standard, even for small areas. For example, a 1997 survey of state demographers found that 32 states used cohort-component methods for projecting county total populations, compared to 4 that employed a structural economic/demographic model, 3 that utilized trend extrapolation techniques, and 3 that applied either univariate or multivariate time series models (Federal-State Cooperative for Population Projections 1997).

The paper concludes by revisiting the debate about modeling complexity by comparing forecast errors obtained with the trend extrapolation techniques used in this study to those from externally produced cohort-component models at the county, state, and sub-county level. Before discussing the comparison, it is important to point out that the focus of this analysis is on projections of total population, which are required in many planning situations, and which form the core of population forecasting. Often, however, demographic detail such as information on the age structure of a population is needed as well, such as when planning for new schools or care facilities for the elderly. Here, the trend models are less suited than more complex models, but they can be useful nonetheless, as will be explained in the concluding section.

Tables 5–7 compare errors for the two types of projection models at the county, state, and sub-county level. At the county level (Table 5), the cohort-component projections were made by state demographers in the mid-1990s for the year 2000; at the state level (Table 6), they include cohort-component projections with 5, 15, and 25 year horizons made by federal demographers since the 1960s; and at the sub-county level, they include cohort-component projections for three metropolitan areas made by state demographers in Massachusetts during the 1990s.

[Table 5 about here.]

Table 5 presents forecast errors for county projections for the year 2000 for a sample of 10 states. The sources for the cohort-component projections are shown in Appendix B. Most of the cohort-component projections use base data from the mid-1990s, resulting in a projection horizon of about 5 years. The base data for the trend extrapolation methods include total population from the 1980 and 1990 censuses, as well as revised 1985 intercensal and original

1995 postcensal estimates, all from the US Census Bureau. Using the revised intercensal and the original postcensal estimates reflect the data that would have been available had the trend extrapolation projections been made at the time of the cohort-component projections. These base data were used to produce three sets of projections, covering 1980–1995, 1985–1995, and 1990–1995 base periods, from which an average was calculated. To keep the discussion succinct, only results for AV5 and AV3 are reported for the trend models.

The data in Table 5 demonstrate that trend extrapolations produce projections of total population with generally similar levels of precision and bias as cohort-component models. For some states, the extrapolations perform better, while in others the cohort-component models shine. The two trend extrapolation averages provide generally similar results, and while there are differences by individual states, they are too small to be of importance. Thus, for counties, and at least for short horizons, projections of total population made with simple trend extrapolation techniques are comparable to those made with cohort-component models.

To broaden the number of projection horizons and target years, one has to turn to projections for states, which have been produced by the US Census Bureau for some time. The Census Bureau projections contain several series that include varying assumptions about fertility and especially migration, which can be thought of as scenarios. In some years, the Census Bureau also produced a series that assumed no interstate migration, which was for illustrative purposes only and is not included here. The acronyms shown in Table 6 (e.g. I-B) are those originally used by the Census Bureau. A description of the specific assumptions applied in the Census Bureau projection series can be found in the *Current Population Reports* referenced in Appendix B.

[Table 6 about here.]

Table 6 shows forecast precision and bias for the two trend technique averages compared to several series of Census Bureau cohort-component projections for 1970, 1980, 1990, and 2000. Four sets of 5-year projections, three sets of 15-year projections, and one set of 25-year projections are examined. Base data used for the trend extrapolations are the two prior censuses before each target year, plus original postcensal estimates for the launch year and revised intercensal estimates for one of the three base years. As before, an average of the three base period lengths is calculated and reported in the table. For example, a five year projection for target year 1990 would use postcensal 1985 estimates for the launch year, and census counts for 1970 and 1980 as well as intercensal estimates for 1975 for the three base years used.

Compared to the county-level projections, there is more variability in the results among the various methods. For the 5-year projections, the MAPEs and MALPEs are similar between the extrapolation and cohort-component models for 1980 and 2000, while the Census Bureau projections are slightly more accurate for 1970 and significantly more accurate for 1990. One should note, though, that the Census Bureau projections for 1990 start with a 1988 launch year, and are thus really a two-year projection. For the longer range projections, the two types of methods provide similar results, with the trend models at times outperforming the cohort-component models both in terms of precision and bias. The data in Table 6 also demonstrate that bias is essentially unpredictable: of the 5-year projections, all extrapolation methods and all cohort-component series for 1970 and 1990 turned out too high, while the opposite was the case in 1980 and 2000. The main conclusion, once again, is that the two types of projection models provide generally comparable results.

Because many forecasting projects in planning involve a specific area rather than all states or all counties, a final comparison is presented for three metropolitan areas in

Massachusetts using minor civil division (MCD) data. The metropolitan areas were selected to provide broad coverage by geography, population size, and population growth rate. The trend extrapolations were calculated as before, using base data from 1980–1995. Also included are results from two cohort-component projections made by Massachusetts state demographers for the year 2000 that were released in 1994 and 1999 (see Appendix B for sources).

[Table 7 about here.]

The results presented in Table 7 provide further evidence that simple projection techniques are at least as accurate as more complex models for projections of total population. Providing similar results for the state overall, for the Barnstable and Boston metropolitan areas the trend extrapolations were slightly more precise than the cohort-component projections, while for Pittsfield the cohort-component models, especially the one produced in 1994, produced smaller errors. The data in Table 7 also nicely illustrate the general error structure of projections by size and growth rate. Of the three metro areas, MCDs in Boston have the largest average population size and generally low rates of population growth, resulting in the smallest forecast errors. The largest errors for the trend extrapolations and the 1999 cohort-component projections are recorded in Pittsfield, which has MCDs with the lowest average population size, and which was the only metro area to decline in population from 1995 to 2000. Barnstable (Cape Cod) falls in between, having MCDs with high growth rates but also larger average population sizes.

Discussion and Conclusion

Planners pursuing population projections face many decisions. First and foremost is the choice of projection techniques, which range from simple trend extrapolations to more complex cohort-component and structural models. Once chosen, the analyst then has to decide which base data to use, how to form assumptions, how to treat special populations, etcetera. All too often, these decisions are based on incomplete information, misconceptions, or legacy. So how should a practitioner approach the forecasting process? If we assume that the ultimate purpose of a population forecast is to provide a realistic picture of likely future population change, then a concern about forecast accuracy is warranted. However, for planners this ideal of value-neutral analytical forecasting has to be reconciled with the realities of the planning process where forecasts also need to be evaluated with respect to their credibility with policy makers and the public (Isserman 2007; Klosterman 2007). Because forecasting does not occur in a vacuum, the issues of technique versus advocacy, of pure versus normative forecasting, need to be considered (Skaburskis and Teitz 2003; Wachs 1986, 1989, 2001). Finally, there is the role of community involvement that shapes forecasts produced by planners (for a summary see Hopkins and Zapata 2007). This study, while acknowledging the constraints of forecasting in planning practice, has focused on the more technical aspects of model specification that planners need to make for each forecasting project. These have important consequences on the outcome, and without a proper understanding of the general characteristics of forecast error, projections remain a black box open to misunderstandings and potential misuse.

The study pursued three primary objectives. It first examined the relationship between the length of the base period and the length of the projection horizon with respect to projection accuracy. This is a decision planners have to make at the beginning of each forecasting project, and it is an issue that has received surprisingly little attention in the literature. The main finding of this paper is that while the length of the base period beyond 10 years has only a limited impact on projection precision, choosing an appropriate base period nevertheless demands attention, because some projection techniques – the exponential model being a prime example – can quickly lead to unrealistic forecasts.

The second objective of the analysis was to assess typical forecast errors for counties. The aggregate analysis revealed that forecast precision decreases about linearly with increases in the projection horizon. The length of the projection horizon had no consistent impact on bias. The disaggregate analysis showed that both size and growth impact forecast precision. As expected, projections become more precise with increasing population size. However, most of the improvement comes at fairly low size levels. Indeed, it could be argued that for all but the smallest areas size alone is only a limited indicator of forecast precision and that growth dynamics are of greater importance. With respect to the latter, the study revealed a u-shaped relationship: forecast precision is lowest for areas that are declining or growing rapidly and highest for areas with little change in either direction over the base period.

In addition to variations in precision, the forecasts also revealed differences in bias by growth category, whereas population size had no consistent impact. Counties that experienced population declines over the base period tend to be under-projected while those that grew rapidly are projected too high. The more rapidly the population declined or increased over the base period, the more negative or positive the bias of the ensuing projections. This result underscores the tendency of population growth patterns to moderate over time and lends strong support to the notion of a regression towards the mean (Beaumont and Isserman 1987; Smith 1987). It should be kept in mind when forming assumptions; otherwise, high growth rates experienced in the recent past may be assumed to continue for too long, leading to unrealistically high forecasts.

These results can be considered benchmarks that are useful for planning purposes. For example, as Table 3a illustrated, for small areas with a population of less than 2,500 people, a twenty year projection will result in a forecast error of about 40%, which can make a big difference when planning for future infrastructure projects. Uncertainty of that kind is unfortunate but needs to be considered. It demonstrates that it is imperative that the analyst pays special attention when projecting the population of small areas, areas undergoing rapid population change, and when making longer-term projections. While projecting small and/or rapidly changing places will always be a challenge, a careful choice of methods, base data, and assumptions, when combined with the application of local knowledge, will lead to the best possible projection outcomes.

The third focus of the paper was on forecast error by forecast technique. For that purpose, individual trend extrapolation techniques were compared to averages, and trend extrapolations were further checked against cohort-component models. With respect to the former, the various averages led to promising results, i.e. to projections with higher precision and lower bias than many of the individual extrapolation techniques. Averaging also worked well when deciding among base periods. Furthermore, averaging works not only for trend extrapolation techniques but can also be useful in a cohort-component setting when deciding which demographic rates to choose (Isserman 1993). For example, a recent set of county population projections by race and Hispanic origin for Minnesota employed a cohort-component model in which two different methods of projecting migration were averaged (Minnesota State Demographic Center 2005).

The generally good performance of averaging raises the question why these techniques are so seldom employed in actual population forecasting. Booth (2006, 570), in a review of the past quarter century of demographic forecasting, cites several studies that have advocated combining forecasts, yet states that "the idea has not been embraced." Why not? Averaging techniques are not always appropriate, and their composition should be carefully considered, but the empirical evidence clearly supports their increased usage.

With respect to the choice of projection type, the cohort-component model has become the de-facto standard, being regularly implemented for areas where simpler techniques, such as trend extrapolations, might be just as suitable. As the comparison of the two projection model types has shown, there were few instances where the more complex techniques outperformed the extrapolations. But why is it that a simple technique such as the linear trend model provides projections that are as accurate, on average, as those derived from more sophisticated techniques such as cohort-component models that specifically account for the demographic processes of births, deaths, and migration by which a population changes? Reasons include that projecting fertility, mortality, and migration rates (or structural variables) are as difficult as, or even more difficult than, projecting changes in total population; because more complex techniques require detailed input data which may not be available or reliable; and because there exists some irreducible level of uncertainty about the future that no method, however sophisticated, can overcome time and again (Smith, Tayman, and Swanson 2001). According to Pant and Starbuck (1990, 442), "a general law seems to be at work: more complex, subtle, or elegant techniques give no greater accuracy than simple, crude, or naïve ones. More complex methods might promise to extract more information from data, but such methods also tend to mistake noise for information. As a result, more complex methods make more serious errors, and they rarely yield the gains they promised."

This does not mean that simple techniques are always appropriate, and informed judgment is needed to determine when and how these methods can best be applied (Smith 1997). Furthermore, there are situations where a cohort-component model would be advisable, e.g.

when demographic characteristics are needed such as when projecting the need for schools, hospitals, nursing homes, or other facilities that serve specific segments of a population (for an evaluation of the accuracy of population projections by age see Smith and Tayman 2003); or a structural model, which is useful for evaluating scenarios and for linking projections to changes in employment, transportation, and land use patterns, which are often important to planners (Smith, Tayman, and Swanson 2001; Tayman 1996b).

This raises the question why a practitioner should bother to deal with trend extrapolation methods at all, and not simply use cohort-component methods for forecasting projects that require demographic characteristics. Yet it can be argued that trend models are useful even when demographic characteristics are also required. For small areas the necessary input data for a cohort-component or structural model are often not available. Even if they can be obtained, they are seldom reliable, requiring numerous adjustments; and even when the data are of sufficient quality, the practitioner still has to make choices regarding which variables to include in the model. Furthermore, trend methods can easily incorporate the most recent estimates, while the inputs required for cohort-component and structural models often lag in time. Perhaps the biggest advantage of trend models is that they reduce the potential for unintentionally biasing the projections, which can happen quite quickly during the assumption specification stage of more complex models. Using averages of various trend techniques and base periods, one is more likely to get a neutral forecast of total population, especially for small areas. The needed demographic characteristics can then be obtained with cohort-component or structural techniques that are controlled to the previously produced population totals. At the very least, the trend projections provide an additional perspective, i.e. population figures that can be compared to results obtained with other models. Trend extrapolations are easy enough to implement that the benefits of their use should outweigh any extra effort. Following Smith, Tayman, and Swanson (2001), Figure 2 provides a brief summary that compares the respective strengths and weaknesses of the various types of projection methods.

[Figure 2 about here.]

Advancing our knowledge about population projections is important, and so is research that further refines the methods used. Using sophisticated projection models is popular, because it conveys professionalism. Yet, as Skaburskis (1995: 200) warns, "the allure of large models may be due to our wanting more certainty when it is most unattainable. To fall for the allure is to decrease the thoughtfulness of planning decisions." Based on the results of this study, one can question whether the limited time and resources many practitioners have when projecting future populations might not be better served by paying more attention to factors that actually make a difference. Dealing with boundary changes, cleaning up and checking the reliability of the data, and accounting for special events come to mind in this regard. These are particularly important for small areas, and can have a major impact on forecast error. Once data quality is established, one should think carefully about the assumptions made about future population trends, because the core assumptions underlying each population forecast tend to be more important on the outcome than the methods used (Ascher 1978). Finally, while all projections involve some judgments, it is important to explain the reasoning for making specific choices in the projection documentation (Pittenger 1977).

Calculations of future populations are only one aspect of the planning process, albeit an important one. Planners are in a unique position not only to project the future but also to shape it. Myers (2001, 394) urged that planners "need to become much more sophisticated in the use of projections than they have in the past if they are to reclaim their leadership of the future."

Projections inevitably involve many unknowns. We will never be able to perfectly forecast a population all of the time. Nevertheless, concentrating on those factors that have been found to make a difference will lead to better projections. The analyses presented in this paper with respect to model choice and other specification issues, when considered within the social, political, and economic contexts of the areas being projected, provide planners with a foundation for making those informed choices.

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Appendix A: Trend Extrapolation Techniques

Simple Methods

LIN: In the linear extrapolation technique, it is assumed that the population will increase (decrease) by the same number of persons in each future decade as the average per decade increase (decrease) observed during the base period:

$$P_t = P_l + (x / y) * (P_l - P_b),$$

where P_t is the population in the target year, P_l is the population in the launch year, P_b is the population in the base year, x is the number of years in the projection horizon, and y is the number of years in the base period.

EXP: In the exponential technique, it is assumed that the population will grow (decline) by the same rate in each future decade as it did, per decade, during the base period:

$$P_t = P_l e^{rx}, \qquad r = [ln\ (P_l / P_b)] / y,$$

where e is the base of the natural logarithm and ln is the natural logarithm.

Ratio Methods

The share-of-growth, shift-share, and constant-share techniques require an independent national projection for the target year population. These were produced by applying the linear and exponential trend extrapolation techniques to the national population for each of the 63 projection horizon / base period combinations. To flatten out the discrepancies between the linear and exponential methods, an average of the two techniques was then calculated and used for the three ratio methods.

Ratio methods express the population (or population change) of a smaller area as a proportion of the population (or population change) of a larger area the smaller area is located in. In the following formulas, lowercase letters denote county-level values, and uppercase letters denote national-level values. The same formulas can be applied to other areas of geography as well, such as when making projections for census tracts, where the lowercase letters would then denote the census tract and uppercase letters would refer to the county.

SHR: In the share-of-growth technique, it is assumed that a county's share of national population growth will be the same over the projection horizon as it was during the base period:

$$P_t = P_l + [(P_l - P_b) / (P^l - P^b)] * (P^t - P^l)$$

SFT: In the shift-share technique, it is assumed that the average per decade change in each county's share of the national population observed during the base period will continue throughout the projection horizon:

$$P_t = P^t * [P_l / P^l + (x / y) * (P_l / P^l - P_b / P^b)]$$

COS: In the constant-share technique, it is assumed that a county's share of the national population will be the same in the target year as it was in the launch year:

$$P_t = (P_l / P^l) * P^t$$

Appendix B:

Sources for County Cohort-Component Projections Used in Table 5

Arizona, 1997, *July 1, 1997 to July 1, 2050 Arizona county population projections*. Arizona Department of Economic Security, Research Administration, Population Statistics Unit.

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Sources for State Cohort-Component Projections Used in Table 6

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Sources for Sub-county Cohort-Component Projections Used in Table 7

Massachusetts, 1994, *Projections of the Population, Massachusetts Cities and Towns, Year 2000 and 2010*. Massachusetts Institute for Social and Economic Research, University of Massachusetts.

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Table 1a. MAPE by Projection Horizon and Base Period (1960–2000 Target Years)

Horizon	Base	LIN	SHR	SFT	EXP	COS	AV5	AV3
10	10	10.5	10.9	12.7	11.0	14.1	9.8	10.6
10	20	9.8	10.2	12.4	10.1	13.6	9.5	9.8
10	30	10.0	10.4	13.4	10.3	13.5	9.8	10.0
10	Ave	9.6	9.9	12.1	9.9	13.7	9.3	9.6
20	10	20.7	22.0	27.8	23.7	27.3	19.9	20.9
20	20	19.4	20.6	27.4	22.7	27.4	19.4	19.5
20	30	19.8	21.0	29.5	22.4	27.5	19.8	19.8
20	Ave	18.8	19.9	26.5	21.7	27.3	18.7	18.9
30	10	32.8	35.6	47.4	4,488.7	43.7	921.4	33.4
30	20	30.6	33.3	45.7	57.7	42.9	34.7	31.2
30	30	31.0	34.0	48.3	70.7	42.3	38.2	32.0
30	Ave	30.1	32.8	45.6	1,537.3	42.9	330.3	30.8

Table 1b. MALPE by Projection Horizon and Base Period (1960–2000 Target Years)

Horizon	Base	LIN	SHR	SFT	EXP	COS	AV5	AV3
10	10	-3.0	-3.0	-5.0	-0.2	6.6	-0.9	-2.5
10	20	-3.2	-3.1	-6.0	-0.2	6.1	-1.3	-2.6
10	30	-3.9	-3.7	-7.9	-0.4	6.0	-2.0	-3.1
10	Ave	-3.4	-3.3	-6.3	-0.3	6.2	-1.4	-2.7
20	10	-3.7	-3.6	-9.3	5.0	15.6	0.8	-2.2
20	20	-5.4	-5.3	-13.7	4.1	16.0	-0.9	-3.8
20	30	-5.9	-5.7	-16.6	3.4	15.9	-1.8	-4.2
20	Ave	-5.0	-4.9	-13.5	4.1	15.9	-0.7	-3.4
30	10	-8.2	-8.0	-20.1	4,458.1	29.3	890.2	-5.3
30	20	-8.1	-7.9	-23.0	29.1	28.5	3.7	-5.2
30	30	-6.1	-5.3	-22.5	43.4	27.7	7.4	-2.8
30	Ave	-7.7	-7.3	-22.9	1,510.2	28.5	300.2	-4.5

Table 2a. MAPE by Projection Horizon and Growth Rate, 20 Year Base Period

Horizon	Growth Rate	LIN	SHR	SFT	EXP	COS	AV5	AV3
20	< -15%	49.1	56.6	86.1	29.0	45.7	36.3	44.5
20	-15% to -5%	18.3	20.6	40.5	15.9	39.3	16.2	18.1
20	-5% to 5%	14.2	14.3	18.9	14.2	27.2	14.4	14.2
20	5% to 15%	17.3	17.9	17.4	18.2	21.0	18.0	17.8
20	15% to 30%	20.9	22.4	23.8	26.6	20.6	22.4	22.3
20	> 30%	30.6	32.8	38.5	107.8	29.3	43.7	33.6

Table 2b. MALPE by Projection Horizon and Growth Rate, 20 Year Base Period

Horizon	Growth Rate	LIN	SHR	SFT	EXP	COS	AV5	AV3
20	< -15%	-48.9	-56.6	-86.1	-27.2	41.2	-35.5	-44.3
20	-15% to -5%	-13.6	-17.0	-39.8	-9.3	37.4	-8.5	-13.3
20	-5% to 5%	-2.0	-2.1	-13.1	-1.7	23.8	1.0	-1.9
20	5% to 15%	2.2	4.3	1.3	5.2	10.8	4.8	3.9
20	15% to 30%	4.4	8.0	11.2	16.2	0.2	8.0	8.0
20	> 30%	5.1	10.6	21.1	98.7	-14.2	24.2	12.2

Table 3a. MAPE by Projection Horizon and Population Size, 20 Year Base Period

Horizon	Population Size	LIN	SHR	SFT	EXP	COS	AV5	AV3
20	< 2,500	41.0	43.9	54.8	51.4	45.3	39.2	40.2
20	2,500 - 7,500	28.6	31.5	44.5	54.8	37.8	32.3	29.1
20	7,500 - 15,000	21.4	23.1	32.9	27.0	33.4	22.0	21.7
20	15,000 - 30,000	17.3	18.2	24.8	19.8	25.3	17.4	17.6
20	30,000 - 100,000	16.1	16.8	19.8	21.5	20.7	16.9	16.7
20	> 100,000	15.7	16.9	19.0	27.4	19.2	17.6	17.0

Table 3b. MALPE by Projection Horizon and Population Size, 20 Year Base Period

Horizon	Population Size	LIN	SHR	SFT	EXP	COS	AV5	AV3
20	< 2,500	-16.2	-17.8	-30.0	12.2	23.6	-5.6	-13.1
20	2,500 - 7,500	-6.0	-7.0	-20.0	29.9	28.0	5.0	-3.6
20	7,500 - 15,000	-4.0	-4.7	-17.7	7.1	26.7	1.5	-2.7
20	15,000 - 30,000	-3.4	-3.1	-12.1	2.7	18.1	0.4	-2.2
20	30,000 - 100,000	-1.3	0.7	-2.1	9.0	7.2	2.7	1.0
20	> 100,000	0.7	4.1	6.6	19.9	-1.3	6.0	4.5

Table 4a. MAPE by Projection Horizon and Extrapolation Technique, 20 Year Base Period

Horizon	LIN	SHR	SFT	EXP	COS	AV5	AV3	C1	C2	C3	C4
10	10.5	10.9	13.0	11.7	14.3	10.5	10.6	10.3	10.1	11.1	11.1
20	19.7	21.1	28.2	27.2	27.8	20.6	20.2	18.2	18.5	21.2	21.3
30	31.0	34.0	46.9	79.7	43.8	39.6	32.1	27.6	28.4	33.7	33.5

Table 4b. MALPE by Projection Horizon and Extrapolation Technique, 20 Year Base Period

Horizon	LIN	SHR	SFT	EXP	COS	AV5	AV3	C1	C2	C3	C4
10	-1.6	-1.4	-4.2	2.1	7.3	0.5	-0.9	-2.5	-1.0	-0.3	-1.2
20	-3.2	-2.7	-10.9	10.0	17.6	2.2	-1.3	-3.9	-1.5	0.2	-2.4
30	-5.2	-4.3	-19.1	53.2	30.0	10.9	-1.8	-4.9	-2.1	1.5	-3.9

Note: Composite averages were created from the following techniques

C1 = EXP if growth rate < -5%
= LIN if growth rate -5% to 15%
= COS if growth rate > 15%

C2 = EXP if growth rate < -5%
= LIN if growth rate > -5%

C3 = Average of LIN/SHR/EXP/COS if growth rate < -5%
= Average of LIN/SHR/SFT/EXP if growth rate -5% to 15%
= Average of LIN/SHR/SFT/COS if growth rate > 15%

C4 = Average of LIN/SHR/EXP if growth rate < 5%
= Average of LIN/SHR/SFT if growth rate 5% to 15%
= Average of LIN/SHR/COS if growth rate > 15%

Table 5a. MAPEs for Counties by State, ~5 Year Horizon for Target Year 2000:
Trend Extrapolations vs. Cohort-Component Methods

	ALL	AZ	CA	IL	MI	MN	MO	OH	PA	SC	WA
AV5	3.4	7.5	3.9	2.6	3.6	3.0	3.6	2.4	2.2	4.6	4.0
AV3	3.4	7.0	4.3	2.5	3.5	3.7	4.0	2.4	2.0	4.6	4.2
Cohort-Comp.	3.5	5.5	3.6	2.9	3.8	3.6	3.4	3.1	3.3	4.5	2.9

Table 5b. MALPEs for Counties by State, ~5 Year Horizon for Target Year 2000:
Trend Extrapolations vs. Cohort-Component Methods

	ALL	AZ	CA	IL	MI	MN	MO	OH	PA	SC	WA
AV5	-0.2	-0.9	1.1	0.3	-2.2	-1.2	-2.1	0.3	-0.1	-2.2	2.9
AV3	-0.9	-1.8	1.3	-0.5	-1.9	-2.5	-2.3	0.6	0.1	-2.8	2.6
Cohort-Comp.	-0.8	-2.3	2.4	-0.1	-2.6	-1.9	-1.0	-1.2	0.0	-2.8	1.3
# of Counties	700	15	58	102	83	87	115	88	67	46	39

Table 6. MAPEs and MALPEs for States: Trend Extrapolations vs. Cohort-Component Methods

	MAPE				MALPE			
Horizon	5	5	5	5	5	5	5	5
Target Year	1970	1980	1990	2000	1970	1980	1990	2000
AV5	3.9	4.3	4.3	2.4	3.1	-2.1	2.6	-1.7
AV3	3.7	3.7	4.4	2.5	2.8	-2.0	2.6	-1.9
I-B	3.3				1.6			
II-B	3.3				1.6			
I-D	3.1				0.3			
II-D	3.0				0.4			
II-A		4.6				-3.2		
II-B		3.6				-2.5		
A			1.6				0.9	
B			2.1				1.3	
C			1.6				0.9	
A				2.5				-1.2
B				2.3				-1.4

	MAPE				MALPE			
Horizon	15	15	15	25	15	15	15	25
Target Year	1980	1990	2000	2000	1980	1990	2000	2000
AV5	8.9	5.8	6.5	7.8	3.5	0.1	0.9	-1.9
AV3	8.5	5.0	7.4	7.2	2.4	-0.1	0.5	-2.6
I-B	9.6				3.2			
II-B	9.8				3.7			
I-D	9.1				-3.7			
II-D	8.9				-3.2			
II-A		6.4		10.1		-1.9		-6.6
II-B		5.5		8.8		-0.3		-4.5
A			7.7				-5.7	
B			6.0				-3.2	
C			6.6				-5.1	

Table 7. MAPEs and MALPEs for Massachusetts MCDs, Target Year 2000:
Trend Extrapolations vs. Cohort-Component Methods

	MAPE				MALPE			
	MA	Barnstable	Boston	Pittsfield	MA	Barnstable	Boston	Pittsfield
AV5	6.8	8.0	5.6	10.2	0.0	-2.3	-1.0	5.1
AV3	7.0	8.5	5.4	11.3	0.7	-2.6	-0.4	6.6
CC_94	7.0	9.2	6.8	7.8	-1.5	-9.1	-2.2	3.0
CC_99	8.1	9.3	6.5	9.9	3.2	0.8	1.5	8.3
N	351	16	97	14	351	16	97	14

Figure 1. Absolute Percent Errors, AV3 Trend Extrapolation Method, 20 Year Projection Horizon, 20 Year Base Period, Average of Target Years from 1940 to 2000

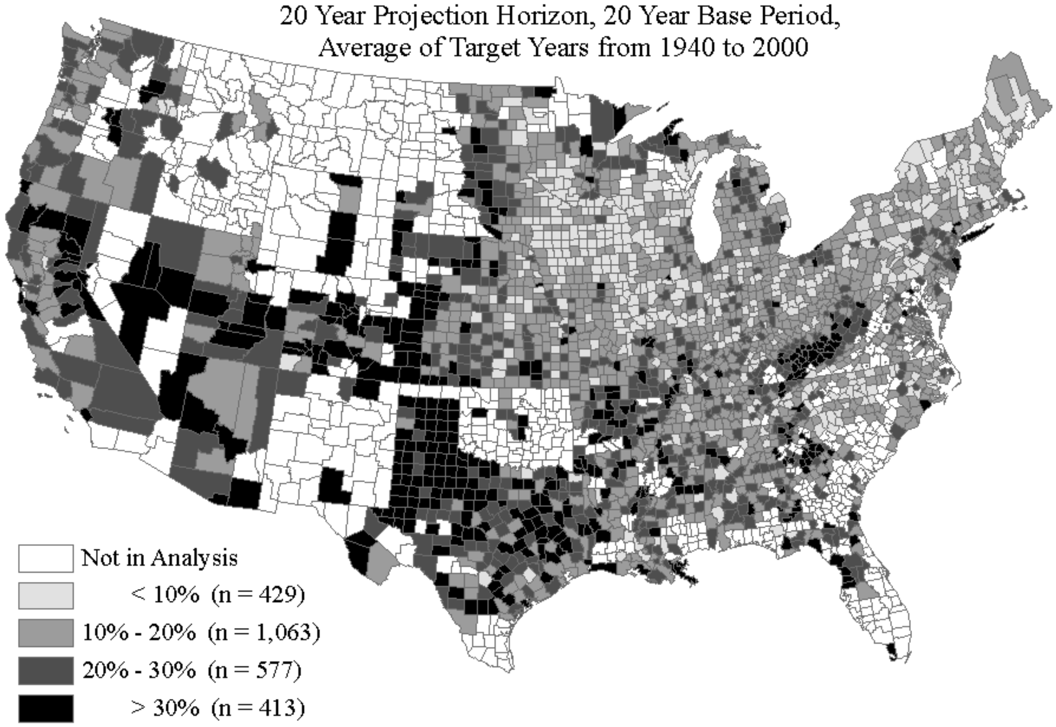

Figure 2. Comparison of Projection Methods

	Extrapolation	Cohort-Component	Structural
Forecast Accuracy	–	–	–
Political Acceptability	–	–	–
Face validity	–	–	–
Plausibility	–	–	–
Cost of Production	***	**	*
Timeliness	***	**	*
Ease of Application	***	**	*
Ease of Explanation	***	**	*
Geographic Detail	***	**	**
Demographic Detail	*	***	***
Temporal Detail	***	***	***
Usefulness for Scenarios	*	**	***

Note: *** good, ** average, * poor, – cannot generalize