An Evaluation of Population Projection Errors for Census Tracts

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Population projections are widely used in both the public and private sectors for planning, budgeting, and analysis. For these purposes, projections are often needed for small areas such as census tracts, zip code areas or traffic analysis zones. Population size, growth constraints, shifting boundaries, and data availability create special problems for small-area projections, however, and very little is known about their forecasting performance. In this article we evaluate the accuracy and bias of projections of total population and population by age group for census tracts in three counties in Florida. We use data from 1970 and 1980 and several simple extrapolation techniques to produce projections for 1990; we then compare these projections with 1990 census counts and evaluate the differences. For the total sample, we find mean absolute errors of 17%–20% for the three most accurate techniques for projecting total population and find no indication of overall bias. For individual age groups, mean absolute errors range from 20%–29%. We believe that this analysis provides valuable information for demographers, planners, marketers, and others who make extensive use of small-area projections.

KEY WORDS: Age-group projections; Demographic projections and forecasts; Forecast accuracy and bias; Small-area projections and forecasts.

1. INTRODUCTION

Population projections at the state and national levels have been made for many years, but such projections are of limited use for planning, budgeting, and analysis at the local level. For these purposes, projections are needed for small subcounty areas, such as census tracts, traffic analysis zones, and zip code areas. Projections for small areas present methodological problems not found in projections for larger areas, however.

One problem is data availability and quality. Demographic data for small subcounty areas are typically available only once every 10 years, from the decennial census. Postcensal (and intercensal) estimates are seldom available, and when they are they may be of questionable accuracy. Even census data are subject to larger enumeration errors for small areas than for large areas. Thus the first step in constructing population projections for small areas is to compile a historical data base and assess its quality. This may require the construction of a new set of population estimates or the revision of data coming from other sources.

Data availability affects the type of projection methodology that can be used. Cohort-component models require age-specific data on births, deaths, and migration; structural models require data on a variety of social, economic, and demographic variables; and time series models require data for many points in time. Such data are seldom available for small subcounty areas. Consequently, simple techniques with minimal data requirements generally must be used. The use of simple techniques does not necessarily imply a loss in forecast accuracy (see, for example, Ascher 1981, Kale, Voss, Palit, and Krebs 1981, Smith and Sincich 1992, and White 1954), but it does limit the range of variables and characteristics that can be projected.

Shifting geographic boundaries create problems as well. Boundaries for states and most counties remain constant over time, but boundaries for cities, census tracts, zip code areas, and other subcounty areas may change substantially. When changes occur, historical data series must be adjusted to maintain spatial consistency over time. This process is tedious but essential.

Finally, population size itself presents formidable problems. Events such as the loss of vacant land, changes in zoning requirements, construction of group quarters facilities, and plans for commercial or residential development generally have little impact on population growth for large areas, because these are localized events whose effects tend to cancel out each other when aggregated. But for small areas, these events may have a substantial impact. As a result, rates of population growth are considerably more volatile for small areas than for large areas, creating a higher level of uncertainty for small-area projections.

Despite these problems, the demand for small-area population projections has grown rapidly in recent years. Private companies and public agencies have responded by producing a variety of such projections, often in minute detail. But research on the methodology and analysis of small-area projections has been quite limited, and little is known about their accuracy and bias. In this article we seek to fill part of this void by evaluating the forecasting performance of a set of projections of total population and population by age group for census tracts in Florida. We believe that this analysis will be helpful to demographers, planners, marketers, and others who make extensive use of small-area projections, giving them insight into the types of techniques that can be used and the degree of forecast error that can be expected.

2. DATA AND TECHNIQUES

We chose three counties in Florida that provide a geographically and demographically diverse sample of census tracts. Dade County in southeast Florida is the largest county

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in the state and has a large Hispanic population and a high proportion of foreign-born residents. Pinellas County on the central Gulf Coast is a rapidly growing county with a large elderly population and a small number of racial/ethnic minorities. Duval County on the northern Atlantic Coast is a slowly growing county with a large African-American population and a high proportion of native Floridians. These counties are the largest in the southern, central, and northern regions of Florida; they contained almost half the state's census tracts in 1970. Although they do not provide a random sample of census tracts in Florida, these counties reflect much of the geographic, cultural, economic, and demographic diversity found in the state. We believe that they provide a useful sample for analyzing population forecast errors. Table 1 provides a summary of socioeconomic and demographic characteristics for Florida and each of these three counties.

Census tract boundaries in these counties have not changed since 1970, except for the subdivision of some 1970 tracts into two or more tracts in 1980 or 1990. Thus it was possible to develop a set of geographic areas with constant boundaries from 1970 to 1990. We included in our analysis all 421 tracts for which there were population data in all three decennial census years (U.S. Bureau of the Census 1972, 1983b, 1992). For some analyses, we combined the tracts from all three counties into one large sample; for others, we analyzed the results for each county individually.

2.1 Projections of Total Population

Using data from 1970 and 1980, we made projections of total population for 1990 using four simple extrapolation techniques: (1) linear extrapolation (LINE), in which it is assumed that each census tract will grow (decline) by the same number of persons between 1980 and 1990 as between 1970 and 1980; (2) exponential extrapolation (EXPO), in which it is assumed that each census tract will grow (decline) at the same percentage growth rate between 1980 and 1990 as between 1970 and 1980; (3) shift share (SHIFT), in which it is assumed that each census tract's share of county population will change by the same numerical amount between 1980 and 1990 as between 1970 and 1980; and (4) share of growth (SHARE), in which it is assumed that each census tract's share of county population growth will be the same between 1980 and 1990 as between 1970 and 1980. The latter two techniques require independent projections of county population; we used the official projections of Florida counties published soon after the release of 1980 census data (Smith and Mandell 1981). No adjustments to the projections were made to account for possible changes in census coverage between 1970 and 1990 or for specific local events such as changes in density constraints, zoning requirements, or planned residential developments.

A number of researchers have concluded that an average of projections from several techniques will often perform better than projections from a single technique (see, for example, Armstrong 1978, Mahmoud 1984, and Voss and Kale 1985). Averages are based on more information than a single technique and are less likely to produce a large error for any individual place. We constructed two sets of projections based on averages. One (AVE) was the average of projections from all four techniques. The other (COMP) used a "composite" approach to construct an average of projections from several techniques, with the specific techniques included in the average varying according to the population growth characteristics of each census tract. We describe the COMP technique more fully later in this article.

Table 1. Selected Demographic and Socioeconomic Characteristics for Florida and Dade, Duval, and Pinellas Counties, 1980

Characteristics	Florida	Dade	Duval	Pinellas
Population	9,746,324	1,625,781	571,003	728,531
Growth rate 1970–1980	43.6	28.2	8.0	39.5
Percent Black	13.8	17.2	24.6	7.6
Percent Spanish origin	8.8	35.7	1.8	1.4
Percent age 65+	17.3	15.7	9.7	27.8
Percent born in Florida	35.0	38.8	50.5	20.4
Percent foreign born	10.9	35.6	2.9	7.5
Percent high school graduates	66.7	64.0	66.8	68.3
Percent below poverty level	13.5	15.0	15.8	9.8

Sources: U.S. Bureau of the Census. *1980 Census of Population*, PC80-1-B11 and PC80-1-C11, Washington, DC, U.S. Government Printing Office.

2.2 Projections by Age Group

Projections by age group are essential for many types of planning and analysis (e.g., school enrollment, nursing home care). Such projections are typically made using cohort-component techniques in which fertility, mortality, and migration are projected separately for each age–sex group in the population. Unfortunately, age-specific fertility, mortality, and migration data are rarely (if ever) available for census tracts. How can age-group projections be made under these circumstances?

One approach is to apply county- or state-level mortality, fertility, and migration rates to each tract. But given the tremendous demographic diversity found among tracts, this approach is not likely to be useful. Another approach is to apply county- or state-level mortality rates to each tract and calculate net migration as a residual from total population change for each age cohort. The resulting net migration rates could then be used with county- or state-level mortality and fertility rates to construct age-group projections. This approach uses tract-specific net migration data but is still subject to errors caused by differences in mortality and fertility rates among tracts.

We decided to test a third approach based solely on tract-specific data that are readily available from the decennial census. This is a modified cohort-component method that combines survival and net migration rates into a single factor for each age group (Hamilton and Perry 1962). Under this method (HP), migration–survival rates for each tract are calculated by dividing the population age i in year t by the population age $i - 10$ in year $t - 10$. These rates are then applied to each age group in year t to provide projections by age in year $t + 10$. The population less than age 10 can be projected in a number of ways; we simply applied the child/adult ratio from year t (i.e., children less than age 10/persons age 15–44) to the population age 15–44 in year $t + 10$.

The HP methodology has several limitations, including the inability to separate survival rates from net migration rates and the difficulty in adjusting projections to fit horizons other than 10 years. But the most severe limitation is the concept of net migration itself (Rogers 1990; Smith 1986). There is no such thing as a "net migrant"; there are only in-migrants and out-migrants. Consequently, there is no clear population at risk for calculating net migration rates. Furthermore, when net migration rates are used for population projections, they can lead to very unlikely outcomes (Smith 1986). But despite these limitations, we believe that the HP method is potentially useful for age-group projections of small areas when the data required by traditional cohort-component techniques are not available; the empirical analysis provides an opportunity to assess the HP method's usefulness.

3. EVALUATING FORECAST ERRORS

Using data from 1970 and 1980 and the techniques described previously, we made projections for 1990 for each census tract in our sample. We then compared those projections with 1990 census counts, calling the differences "forecast errors" although they may reflect enumeration errors as well. Ignoring the distinction often made between projections and forecasts (Isserman 1984; Smith 1987), we treat projections as though they were intended to be used as forecasts (i.e., predictions) of future population size.

We evaluated several different measures of forecast accuracy and bias. Mean absolute percent error (MAPE) is the average error when the direction of error is ignored. The proportion of absolute errors less than 10% and greater than 25% represents the frequency of small errors and large errors. Mean algebraic percent error (MALPE) is the average error when the direction of error is accounted for; this is a measure of bias. Because a few extreme errors in one direction can disproportionately affect the sign of the MALPE, the proportion of positive errors (%POS) was used as another measure of bias.

3.1 Projections of Total Population

Table 2 provides a summary of forecast errors for projections of total population for all census tracts in the three-county sample. Of the four individual techniques, SHARE and LINE were the most accurate, with MAPE's of 17.3% and 19.7%. More than 35% of the census tracts had small errors (<10%), and fewer than 25% had large errors (≥25%). The EXPO and SHIFT techniques were considerably less accurate, with MAPE's of 27.6% and 26.7%. For EXPO, 37% of the projections had small errors, but 30% had large errors; for SHIFT, only 25% had small errors and almost 40% had large errors.

SHARE and LINE each had a slight upward bias, with MALPE's of 1.4% and 2.0%; both techniques had 54% positive errors. EXPO had a strong upward bias, with 60% positive errors and a MALPE of 17.3%. SHIFT had a strong downward bias, with only 37% positive errors and a MALPE of −7.2%.

How do the errors shown in Table 2 compare with those found in other studies? Tayman (1992) reported a MAPE of 20.9% for 10-year projections of census tracts in San Diego County; these projections were derived from allocation models based on population density, land use plans, and distances from various activities. Voss and Kale (1985) reported MAPE's of approximately 15% for 10-year projections of Minor Civil Divisions (MCD's) in four Wisconsin counties; these projections were based on a variety of extrapolation techniques. Isserman (1977) reported MAPE's ranging from 11% to 17% for 10-year projections of townships in Illinois; these projections were also based on a variety of extrapolation techniques. Murdock, Leistritz, Hamm, Hwang, and Parpia (1984) reported a MAPE of 17.2% for 10-year projections of places in Texas and North Dakota with populations between 2,500 and 10,000 (making them similar in size to most census tracts); these projections were based on ratio procedures combined with economic–demographic models. These studies covered a variety of techniques, time periods, demographic scenarios, and geographic regions, but all found errors similar to those shown here for LINE, SHARE, COMP, and AVE.

Table 2. Summary of 1990 Forecast Errors for Census Tracts: Three-County Sample

Measure	LINE	EXPO	SHIFT	SHARE	AVE	COMP
MAPE	19.7	27.6	26.7	17.3	21.7	17.6
MALPE	2.0	17.3	−7.2	1.4	3.4	2.0
%POS	53.9	60.3	36.8	53.9	49.9	53.4
% of absolute errors:						
<10%	35.6	37.1	25.2	40.6	36.1	41.1
10–25%	39.7	32.8	35.6	38.2	36.3	37.3
≥25%	24.7	30.1	39.2	21.2	27.6	21.6

Many studies have found that forecast errors vary according to population size and growth rate (Isserman 1977; Keyfitz 1981; Smith 1987; White 1954). Tables 3–6 show MAPE's and MALPE's for census tracts in the three-county sample, separated by population size in 1970 and by growth rates from 1970 to 1980. We used population size in 1970 because census tracts were defined according to their 1970 boundaries; we used 1970–1980 growth rates because that was the base period for the projections. We do not report results for %POS and the proportion of large and small errors, because they followed the same patterns shown here for MALPE and MAPE.

As shown in Table 3, MAPE's for all techniques declined as population size increased; this is a common empirical finding (Murdock et al. 1984; Smith 1987; White 1954). Except for SHIFT, differences in MAPE's were very small in the top size categories.

MALPE's for LINE and SHARE were negative for small tracts and positive for large tracts; MALPE's for SHIFT were negative for all size categories; and MALPE's for EXPO were positive for all categories (see Table 4). When differences in growth rates were accounted for, differences in MALPE's by population size largely disappeared (not shown here). Based on this and other studies (see, for example, Smith 1987, Smith and Sincich 1988), it appears that differences in population size have little impact on bias.

Table 3. Mean Absolute Percent Errors for Census Tracts by Population Size in 1970: Three-County Sample

Size	N	LINE	EXPO	SHIFT	SHARE	AVE	COMP
<2,500	37	34.5	44.4	44.1	32.4	36.5	32.2
2,500–4,999	165	19.3	26.6	27.6	16.7	21.5	16.9
5,000–7,499	147	17.6	25.5	24.3	15.2	19.6	15.7
7,500+	72	17.2	25.4	20.7	15.5	18.9	15.5
Total	421	19.7	27.6	26.7	17.3	21.7	17.6

As shown in Table 5, there was a strong U-shaped relationship between MAPE's and the population growth rate during the base period. Errors were large for tracts with growth rates of less than −10%, became smaller as growth rates increased to moderate levels, and became larger as growth rates increased to higher levels. This relationship was found for all projection techniques and remained strong even when differences in population size were controlled for (not shown here). A U-shaped relationship between MAPE's and growth rates has also been noted before (Smith 1987).

There were substantial differences in the accuracy of individual techniques within specific growth-rate categories. EXPO had the smallest MAPE for the lowest category but the largest for the two highest categories. SHIFT had the smallest MAPE for tracts with growth rates between 10% and 50% but the largest in the three lowest categories. EXPO thus performed well for tracts growing slowly or losing population but poorly for tracts growing very rapidly, whereas SHIFT performed well for tracts with moderate growth rates but poorly for tracts growing slowly or losing population. The large errors for EXPO and SHIFT shown in Table 2 thus reflect large errors for tracts with specific characteristics, not large errors for all types of tracts.

Bias was also strongly related to growth rates (see Table 6). For all projection techniques, MALPE's were negative for tracts with population losses greater than 10% and became larger as growth rates increased. What caused this positive relationship? We believe that the answer lies with the "regression to the mean" phenomenon reported by Smith (1987). Very high or low growth rates usually do not persist for long periods; rather, they tend to move toward more moderate levels. Consequently, projections that extrapolate population losses often turn out to be too low and projections that extrapolate high rates of growth often turn out to be too high.

3.2 The Composite Approach

The composite approach to population projection is based on the assumption that some techniques perform substantially better than others for places with particular characteristics (Isserman 1977). Examination of Tables 5 and 6 suggests that the SHIFT technique should not be used in places losing population or growing either very slowly or very rapidly and that the EXPO technique should not be used in places growing very rapidly.

To test the composite approach, we constructed a set of projections (COMP) in which the techniques included in the average varied according to the census tract's growth rate during the base period. For tracts with growth rates of less than 10%, we used an average of LINE, SHARE, and EXPO; for tracts with growth rates of 10% to 50%, an average of LINE, SHARE and SHIFT; and for tracts with growth rates of 50% and higher, an average of LINE and SHARE. The results are shown in the last column of Tables 2–6.

Compared to other techniques, the performance of the COMP technique was quite good. The overall MAPE was 17.6%, with 41.1% of census tracts having small errors and only 21.6% having large errors. COMP projections displayed little bias, with 53.4% positive errors and a MALPE of 2.0%. Within individual size and growth-rate categories, the performance of COMP was always similar to that of the most accurate individual technique and was often considerably better than the performance of AVE.

The individual techniques included in COMP were chosen only after analyzing their performance over the 1980–1990 projection horizon. Of course, when the composite approach is actually used for population projections, data regarding errors over the projection horizon will not be available. Instead, choices regarding which techniques to include must be based on historical evidence. The COMP technique will be useful only if relationships between growth rates and forecast errors are consistent across places and remain constant over time. Is this likely to be true?

We believe that it is. Relationships similar to those reported here have been found for different places and time periods (Smith 1987; Smith and Sincich 1988), and a logical explanation for their existence can be given (Smith 1987). We can provide additional evidence from the present study

Table 4. Mean Algebraic Percent Errors for Census Tracts by Population Size in 1970: Three-County Sample

Size	N	LINE	EXPO	SHIFT	SHARE	AVE	COMP
<2,500	37	−6.7	21.4	−18.4	−6.0	−2.4	−4.5
2,500–4,999	165	.1	15.5	−10.1	−.3	1.3	.2
5,000–7,499	147	4.4	17.5	−4.5	3.5	5.2	3.9
7,500+	72	6.3	18.7	−.5	4.8	7.3	5.5
Total	421	2.0	17.3	−7.2	1.4	3.4	2.0

Table 5. Mean Absolute Percent Errors for Census Tracts by Population Growth Rate 1970-1980: Three-County Sample

Growth rate	N	LINE	EXPO	SHIFT	SHARE	AVE	COMP
< −10%	81	27.5	16.4	49.2	22.1	27.7	21.8
−10%–0%	68	10.5	10.3	22.0	10.2	12.5	10.3
0%–10%	75	9.9	10.0	14.1	9.5	9.4	9.8
10%–25%	70	13.8	15.9	9.2	12.2	12.3	11.3
25%–50%	43	23.1	27.3	21.1	21.5	23.1	21.8
50%+	84	31.3	77.9	37.6	27.6	41.4	29.4
Total	421	19.7	27.6	26.7	17.3	21.7	17.6

by looking at forecast errors separately for each county. If the results reported for the entire sample are found in each individual county, then they reflect consistency across places and confirm the potential usefulness of the COMP technique.

As shown in Table 7, overall MAPEs for LINE, SHARE, and COMP were similar in all three counties, ranging only from 19% to 22% for LINE, from 16% to 19% for SHARE, and from 17% to 20% for COMP. Ranges were wider for EXPO, SHIFT, and AVE, with Pinellas County having the largest errors for all three techniques and Duval County having the smallest. These differences were most likely caused by differences in growth rates during the base period, as Pinellas County had the highest rate and Duval County had the lowest.

Projections for Pinellas and Dade Counties had an upward bias for all techniques except SHIFT; projections for Duval County had a downward bias for all techniques except EXPO (see Table 8). These differences were most likely caused by differences in growth trends: Pinellas and Dade counties grew faster during the 1970s than the 1980s, leading to a majority of overprojections, whereas Duval County grew faster during the 1980s than the 1970s, leading to a majority of underprojections.

Many of the results found for the sample as a whole were repeated in each county. Of the four individual techniques, LINE and SHARE generally had the smallest MAPE's, and EXPO and SHIFT had the largest; the only exception was Duval County, where the MAPE for LINE was slightly larger than the MAPE for EXPO. EXPO had the strongest upward bias in all three counties, and SHIFT had the strongest downward bias. A U-shaped relationship between MAPE's and growth rates was found for all techniques in all counties, although it was not quite as distinct for Duval as it was for Dade and Pinellas. A positive relationship between MALPE's and growth rates was found for all techniques in all counties; again, this relationship was not as distinct for Duval as it was for the other two counties. Large tracts generally had smaller errors than small tracts for all projection techniques in all three counties (not shown here).

The results that prompted the construction of the COMP technique are clearly evident. In all three counties, SHIFT had the largest errors and strongest downward bias for tracts losing population during the base period, and EXPO had the largest errors and strongest upward bias for tracts with high growth rates. Differences in errors were often quite large. Consequently, the performance of COMP was better than the performance of AVE in most size categories in all counties. These results strongly support the validity of the COMP technique.

The composite method is a general approach to population forecasting rather than a specific technique. The COMP technique described in this article is one specific way to apply this approach, but it is certainly not the only way (nor necessarily the best way). Further research is needed to discover other projection techniques that perform particularly well (or poorly) in places with particular characteristics and to determine the best ways to combine those techniques. One direction this research might take is the use of multiple regression analysis to uncover important variables and develop optimal weights for averages of projections. (We are indebted to the editor for this suggestion.) We believe the composite approach offers a potentially valuable alternative to the use of individual techniques or averages based on all techniques.

3.3 Projections by Age Group

Population forecast errors by age group for the three-county sample are shown in Table 9. We report errors both

Table 6. Mean Algebraic Percent Errors for Census Tracts by Population Growth Rate 1970-1980: Three-County Sample

Growth rate	N	LINE	EXPO	SHIFT	SHARE	AVE	COMP
< −10%	81	−26.7	−13.4	−49.2	−20.3	−27.4	−20.2
−10%–0%	68	−.9	−.6	−17.7	0	−4.8	−.5
0%–10%	75	3.7	4.0	−10.3	3.1	.1	3.6
10%–25%	70	12.2	14.7	4.0	10.2	10.3	8.8
25%–50%	43	13.1	21.1	10.9	9.6	13.7	11.2
50%+	84	16.5	73.3	25.7	10.6	31.5	13.6
Total	421	2.0	17.3	−7.2	1.4	3.4	2.0

Table 7. *Mean Absolute Percent Errors by Population Growth Rate 1970–1980, by County*

County and growth rate	N	LINE	EXPO	SHIFT	SHARE	AVE	COMP
DADE							
< −10%	33	26.9	14.9	53.4	23.3	28.8	21.4
−10%–0%	23	9.0	8.7	23.7	8.5	12.2	8.7
0%–10%	46	9.1	9.2	12.2	8.9	8.9	9.0
10%–25%	43	13.2	15.2	9.3	11.8	12.0	11.1
25%–50%	23	23.2	27.5	22.5	21.6	23.7	22.4
50%+	42	31.0	86.8	38.0	26.9	43.2	28.9
Total	210	18.6	28.8	25.6	16.7	21.5	16.8
DUVAL							
< −10%	36	23.9	12.6	33.2	16.1	21.3	17.4
−10%–0%	24	12.7	12.6	13.7	12.5	12.7	12.6
0%–10%	6	12.2	12.4	10.1	11.4	11.5	11.9
10%–25%	8	21.0	22.4	20.2	19.2	20.7	20.1
25%–50%	9	18.1	17.9	18.1	18.7	18.0	18.3
50%+	14	23.5	34.6	24.0	22.0	23.9	22.7
Total	97	19.6	17.1	23.2	16.3	18.6	17.0
PINELLAS							
< −10%	12	39.9	31.6	85.6	36.8	44.3	36.1
−10%–0%	21	9.5	9.4	29.6	9.4	12.8	9.4
0–10%	23	10.8	11.1	18.9	10.4	9.7	10.8
10%–25%	19	12.1	14.8	4.3	10.2	9.5	7.9
25%–50%	11	27.0	34.7	20.8	23.7	26.2	23.6
50%+	28	35.9	86.2	43.7	31.5	47.4	33.7
Total	114	21.6	34.3	31.7	19.4	24.7	19.6

for the uncontrolled HP projections and for a set in which HP age-group projections were controlled to the COMP projection of total population for each tract.

The total populations projected by the uncontrolled HP method for each tract had a MAPE of 31.0% and a MALPE of 20.7%. These errors are similar to those reported for EXPO in Table 2. This is not surprising, given that the EXPO projections were based on the growth rate of the total population from 1970 to 1980, whereas the HP projections were based on the growth rates of individual age cohorts. MAPEs by age group were quite large, ranging from 30% to 41%. Projections for all age groups displayed an upward bias, which generally grew stronger as age increased.

Controlling the HP age-group projections to the COMP projections of total population greatly improved their forecasting performance. MAPE's for every age group declined substantially, and the overall MAPE declined from 31.0% to 17.6%. Bias was also reduced, with the overall MALPE declining from 20.7% to 2.0%. Due to the small population size of individual age groups and the explosive nature of net migration rates, we believe that it generally will be beneficial to control HP age-group projections to independent projections of total population in small areas.

For individual age groups, MAPE's for the controlled projections ranged from 20% to 29%. For the three counties individually, MAPE's fell between 20% and 30% in 20 out of 24 age groups, between 31% and 32% in two age groups, and between 14% and 16% in two age groups (not shown here). Given the tremendous diversity within and among these counties, these findings reflect a surprisingly high degree of consistency.

MALPE's for the controlled projections retained their positive relationship with age. We are puzzled by this result. We suspect that it was caused by the unique characteristics of this sample and time period and does not reflect a general characteristic of age-group projections. We believe the MALPE was negative for ages 0–9 because birth rates rose in Florida during the 1980s, causing the projection of children based on 1980 child/adult ratios to be too low, and that it was positive for ages 65+ because the net in-migration of older adults compared to younger adults declined in Florida during the 1980s, causing projections for the elderly to be too high.

We are not aware of any other studies of age-group projections for small areas; in fact, very few studies evaluating errors by age group have been done even at the state or national level. Consequently, we cannot draw any general conclusions regarding forecast accuracy and bias. Nevertheless, we believe that the HP method tested in this study is potentially useful for small area age-group projections when the data required by traditional cohort-component techniques are not available. Further research is clearly needed, covering other samples, time periods, and techniques for producing age-group projections.

4. CONCLUSION

Can the empirical results reported in this study be generalized to other places and time periods? We believe that they can, at least to some extent. The three counties in our sample differed tremendously in terms of growth rates, age structure, racial/ethnic composition, and numerous other characteristics, but tract-level MAPE's ranged only from 16% to 19% for SHARE, from 17% to 20% for COMP, and from 19% to 22% for LINE. These errors are similar to those found in several other studies of forecast accuracy for subcounty areas (see, for example, Murdock et al. 1984, Tayman 1992,

Table 8. Mean Algebraic Percent Errors by Population Growth Rate 1970-1980, by County

County and growth rate	N	LINE	EXPO	SHIFT	SHARE	AVE	COMP
DADE							
< −10%	33	−26.4	−12.8	−53.4	−22.4	−28.8	−20.5
−10%–0%	23	−6.5	−6.1	−23.6	−5.7	−10.5	−6.1
0%–10%	46	3.6	3.9	−8.5	3.0	.5	3.5
10%–25%	43	11.8	14.1	4.4	9.9	10.0	8.7
25%–50%	23	11.8	20.0	10.9	8.6	12.8	10.4
50%+	42	16.1	79.5	26.1	10.5	33.1	13.3
Total	210	2.9	19.1	−5.5	1.6	4.5	2.5
DUVAL							
< −10%	36	−23.5	−11.8	−33.2	−15.0	−20.9	−16.8
−10%–0%	24	1.8	2.3	−3.0	3.3	1.1	2.5
0%–10%	6	12.2	12.4	9.3	11.0	11.2	11.9
10%–25%	8	15.4	17.5	14.1	12.3	14.8	14.0
25%–50%	9	−.3	7.3	.5	−5.0	.6	−1.6
50%+	14	−1.6	29.4	1.3	−8.6	5.1	−5.1
Total	97	−6.5	3.3	−11.1	−4.7	−4.8	−4.6
PINELLAS							
< −10%	12	−37.4	−19.9	−85.6	−30.7	−43.4	−29.3
−10%–0%	21	1.9	2.2	−28.0	2.6	−5.3	2.2
0%–10%	23	1.9	2.2	−18.9	1.2	−3.4	1.8
10%–25%	19	11.9	14.8	−1.1	9.8	8.9	6.9
25%–50%	11	27.0	34.7	19.4	23.6	26.2	23.3
50%+	28	26.2	85.8	37.4	20.1	42.4	23.2
Total	114	7.8	25.6	−7.1	6.4	8.2	6.8

and Voss and Kale 1985). Given that the distribution of absolute percent errors appears to remain fairly stable over time (see, for example, Kale et al. 1981, Stoto 1983, and Smith and Sincich 1988), we believe that it is reasonable to expect MAPE's of approximately 15% to 20% for 10-year projections of total population for census tracts and similar small areas. Such a range will not always encompass the MAPE, of course, but we believe that it provides a reasonable forecast under many circumstances.

With respect to bias, one generalization can be made. When extrapolatory techniques are used, places losing population during the base period are likely to be underprojected and places growing rapidly are likely to be overprojected. But in terms of overall bias, we cannot draw any general conclusions. MALPE's tend to fluctuate over time and from sample to sample (see, for example, Kale et al. 1981, Smith and Sincich 1988, and Stoto 1983). We believe that it is impossible to accurately predict whether a given set of projections will have an upward or a downward bias.

Several studies have found MAPE's to grow about linearly with the length of the projection horizon (see, for example, Kale et al. 1981, Stoto 1983, and Smith and Sincich 1991). Based on the results reported here, this would imply MAPE's of 30% to 40% for 20-year projections of total population and 40% to 60% for 20-year projections of individual age groups. Do such projections have any practical usefulness for planning and analysis? We are doubtful. For horizons that extend much beyond 10 years, we believe that the predictive usefulness of census tract projections is quite limited, given the current state of the art. Data users must be prepared to accept a high level of uncertainty when using population projections for small areas, and that level will grow with the degree of demographic detail projected and the length of the projection horizon.

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Table 9. Mean Absolute and Algebraic Percent Errors for Census Tracts, by Age Group in 1990: Three-County Sample

Age group (years)	MAPE		MALPE	
	HP	Controlled	HP	Controlled
0–9	38.2	26.2	11.3	−7.3
10–14	37.6	25.1	17.7	−1.0
15–24	35.0	24.5	16.3	−1.7
25–34	41.4	29.3	15.1	−3.8
35–44	37.4	22.8	20.2	0.7
45–54	31.5	20.2	18.7	0.4
55–64	30.3	20.7	22.0	5.0
65+	36.7	28.0	28.2	11.4
Total	31.0	17.6	20.7	2.0

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