FACTORS AFFECTING THE ACCURACY OF SUBCOUNTY POPULATION FORECASTS

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ABSTRACT

Small area population forecasts are used for a wide variety of planning and budgeting purposes. Using 1970–2005 data for incorporated places and unincorporated areas in Florida, we evaluate the accuracy of forecasts made with several extrapolation techniques, averages, and composite methods, and assess the effects of differences in population size, growth rate, and length of forecast horizon on forecast errors. We further investigate the impact of adjusting forecasts to account for changes in special populations and annexations. The findings presented in this study will help practitioners make informed decisions when they construct and analyze small area population forecasts.

KEYWORDS

Population projections; forecast accuracy; averaging techniques; special populations; annexations; small areas.

INTRODUCTION

Small-area population forecasts play a critical role in many types of planning, budgeting, and policy decisions. They are used for a wide variety of purposes, such as planning for changes in public school enrollment (McKibben 1996), developing conservation strategies (Steinitz, Aris, Bassett, Flaxman, Goode, Maddock, Mouat, Peiser, and Shearer 2003), selecting locations for new fire stations (Tayman, Parrott, and Carnevale 1994), planning for future water consumption (Texas Water Development Board 1997), and evaluating the demand for additional hospital services (Thomas 1994). Furthermore, they are often mandated by state and local governments for the development of comprehensive plans. For example, Chapter 9J-5 of the Florida Administrative Code requires estimates and projections of permanent and seasonal residents and states that “the department will evaluate the application of the methodology utilized by a local government in preparing its own population estimates and projections and determine whether the particular methodology is professionally accepted” (Florida Administrative Code 2001: 9J-5.005(2)(e)).

What determines whether a particular technique is “professionally accepted”? For researchers, accuracy is generally the primary criterion used in evaluating forecasting techniques (Yokum and Armstrong 1995). Planners, however, must consider a variety of additional factors such as costs of production, timeliness, ease of application and explanation, provision of necessary detail, validity of assumptions, usefulness as an analytical tool, political acceptability, and internal and external consistency (Smith, Tayman, and Swanson 2001; Murdock, Hamm, Voss, Fannin, and Pecotte 1991). As Sawicki (1989, 53) put it, “Accuracy is not everything.”

Further complicating the issue is that planners are often called upon to balance the merits of pure or objective forecasts against those of normative or advocacy forecasts (Isserman 2007;

Skaburskis and Teitz 2003; Wachs 1989). For advocacy purposes, forecasts need not be accurate in order to have their intended political effects (Wachs 2001). In some instances, in fact, greater accuracy may be counterproductive because less objective forecasts may help projects gain approval or funding (Flyvbjerg, Skamris Holm, and Buhl 2005). Planners may also need to consider the role of community participation (Hopkins and Zapata 2007) and the involvement of policy makers (Klosterman 2007) in the forecasting process.

Planners thus face a variety of conflicting interests and objectives when constructing or evaluating population forecasts. Regardless of the circumstances, however, well-informed decisions require at least a basic assessment of the expected level of forecast accuracy. Planners must therefore be knowledgeable regarding typical error patterns and how those patterns vary from one forecasting technique to another and according to the characteristics of the geographic areas being forecasted. Although other considerations are important, accuracy cannot be ignored and often plays a major role in determining whether a particular forecasting technique is judged to be "professionally acceptable."

We have three main objectives in this paper. First is to provide a comprehensive analysis of population forecast errors for subcounty areas. Although many studies have evaluated forecast accuracy for large geographic areas such as nations, states, and counties, few have done so for subcounty areas. Analyses at the subcounty level are important because there are far more subcounty governments than state or county governments in the United States and a great deal of government and business planning is conducted at that level. Our focus is on Florida, a large state with subcounty areas covering a wide range of population size and growth categories. We believe an analysis of subcounty forecast errors in Florida will provide insights into small-area error patterns more generally.

Second is to examine the potential benefits of using a combination of forecasts rather than forecasts based on a single technique. Combinations often provide greater accuracy and less variability than individual forecasts because they incorporate more information and reduce the impact of outliers (Ahlburg 1995; Isserman 1977; Rayer 2008; Smith and Shahidullah 1995). The combinations we investigate include averages of individual forecasts and a "composite" method in which the choice of forecasting technique is based on the characteristics of an area.

Third is to investigate whether accounting separately for special populations (e.g., prison inmates, residents in college dormitories) and annexations can reduce forecast errors. Special populations and annexations can confound the forecasting process, but to our knowledge no study has evaluated their impact on forecast errors. Although changes in special populations affect growth trends for states and counties, they are of greater concern at the subcounty level because they typically account for a much larger proportion of the total population. The same is true for annexations, which occur almost exclusively at the subcounty level.

METHODS

Following Smith, Tayman, and Swanson (2001), we use the following terminology to describe population forecasts: 1) *Base Year* refers to the year of the earliest population size used to make a forecast; 2) *Launch Year* refers to the year of the latest population size used to make a forecast; 3) *Target Year* refers to the year for which population size is forecasted; 4) *Base Period* refers to the interval between the base year and launch year; and 5) *Forecast Horizon* refers to the interval between the launch year and target year. For example, if data from 1970 and 1980 were used to forecast population in 1990, then 1970 would be the base year, 1980 would be the launch year, 1990 would be the target year, 1970–1980 would be the base period, and 1980–1990 would be the forecast horizon.

The population data used in this study are based on census counts for 1970, 1980, 1990, and 2000, mid-decade estimates for 1975, 1985, and 1995, and postcensal estimates for 2005 for subcounty areas in Florida. The subcounty areas cover the entire territory of each county and consist of incorporated places and unincorporated areas. The former include cities, towns, and villages; the latter make up the remainder of each county. Only places that have been incorporated throughout the entire study period are included in the analysis, resulting in a sample of 383 incorporated places. Places that incorporated after 1970 were assigned to the unincorporated area of their respective counties. There are 66 unincorporated areas in the analysis, one for each county in Florida except Duval County, whose entire territory is incorporated.

We produced the mid-decade estimates using residential electric customer data, decennial census counts, and interpolated population/customer ratios. Estimates for 2005 were produced by the Bureau of Economic and Business Research (BEBR) at the University of Florida (Bureau of Economic and Business Research 2006). Although estimates are generally less accurate than census counts, using a mixture of estimates and census counts when constructing and evaluating forecasts reflects actual forecasting practice and expands the number of forecast horizons that can be examined in the present study. In an analysis of alternative data sets, we found that forecast errors based on data that included both census counts and mid-decade estimates were very similar to errors based solely on census counts (data not shown).

We constructed forecasts with 10- and 20-year horizons for launch years 1980, 1985, 1990, and 1995. For each launch year and horizon, we applied six techniques: linear, exponential, share-of-growth, shift-share, constant-share, and constant-size. The first four are trend extrapolations while the latter two hold one data point constant: share of population and population size, respectively. A mathematical description of these techniques is shown in the appendix.

Extrapolation techniques such as these are commonly used for small-area population forecasts because they have small data requirements, can incorporate recent data, and are easier to apply than more complex cohort-component and structural models. Although simple in design, these techniques do not sacrifice accuracy for simplicity: Numerous studies have found extrapolation techniques to provide forecasts of total population that are at least as accurate as those derived from more complex models (see e.g. Ascher 1978; Chi 2009; Isserman 1977; Long 1995; Morgenroth 2002; Pflaumer 1992; Rayer 2008; Smith and Sincich 1992; Smith and Tayman 2003; Stoto 1983). Similar results have been found in other fields as well (Goldstein and Gigerenzer 2009; Mahmoud 1984; Makridakis 1986; Makridakis and Hibon 1979, 2000).

We examine forecast accuracy in two ways, one reflecting *precision* and the other *bias*. Precision refers to the difference between forecasts and subsequent census counts or population estimates, ignoring the direction of errors. Bias refers to the tendency for forecasts to be too high or too low by accounting for the direction of errors.

We use the *mean absolute percent error* (*MAPE*) as our measure of precision. 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. Forecasts that are perfectly precise result in a MAPE of zero. The MAPE has no upper limit – the larger the MAPE, the lower the precision of the forecasts.

We use the *mean algebraic percent error* (*MALPE*) as our measure of bias. It can be calculated analogously to the MAPE, using algebraic rather than absolute percent errors:

$$MALPE = \Sigma\ PE_t / n$$

Negative values of the MALPE indicate a tendency for forecasts to be too low, whereas positive values indicate a tendency to be too high.

Being arithmetic means, the MAPE and MALPE are susceptible to outliers, but both provide useful summary measures that are commonly used for evaluation purposes (Isserman 1977; Rayer 2007; Smith 1987; Tayman, Schafer, and Carter 1998). For some purposes, of course, planners will be more concerned about absolute numerical errors than percent errors (e.g., when using population forecasts to determine whether to build a new school). For evaluating forecast accuracy and comparing places with different characteristics, however, we believe percent errors provide the most useful summary measures.

BASIC RESULTS

Overall Accuracy

A fundamental part of every forecasting project is deciding which base data to include. Previous studies have found that 10 years of base data are generally necessary and are often sufficient to achieve the greatest possible precision for short- to medium-range population forecasts, though some extrapolation techniques – in particular, the exponential method – sometimes benefit from longer base periods (Beaumont and Isserman 1987; Smith and Sincich 1990; Rayer 2008). In this study, we evaluated forecasts with base periods ranging in five-year intervals from five to 20 years and found that increasing the length of the base period from five to 10 years generally improved precision but that further increases had little additional impact (data not shown). Accordingly, we report results only for forecasts with 10-year base periods.

Table 1 shows MAPEs and MALPEs for 10- and 20-year horizons for each forecasting technique. This table shows average errors for forecasts of all target years within each forecast horizon (four sets of forecasts for 10-year horizons and two sets for 20-year horizons). For every technique, precision declines with increasing horizon length. This is not surprising, of course, and is a well established finding in the population forecasting literature (Keyfitz 1981; Smith and Sincich 1992; Stoto 1983). Of the six techniques, linear provides the most precise forecasts for both horizons, followed by the constant-size and share-of-growth techniques. The exponential technique produces the largest errors, especially for longer horizons. Although this technique can be an appropriate choice in some instances, it must be applied judiciously because it often produces unreasonable forecasts. We address the particular strengths and weaknesses of individual techniques later in the paper.

(Table 1 about here)

Table 1b shows the results for MALPEs. Both the linear and shift-share techniques have a slight downward bias for 10-year horizons and a slight upward bias for 20-year horizons. The exponential and constant-share techniques have a substantial upward bias for both horizons and the constant-size technique has a substantial downward bias for both. In contrast to precision, previous research has found no consistent relationship between bias and length of forecast horizon (Smith and Sincich 1991). Although the data in Table 1b show a positive relationship between bias and length of horizon for most techniques, we believe this result is spurious because an examination of MALPEs for individual target years found them to vary significantly within each horizon (data not shown).

It is likely that forecast accuracy varies systematically with the characteristics of the areas being analyzed. We turn next to two characteristics that have often been considered: population size and growth rate. The effects of other characteristics could also be investigated. In particular, the spatial pattern of forecast errors is a topic deserving further analysis.

Accuracy by Population Size

Previous research has found population size to affect the precision but not the bias of population forecasts (e.g., Rayer 2008; Smith and Shahidullah 1995; Smith and Sincich 1988; Tayman, Schafer, and Carter 1998). Forecasts generally become more precise as population size increases; consequently, forecasts for the nation tend to be more precise than forecasts for states, forecasts for states more precise than forecasts for counties, and forecasts for counties more precise than forecasts for subcounty areas. The largest improvements in precision typically occur in the smallest size categories; that is, errors generally become smaller as population size increases, but at a declining rate.

Figure 1a shows MAPEs by population size in the launch year for the six forecasting techniques. To save space, we present results only for forecasts with a 10-year horizon; the patterns were similar, though more accentuated, for forecasts with a 20-year horizon. For four of the six techniques, the forecasts become steadily more precise as population size increases. The largest improvements occur in the smallest size categories. MAPEs are very large for the smallest subcounty areas, but decline considerably as population size increases to about 5,000; beyond that point, further increases in size lead to relatively small additional improvements in precision. For the exponential and constant-size techniques, MAPEs have a u-shaped relationship with population size. This apparent anomaly can be explained by the confounding influence of the population growth rate. As discussed in the following section, high growth rates are generally associated with relatively large MAPEs, and subcounty areas in the two largest size categories generally experienced higher growth rates than those in the smaller size categories (data not shown).

(Figure 1 about here)

Figure 1b shows conflicting results regarding the relationship between population size and bias. MALPEs sometimes decline as population size increases, sometimes increase, sometimes display a u-shaped relationship, and sometimes follow no clear pattern. Similar results have been reported in several previous studies (Murdock, Leistritz, Hamm, Hwang, and Parpia 1984; Smith and Sincich 1988; Tayman, Schafer, and Carter 1998). We believe these inconsistent results are caused both by the lack of a strong relationship between bias and population size and by the confounding influence of growth rates.

Accuracy by Growth Rate

Previous research has found population growth rates to have a consistent impact on both precision and bias. In general, forecasts tend to be most precise for areas with slow but positive growth rates during the base period and least precise for areas experiencing large positive or negative growth rates (e.g., Keyfitz 1981; Murdock, Leistritz, Hamm, Hwang, and Parpia 1984; Smith and Sincich 1992; Stoto 1983; White 1954). In addition, forecasts tend to be too high in areas that grew rapidly during the base period and too low in areas that declined or grew very slowly (e.g., Isserman 1977; Rayer 2008; Smith 1987; Smith and Sincich 1988; Tayman 1996).

Figure 2a confirms the well-known u-shaped relationship between growth rates and precision. For the four trend extrapolation techniques, MAPEs are highest for areas that either grew or declined rapidly during the base period and lowest for areas with slow to moderate growth rates. The two constant techniques display similar patterns, but they are not as pronounced. Error levels themselves differ substantially from one technique to another. For areas with declining populations, the constant-size and exponential techniques provide the most precise forecasts and shift-share the least precise, on average. For areas that grew particularly rapidly, the linear technique has the smallest errors and the exponential technique the largest. We discuss a technique that builds on these findings later in the paper.

(Figure 2 about here)

Figure 2b confirms previous results regarding bias: for the four trend extrapolation techniques, forecasts tend to be too low in areas that declined during the base period and too high in areas that grew rapidly. In every instance MALPEs follow a stepwise pattern, increasing monotonically with increases in the rate of population growth. The two constant techniques follow a different pattern: The constant-share technique exhibits a positive bias that declines as the growth rate increases, whereas the constant-size technique exhibits a negative bias that becomes greater as the growth rate increases.

Accuracy by Population Size and Growth Rate

The preceding discussion touched on the potential interrelationship between population size and the growth rate. To disentangle the effects of these two variables, we evaluate forecast errors for combined size and growth-rate categories. We present the results in Figures 3a and 3b. For ease of illustration, we divide population size into two categories (< 2,000, ≥ 2,000) and growth rate into three categories (< 0%, 0 to 50%, > 50%).

(Figure 3 about here)

For all six techniques, precision increases with increasing population size within each growth-rate category (see Figure 3a). These results are consistent with those reported previously and indicate that errors tend to be smaller for large places than small places even when differences in growth rates are accounted for.

For the four trend extrapolation techniques, errors are largest for places with either declining or rapidly growing populations (especially the latter) and smallest for places with moderate growth rates. These results are found for places in both size categories and confirm the u-shaped relationship reported previously. The patterns are not as clear for the constant-share and constant-size techniques.

Of the six techniques, the constant-size technique performs particularly well for places with declining or slowly growing populations, regardless of population size; the exponential and linear techniques also perform well for these places. For places with growth rates greater than 50% and population sizes below 2,000, the constant-size technique is again the most precise, but for larger areas within this growth-rate category the linear technique produces the smallest errors. The shift-share technique performs particularly poorly for small places with declining populations and the exponential technique performs particularly poorly for rapidly growing places in both population size categories.

Figure 3b shows the results for bias. For the four trend extrapolation techniques, there is a positive relationship between MALPEs and population growth for places in both size categories: errors are negative for places losing population and positive for places with growing populations, especially if those growth rates are very high. Again, the results are consistent with those shown previously. The constant-size and constant-share techniques display different patterns than the other four techniques, but those patterns are also consistent with those shown previously.

Within growth-rate categories, population size impacts bias only indirectly. Forecasts made with the four extrapolation techniques for areas with declining populations tend to be too low, and that bias becomes less negative with increasing population size; forecasts for areas with growing populations tend to be too high, and that bias becomes less positive with increasing population size. Consequently, in contrast to the growth rate, population size does not influence the direction of bias; rather, the greater precision associated with larger population sizes merely reduces the level of bias, whether it is positive or negative. The absence of a relationship between population size and direction of error is consistent with the results shown above and with the findings of several previous studies. Results for the two constant techniques are not as consistent in this regard.

The constant-size technique again performs particularly well for places with declining or slowly growing populations, regardless of population size. The linear technique performs particularly well for large places, especially those with positive growth rates. The shift-share technique performs particularly poorly for places losing population (especially small places) and the exponential technique performs particularly poorly for places with high growth rates (especially small places).

COMBINING FORECASTS

Combinations of forecasts can potentially provide greater accuracy and less variability than individual forecasts because they incorporate more information and reduce the impact of outliers.

In population forecasting, these “combined” forecasts have often been found to be more accurate than most – sometimes all – of the individual forecasts used in their construction (Ahlburg 1995; Isserman 1977; Rayer 2008; Smith and Shahidullah 1995). Similar results have been found in other fields as well (e.g., Armstrong 2001; Clemen 1989; Hendry and Clements 2004; Makridakis, Wheelwright, and Hyndman 1998; Webby and O’Connor 1996). Overall averages or trimmed averages have been the most common techniques used in combining forecasts, but other approaches can also be applied.

Table 2 is structured similarly to Table 1, but adds results for two averages and one composite technique. The overall average was calculated as the mean of the forecasts from the six individual techniques; the trimmed average was calculated as the mean of those forecasts after the highest and lowest were excluded. For 10-year horizons, the overall average provides competitive results, but for longer horizons it becomes affected by the large errors associated with the exponential technique. This suggests that it may not be advisable to rely on an overall average because outliers associated with a single technique can greatly affect the results. The trimmed average fares better than the overall average, but is slightly less precise and more biased than the linear technique.

(Table 2 about here)

The results summarized in Figures 1–3 show that some techniques perform better than others for areas with particular population size and/or growth-rate characteristics. This information can be used to develop composite forecasts based on specific combinations of individual techniques (e.g., Isserman 1977). We calculated a variety of composites based on the performance of individual techniques by population size and growth rate and selected the one that worked best. In accordance with the results shown in Figures 3a and 3b, the composite in

Table 2 selects the constant-size technique for areas that experienced population declines over the base period and for areas that grew but had a launch year population below 2,000, and the linear technique for areas that grew and had a launch year population of 2,000 and above.

Table 2a shows that forecasts made with the composite technique are more precise than those made with any of the individual or average techniques for both forecast horizons. With respect to bias (Table 2b), the composite shows less bias than the other techniques in most instances, although linear and shift-share also perform well. The low overall bias of the linear and shift-share techniques is somewhat deceiving, however, because as Figure 3b showed, all four extrapolation techniques exhibit a negative bias for areas with declining populations and a positive bias for areas experiencing high rates of growth, which to some extent cancel each other out in the aggregate. Consequently, while the overall bias of forecasts made with the linear and shift-share techniques is low, the bias for individual areas with high positive or negative growth rates can be quite high. This demonstrates the importance of examining forecast accuracy by population size and growth-rate characteristics, and strengthens the case for using averaging and composite techniques.

The composite approach clearly excels for the subcounty population forecasts analyzed in this study. Would similar results be found for forecasts from other time periods and geographic areas? To examine this issue, we used decennial census data from 1900 to 2000 and the techniques described above to develop forecasts for a large sample of counties in the continental United States. We found that the relative performance of the individual techniques by population size and growth rate was about the same for the national sample of county forecasts as for subcounty forecasts in Florida. Next to the linear technique, the composite and the trimmed average provided the most precise and least biased forecasts throughout, though the differences among the various techniques were smaller at the county than the subcounty level (data not shown). Several previous studies have reported similar results (Isserman 1977; Rayer 2008; Smith and Shahidullah 1995).

Given this evidence, we believe combinations of forecasts – especially trimmed averages and composite techniques – will generally produce more accurate small-area forecasts than can be obtained using individual techniques by themselves. Perhaps more important, combinations of techniques are less likely to produce large forecast errors for specific places than individual techniques because – at the time a forecast is made – it is not known which individual technique will produce the most accurate forecast for any particular place. Future research may uncover new and better techniques for combining forecasts than those presented here.

EXTENDING THE ANALYSIS

The analysis thus far has focused on the effects of differences in population size and growth rate on forecast accuracy and the potential benefits of combining forecasts. We turn now to two additional factors of particular relevance to small areas: special populations and annexations. To our knowledge, the effects of these two factors on population forecast accuracy have not been previously studied.

Accounting for Special Populations

A special population can be defined as "a group of persons that is found in a locality usually by reason of an administrative decision or legislative fiat" (Pittenger 1976, 205). These include groups such as college students, inmates of correctional facilities, and residents of military barracks and nursing homes. Special populations can present a challenge to population forecasters because they often have unique demographic characteristics and may follow different growth trajectories than the rest of the population. For example, college students are heavily concentrated in the 18–24 age group and maintain the same age profile over time, and the number of prison inmates in a particular locality can increase or decline regardless of overall population growth trends. If special populations are not explicitly accounted for in the forecasting process, they may lead to unrealistic forecasts of population change.

In general, adjustments for special populations are needed only when these groups comprise a substantial proportion of the total population and when their growth patterns differ markedly from those of the rest of the population. Unfortunately, there are no general guidelines that define how ‘different’ and ‘substantial’ a special population must be to cause problems in population forecasting, and it is up to the analyst to make that assessment (Smith, Tayman, and Swanson 2001).

A common method for adjusting for special populations is to subtract them from the base-period data, make a forecast of the remaining population, and add back an independent forecast of the special population in the target year (Smith, Tayman, and Swanson 2001). We use this method to investigate whether accounting separately for special populations improves forecast accuracy. The special populations we consider are inmates and patients in institutions operated by the federal government, the Florida Department of Corrections, and the Florida Department of Children and Family Services.

We follow two different approaches when adding back a forecast of the special population in the target year: 1) We hold the special population constant at its launch year value (SP1), and 2) We use the actual value of the special population in the target year as the forecast value (SP2). The former reflects the naïve albeit potentially useful assumption that the special population will not change, whereas the latter reflects a best-case scenario showing the improvement that would occur with a perfect forecast of the special population.

We made three forecasts for each area: one with no adjustment for special populations, one using the SP1 adjustment, and one using the SP2 adjustment. Table 3 summarizes the impact of these adjustments on forecast precision, showing the percent reduction (or increase) in MAPEs produced by each of the two adjustments for the linear technique. We focus on the linear technique because it was the most precise and least biased of the individual techniques analyzed in this study. To check whether the adjustments are sensitive to the technique chosen, we also calculated them using the composite technique, and found the results to be comparable (data not shown). We present the results for all target years for all 141 subcounty areas with special populations and for areas in which special populations exceeded 2.5% and 5% of the total population. We report results only for precision because we found that adjusting for special populations had no consistent effect on bias.

(Table 3 about here)

As shown in Table 3, holding special populations constant over the forecast horizon (SP1) provides mixed results; in some instances this adjustment improves precision, but for the majority of target years it actually reduces precision. With perfect forecasts, however, adjusting for special populations produces substantial improvements (SP2). These improvements become consistently larger as special populations increase as a percentage of total population.

To illustrate the impact of these adjustments for several specific subcounty areas, Table 4 focuses on three localities in Florida with different special population characteristics: the City of Chattahoochee, the Town of Malone, and the unincorporated area of Sumter County. The special population in Chattahoochee is made up of residents of the Florida State Hospital, while in

Malone and Sumter it consists of inmates in correctional facilities. In addition to total and special population counts, Table 4 shows three sets of algebraic percentage errors (ALPEs) – reflecting no adjustment for special populations, the SP1 adjustment, and the SP2 adjustment – for 10-year forecasts for target years 1990 and 2000 and 20-year forecasts for target year 2000. We report algebraic rather than absolute percent errors because for individual areas the two are identical in value, but the sign shows whether the forecast was too high or too low.

(Table 4 about here)

The results can be interpreted as follows: the closer to zero the error, the lower the bias and the higher the precision of the forecast. For example, for Chattahoochee, a 10-year forecast for target year 1990 using the linear technique with no adjustment for special populations was 37.9% below the 1990 census count; with the SP1 adjustment it was 26.5% above; and with the SP2 adjustment it was 14.9% above. The forecast with the SP2 adjustment thus was the most precise and least biased of the three. Chattahoochee provides a good example of the unpredictable nature of forecasts for small areas with declining populations; forecast errors are large and change erratically over time, though both adjustments lead to improvements in accuracy for two of the three forecasts. The up-and-down pattern of Malone's population from 1970 to 1990 also results in large forecast errors, but knowledge of the new state prison opening in 1991 produces a significantly improved 10-year forecast for 2000 (SP2 adjustment). The Sumter unincorporated area houses both federal and state correctional facilities that expanded substantially between 1990 and 2000. Because the special population's share of total county population is much lower than in either Chattahoochee or Malone, the impact of the institutional adjustment in the Sumter unincorporated area is more modest.

To summarize, accounting for special populations can reduce forecast errors, but only if fairly accurate forecasts of special population are available. Although the evidence is not overwhelming, we believe that accounting for special populations is generally worth the additional effort – especially in areas where they account for a significant proportion of the total population – for the following reasons. First, in most instances there is reasonably accurate information regarding the eventual size of the special population, leading to results more similar to adjustment SP2 than adjustment SP1. Second, it is often politically advantageous to demonstrate that potentially relevant factors such as special populations have been accounted for in the forecasting process. Third, even when improvements in forecasts of total population are small, accounting for special populations may improve forecasts of population characteristics – e.g., the age, sex, and racial profile – which are often of concern as well.

Accounting for Annexations

Annexations can also pose a challenge when making small-area population forecasts because they introduce changes in geographic boundaries into the forecasting process. Although annexations are rare at the state and county level, in many states – including Florida – they are a common occurrence at the subcounty level and often have significant demographic consequences (Raymondo 1992). Some incorporated places annex adjoining areas on a regular basis, while others annex infrequently and irregularly. If the demographic effects of annexations during the base period are not accounted for explicitly, the analyst is essentially forecasting that similar effects will continue into the future. That may not be a reasonable assumption.

In order to evaluate the effect of adjusting for annexations, we compare unadjusted forecasts with forecasts in which the population annexed during the base period is subtracted from the total population in the launch year, a forecast of the non-annexed population is made using the techniques described previously, and a forecast of the annexed population in the target year is added. Once again, we present results for two different approaches to making adjustments. Under the first, we assume that no further annexations occur (A1); under the second, we add the population effects of annexations that actually occurred during the forecast horizon (A2). The first approach reflects a naïve but perhaps reasonable assumption and the second represents a best-case scenario. Again, we report the results for the linear technique and differentiate among all subcounty areas that experienced annexations and those with annexations greater than 2.5% and 5% of the total population.

Evaluating the impact of annexations involves one complication not present in analyses of special populations. Annexations typically involve the expansion of a city or town's boundaries to encompass a previously unincorporated area; consequently, cities and towns generally experience a population increase and unincorporated areas generally experience a population decline. We limit our analysis to incorporated places. Annexations often occur more or less continuously in unincorporated areas and we found that accounting for them separately provided no consistent benefits in terms of forecast accuracy (data not shown).

Adjusting for annexations almost always improves precision for the 183 incorporated places in this subsample (see Table 5). The improvements become larger as the relative size of the annexation increases. In contrast to accounting for special populations, where only the scenario with perfect information (SP2) improves precision consistently, both annexation adjustment techniques lead to improvements in precision, though the effects are stronger for A2 than for A1.

(Table 5 about here)

We conclude our examination of annexation effects by focusing on four cities with varying frequencies and magnitudes of annexations: Gretna, Ocala, Plantation, and Seminole. Table 6 shows total population and annexation counts for 1970–2000 and the number of years these cities experienced at least one annexation. It also shows three sets of algebraic percentage errors – reflecting no adjustment for annexations, the A1 adjustment, and the A2 adjustment – for 10-year forecasts for target years 1990 and 2000 and 20-year forecasts for target year 2000.

(Table 6 about here)

For Gretna and Plantation, annexations are rare events occurring only in the 1970s. In Gretna, adjusting for annexations reduces forecast error for the 20-year forecast for 2000 but raises it for the 10-year forecast for 1990. The City of Plantation, in contrast, experienced consistent population growth, and factoring in its two substantial annexations leads to significant improvements in forecast accuracy. Ocala and Seminole represent cities that annex adjacent areas on a frequent basis. In Ocala, with one exception, the annexations account for only a small proportion of total population, and adjusting for the major annexation that occurred in 1976 reduces forecast error significantly. Because the remaining annexations were small, the differences between adjustments A1 and A2 are quite modest. This is not the case for Seminole, which experienced six annexations exceeding 5% of its total population between 1970 and 2000. Here, the impact of adjusting for annexations is more mixed; the A1 adjustment increases forecast error for two of three forecasts while the A2 adjustment reduces forecast error for all three.

We conclude that adjusting for annexations can reduce forecast errors in many but not all circumstances. In general, annexations are less predictable than changes in special populations. Consequently, forecast results for annexations may more closely resemble adjustment A1 than

A2, whereas for special populations they may more closely resemble adjustment SP2 than SP1. Nonetheless, we believe it is generally advisable to adjust for annexations when making small-area forecasts, at least for areas in which annexations occur infrequently and account for more than a trivial proportion of total population. These adjustments often significantly improve accuracy; when they do not, the outcome may have more to do with erratic and unpredictable population changes (e.g. Gretna in 1990) than with the annexation adjustment itself. When areas have a history of frequent annexations, however, such adjustments are not likely to lead to much improvement in forecast accuracy and may even make it worse. Thus, the analyst once again has to weigh the potential gains in accuracy and the political advantages of making adjustments against the costs of collecting additional data and amending the forecasting methodology.

SUMMARY AND CONCLUSIONS

Planners must consider a number of factors when constructing small-area population forecasts or using them for decision-making purposes: costs of production, timeliness, ease of application and explanation, provision of necessary detail, validity of assumptions, usefulness as an analytical tool, and the political acceptability of the forecasting process and the final results. The relative importance of these factors may vary considerably from one project to another. Regardless of the purposes for which they are used, however, the planner must be aware of the likely degree of accuracy of the forecasts.

What can we say about forecast accuracy that might help planners as they construct or evaluate small-area population forecasts? Based on this study and the results of previous research, we have drawn the following conclusions:

1) For trend extrapolation techniques such as those evaluated in this paper, 10 years of base data are generally necessary to achieve the greatest possible forecast accuracy for 10- and 20-year forecast horizons. In most instances, 10 years are also sufficient, as increases beyond 10 years generally do not lead to further improvements in accuracy.

2) Precision declines steadily with the length of the forecast horizon – often in a nearly linear manner – but bias follows no clear pattern. Forecast errors for subcounty areas are sometimes very large, especially for areas with small populations and high rates of population change. The size of the errors reported in this paper may be disappointing to data users, but we believe it is a realistic indication of the degree of uncertainty inherent in small-area population forecasts.

3) Precision is strongly affected by differences in population size, but bias is not. We found precision to be lower for subcounty areas with fewer than 1,000 residents than for areas in any other size category, often by a substantial amount. For most techniques, precision improved steadily as population size increased to about 5,000, but further increases led to only minor improvements.

4) Population growth rates over the base period have a substantial impact on forecast accuracy. For most techniques, precision tends to be highest for areas with moderate growth rates and decreases as growth rates deviate in either direction from those moderate levels. In terms of bias, average errors for most techniques are large and negative for areas with the largest negative growth rates and increase as the growth rate increases, becoming large and positive for rapidly growing areas.

5) Taking averages of forecasts from several techniques often improves forecast accuracy. We found that the trimmed average produced errors that were smaller than the errors for most of the individual techniques making up the average, and that the composite technique performed even

better. We believe the use of averaging and the development of new composite techniques hold a great deal of promise for future improvements in small-area forecasting.

6) Accounting for changes in special populations can improve the average precision of population forecasts when there is good information on future changes in the special population. Fortunately, such information is often available, and we believe that adjusting for special populations is generally advisable, both for public relations purposes and because such adjustments may improve forecast accuracy for some places.

7) Accounting for the effects of annexations also can improve the average precision of population forecasts. We found that these improvements became greater as annexations became larger relative to the size of the entire population. Better information on future annexations leads to better forecasts, but even accounting only for annexations that happened in the past seems to improve average forecast accuracy. We believe it is generally advisable to account for annexations when making subcounty population forecasts, at least for places in which annexations occur infrequently and constitute a significant proportion of total population. Furthermore, accounting for the characteristics of an annexed area can be helpful in determining its likely impact on future population change. For example, the annexation of an already built-out suburban neighborhood has different growth implications than the annexation of vacant land next to a developing growth corridor.

Population forecasts cannot provide perfect predictions of future population change, of course. However, they can help planners identify relevant policy issues, define potential scenarios, and rule out unlikely outcomes. The techniques described in this paper offer useful tools for constructing small-area forecasts, and the empirical results will help planners and other analysts form realistic expectations regarding the likely precision and bias of those forecasts.

Given their low data requirements, ease of application, and track record for accuracy, we encourage planners to consider the use of simple extrapolation techniques. Although greater complexity may be needed for some applications (e.g., providing demographic detail, accounting for density constraints, or answering "what if" questions), simple techniques at least can offer helpful checks for evaluation purposes (Sawicki 1989). Chosen judiciously, we believe simple extrapolation techniques can often provide everything that is needed for constructing small-area population forecasts.

APPENDIX: FORECASTING TECHNIQUES

Extrapolation techniques express future population values as a function of past population values:

Linear: In the linear technique, the population increases (or declines) by the same number of persons in each future year as the average annual increase (or decline) 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 forecast horizon, and y is the number of years in the base period.

Exponential: In the exponential technique, the population grows (or declines) by the same rate in each future year as the average annual rate during the base period:

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

where r is the average annual growth rate, e is the base of the natural logarithm, and ln is the natural logarithm.

Share-of-Growth: In the share-of-growth technique, a smaller area's share of population growth of the larger area is the same throughout the forecast horizon as it was during the base period:

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

Shift-Share: In the shift-share technique, the annual change in a smaller area's share of population of the larger area is the same throughout the forecast horizon as it was during the base period:

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

Both the share-of-growth and shift-share techniques are extrapolations using ratios. That is, they express population (or population change) of a smaller area as a proportion of population (or population change) of a larger area in which the smaller area is located. In our analysis of subcounty areas we use counties as the larger areas. In general, forecasts made with ratio techniques are not particularly sensitive to the choice of forecast used for the larger area (Rayer 2007; Smith and Sincich 1988); we produce county population forecasts by taking an average of forecasts from the linear and exponential techniques. In the formulas for the share-of-growth and shift-share techniques shown above, as well as the constant-share technique shown below, subscripts denote subcounty-level values and superscripts denote county-level values.

In addition to the four extrapolation techniques, we apply two constant techniques, which hold one data point – the share of population and population size, respectively – constant:

Constant-Share: In the constant-share technique, a smaller area's share of the larger area's population is the same in the target year as it was in the launch year:

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

Constant-Size: In the constant-size technique, the population in the target year is the same as it was in the launch year:

$P_t = P_l$.

REFERENCES

Ahlburg, D. 1995. Simple versus complex models: Evaluation, accuracy, and combining. *Mathematical Population Studies* 5:281–290.

Armstrong, S. 2001. Combining forecasts. In *Principles of forecasting*, ed. S. Armstrong, 417–439. Norwell, MA: Kluwer.

Ascher, W. 1978. *Forecasting: An appraisal for policy makers and planners.* Baltimore, MD: Johns Hopkins University Press.

Beaumont, P., and A. Isserman. 1987. Comment on "Tests of forecast accuracy and bias for county population projections," by S. Smith. *Journal of the American Statistical Association* 82:1004–1009.

Bureau of Economic and Business Research. 2006. *Florida Estimates of Population: April 1, 2005*. Gainesville: University of Florida.

Chi, G. 2009. Can knowledge improve population forecasts at subcounty levels? *Demography* 46:405–427.

Clemen, R. 1989. Combining forecasts: A review and annotated bibliography. *International Journal of Forecasting* 5:559–583.

Florida Administrative Code. 2001. Rule 9J-5.005: General Requirements.

Flyvbjerg, B, M. Skamris Holm, and S. Buhl. 2005. How (in)accurate are demand forecasts in public works projects? The case of transportation. *Journal of the American Planning Association* 71:131–146.

Goldstein, D., and G. Gigerenzer. 2009. Fast and frugal forecasting. *International Journal of Forecasting* 25:760–772.

Hendry, D., and M. Clements. 2004. Pooling of forecasts. *Econometrics Journal* 7:1–31.

Hopkins, L., and M. Zapata. 2007. Engaging the future: Tools for effective planning practices. In *Engaging the Future: Forecasts, Scenarios, Plans, and Projects*, eds. L. Hopkins and M. Zapata, 1–17. Cambridge, MA: Lincoln Institute of Land Policy.

Isserman, A. 1977. The accuracy of population projections for subcounty areas. *Journal of the American Institute of Planners* 43:247–259.

———. 2007. Forecasting to learn how the world can work. In *Engaging the future: Forecasts, scenarios, plans, and projects*, eds. L. Hopkins and M. Zapata, 175–197. Cambridge, MA: Lincoln Institute of Land Policy.

Keyfitz, N. 1981. The limits of population forecasting. *Population and Development Review*, 7:579–593.

Klosterman, R. 2007. Deliberating about the future. In *Engaging the Future: Forecasts, Scenarios, Plans, and Projects*, eds. L. Hopkins and M. Zapata, 199–219. Cambridge, MA: Lincoln Institute of Land Policy.

Long, J. 1995. Complexity, accuracy, and utility of official population projections. *Mathematical Population Studies* 5:203–216.

Mahmoud, E. 1984. Accuracy in forecasting: A survey. *Journal of Forecasting* 3:139–159.

Makridakis, S. 1986. The art and science of forecasting: An assessment and future directions. *International Journal of Forecasting* 2:15–39.

Makridakis, S., and M. Hibon. 1979. Accuracy of forecasting: An empirical investigation. *Journal of the Royal Statistical Society A* 142:97–145.

———. 2000. The M3-competition: Results, conclusions, and implications. *International Journal of Forecasting* 16:451–476.

Makridakis, S., S. Wheelwright, and R. Hyndman. 1998. *Forecasting: Methods and applications*. New York: Wiley.

McKibben, J. 1996. The impact of policy changes on forecasting for school districts. *Population Research and Policy Review* 15:527–536.

Morgenroth, E. 2002. Evaluating methods for short to medium term county population forecasting. *Journal of the Statistical and Social Inquiry Society of Ireland*, 31:111–136.

Murdock, S., R. Hamm, P. Voss, D. Fannin, and B. Pecotte. 1991. Evaluating small-area population projections. *Journal of the American Planning Association* 57:432–443.

Murdock, S., L. Leistritz, R. Hamm, S.-S. Hwang, and B. Parpia. 1984. An assessment of the accuracy of a regional economic-demographic projection model. *Demography* 21:383–404.

Pflaumer, P. 1992. Forecasting U.S. population totals with the Box-Jenkins approach. *International Journal of Forecasting*, 8:329–338.

Pittenger, D. 1976. *Projecting State and Local Populations.* Cambridge, MA: Ballinger.

Rayer, S. 2007. Population forecast accuracy: Does the choice of summary measure of error matter? *Population Research and Policy Review* 26:163–184.

———. 2008. Population forecast errors: A primer for planners. *Journal of Planning Education and Research* 27:417–430.

Raymondo, J. 1992. Population estimation and projection: Methods for marketing, demographic, and planning personnel. New York: Quorum Books.

Sawicki, D. 1989. Demographic analysis in planning: A graduate course and an alternative paradigm. *Journal of Planning Education and Research* 9:45–56.

Skaburskis, A., and M. Teitz. 2003. Forecasts and outcomes. *Planning Theory & Practice* 4:429–442.

Smith, S. 1987. Tests of forecast accuracy and bias for county population projections. *Journal of the American Statistical Association* 82:991–1003.

Smith, S., and M. Shahidullah. 1995. An evaluation of population projection errors for census tracts. *Journal of the American Statistical Association* 90:64–71.

Smith, S., and T. Sincich. 1988. Stability over time in the distribution of population forecast errors. *Demography* 25:461–474.

———. 1990. The relationship between the length of the base period and population forecast errors. *Journal of the American Statistical Association* 85:367–375.

———. 1991. An empirical analysis of the effect of length of forecast horizon on population forecast errors. *Demography* 28: 261–274.

———. 1992. Evaluating the forecast accuracy and bias of alternative population projections for states. *International Journal of Forecasting* 8:495–508.

Smith, S., and J. Tayman. 2003. An evaluation of population projections by age. *Demography*, 40:741–757.

Smith, S., J. Tayman, and D. Swanson. 2001. *State and local population projections: Methodology and analysis*. New York: Kluwer.

Steinitz, C., H. Arias, S. Bassett, M. Flaxman, T. Goode, T. Maddock, D. Mouat, R. Peiser, and A. Shearer. 2003. *Alternative futures for changing landscapes. The Upper San Pedro River Basin in Arizona and Sonora.* Washington DC: Island Press.

Stoto, M. 1983. The accuracy of population projections. *Journal of the American Statistical Association*, 78:13–20.

Tayman, J. 1996. The accuracy of small area population forecasts based on a spatial interaction land use modeling system. *Journal of the American Planning Association* 62:85–98.

Tayman, J., B. Parrott, and S. Carnevale. 1994. Locating fire station sites: The response time component. In *Applied Demographics: A Casebook for Business and Government,* eds. H. J. Kintner, P. R. Voss, P. A. Morrison, and T. W. Merrick, 203–217. Boulder, CO: Westview Press.

Tayman, J., E. Schafer, and L. Carter. 1998. The role of population size in the determination and prediction of population forecast errors: An evaluation using confidence intervals for subcounty areas. *Population Research and Policy Review* 17:1–20.

Texas Water Development Board. 1997. Water for Texas: A consensus-based update to the State Water Plan. Volume 2, Technical Planning Appendix, GF-6-2: Austin, TX.

Thomas, R. 1994. Using demographic analysis in health services planning: A case study in obstetrical services. In *Applied Demographics: A Casebook for Business and Government,* eds. H. J. Kintner, P. R. Voss, P. A. Morrison, and T. W. Merrick, 159–179. Boulder, CO: Westview Press.

Wachs, M. 1989. When planners lie with numbers. *Journal of the American Planning Association* 55:476–479.

———. 2001. Forecasting versus envisioning: A new window on the future. *Journal of the American Planning Association* 67:367–372.

Webby, R., and M. O'Connor. 1996. Judgemental and statistical time series forecasting: A review of the literature. *International Journal of Forecasting* 12:91–118.

White, H. 1954. Empirical study of the accuracy of selected methods for projecting state populations. *Journal of the American Statistical Association*, 49:480–498.

Yokum, T., and S. Armstrong. 1995. Beyond accuracy: Comparison of criteria used to select forecasting methods. *International Journal of Forecasting* 11:591–597.

Table 1a. MAPE by Horizon and Technique

Horizon	Linear	Exponential	Share-of-Growth	Shift-Share	Constant-Share	Constant-Size
10	17.1	30.0	19.0	24.1	23.0	19.1
20	30.5	231.5	40.2	56.1	51.8	31.0

Table 1b. MALPE by Horizon and Technique

Horizon	Linear	Exponential	Share-of-Growth	Shift-Share	Constant-Share	Constant-Size
10	-0.2	17.8	3.3	-2.2	13.2	-13.5
20	3.9	215.3	17.6	4.7	37.8	-23.5

Table 2a. MAPE by Horizon and Technique

Horizon	Linear	Exponential	Share-of-Growth	Shift-Share	Constant-Share	Constant-Size	Average	Trimmed Average	Composite
10	17.1	30.0	19.0	24.1	23.0	19.1	17.4	17.1	14.4
20	30.5	231.5	40.2	56.1	51.8	31.0	61.6	34.1	24.1

Table 2b. MALPE by Horizon and Technique

Horizon	Linear	Exponential	Share-of-Growth	Shift-Share	Constant-Share	Constant-Size	Average	Trimmed Average	Composite
10	-0.2	17.8	3.3	-2.2	13.2	-13.5	3.1	2.1	-2.0
20	3.9	215.3	17.6	4.7	37.8	-23.5	42.6	12.8	-3.3

Table 3. Percent Reduction in MAPEs, Accounting for Special Populations

		SP1			SP2		
Year	Horizon	All	> 2.5%	> 5%	All	> 2.5%	> 5%
1990	10	1.2	3.3	4.2	4.3	11.0	12.9
1995	10	(0.4)	(0.9)	(2.0)	10.1	23.0	27.2
2000	10	(1.7)	(4.0)	(5.8)	14.3	28.1	33.6
2005	10	(2.5)	(6.8)	(5.4)	2.9	7.4	11.7
2000	20	(0.2)	(0.3)	(0.3)	2.5	5.8	6.6
2005	20	1.7	4.3	4.2	8.8	20.9	23.5
All	10	(0.8)	(2.1)	(2.2)	7.9	17.4	21.3
All	20	0.8	2.0	2.0	5.6	13.4	15.1

Note:
This table is restricted to the subset of subcounty areas with special populations (N=141).
Columns titled "2.5%" and "5%" further restrict the analysis to subcounty areas where the special population exceeds 2.5% (N=45) and 5% (N=36) of total population.
Numbers in paratheses mean accounting for special populations increased error.

SP1 = Accounts for special populations by holding them constant at the launch year value.
SP2 = Accounts for special populations using the actual target year value.

Table 4. Impact of Adjusting for Special Populations: Case Studies

Variable	Year	Horizon	Chattahoochee	Malone	Sumter UI
Population	1970	-	7,944	667	10,333
Population	1980	-	5,332	897	17,995
Population	1990	-	4,382	765	23,681
Population	2000	-	3,287	2,007	45,009
Special Population	1970	-	5,053	0	604
Special Population	1980	-	2,230	0	956
Special Population	1990	-	1,720	0	1,151
Special Population	2000	-	901	1,582	5,731
ALPE - No Adjustment	1990	10	-37.9	47.3	8.3
ALPE - SP1 Adjustment	1990	10	26.5	47.3	6.9
ALPE - SP2 Adjustment	1990	10	14.9	47.3	7.7
ALPE - No Adjustment	2000	10	4.4	-68.5	-34.8
ALPE - SP1 Adjustment	2000	10	19.9	-68.5	-35.2
ALPE - SP2 Adjustment	2000	10	-5.0	10.4	-25.0
ALPE - No Adjustment	2000	20	-96.7	-32.4	-26.0
ALPE - SP1 Adjustment	2000	20	75.1	-32.4	-27.5
ALPE - SP2 Adjustment	2000	20	34.6	46.4	-16.9

Table 5. Percent Reduction in MAPEs, Accounting for Annexations (Incorporated Places)

		A1			A2		
Year	Horizon	All	> 2.5%	> 5%	All	> 2.5%	> 5%
1990	10	2.1	2.9	3.5	3.6	5.0	5.7
1995	10	5.5	8.8	10.3	12.5	19.8	23.4
2000	10	0.3	0.6	0.3	1.2	1.7	1.6
2005	10	(1.5)	(2.2)	(1.9)	14.7	23.9	27.9
2000	20	5.1	7.3	9.0	5.9	8.5	10.7
2005	20	4.9	7.8	9.0	13.9	21.5	25.0
All	10	1.6	2.5	3.0	8.0	12.6	14.6
All	20	5.0	7.5	9.0	9.9	15.0	17.9

Note:
This table is restricted to the subset of incorporated places with annexations (N=183). Columns titled "2.5%" and "5%" further restrict the analysis to incorporated places where the annexed population exceeds 2.5% (N=100) and 5% (N=71) of total population. Numbers in paratheses mean accounting for annexations increased error.

A1 = Accounts for annexations that occurred between the base year and launch year.
A2 = Accounts for annexations that occurred between the base year and target year.

Table 6. Impact of Adjusting for Annexations: Case Studies

Variable	Year/Period	Horizon	Gretna	Ocala	Plantation	Seminole
Population	1970	-	883	22,583	23,523	2,121
Population	1980	-	1,557	37,170	48,653	4,586
Population	1990	-	1,981	42,045	66,814	9,251
Population	2000	-	1,709	45,943	82,934	10,890
Annexed Population	1970-1980	-	994	8,366	4,985	1,629
Annexed Population	1980-1990	-	0	941	0	3,022
Annexed Population	1990-2000	-	0	59	0	669
Number of Annexations	1970-2000	-	1	18	2	13
Number of Annexations > 2.5%	1970-2000	-	1	1	2	8
Number of Annexations > 5%	1970-2000	-	1	1	2	6
ALPE - No Adjustment	1990	10	12.6	23.1	10.4	-23.8
ALPE - A1 Adjustment	1990	10	-37.6	3.2	3.0	-41.4
ALPE - A2 Adjustment	1990	10	-37.6	5.4	3.0	-8.7
ALPE - No Adjustment	2000	10	40.7	2.1	2.5	27.8
ALPE - A1 Adjustment	2000	10	40.7	0.1	2.5	0.0
ALPE - A2 Adjustment	2000	10	40.7	0.2	2.5	6.2
ALPE - No Adjustment	2000	20	70.0	44.4	19.3	-12.6
ALPE - A1 Adjustment	2000	20	-46.3	8.0	7.2	-42.5
ALPE - A2 Adjustment	2000	20	-46.3	10.2	7.2	-8.6

Figure 1a. MAPE by Population Size and Technique, 10 Year Horizon

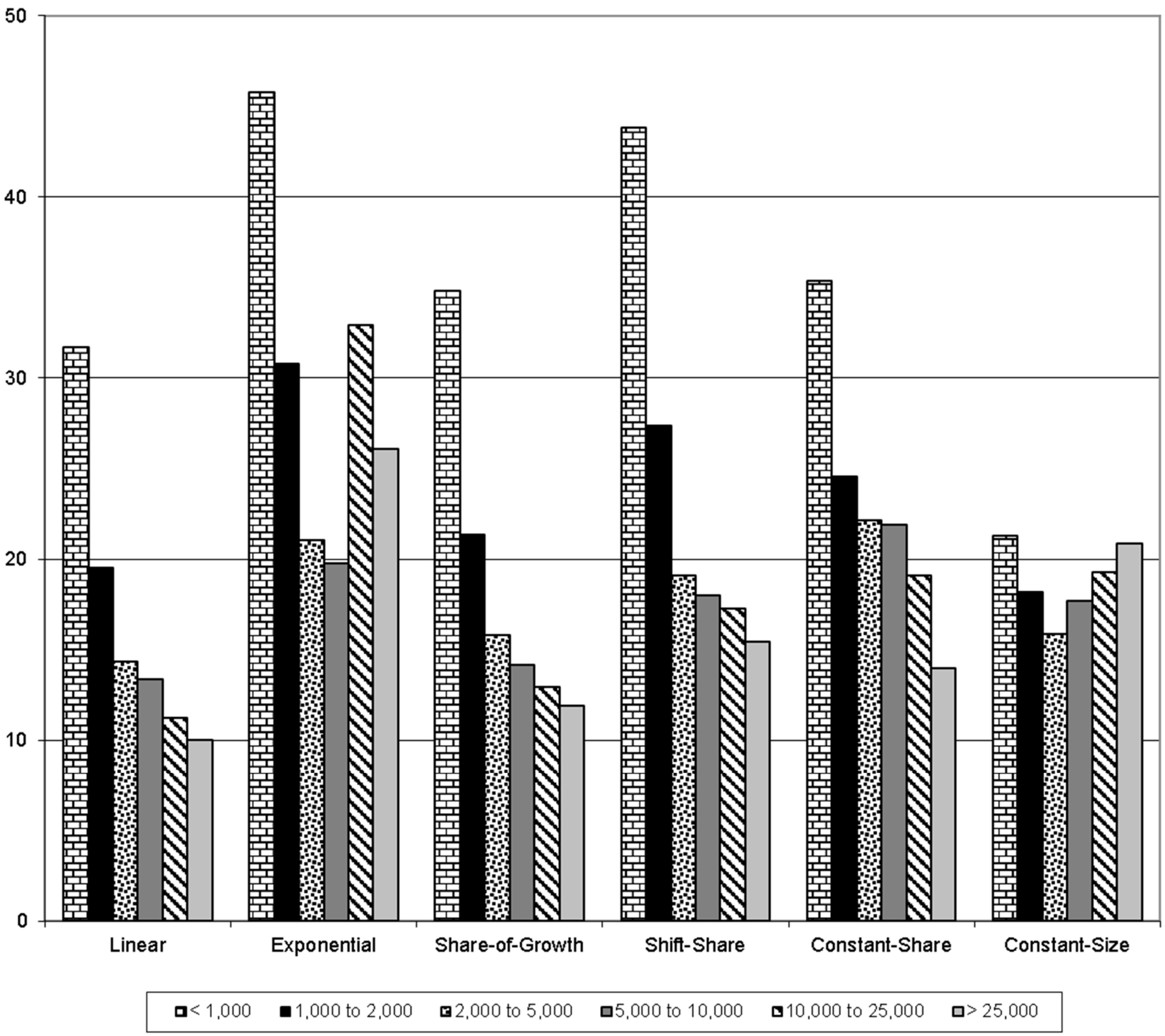

Figure 1b. MALPE by Population Size and Technique, 10 Year Horizon

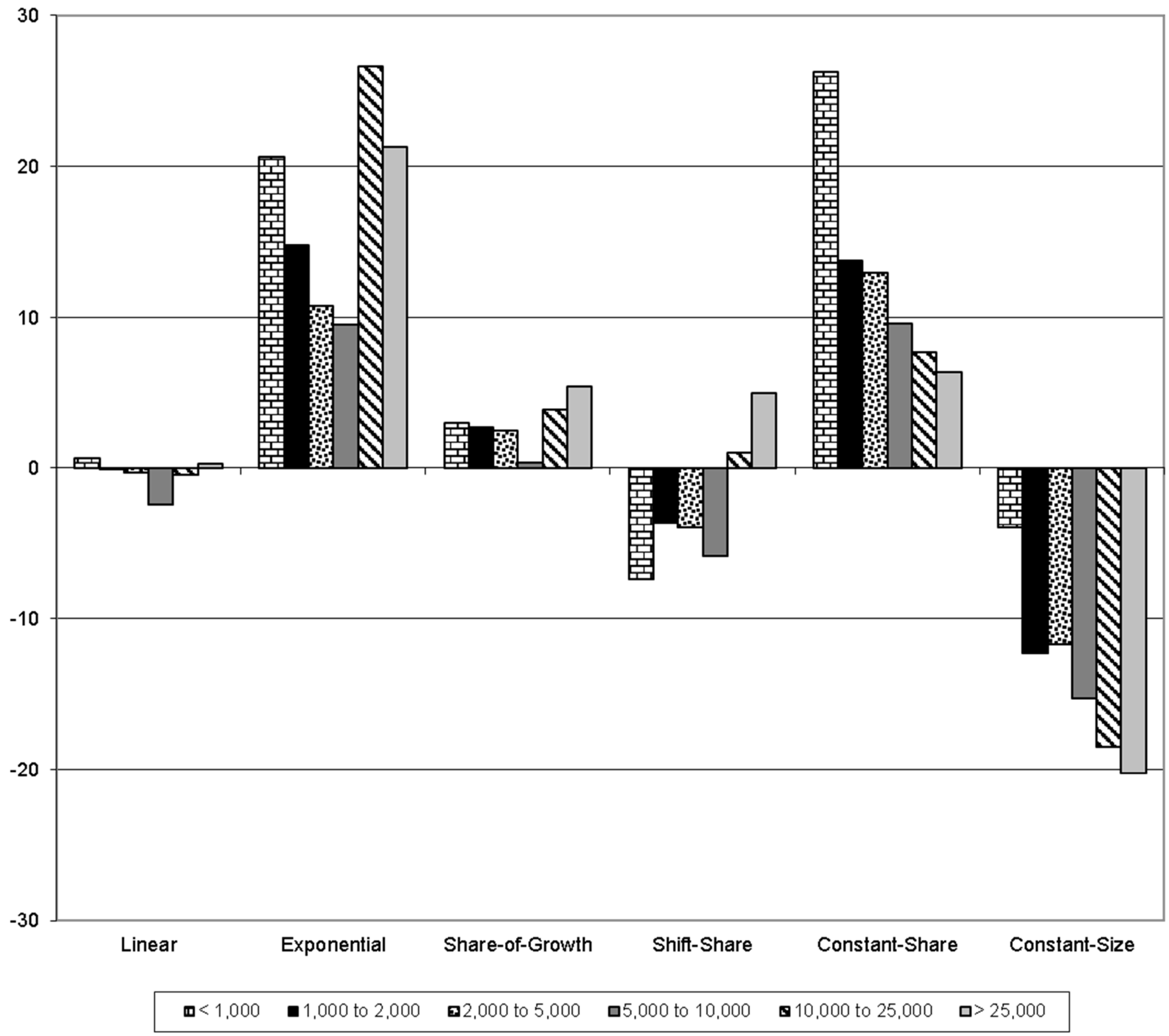

Figure 2a. MAPE by Growth Rate and Technique, 10 Year Horizon

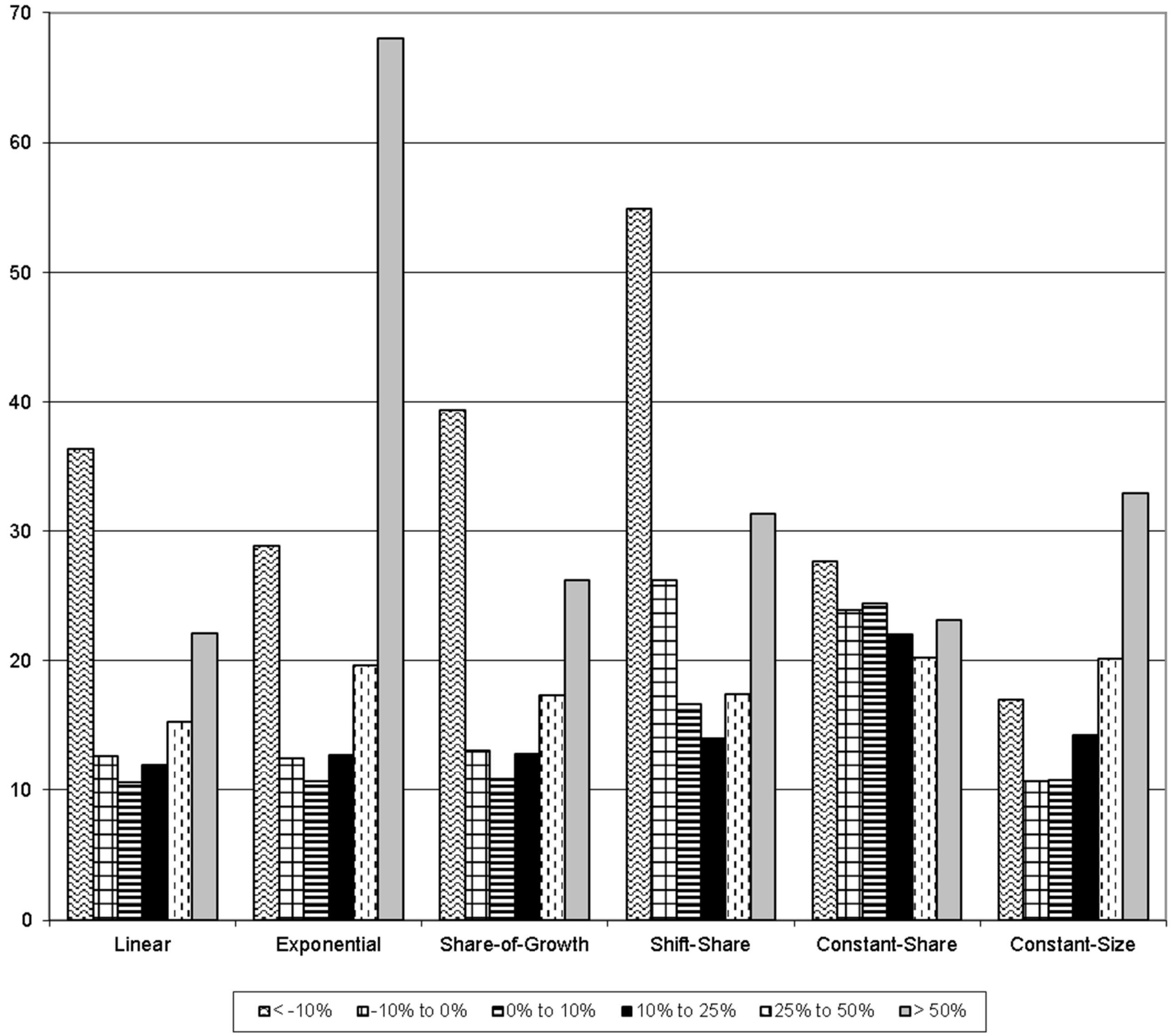

Figure 2b. MALPE by Growth Rate and Technique, 10 Year Horizon

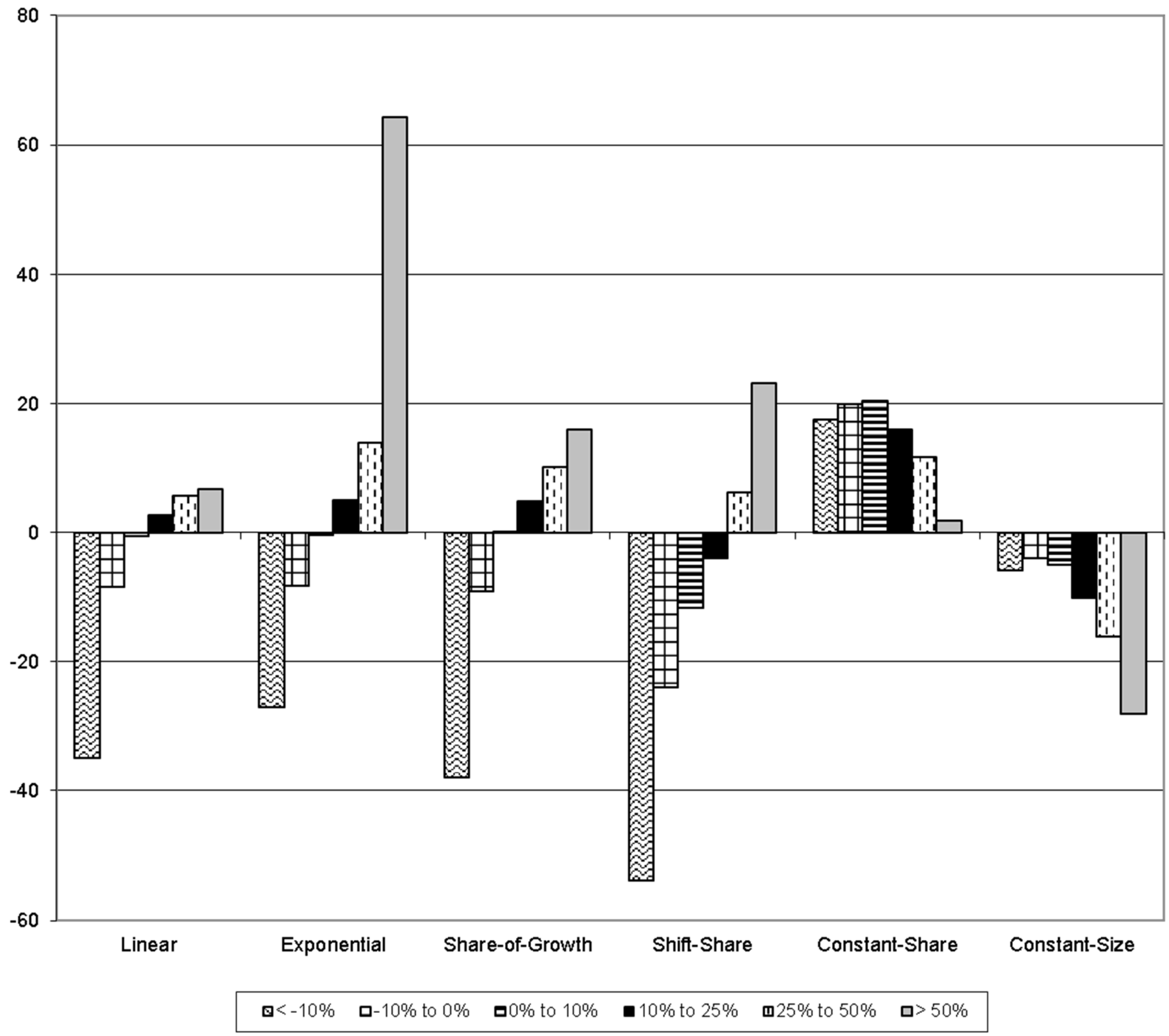

Figure 3a. MAPE by Population Size, Growth Rate, and Technique, 10 Year Horizon

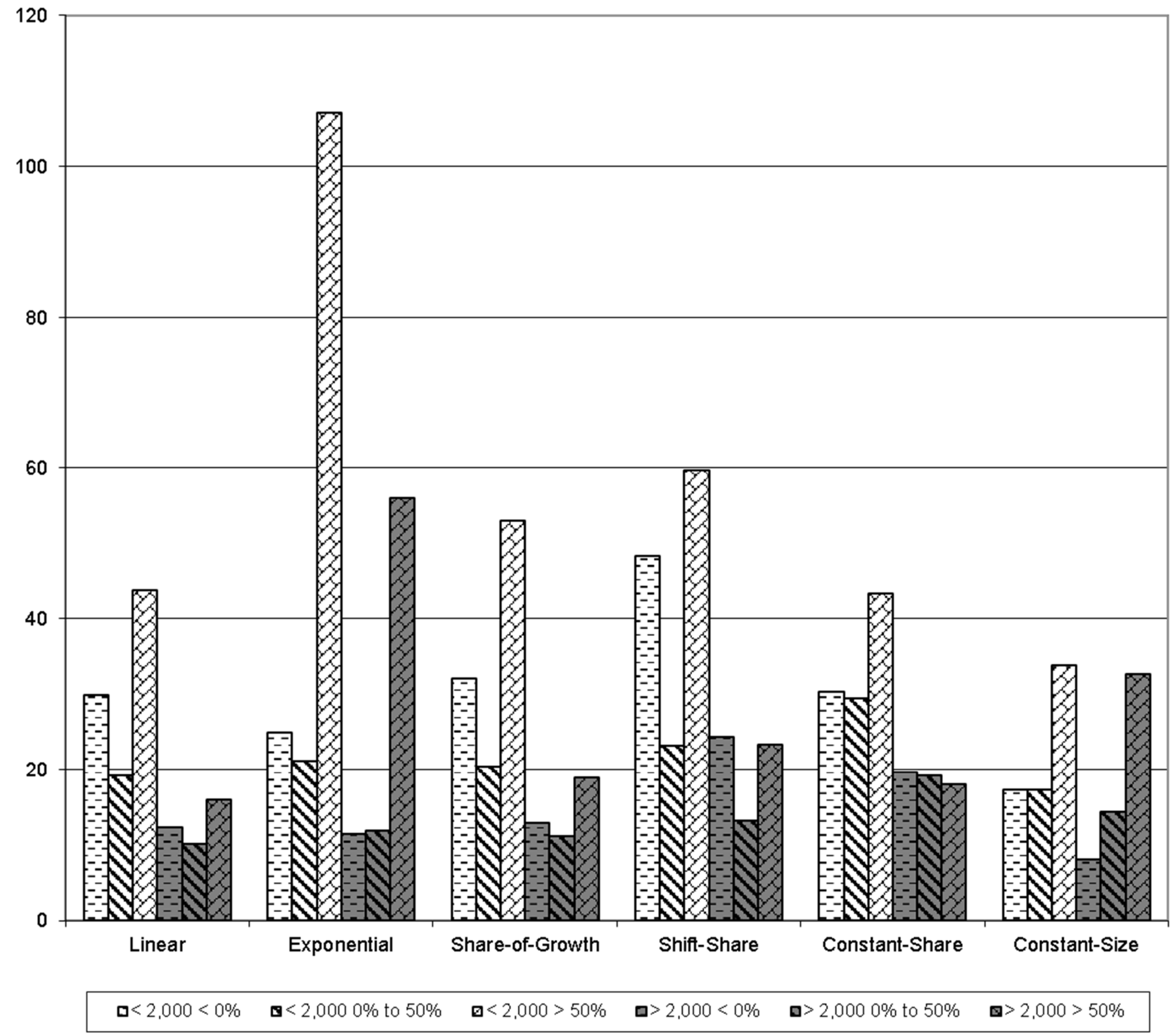

Figure 3b. MALPE by Population Size, Growth Rate, and Technique, 10 Year Horizon