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Evaluating Deterministic Approaches to Forecast Population by Educational Attainment in the United States

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EVALUATING DETERMINISTIC APPROACHES TO FORECAST POPULATION BY EDUCATIONAL ATTAINMENT IN THE UNITED STATES

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This dissertation is approved as a creditable and independent investigation by a candidate for the Doctor of Philosophy degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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ABSTRACT

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Forecasting population by educational attainment not only benefit government planning on allocating educational resources, labor market demand, and long-term human capital and overall well-being of society (Lutz et al. 2008), but also help predicting size and structure of future population (Lutz and KC 2011). To seek effective method to produce precise results with limited resources, this dissertation compared the Cohort Component Method (CCM) and Hamilton Perry (HP) method to forecast population that are 25 years and older with Associate's degree and above, and evaluated how factors may impact the accuracy, and how factors interact with each other to influence the accuracy.

The results reveal that differences in methods, lengths of predicting period, educational attainment levels, forecast years (year before COVID-19 and year after), measurements, geography levels and characteristics are related to different levels of forecasting accuracy, and these factors may interact with each other to impact the pattern of accuracy. This dissertation found that the HP method is generally more accurate than the CCM method to forecast population 25 years and older and with Associate's degree and above overall at the national level and the CCM method is more accurate than the HP method at the state level in Florida and South Dakota for 1-year forecast in 2019. Longer predicting period is likely to have less accurate forecasts regardless of choices of tested methods and geographies, but with adjustment of measurements, forecasting for longer

predicting period may have comparable accuracy result. Educational attainment levels had different preferences with the methods depending on the geography. The impact of COVID-19 pandemic on forecasting accuracy also depends on the choice of method and measurements in different geographies. This dissertation suggests considering the HP method for forecasts with longer period of forecasting, larger population groups, larger geographies, population group with clear trend patterns; and considering the CCM forecast for smaller population groups, smaller geographies, groups with no clear change patterns, when groups in the geography have reliable data sources for estimating population components (Birth, Death, Migration) changes.

The dissertation emphasized the uniqueness of each forecasting project with the combination of different predicting features and elements (different population groups with distinct demographic attributes, geographies, lengths of prediction period) and discussed the importance of the evaluation process of each project to help selections on methods and measurements. The dissertation also discussed data and resource limitations, and the importance of data quality. With the rapid development of Machine Learning and Artificial Intelligence techniques, more effectively and efficiently toolboxes and software may be developed and applied in the demography field in the near future.

BACKGROUND

The background section first introduces the field of applied Demography and discusses how it differs from academic Demography, focusing on population projections as a primary form of methods in applied Demography. The section then includes a brief review of the current population and educational attainment patterns in the United States (U.S.) and why it is important to study and project populations by educational attainment. Finally, this section introduces the purpose of this dissertation and the research questions.

Applied Demography

In general, demography can be categorized as academic demography (also known as basic demography) and applied demography (Swanson 2015). To begin, I would like to discuss how the field of applied demography is different from academic demography. First, the purpose and motivations are different in these two fields. Academic demography focuses on the theoretical and causal explanation of demographic facts and trends and often studies self-defined or self-interested research questions (Swanson 1996). The work in applied demography is usually defined by customers or clients from the public or private sectors and is used to inform decision-making (Swanson 2015). As the different purposes between academic demography and applied demography, researchers in these two fields have different opinions toward the time and resources involved in working on projects. Scholars in academic demography view time and resources as barriers to overcome to obtain more accurate and explanatory results (Swanson 1996) but applied demographers try to create requested deliverables effectively and efficiently. Applied demographers are often expected to accomplish required projects within limited resources in a timely manner (Swanson 1996); this limitation keeps them seek effective methods to produce precise results with the least time and resources. Applied demography supports practical decision-making by dealing with specific and real-world problems and providing necessary and concrete demographic phenomena and trends (Swanson 1996). Therefore, applied demography can be viewed as a decision-making science (Swanson 1996).

Population Projections in Applied Demography

As an important application method in applied demography, population projections are used to inform planning and support decision-making by forecasting future demographic changes and trends. For example, an elementary school enrollment projection is critical to decide whether the area needs to build a new elementary school; the projection of changes in the occupational structure and the demand of the workforce of certain educational attainment levels in the labor market inform educational institutions to do strategic plans to promote expected educational goals.

The Importance of Projecting Educational Attainment

Firstly, educational attainment is closely related to earnings and unemployment. According to the Current Population Survey in 2020, individuals who have higher degrees had higher median weekly earnings and lower unemployment rates than those with lower degrees. The U.S. Bureau of Labor Statistics[1] projected that occupations would require more education overall between 2020 to 2030, and the forecasted employment percentage increases more for higher educational levels. The forecasted employment percentage growth for persons aged 25 and over with Associate's degrees

[1] Education level and projected openings, 2019–29. https://www.bls.gov/careeroutlook/2020/article/education-level-and-openings.htm

(10.5%), Bachelor's degrees (9.9%), Master's degrees (16.4%), Doctor's degrees (8.9%) are higher than people with postsecondary non-degree awards (9.7%), some college without degree (3.0%), high school diplomas or equivalent (5.1%), and no formal educational credentials (8.9%).

Secondly, educational attainment is one of the important population dimensions to consider in population projections in addition to age and sex because it is related to different patterns of fertility, mortality, and migration, the three key components driving population changes (Lutz and KC 2010). Better education is usually associated with lower fertility, lower mortality, and higher ability to migrate, and plays an important role in human development such as health status, social-economic status, and democracy (Ginebri and Lallo 2021; Lutz and KC 2011). Therefore, the current education status and further progress of education will influence the size and structure of future populations (Lutz and KC 2011).

Thirdly, educational attainment matters for economic improvement and planning. Education is positively associated with individuals' economic status and overall well-being (Lutz et al. 2008). Forecasting education dynamics helps government planning on allocating educational resources, labor market demand, and long-term human capital and overall well-being of society (Lutz et al. 2008).

Population and Educational Attainment Pattern in the U.S.

According to the U.S. Census Bureau Vintage 2021 population estimates[2], the total population increased 0.1% from 331,449,281 in April 2020 to 331,893,745 in July

[2] New Vintage 2021 Population Estimates Available for the Nation, States and Puerto Rico. https://www.census.gov/newsroom/press-releases/2021/2021-population-estimates.html

2021. The national population gain was from natural increase (148,043) and net international migration (244,622). The gain of natural increase means the number of births exceeds the number of deaths, and net migration gain means the number of people who moved into the county is over the number of people who moved out of the county. This is the first time that annual net migration went over natural increase[3]. According to the annual vintage estimates and the decennial census, the annual population increase rate is getting slower, from almost 1% to 0.1% since 2001. The total number of births started to decrease since 2007 and the total number of deaths increased starting in 2010. International migration also declined in the recent six years from 2016 to 2021, but it is still the major driver of population gain in 2021.

The educational attainment for people aged 25 years and over is improving according to the U.S. Current Population Survey in 2010 and 2019. From 2010 to 2019, the percentage of people aged 25 years and over with Bachelor's degrees and above increased from 29.9% to 36.0%, and people with less than high school degrees decreased from 44.1% to 38.0%[4].

INTRODUCTION

To seek more effective means and methods to accomplish the applied projects, applied demographers need to make a balance between projection accuracy and methods complexity by asking questions such as 1) How do the simple and time-saving trend-

[3] COVID-19, Declining Birth Rates and International Migration Resulted in Historically Small Population Gains. https://www.census.gov/library/stories/2021/12/us-population-grew-in-2021-slowest-rate-since-founding-of-the-nation.html

[4] U.S. Census Bureau Releases New Educational Attainment Data. https://www.census.gov/newsroom/press-releases/2020/educational-attainment.html

extrapolation methods perform in terms of accuracy and bias? 2) Is it worth spending time to develop complex procedures and models to estimate and project population? To answer these questions, empirical studies are needed to document and compare the performance of different methods to forecast population.

Previous studies have evaluated the population projection methods 1) within different geographic levels such as counties (Smith and Tayman 2003) and census tract (Backer et al. 2013), or 2) by demographic characteristics such as age groups (Rayer and Smith 2014), or 3) by components of population such as migration (Wilson 2016), or 4) test which factors impact population forecast accuracy (Chi and Wang 2017; Tayman, Smith, and Rayer 2011). In general, complex procedures didn't improve the accuracy and reduce the bias of 10-year period population projection results using component-based projection methods (Baker et al. 2013; Smith and Sincich 1990; Smith and Tayman 2003). It is important to evaluate population projection accuracy and understand why some areas have more accurate projection results and get easier to predict than others (Chi and Wang 2017; Wilson 2015). Population size and growth rate, employment opportunities, public infrastructure, land development, characteristics of neighborhood places (such as education and income) were found to have an impact on the accuracy of projections (Chi and Wang 2017; Tayman et al. 2011).

Most empirical studies compared the performance of population projections in general or by geographic areas of different size. Limited research documents or compares population projections by specific achievement status such as educational attainment. Considering the importance of forecasting population by educational attainment, this study will conduct evaluations of different population projection models that incorporate educational attainment by comparing the accuracy, bias, and application limitations. Following the introduction, this proposal has three sections. 1) literature review, 2) research questions, 3) data and methods.

LITERATURE REVIEW

The literature review section first goes through the typical framework of population projection approaches and methods, then summaries existing documented journal articles on population projections by educational attainments. After introducing the most popular projection method to forecast population by educational attainment (Demographic Multi-state projection), the section further explains how mortality, fertility, migration patterns are related to educational attainment. Finally, this section talks about the use of a time-saving and simple version of the Cohort Components Method population method (Hamilton-Perry) in population forecasting and discusses strategies to improve accuracy.

Population Projection

Forecasting future population trends is very important for planning and decision-making for social, political, and businesses purposes (Mazzuco and Keilman 2020; Vanella, Deschermeier and Wilke 2020). For example, population growth in one geography indicates the increasing demand for resources such as basic needs and facilities. It not only informs government to think about building facilities to meet the future needs of education, health care, transportation, but also helps businesses to make decisions such as investment in grocery stores and shopping centers (Mazzuco and Keilman 2020). Different groups of population change indicate different needs. For example, decreasing children population indicates less demand on daycare centers and schools; elder population change impacts the needs of nursing homes and health care facilities; the increasing pattern of health-related issues on a certain gender, age, or race group suggests the attention to promote preventative care of the corresponding groups; and educational attainment of working-age population indicates the overall capability of the labor force population. Therefore, population projections can be generally forecast on the total population or certain population groups depending on the needs and purposes.

Booth (2006) summarized three approaches or families of methods that are often used to forecast population: extrapolation, expectation, and explanation. As the most common method in demographic forecasting, extrapolation approaches summarize population change patterns from existing data and assume the past trend remains the same in the future (Booth 2006). Expectation approaches use targeted individuals' expectations on future demographic events (e.g., females' expectation on numbers of kids they are going to have), and opinions, judgment, experience, and knowledge of experts to forecast population trends (Booth 2006). Decomposition and causal structural modeling could be viewed as two alternatives for explanation approaches. Decomposition is explained through multiple-decrement life tables which break down the life table of a specific demographic event by multiple causes (Booth 2006). For example, a multiple-decrement life table of marital status can decompose marriage termination categories by widowhood, separation, and divorce. The decomposition approach improves the understanding of demographic change through the explanation of specific causal components. Causal structural modeling explains demographic change by social-economic factors and other related determinants (Booth 2006). Disaggregation is another explanatory approach explained by multi-state modeling, which extended the dimension of cohort-components method from age and sex to ethnicity, education level, or other demographic characteristics (Booth 2006). Figure 1 below demonstrates this classification.

Figure 1. Population projection method classification I

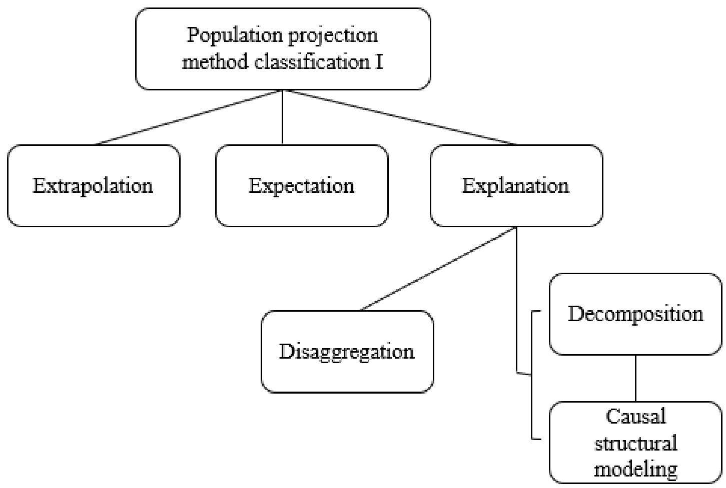
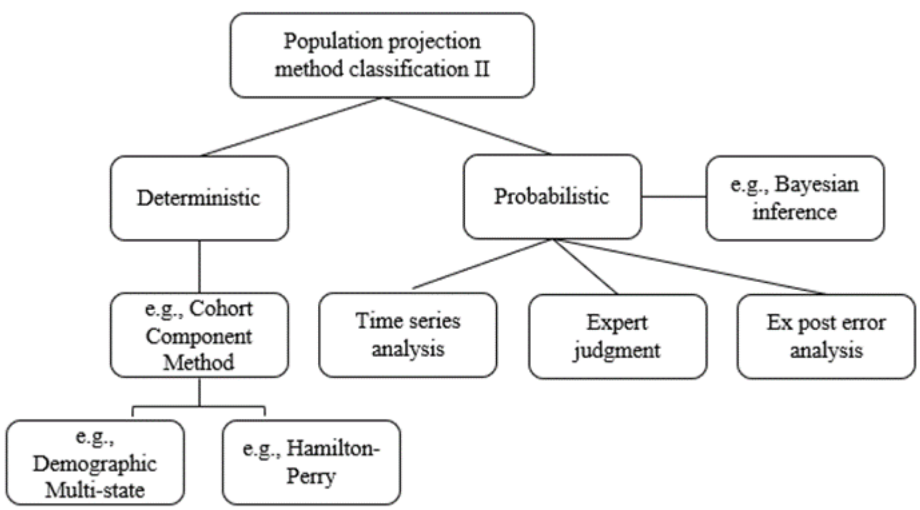


Figure 2. Population projection method classification II



Population projection methods can also be classified as deterministic or probabilistic approaches (Keilman 2020; Raftery and Ševčíková 2021) (Figure 2 demonstrates this classification). Fertility, mortality, and migration are the three main components that determine future population trends (Vanella et al. 2020). Traditional deterministic population projection uses the cohort-component method to calculate population change by cohorts based on specific assumptions on future change of fertility, mortality, and migration, and cohorts are usually classified by age and sex across time intervals. The cohort components method was first developed by Cannan (1895), and then developed by Whelpton (1928, 1936), and became the standard method applied by the United States Census Bureau since the 1940s (Raftery and Ševčíková 2021). Rogers and Ledent (1975) extended the traditional cohort components and added geographic region as a dimension besides age and sex, which is known as multiregional model. Then, Rogers (1980) further extended the multiregional model to the multi-state model. The state refers to the status change of individuals such as marital status, educational attainment level, or residential locations, and the multi-state method was based on a group of increment-decrement life tables by “state” of interests or so-called multi-state life tables (Philipoc and Rogers 1981).

The probabilistic approach is not designed to produce more accurate projection than the traditional deterministic methods but attempt to provide a better sense of forecasting uncertainty (Keilman 2020). While deterministic methods create a fixed number of demographic projections based on giving assumptions of population change patterns, the probabilistic approaches create a set range of numbers of projections with certain confidence intervals. In probabilistic approaches, a large sample of future numbers of population size will be built first, and then median values will be calculated as point projection values in a certain time (Alkema et al. 2015). After that, percentiles of the sample will be usually used as prediction intervals according to the defined confidence levels (Alkema et al. 2015).

There are three main kinds of probabilistic approaches: 1) time series analysis, 2) expert judgment 3), and ex post error analysis (Booth 2006; Keilman 2020). Time series analysis models future projections based on previous data, and it may create wide prediction intervals if the past data trend is not clear enough (Keilman 2020). Expert judgment method models plausible values, confidence intervals, median values of future projections that experts provided (Mazzuco and Keilman 2020). Ex post error use observed previous projection error as a reference to model current projection errors (Alders et al. 2015). Recently, population studies using Bayesian probabilistic inference have gained popularity rapidly (Mazzuco and Keilman 2020). One of the reasons that Bayesian method is attractive for population forecasting is because it can effectively incorporate information from previous study results or experts' opinions into the forecast models (Mazzuco and Keilman 2020). Moreover, Bayesian inference applies the conditional probability based on what can be known from empirical data to forecast what hasn't been known or what are missing in demographic contents, and this method is different than the traditional frequentist approach which considers the probability of an event happening as the frequency of occurrence (Keilman 2020).

In the real world, there is no clear line among approaches or methods to forecast population change (Booth 2006). Demographers project population change based on the needs and specific situations and often mix approaches and methods to make more reasonable projections. For example, the migration component in CCM method may use HP method to project.

Past Population Projections by Educational Attainment

The most appropriate method to project population by education level is the multi-stage demographic projection method, as it takes the influence of fertility, mortality, and migration on educational attainment (Lutz, Goujon, and Wils 2005). The documented population projections by education level have been done all over the world in applied projects. The International Institute for Applied Systems Analysis (IIASA) and the Education Policy and Data Center (EPDC) are two main institutions that document population projections by education level. The multi-state projection method was developed by Andrei Rogers (Rogers 1975), and then started to apply to project educational attainments in the Population Development Environment (PDE) studies in Mauritius (Lutz and Wils 1994). Researchers in IIASA and EPDC applied the multi-state projection method to different developing countries in the world. Yousif, Goujon, and Lutz (1996) also used this method to project population by education level in Algeria, Egypt, Libya, Morocco, Sudan, and Tunisia in North Africa. Goujon and McNay (2003) applied this method to project educational composition for selected states in India. More case studies using this method to project population by education level including in China by rural-urban regional level (Cao 2000), in Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam (Goujon and KC 2006), in Egypt by governorates level (Goujon et al. 2007), in Libya, Tunisia, Morocco, Bahrain, Kuwait, and Saudi Arabia (Goujon 2002), in Portugal (Martins, Rodrigues, and Rodrigues 2014), in Italy (Ginebri and Lallo 2021), and among 120 countries over the world (KC et al. 2010),

Demographic Multi-state Projection Method – A Method based on Cohort Components

The demographic multi-state projection method was developed from the life table (or so-called increment-decrement tables) and Cohort Component Method (CCM) by International Institute for Applied Systems Analysis (IIASA) in the 1970s (Rogers 1975:29). The life table is a deterministic approach to model mortality and survivorship (Keyfitz and Caswell 2005), it studies survivorship, mortality, and life expectancy by age groups through corresponding survival rates. The CCM models population change through three causing components of the population, and they are birth, death, and migration. The cohort refers to a group of people experiencing the same live events or sharing similar demographic characteristics (Shryock and Siegel 1973:712.) Population projections often divide the total population by age cohorts, and age cohorts are typically broken by gender and/or race and ethnicity groups (Smith, Tayman, and Swanson 2013).

The multi-state projection approach allows demographic studies to expand additional attributes or cohorts in population dynamics other than age and sex (Keyfitz and Caswell 2005; Martins et al. 2014). The "state" originally refers to geographic units in multi-regional projection models and was created to capture the migration flow (Lutz and Goujon 2001). A "state" was further extended to other subgroups based on different interesting population elements such as marital status, educational attainment, unemployment (Kayfitz and Caswell 2005). However, the demographic multi-state projection was not well known by scholars outside of mathematical demographers (Lutz et al. 2005).

Similar to the survivor rate function in the increment-decrement life table to study mortality, the multi-state models use the state transition rate to generate multi-state life tables such as working life tables, marriage life tables, or education life tables. The state transition refers to people changing experiences in the life course by transition from one state to another state (Rogers 1980). For example, the transition of being unemployed from employed, from being married to divorced, or being students to graduates with degrees.

Population projection by levels of educational attainment by age and sex is the typical example of the multi-dimensional cohort component model (Luts and Goujon 2001). In the multi-state educational attainment projection model, states mean different levels of educational attainment, and state transitions refer to transition from one educational attainment level to another higher educational attainment level. Education transitions usually focus on the population aged 25 years or below and were assumed that people after 25 years old will not have education improvement (Luts and Goujon 2001), although some people may continue receiving education and having upward educational transitions after 25 years or older. Therefore, the multi-state model is based on population projection matrices that calculated the occurrences of transition from one state to another state in discrete time (Martins et al. 2014).

Mortality, Fertility, and Migration Patterns by Educational Attainment

For population projections, it is recommended to separate mortality, fertility, and migration components and create projections for each component, respectively (Smith et al. 2013). This is because of three main reasons: 1) separation projections by component allow projections to take into account different demographic processes leading to population changes in birth, death, and migration; 2) population change from each component may react differently to social, economic, political, medical, environmental, and culture impacts; 3) the change and trend of each component vary by locations and geographies (Smith et al. 2013). These reasons also apply to population projections by educational attainment, and previous studies indicated mortality, fertility, and migration showed distinct patterns among populations of different levels of educational attainment.

Increased schooling and education are generally associated with lower women's fertility rates; the fertility rate was significantly lower for more educated women than women receiving less education in both developing and developed countries (Skirbekk, 2008). Lower levels of education can relate to limited knowledge about reproduction and access to contraception (KC et al. 2010), and women with less education are also more likely to have traditional views on gender roles and consider high fertility as a form of high social status (Jejeebhoy 1995). Moreover, less educated women may follow more strictly with the religious ideas to keep high fertility and prohibit birth control (McQuillan 2004). Using the U.S. Current Population Survey in 2019, Hamilton (2021) compared the total fertility rates among women aged 15 to 49 by different levels of educational attainment and found that women with higher levels of educational attainment generally had lower total fertility rate than that of women with lower levels of educational attainment.

Mortality is also related to education; more years of education are associated with lower chance of mortality and longer life expectancy (Brown et al. 2012). Healthier behavior and better financial and health resources might be the mechanism for more educated people to have a lower chance of death and longer life expectancy (Brown et al. 2012, Buckles et al. 2016). People with college education have lower rates of death caused by poor health behaviors, and they are more likely to have higher earnings and a higher rate of insurance coverage (Buckles et al. 2016). Lleras-Muney (2005) found one more year of education decreased the mortality rate by approximately 3% and increased life expectancy gains for about 1.7 years for the population 35 years and older in the United State. Xu et al. (2010) noted that for the population aged 25 to 64, the age-adjusted mortality rate for people with less than high school degree was 14.1% higher than people with high school degree or equivalent and 2.7 times higher compared to people with some college or collegiate degree in 2007.

Migration patterns are different for people with different levels of educational attainment. Job and employment opportunities are primary motivations for movers move across counties and states (Molly and Smith 2019), especially for people of working age. Better educated individuals have a higher probability to move than those less educated according to the Current Population Survey in 2017 in the U.S. (Molly and Smith 2019). Molly and Smith (2019) defined low-to-high labor demand metropolitans by predicting local employment growth using the Quarterly Census of Employment and Wage data, and they found people are more likely to move from low-labor demand metropolitans to high-labor demand metropolitans. The probability of individuals with four or more years of college and having this moving pattern was about 3% higher than people with high school degrees (Molly and Smith 2019). Bound and Holzer (2000) documented that less educated individuals are less informed by potential alternative labor market opportunities and have less ability and resources to migrate. College graduated workers selected to live in high wage, high rent, and high amenity cities and benefited more in these cities than high school graduates (Diamond 2016), suggesting migration patterns differs among education levels and locations characteristics. Alsharif (2019) summarized a few locational characteristics such as economy, housing, amenities, environment, socio-cultural atmosphere, and policy may impact the migration pattern, indicating different areas may experience different migration patterns due to the locational characteristics. Therefore, population projections for educational attainment need to take into account the distinct migration patterns in groups with different levels of education and geographic variations should also be considered.

Hamilton-Perry Population Projection Method

The Hamilton-Perry (HP) method has been used by applied demographers to project population change due to the accuracy result, time-saving process, and practical value (Tayman and Swanson 2017). HP is a simple version of the cohort-component population projection method that requires fewer details of data inputs (Baker, Swanson, and Tayman 2021; Tayman and Swanson 2017), and it assumed that age-based fertility, mortality, and migration rates of the past stay constant in the forecasting period (Hamilton and Perry, 1962). The HP method only requires data by age groups at two-time points to capture the Cohort Change Ratios (CCRs), then use this ratio to project population change for the next period. The Cohort Change Ratios captures a blended impact from birth, death, and migration by cohort in the defined period (Wilson and Grossman 2022). The population of the first or initial age group is projected differently. For example, in projections that age cohorts defined with five years gap, the 0 to 4 age group is usually projected using Child Woman Ratios which uses the current proportion of population ages 0-4 among the total female population in childbearing age multiplied by the projected female population in childbearing age (Hauer 2019; Wilson and Grossman 2022). Besides population projections by age groups, the HP method can be extended by other ascribed characteristics (such as race, ethnicity, and gender) and achieved characteristics (such as educational attainment, marital status, and health behaviors) based on the need and interest of the projection project (Baker et al. 2017:119-141).

Complex methods and models are not necessarily more accurate than simple methods (Green and Armstrong 2015), and the CCM does not always produce more accurate forecasting results than the HP method (Smith 2017). It is usually a time-consuming and costly process because of requiring detailed data inputs broken down for mortality, fertility, and migration by age and sex (Wilson and Grossman 2022). Therefore, HP method is a good option for short-term (up to 10 years) small areas population projections where data on the three determinants of population change (fertility, mortality, and migration) are limited or for projects that budgeted for limited time and resources (Baker et al. 2021; Wilson and Grossman 2022). The HP method also gained attention in applied projections.

Empirical studies found the accuracy of HP projection method can be improved by data adjustment or modification strategies. Baker et al. (2014) grouped census tracts using contiguity and proximity spatial relationships and adopted the average value of the initial HP forecasted results on each urban census tracts groups as the final forecasted population results. Tayman and Swanson (2017) found the HP forecasting errors can be reduced by modifying the Cohort Change Ratios and Child-woman Ratios using the synthetic method. The synthetic method that Tayman and Swanson used applied the rate of forecasted Cohort Change Ratios change in Washington state (larger geography) to the counties in Washington State (smaller geographies). Hauer (2019) combined Cohort

Change Ratios and Cohort Change Differences to forecast population between 2020 to 2100 for all U.S. counties, and he applied Cohort Change Differences to counties with growing populations and Cohort Change Ratios to counties with declining populations. Basically, Cohort Change Differences created a linear growth rather than exponential growth to avoid unreasonable accelerated forecasting growth (Hauer, 2019). Moreover, controlling or constraining using the independent total population forecast reduced the forecasting error of HP method (Tayman et al. 2021; Wilson and Grossman 2022). The procedure of independent total population controlling first create a population projection (e.g., Tayman et al. 2021) or use an existing population projection (e.g., Wilson and Grossman 2022), then using this forecasted population total multiply by the proportion of each age and gender groups calculated from population forecast that produced by HP method (Baker et al. 2021). After that, you sum up each multiplied population element by age and gender groups to get the controlled or constrained total forecasted population result.

Other Factors

It is important to evaluate the factors that impact population projection accuracy. Methods are not the only components that influence the population forecasting accuracy. Previous studies evaluated how other factors may influence the population projection results, including different age groups (Rayer and Smith 2014; Smith and Tayman 2003), level of geography (Rayer and Smith 2014), different measurements of change (Wilson 2016), geography characteristics (Chi and Wang 2017), length of projection horizons (Smith and Tayman 2003; Wilson 2016), and public health crises (Matthay et al. 2022, Ramani and Bloom 2022).

Age Group. Younger and older population groups are often found to have relatively higher levels of predicting errors (Rayer and Smith 2014). Young kids ages from 0 to 4 experienced higher errors because they usually predicted from uncertain fertility rate (Smith and Tayman 2003), and the unclear migration pattern among younger adults and rapid change motility rate among older groups made younger adults and older adults harder to predict (Rayer and Smith 2014).

Length of Projection Horizon. Longer-term population forecasts tend to have higher predicting errors than the shorter-term forecasts (Smith and Tayman 2003). Rayer and Smith (2014) compared projections made between 1995 to 2009 for total population in 2010 in Florida at both county and state levels and noticed that the longer predicting period from census year, the less accurate of the projection. Wilson (2016) evaluated alternative CCM models with different measurements of migration in New South Wales and found the projections with 20 years prediction horizons were less accurate than the projections with 10 years predicting horizon regardless of the different measurements used for migration.

Level of Geography. The population projection errors in lower level of geographies are usually higher than the higher level of geographies. The projection of total population in 2010 at the Florida county level had larger errors than that of the state level (Rayer and Smith 2014).

Characteristics of Geography. Chi and Wang (2017) examined the relationship between population projection errors and county characteristics and found the population size, employment rate, commuting time and land developability of the county are statistically significantly negatively related with population projection errors. The higher the values in total population size, employment rate, the percentage of workers travelling 30 minutes or less to work, and land developability index, the smaller the projections errors (Chi and Wang 2017).

Measurement of Change. Previous studies used change rates, change differences, or blended change rates and differences to forecast the population change (Hauer 2019; Wilson 2016). The change rates create exponential growth or decrease, and the change differences create linear growth or decrease for future population. The disadvantage of using change rates may cause exaggerated population growth in projection and the disadvantage of using change difference may create the negative population issues (Wilson 2016). Wilson (2016) evaluated the alternative cohort component models using different measurements of net migration including net migration rate, net migration number, composite the net migration rate and number to predict population in 67 local government areas in New South Wales. In the composite method, Wilson (2016) applied net migration rates to areas with negative net migration and net migration numbers to areas with positive net migration. Wilson (2016) found that methods using net migration number have almost the same prediction performance as using composite net migration; and they have more accurate prediction results than the methods using net migration rate. The accuracy evaluations Wilson (2016) conducted was based on averaged total error indicator to project total population among all local government areas rather than each individual area, so the accuracy among different areas using difference net migration measurements for population projection is not clear and the accuracy of using different measurements to projecting migration itself was not tested in Wilson's (2016) study. Hauer (2019) applied change rates to the population group that projected to decrease and applied change differences to the population group that projected to increase. There are different ways to measure the change number and change rate. Instead of applying the commonly used average method to capture the measurement of change, Hauer (2019) used time series Autoregressive Integrated Moving Average model (ARIMA (0,1,1) - similar to Single Exponential Smoothing) created the change rates or predicted numbers for all groups, which may not capture the change trend well enough for groups have growth or decline patterns. Time series single exponential smoothing is a technique to create forecast with the exponential weighted values from the data during the past. This technique often treats the past data in more recent time with more impacts for the forecasting values by distributing the weights ratios from high to low by the recentness of time. Time series double exponential smoothing is a technique to include both time sequence level impact and the trend impact (Nazim and Afthanorhan, 2014), and it is a good choice to forecast data that has trends (Nazim and Afthanorhan, 2014).

Public Health Crises. The COVID-19 impacted population projections by educational attainment through the mortality component. Lower education levels were associated with higher risk of mortality than the higher educational levels (Matthay et al. 2022). Matthay et al. (2022) compared the proportion of California COVID-19 decedents aged 18 to 65 years older by four educational levels among the total population in California (no high school degree and no GED, high school degree or GED, some college or associated degree, Bachelor’s degree or higher), and found the lower the educational attainment level, the higher the proportion of decedents. After comparing the mortality rate for three educational categories (high school graduates or less, some colleges, college graduates or higher) from 2017 to 2020 in the United States, Marlow et al. (2022) noticed that more educated groups have lower mortality rates than the less educated groups. Moreover, the disparities between levels of educational attainment widened during the pandemic in 2020 compared than in 2019, 2018 and 2017 (Marlow et al. 2022). The widened mortality rate gaps between lower levels of educational attainment and high levels during the pandemic in 2020 indicates that COVID-19 had stronger impacts on lower levels of educational attainment in terms of mortality. Additionally, the COVID-19 pandemic changed migration intentions and actions. Ramani and Bloom (2022) used US Postal Service and Zillow data found that households and businesses tend to shift from central business districts to suburbs and exurb in large US metro areas, and most of these household shifts happened in the same city potentially due to the remote or hybrid working model (Ramani and Bloom 2022). The pandemic also reduced people's preference of residential locations of high population density in urban cities and increased the preference of suburban (Parker et al. 2021) and rural counties (Petersen et al. 2024). Petersen et al. (2024) found rural recreation counties had higher gain in net migration rate than rural non-recreation counties in the first year of the COVID-19 pandemic, but this difference had balanced in the third year of COVID-19 occurred. COVID-19 not only impacted the internal migration in the U.S., but also influenced international migrations. During health crisis, immigrants were more likely labeled as disease carriers (Kraut 2010), so migration across counties is more likely restricted especially during the early stage of COVID-19 pandemic.

As a detailed version of population projection, the accuracy of population forecasts by educational attainments are likely to be impacted by the factors discussed above. The accuracy of population forecasts by different educational attainment levels may differ. Also, certain educational attainment levels may prefer using CCM method considering death and migration, because there are migration and mortality differentials by educational attainment levels. People with higher educational attainment levels are more capable to migrate (Molly and Smith 2019) and are more likely to have longer life expectancy (Brown et al. 2012, Buckles et al. 2016). Higher educational groups might have more accurate projection result when considering the mortality and migration components, meaning the group with higher educational attainment level may prefer the CCM with consideration of mortality and migration. Due to the impact of public health crisis on mortality and international migration, the projections during COVID-19 years may also prefer the CCM to consider the COVID-19 impacts to mortality and international migration. The longer period usually generates larger errors or uncertainties for population projections (Smith and Tayman 2003). Therefore, the simple HP method may be suitable for the longer length of projections rather than the CCM while longer period brings more uncertainties to the population change components.

CURRENT STUDY AND RESEARCH QUESTIONS

Educational attainment is not only an important dimension of population projections but also related to the economic and labor market development and government planning. Therefore, it is significant to project population by educational attainment. To find an accurate and effective way to forecast population by educational attainment, this study will evaluate the performance of using the CCM and HP method (a simplified version of CCM) to project population by educational attainment in the Unites States and how the associated factors impact the performance of projection models at national level and state level. This study is interested in forecasting the educational attainment for the population aged 25 and over.

Basically, this study tries to answer two questions: 1) Which approach produces more accurate population projections by educational attainment? 2) How are differences in length of predicting horizons, educational levels, years before and after public health crisis, geography locations related to the accuracy of each method, and how do different methods, measurements and geographic locations may interact with these impacts?

By answering these two questions, this study will design different groups of projections for comparison to evaluate the performance of the two methods and test how the factors influence the population projections result at national level. I will then apply the same process to two different states to exam how these two methods work in different states, and what are the similarities and differences between the state level forecasts and national level forecasts. The two selected states are South Dakota and Florida. Overall, South Dakota is less desirable than Florida indicated by the net migration trend. Florida was the top moving destination and with the highest net migration[5].

METHODS

Using Cohort Component Method (CCM) not the Demographic Multi-state Projection Method

This study will use the CCM not the Demographic Multi-state Projection with transition rate as a reference method to compare with the HP method. The transition trajectories of people that are 25 years and older in secondary educational attainment

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[5] State-to-State Migration Trends in 2022. https://www.nar.realtor/blogs/economists-outlook/state-to-state-migration-trends-in-2022

levels are more complicated than the K-12 grades. The students from Kindergarten to 12th grade are most likely to follow the sequence from K-12 grade paths gradually, and move up the next grade each year with few exceptions to skipping a grade or staying a grade. But people who are 25 years and older in secondary education are more complicated. First of all, it is not sure when people are interested to go to the next educational level and how long it takes to graduate, because people that are 25 years and older may start to work or have families and it is hard to predict when they are going to enroll for the next level of education and whether they study as full time or part time to complete the degree. Secondly, there are different paths to get secondary educational degrees. For example, people with Associate's degrees can transit to Bachelor 's degree, and then Master degrees, or just from Associate's degrees to Master's degree without Bachelor's degrees. People with high school degrees may transit to Professional degrees with or without Associate's or Bachelor's Degrees. Therefore, this study will not consider the transition rate in secondary education and will track the annual population change of each component (new graduates, death, migration) for the defined population group, instead.

Comparison among the approaches

Both the CCM and HP method are deterministic projection approaches to forecast population by educational attainment. The main difference is that the CCM considers three determinants of population change (birth, death, migration) separately, while the HP method focuses on overall population change patterns over time without breaking down the changes in the population by the birth, death, and migration components. The most important parameters of the CCM are three sets of cohort population change measurements of changes in births, deaths, and migrations. The key parameter of the HP method is the overall cohort change measurement.

In general population projections, the CCM assumes that the component change of birth, death, and migration during the forecasting period remains the same with the past observed trend, while the HP method assumes that the cohort change ratio in the forecasting period stays the same with the past. Assumptions for these two methods are different as well when used for forecasting population by educational attainment. The CCM assumes that differentials of birth, death, and migration by educational attainment level observed from the past stay constant in the forecasting period. However, the HP method assumes that the differentials of cohort changes by different levels of educational attainment in the forecasting period stay the same as the past. Previous studies found that more educated people are more likely to have a lower fertility rate, lower mortality rate, and more capable to migrate. The CCM allows the projection model to consider the influence of educational attainment level on fertility, mortality, and migration, so CCM maybe more accurate than the HP method in making projections by educational level. However, the data on fertility, mortality, and migration by educational attainment levels may not be available and are usually not from the same source. The fertility, mortality, and migration by educational attainment levels may be estimated from different data sources. The estimation process from different data sources may create data errors and biases in projections.

Evaluation Indicator

In this study, evaluation is a comparing process of error terms using mathematical calculations between the forecasting results and the observed value. The errors in this paper refer to the difference between the population forecasts by educational attainment (the forecasted value) and the population by educational attainment from census estimates (the observed counts are considered as true value). This study will use the difference value (DIF), Percentage Error (PE), and, most importantly, the Absolute Percentage Error (APE) to make comparisons.

DIF is the difference between forecasted value (F) and observed counts (P). It can be defined as

$$DIF = F-P$$

PE is the difference between forecasted value (F) and observed counts (P) divided by the observed counts (P), multiplying by 100 to get the percentage. It can be defined as

$$PE = (F-P)/P * 100\%, \text{ or } PE = DIF/P*100\%.$$

Absolute Percentage Error (APE) is the absolute value of PE. it can be defined as

$$APE = |PE|$$

The smaller APE indicates higher accuracy, the larger value of APE indicates lower accuracy. The positive DIF value means how many counts that the forecasted value overestimated the observed counts, and negative DIF value means how many counts that the forecasted value underestimated the observed counts. Comparing the errors between different forecasting models using different methods or different projection categories will suggest which models are more accurate. DIF means the difference of population counts and it measures how many population the forecasts are over or under the observed counts. It is the error term used for the comparison in each projection with same methods with different measurements. PE and APE are the percentage error, and it is used for compare different projections across different methods, different groups, different period, and different geographies. The difference between PE and APE is that PE can have both negative and positive value indicate the forecast is over projected or under projected, while APE only has positive value to compare the amount of the percentage error across different forecasts.

Forecasting Procedures

In this dissertation, four educational attainment categories will be forecasted, and they are Associate's degree and above and its three subdivision categories (Associate's degree, Bachelor's degree, and Graduate or Professional degrees). Two projection lengths will be compared, and they are 1-year projection and 4-year projection in the year of 2019. The projection length of 4 years was proposed because the data was available since 2010. The past trend will be captured by the change from 2010 to 2015 to predict the change between 2015 to 2019. The projections for the year 2019 (before Covid-19) and 2021 (after COVID-19 happened) will be compared to get a general understanding of how COVID-19 might have impacted the projection accuracy. The new graduates are considered as the "birth" of each educational attainment level for the population that are 25 years and older. Newborns and fertility differentials by educational attainment do not need to be considered because people aged 15 are the starting age group for the 10-year forecast by educational attainment for people aged 25 years old. That is to say, the population under 15 years old in the base year (2010) and the newborn population during the 10-year forecast period (2010 to 2020) are not involved in the process. Due to data limitations, national migration by educational attainment only considered immigration by educational attainment. Emigration is not tracked which also means that this study assumes the emigrants dissolves the undercounted immigrants. Therefore, this study considers new graduate completions, mortality, and immigration into the CCM at the national level to forecast population by educational attainment. At the state level, migration and mortality are different from the national level. The mortality rate is approximated using the national level mortality rates by educational attainment categories. The net migration at state level considers the migrants moved into the state and migrants moved out to other states in the United States.

Predictions are based on population changes by educational attainments during the base year and forecasted years in both HP and CCM methods. In the HP method, this study will use different measurements to calculate forecasted population changes by educational attainment levels. Then add the changes (P_c) into the base year population (P_n) in year n by educational attainments to get the forecasted population (P_{n+x}) by educational attainment in the projection year (n+x). It can be defined as:

$$P_{n+x} = P_n + P_{c.}$$

In CCM method, the change of population in each educational attainment category will be captured by the observed counts of new graduates (P_g), mortality (P_d), and net migration (P_m) . Then, based on the population by educational attainment data in the most recent hypothetical base year, observed counts of new graduates and migrations will be added, and mortality counts will be subtracted during the forecast period to get the forecasted values in each educational attainment category.

$$P_{n+x} = P_n + P_g - P_d + P_{m.}$$

The hypothetical forecasted years are 2019 and 2021 in both HP and CCM method. For population by educational attainments forecasts in 2019, and the hypothetical base years are 2018 for 1-year forecast and 2015 for 4-year forecast in 2019. Due to the challenges of the Covid -19 pandemic on data collection, the U.S. Census Bureau did not release the standard 1-year American Community Survey estimates in 2020[6]. For population by educational attainments forecasts in 2021, and the hypothetical base year are 2019 for 2-year forecasts.

The next step is to make a list of population projections, then calculate the error terms of each projection based on the projected value and Census estimates. The projections with smaller errors indicate better performance. After that, this study will compare the accuracy of the HP and CCM approaches, and test the impact of the factors by comparing the error terms among different groups of projections.

Measurements

Change rates and change differences are the two very classic measurements to do population projections. Besides the mathematical change rates and change differences, this study will also include the time series smoothing techniques to predict the total population or change rate for comparisons with classic measurements. There will be six measurements involved in this study, and they are 1) Average Annual Change Difference (M1) - the mean annual change differences of total population of the targeted group; 2) Average Annual Change Rate (M2)- the mean annual change rates in total population of the targeted group; 3) Single Exponential Smoothing Rate (M3) - the annual change rate

[6] Census Bureau Announces Changes for 2020 American Community Survey 1-Year Estimates. https://www.census.gov/newsroom/press-releases/2021/changes-2020-acs-1-year.html.

that forecasted using single exponential smoothing time series techniques; 4) Double Exponential Smoothing Total (M4) - the forecasted total population using double exponential smoothing time series techniques; 5) Single Exponential Smoothing Total (M5) - the forecasted total population using single exponential smoothing time series techniques; 6) The Average (M6) - the mean value of forecasted results with all selected measurements in the HP method and it is created for overall HP method comparison with CCM method. This Average will exclude forecast with the Single Exponential Smoothing Total which will be discussed in the past trend later. All these measurements of change will be captured using the data in previous years since 2010. The population will be forecasted as below using these measurements with HP method:

$$P_{n+x} = P_n + X*M1;$$

$$P_{n+x} = P_n + X*M2*P_{n;}$$

$$P_{n+x} = P_n + X*M3*P_{n;}$$

$$P_{n+x} = M4_{;}$$

$$P_{n+x} = M5_{;}$$

Where X means the number of years between base year and forecasted year.

Evaluation Design

The population projections by educational attainment that will be made are listed below with Table 1 listing the features and elements of each forecast and Table 2 demonstrating the reference forecasting groups and comparison forecasting groups with the factors and interactions trying to test from each group comparisons.

Table 1. Features and Elements of Each Forecast

Forecast Symbol	Base Year	Forecast Year	Forecast Length (years)	Educational Attainment Level	COVID-19	Measurement of Change	Data
H1	2018	2019	1	Associate's Degree and Above	Before	Average Annual Change Difference, 2010-2018	ACS
H1	2018	2019	1	Associate's Degree and Above	Before	Average Annual Change Rate, 2010-2018	ACS
H1	2018	2019	1	Associate's Degree and Above	Before	Single Exponential Smoothing Rate, 2010-2018	ACS
H1	2018	2019	1	Associate's Degree and Above	Before	Double Exponential Smoothing Total, 2010-2018	ACS
H1	2018	2019	1	Associate's Degree and Above	Before	Single Exponential Smoothing Total , 2010-2018	ACS
H1	2018	2019	1	Associate's Degree and Above	Before	HP Average (mean of the first four HP forecasts)	ACS
C1	2018	2019	1	Associate's Degree and Above	Before	New Graduates + Net Migration - Deaths, 2018-2019	ACS, IPED, NCHS
H2	2017	2019	2	Associate's Degree and Above	Before	Average Annual Change Difference, 2010-2017	ACS
H2	2017	2019	2	Associate's Degree and Above	Before	Average Annual Change Rate, 2010-2017	ACS
H2	2017	2019	2	Associate's Degree and Above	Before	Single Exponential Smoothing Rate, 2010-2017	ACS
H2	2017	2019	2	Associate's Degree and Above	Before	Double Exponential Smoothing Total, 2010-2017	ACS
H2	2017	2019	2	Associate's Degree and Above	Before	Single Exponential Smoothing Total , 2010-2017	ACS
H2	2017	2019	2	Associate's Degree and Above	Before	HP Average (mean of the first four HP forecasts)	ACS
C2	2017	2019	2	Associate's Degree and Above	Before	New Graduates + Net Migration - Deaths, 2017-2019	ACS, IPED, NCHS
H3	2015	2019	4	Associate's Degree and Above	Before	Average Annual Change Difference, 2010-2015	ACS
H3	2015	2019	4	Associate's Degree and Above	Before	Average Annual Change Rate, 2010-2015	ACS
H3	2015	2019	4	Associate's Degree and Above	Before	Single Exponential Smoothing Rate, 2010-2015	ACS

H3	2015	2019	4	Associate’s Degree and Above	Before	Double Exponential Smoothing Total, 2010-2015	ACS
H3	2015	2019	4	Associate’s Degree and Above	Before	Single Exponential Smoothing Total , 2010-2015	ACS
H3	2015	2019	4	Associate’s Degree and Above	Before	HP Average (mean of the first four HP forecasts)	ACS
C3	2015	2019	4	Associate’s Degree and Above	Before	New Graduates + Net Migration - Deaths, 2015-2019	ACS, IPED, NCHS
H4	2019	2021	2	Associate’s Degree and Above	After	Average Annual Change Difference, 2010-2019	ACS
H4	2019	2021	2	Associate’s Degree and Above	After	Average Annual Change Rate, 2010-2019	ACS
H4	2019	2021	2	Associate’s Degree and Above	After	Single Exponential Smoothing Rate, 2010-2019	ACS
H4	2019	2021	2	Associate’s Degree and Above	After	Double Exponential Smoothing Total, 2010-2019	ACS
H4	2019	2021	2	Associate’s Degree and Above	After	Single Exponential Smoothing Total , 2010-2019	ACS
H4	2019	2021	2	Associate’s Degree and Above	After	HP Average (mean of the first four HP forecasts)	ACS
C4	2019	2021	2	Associate’s Degree and Above	After	New Graduates + Net Migration - Deaths, 2019-2021	ACS, IPED, NCHS
H5	2018	2019	1	Associate’s Degree; Bachelor’s Degree; Graduate or Professional Degrees.	Before	Average Annual Change Difference, 2010-2018	ACS
H5	2018	2019	1	Associate’s Degree; Bachelor’s Degree; Graduate or Professional Degrees.	Before	Average Annual Change Rate, 2010-2018	ACS
H5	2018	2019	1	Associate’s Degree; Bachelor’s Degree; Graduate or Professional Degrees.	Before	Single Exponential Smoothing Rate, 2010-2018	ACS

H5	2018	2019	1	Associate’s Degree; Bachelor’s Degree; Graduate or Professional Degrees.	Before	Double Exponential Smoothing Total, 2010-2018	ACS
H5	2018	2019	1	Associate’s Degree; Bachelor’s Degree; Graduate or Professional Degrees.	Before	Single Exponential Smoothing Total , 2010-2018	ACS
H5	2018	2019	1	Associate’s Degree; Bachelor’s Degree; Graduate or Professional Degrees.	Before	HP Average (mean of the first four HP forecasts)	ACS
C5	2018	2019	1	Associate’s Degree; Bachelor’s Degree; Graduate or Professional Degrees.	Before	New Graduates + Net Migration - Deaths, 2018-2019	ACS, IPED, NCHS

Table 2. Reference and Comparison Groups with Testing Factors and Interactions for each Group

Comparison Groups	Reference Groups	Main Factor	Possible Interactors		
H1	CCM1	Method	Measurement	Geography	
H3, CCM3	H1, CCM1	Length of Projection	Method	Measurement	Geography
H5	CCM5	Educational level	Method	Measurement	Geography
H4, CCM4	H2, CCM2	Public Health Crisis	Method	Measurement	Geography

H1. HP 1-year Forecast in 2019. Using HP method and apply the measurements of change to forecast population by educational attainment in 2019. The base year is 2018. The measurements of change will be captured through the change of population with Associate's degree and above annually from 2010 to 2018.

H2. HP 2-year Forecast in 2019. Using HP method and apply the measurements of change to forecast population by educational attainment in 2019. The base year is 2017. The measurements of change will be captured through the change of population with Associate's degree and above annually from 2010 to 2017.

H3. HP 4-year Forecast in 2019. Using HP method and apply the measurements of change to forecast population by educational attainment in 2019. The base year is 2015. The measurements of change will be captured through the change of population with Associate's degree and above annually from 2010 to 2015.

H4. HP 2-year Forecast in 2021. Using HP method and apply the measurements of change to forecast population by educational attainment in 2021. The base year is 2019. The measurements of change will be captured through the change of population with Associate's degree and above annually from 2010 to 2019.

H5. HP 1-year Forecast by Three Education Categories in 2019. Using HP method and apply the measurements of change to forecast population by educational attainment by three educational attainment categories in 2019. The base year is 2018. The measurements of change will be captured through the change of population with each educational category annually from 2010 to 2018.

<u>C1. CCM 1-year Forecast Tracking Migrant, Mortality, Completion in 2019.</u> The base year is 2018. The change of population with Associate's degree and above will be captured among immigration (net migration for national level), mortalities, and completions from 2018 to 2019.

<u>C2. CCM 2-year Forecast Tracking Migrant, Mortality, Completion in 2019.</u> The base year is 2017. The change of population with Associate's degree and above will be captured among immigration (net migration for national level), mortalities, and completions from 2017 to 2018.

<u>C3. CCM 4-year Forecast Tracking Migrant, Mortality, Completion in 2019.</u> The base year is 2015. The change of population with Associate's degree and above will be captured immigration (net migration for national level), mortalities, and completions from 2015 to 2019.

<u>C4. CCM 2-year Forecast Tracking Migrant, Mortality, Completion in 2021.</u> The base year is 2019. The change of population with Associate's degree and above will be captured among immigration (net migration for national level), mortalities, and completions from 2019 to 2021.

<u>C5. CCM 1-year Forecast Tracking Migrant, Mortality, Completion by Three Education Categories in 2019.</u> The base year is 2018. The change of population will be captured among immigration (net migration for national level), mortalities, and completions in each educational attainment categories (Associate's degree, Bachelor's degree, and Graduate or Professional degrees) from 2018 to 2019.

Projections will be divided into different groups to conduct accuracy comparisons. These groups are designed to compare projection with different methods, different lengths of predicting horizons, different educational levels, different years (before COVID-19 pandemic and after), and possible interaction with measurements and geographic locations. APE will be compared to indicate which projection is more accurate and DIF will be compared to indicate how many counts the projected value is over or under the observed population counts by each educational attainment categories. Comparison within each group reflects the impacts of different educational levels, length of predicting horizons, public health crisis on the accuracy of population projection by educational attainment in both HP and CCM method. These groups are:

1) To evaluate the impact of different methods on accuracy of projection, the APEs of 1-year projection in 2019 using HP methods (projection H1 Average) and CCM method (projections C1) will be compared. Cross comparison will be made to test the interactions of methods with different measurements and geographic locations.
2) To evaluate the impact of length of projection horizon on accuracy of projections, the APEs of 1-year projection and 4-year projection of the year 2019 will be compared in HP methods (projections H1 Average, H3 Average) and CCM method (projections C1, C3). Cross comparison will be made to test the interactions of length of projection horizon with methods, measurements, and geographic locations.
3) To evaluate the impact of educational attainment levels on accuracy of projection, the APEs of projections in 2019 with different educational attainment levels will

be compared in HP methods (projections H4 Average) and CCM method (projections C4). Cross comparison will be made to test the interaction of educational attainment levels with methods, measurements, and geographic locations.

4) To evaluate the impact of COVID-19 on accuracy of projections, the APEs of projections in 2019 and 2021 will be compared in HP methods (projection H2 Average and H5 Average) and CCM method (projection C2 and C5). Cross comparison will be made to test the interaction of COVID-19 with methods, measurements, and geographic locations.

Data

The data input for HP method requires the previous data of total population that are 25 years old and over by each secondary educational attainment level from 2010 to projection base year. The total population in each secondary attainment level from 2010 to the base year will use the data from Census Bureau's American Community Survey (ACS[7]). The CCM method requires more data than the HP method. It not only requires total population that are 25 years old and over by each educational attainment level at the projection base year, but also needs the population change from the three components (new graduates, deaths, migrations) by age and educational attainment level between the base year and the forecast year. These requirements limited the data selection for this dissertation, and three data resources will be utilized. They are 1) the population estimates data and migration data from Census Bureau's American Community Survey (ACS), 2) the multiple cause of mortality data from National Center for Health Statistics

[7] American Community Survey (ACS). https://www.census.gov/programs-surveys/acs.

(NCHS), 3) the degree completion data summarized by Integrated Postsecondary Education Data System (IPEDS).

ACS is an ongoing nation-wide survey that provides data on social, economic, demographic, housing characteristics, and migration for various geographies every calendar year since 2005. This survey data helps local officers, community leaders, businesses, and the general public to understand changes in various geographic levels. These data will be accessed through the Integrated Public Use Microdata Series (IPUMS USA)[8]. IPUMS USA is a website that preserves and provides harmonized database and documentation of U.S. Census microdata (individual and household level) which includes ACS from 2000 to 2020.

The ACS 1-year microdata contains 1% of the national random sample of the population. The ACS 1-year estimates subject table[9] (S1501) provide tabulated population estimates by educational attainment by age groups. It provides summarized data for population 25 years and over by educational categories starting in 2010, including the detailed secondary education degrees and they are 1) Associate's degree; 2) Bachelor's degree; and 3) Graduate or Professional degree.

The ACS data also include estimates of the immigrants who entered the U.S. in the past year and the movers (the in-migrants and out-migrants) for a defined geography such as state by age and educational attainment. The calculation is based on age, educational attainments, state or county residency one year ago, one year migration status, and current residency state. In this study, immigrants are defined as the current

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[8] U.S. Census Data for Social, Economic, and Health Research. https://usa.ipums.org/usa/.
[9] ACS Subject Tables. https://www.census.gov/acs/www/data/data-tables-and-tools/subject-tables/.

residents in the United States whose country residence was abroad 1 year ago. The in-state migration is captured by the current residents in the defined state whose state residency one year ago was in another state. The out-state migration is captured by the state residency one year ago was in the defined state but current resided in another state.

The multiple Cause-of-Death Mortality[10] data from the National Center for Health Statistics (NCHS) provides mortality information derived from individual death certificates recorded in vital statistics offices in each state and District of Columbia[3]. The data provided the number of deaths and selected mortality measures break down by demographic indicators such as age and educational attainment but did not deliver geographic locations. The state level deaths by age and educational attainment level are estimated and derived from the mortality rate of each defined population group in the national level and the total population of the defined group at state level.

IPEDS[11] is a system of correlated survey data corrected annually by the U.S. Department of Education's National Center (NCES) for Education Statistics[4]. NCES is located in the U.S. Department of Education and Institute of Education Science, and attains a Congressional mandate to report, collect, and analyze the American educational data. The data of student completion counts by award level is obtained from the aggregated summary table in IPEDS. The Number of Students Receiving a Degree or Certificate summary table in IPEDS data center provides aggregated number of students receiving a degree or certificate each year by eight award levels and four age groups. For example, the award levels include categories of Associate's degree, Bachelor's degree,

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[10] Multiple Cause-of-Death Mortality. https://www.nber.org/research/data/mortality-data-vital-statistics-nchs-multiple-cause-death-data.
[11] Integrated Postsecondary Education Data System. https://nces.ed.gov/ipeds/about-ipeds.

Master's degree, and Doctor's degree; and age groups categories include people who are under 18 years old, 18 to 24 years old, 25 to 39 years old, and 40 years old and above. This data is available starting 2012 to 2021. The total number of students receiving a degree includes both public and private postsecondary educational institutions. The completion of the year includes new graduates awarded degrees from July of the past year to the June of the current year.

Past Trend Analysis and Selection of Measurements with Time Series

The Average Annual Change Difference and the Average Annual Change Rate are generalizable for different kinds of trends and are commonly used in population projections. Time series related measurements need to be chosen with caution. The measurements using time series techniques in HP method will be selected based on the past trend of population change by educational attainment. The Single Exponential Smoothing is used when the past trend of total population change has no clear patterns (Nazim and Afthanorhan, 2014). The Double Exponential Smoothing is used for the data has patterns (Nazim and Afthanorhan, 2014). This study will use time series exponential smoothing to forecast the total population in the forecasting year and annual change rate between base year and forecasting year.

Figure 3, Figure 4, and Figure 5 below demonstrate the numbers of population change by Associate's degree and above and its sub-educational categories from 2010 to 2019 in the United States, Florida, South Dakota, followed by the population totals and percentages of each educational attainment category in Table 3, Table 4, and Table 5. The number of populations in each educational attainment category displayed growth trends from 2010 to 2019 in the United States, the state of Florida and South Dakota, and the growth trend of Associate's degree displays less stable growth patterns than the Bachelor's degree and graduate and professional degree. The increasing trend of educational groups indicate the Double Exponential Smoothing is more appropriate than the Single Exponential Smoothing to forecast the total population in HP method.

Figure 6, Figure 7, and Figure 8 below shows the annual population change rate of Associate's degree and above and its sub-educational categories from 2011 to 2019 in the United States, Florida, South Dakota, followed by the annual population change rates in Table 6, Table 7, Table 8. There is no clear pattern in terms of annual population change rates in the United States, Florida, and South Dakota, so the Single Exponential Smoothing would be an appropriate measurement to forecast the change rate in HP method.

Therefore, this study will use the Average Annual Change Difference, the Average Annual Change Rate, the Single Exponential Smoothing for the annual change Rate (Single Exponential Smoothing Rate), and the Double Exponential Smoothing for the total population in forecasting year (Double Exponential Smoothing Total) as measurements in HP method in the United States, Florida, South Dakota. Although the Single Exponential Smoothing for total population (Single Exponential Smoothing Total) was not recommended according to the past data trends, this study will still include it in the analysis for evaluation purposes. The mean value of HP population forecasts with set of measurements (HP Average) with generate for overall comparison with CCM method. However, results using Single Exponential Smoothing Total will be excluded in generating the HP Average forecast.

Figure 3. Population by levels of Educational Attainments from 2010 to 2019 in the United States

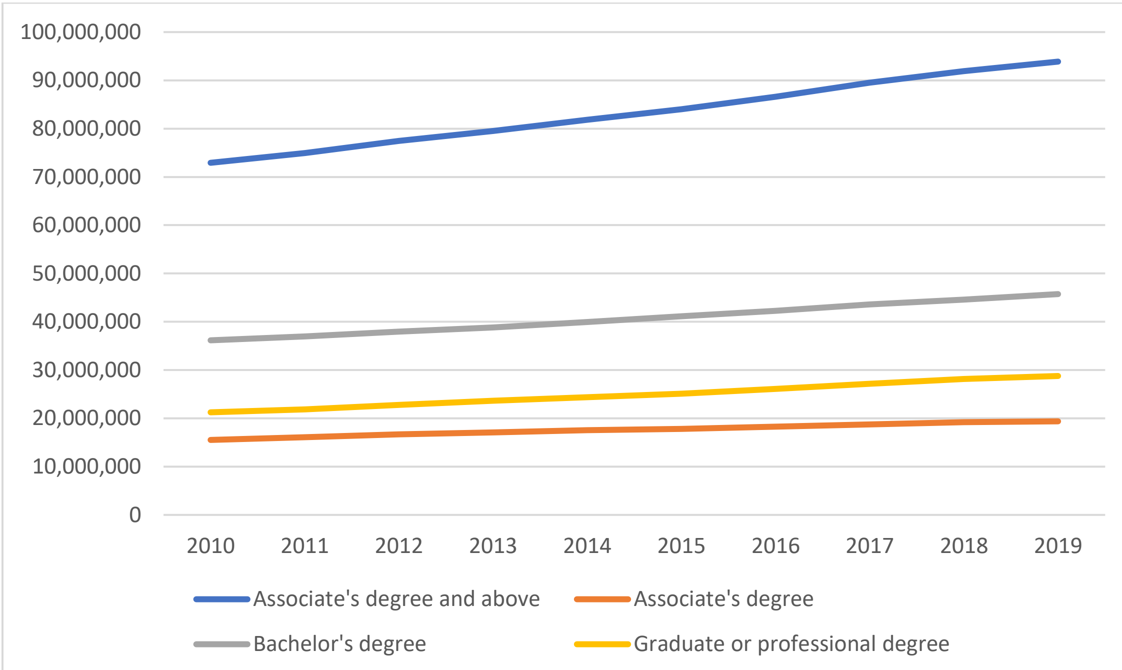


Table 3. Population by Educational Attainment Levels in the United States, 2010-2019

Year	Associate's degree and above	Associate's degree		Bachelor's degree		Graduate or Professional degree	
		Total	%	Total	%	Total	%
2010	72,931,149	15,525,959	21.3%	36,159,141	49.6%	21,246,049	29.1%
2011	74,949,216	16,104,790	21.5%	36,958,429	49.3%	21,885,997	29.2%
2012	77,439,386	16,698,520	21.6%	37,989,133	49.1%	22,751,733	29.4%
2013	79,513,302	17,083,760	21.5%	38,807,553	48.8%	23,621,989	29.7%
2014	81,856,914	17,525,501	21.4%	39,966,692	48.8%	24,364,721	29.8%
2015	84,048,303	17,806,750	21.2%	41,152,388	49.0%	25,089,165	29.9%
2016	86,594,118	18,259,841	21.1%	42,242,395	48.8%	26,091,882	30.1%
2017	89,526,674	18,760,759	21.0%	43,585,028	48.7%	27,180,887	30.4%
2018	91,928,137	19,177,676	20.9%	44,599,186	48.5%	28,151,275	30.6%
2019	93,883,588	19,381,937	20.6%	45,730,479	48.7%	28,771,172	30.6%

Figure 4. Population by levels of Educational Attainments from 2010 to 2019 in Florida

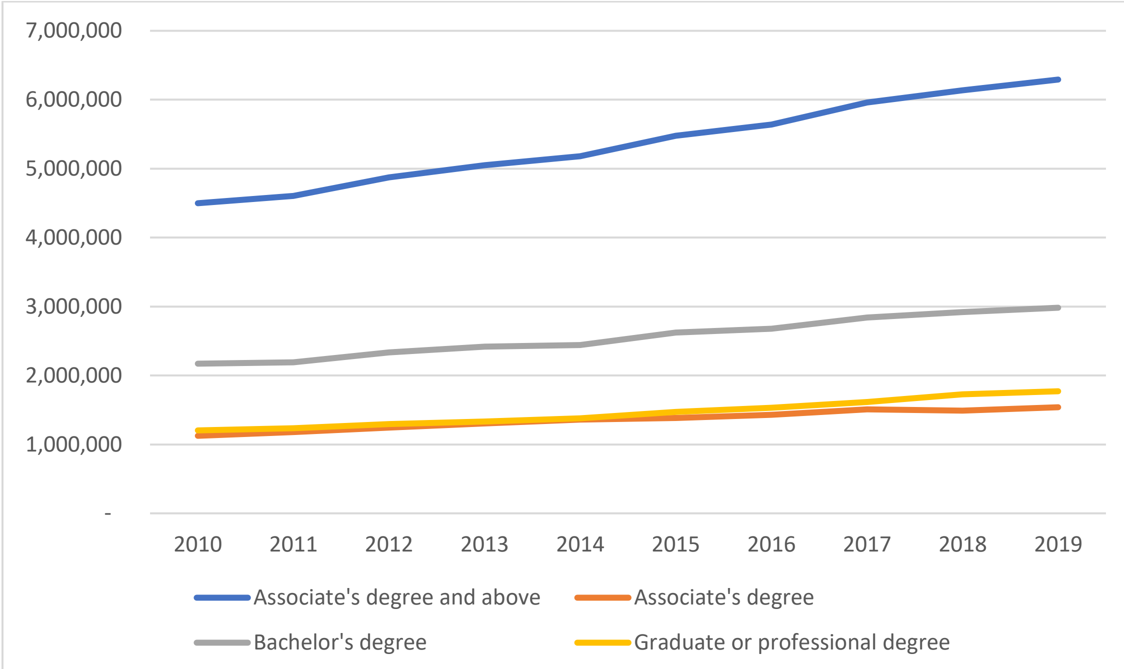


Table 4. Population by Educational Attainment Levels in Florida, 2010-2019

Year	Associate's degree and above	Associate's degree		Bachelor's degree		Graduate or Professional degree	
		Total	%	Total	%	Total	%
2010	4,498,550	1,124,637	25.0%	2,170,812	48.3%	1,203,100	26.7%
2011	4,603,851	1,180,815	25.6%	2,189,151	47.6%	1,233,885	26.8%
2012	4,874,853	1,242,345	25.5%	2,336,148	47.9%	1,296,360	26.6%
2013	5,051,535	1,304,065	25.8%	2,415,951	47.8%	1,331,519	26.4%
2014	5,181,201	1,361,996	26.3%	2,443,168	47.2%	1,376,037	26.6%
2015	5,475,903	1,383,565	25.3%	2,620,339	47.9%	1,471,999	26.9%
2016	5,637,577	1,429,121	25.3%	2,675,907	47.5%	1,532,549	27.2%
2017	5,961,926	1,507,434	25.3%	2,839,500	47.6%	1,614,992	27.1%
2018	6,136,740	1,489,510	24.3%	2,920,459	47.6%	1,726,771	28.1%
2019	6,292,364	1,538,727	24.5%	2,982,643	47.4%	1,770,994	28.1%

Figure 5. Population by levels of Educational Attainments from 2010 to 2019 in South Dakota

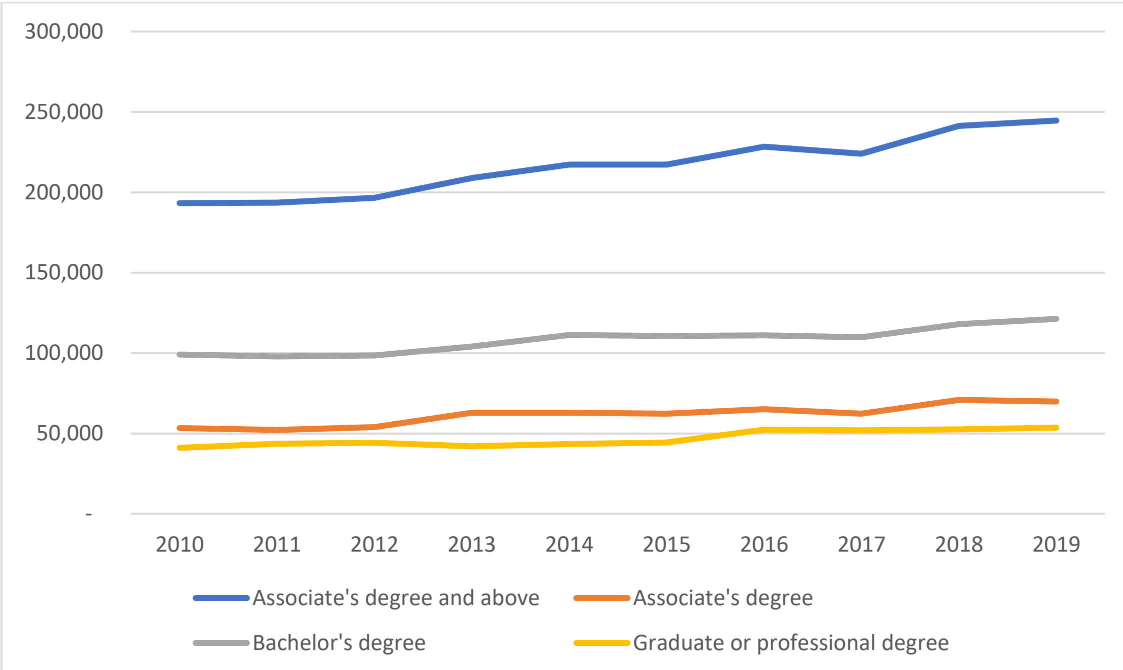


Table 5. Population by Educational Attainment Levels in South Dakota, 2010-2019

Year	Associate's degree and above	Associate's degree		Bachelor's degree		Graduate or Professional degree	
		Total	%	Total	%	Total	%
2010	193,254	53,238	27.5%	99,022	51.2%	40,993	21.2%
2011	193,532	52,146	26.9%	97,841	50.6%	43,545	22.5%
2012	196,489	53,885	27.4%	98,517	50.1%	44,088	22.4%
2013	208,813	62,809	30.1%	104,131	49.9%	41,873	20.1%
2014	217,196	62,770	28.9%	111,098	51.2%	43,328	19.9%
2015	217,179	62,294	28.7%	110,562	50.9%	44,323	20.4%
2016	228,354	65,093	28.5%	111,002	48.6%	52,259	22.9%
2017	223,942	62,204	27.8%	109,803	49.0%	51,935	23.2%
2018	241,236	70,838	29.4%	117,943	48.9%	52,455	21.7%
2019	244,615	69,831	28.5%	121,231	49.6%	53,553	21.9%

Figure 6. Annual Population Change Rate by levels of Educational Attainments from 2011 to 2019 in the United States

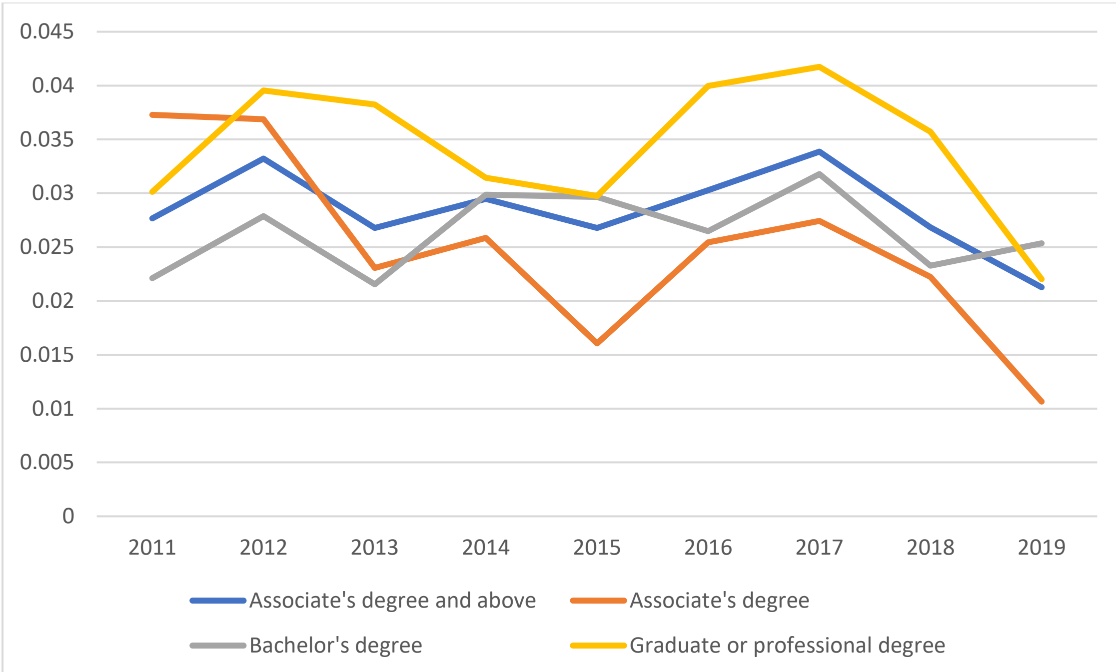


Table 6. The Annual Population Change Rate by Educational Attainment Levels from 2010 to 2019 in the United States

Year	Associate's degree and above	Associate's degree	Bachelor's degree	Graduate or Professional degree
2010-2011	2.77%	3.73%	2.21%	3.01%
2011-2012	3.32%	3.69%	2.79%	3.96%
2012-2013	2.68%	2.31%	2.15%	3.83%
2013-2014	2.95%	2.59%	2.99%	3.14%
2014-2015	2.68%	1.60%	2.97%	2.97%
2015-2016	3.03%	2.54%	2.65%	4.00%
2016-2017	3.39%	2.74%	3.18%	4.17%
2017-2018	2.68%	2.22%	2.33%	3.57%
2018-2019	2.13%	1.07%	2.54%	2.20%

Figure 7. Annual Population Change Rate by levels of Educational Attainments from 2011 to 2019 in Florida

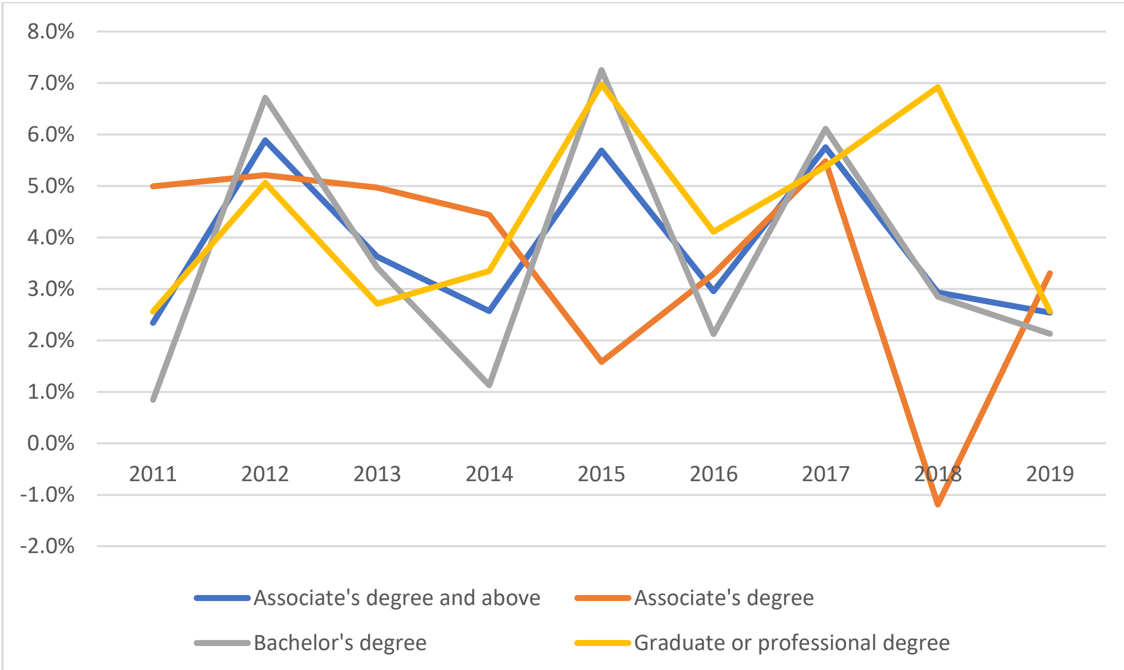


Table 7. The Annual Population Change Rate by Educational Attainment Levels from 2010 to 2019 in Florida

Year	**Associate's degree and above**	**Associate's degree**	**Bachelor's degree**	**Graduate or Professional degree**
2010-2011	2.34%	5.00%	0.84%	2.56%
2011-2012	5.89%	5.21%	6.71%	5.06%
2012-2013	3.62%	4.97%	3.42%	2.71%
2013-2014	2.57%	4.44%	1.13%	3.34%
2014-2015	5.69%	1.58%	7.25%	6.97%
2015-2016	2.95%	3.29%	2.12%	4.11%
2016-2017	5.75%	5.48%	6.11%	5.38%
2017-2018	2.93%	-1.19%	2.85%	6.92%
2018-2019	2.54%	3.30%	2.13%	2.56%

Figure 8. Annual Population Change Rate by levels of Educational Attainments from 2011 to 2019 in South Dakota

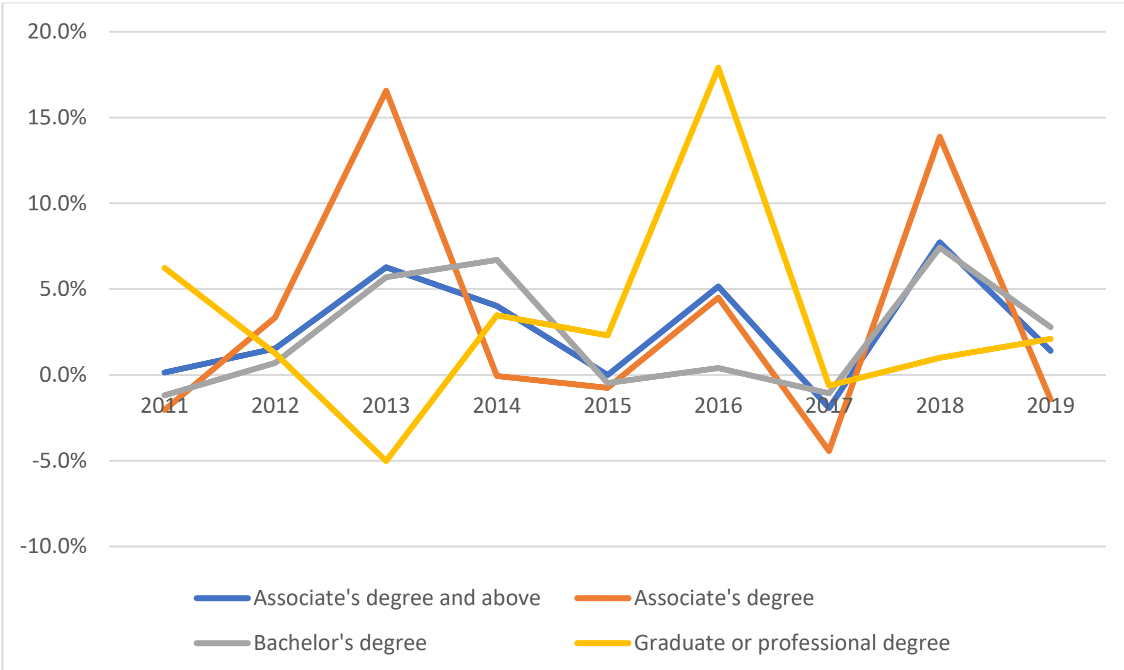


Table 8. The Annual Population Change Rate by Educational Attainment Levels from 2010 to 2019 in South Dakota

Year	Associate's degree and above	Associate's degree	Bachelor's degree	Graduate or Professional degree
2010-2011	0.14%	-2.05%	-1.19%	6.22%
2011-2012	1.53%	3.33%	0.69%	1.25%
2012-2013	6.27%	16.56%	5.70%	-5.02%
2013-2014	4.01%	-0.06%	6.69%	3.48%
2014-2015	-0.01%	-0.76%	-0.48%	2.30%
2015-2016	5.15%	4.49%	0.40%	17.90%
2016-2017	-1.93%	-4.44%	-1.08%	-0.62%
2017-2018	7.72%	13.88%	7.41%	1.00%
2018-2019	1.40%	-1.42%	2.79%	2.09%

RESULTS

The United States (national level)

H1 projections. HP 1-year forecast in 2019 with different measurements

Table 9 presents the results of H1, H2, H3, and H4 forecasts with different measurements in the United States. The total population with Associate's degree and above from ACS estimates was 93,883,588 in 2019. All the measurements over the projected population with Associate's degree and above in HP 1-year forecast in 2019 except the Single Exponential Smoothing. The accuracy of HP 1-year forecast using different measurements varies substantially. The forecasted population with Associate's degree and above using the Average Annual Change Difference is the most accurate with the smallest APE (0.45%) and smallest predicting gap (419,172). The forecast using Double Exponential Smoothing Total had relatively small APE (0.50%) with an over projected population of 472,898, followed by forecast with Single Exponential Smoothing Rate (APE=0.76%), and then forecast with Average Annual Change Rate (APE=0.79%). The forecast with Single Exponential Smoothing Total had the least accurate forecast with the largest APE (2.09%), and it under-projected this population group by 1,957,855.

H2 projections. HP 2-year forecast in 2019 with different measurements

The accuracies of HP 2-year forecasts varied among different measurements. Most of the measurements over projected the population with Associate's degree and above except the Single Exponential Smoothing Total measurement for HP 2-year forecast in 2019. The forecasted population with Associate's degree and above using Average Annual Change Difference had the most accurate result with the smallest APE (0.41%) and smallest predicting difference (384,665), followed by forecasts using Single

Exponential Smoothing Rate (APE=0.94%, DIF= 882,251) and then forecast with Average Annual Change Rate (APE=1.03%, DIF= 965,514). The forecast using Double Exponential Smoothing Total had a relative lower accuracy level (APE=1.58%, DIF= 1,484,989). The forecast with Single Exponential Smoothing had the least accurate forecast (APE =4.64%, DIF=-4,359,849). Are the 2-year projection errors on average smaller than the 1-year projection errors?

H3 projections. HP 4-year forecast in 2019 with different measurements

All the HP 4-year forecasts in 2019 were under projected. The accuracies of HP 4-year forecast were different among forecasts using different measurements. The forecasts using rates generated the most accurate results. The forecast with Average Annual Change Rate (APE=0.17%, DIF= -158,152) performed better than the forecast with Single Exponential Smoothing Rate (APE=0.33%, DIF= -311,360), followed by forecast with Average Annual Change Difference (APE=1.0%, DIF= -941,562), and then the forecast with Double Exponential Smoothing Total (APE=1.12%, DIF= -1,047,145). Single Exponential Smoothing Total is the measurement created the largest error (APE=10.48%, DIF= -9,837,479).

H4 projections. HP 2-year forecast in 2021 with different measurements

The total population with Associate's degree and above from ACS estimates was 99,875,698 in 2021. The forecasts using rates created the most accurate results. The forecast with Average Annual Rate (APE=0.65%, DIF= -647,565) performed better than the forecast with Single Exponential Smoothing Rate (APE=0.8%, DIF= -803,198). The forecasts with Average Annual Change Difference (APE=1.34%, DIF= -1,336,012) and Double Exponential Smoothing Total (APE=2.06%, DIF= -2,057,142) had larger errors than forecasts using rate measurements. Single Exponential Smoothing Total generated the largest error (APE=6.00%, DIF= -5,994,068). The HP 2-year forecasts with all these five measurements in 2021 are under projected, while the forecasts with most measurements in 2019 were over projected except the measurement using Single Exponential Smoothing Total. How about the comparison between the projections using average vs trend smoothing? It seems to me that the projections based on the average changes (either in population totals or rates) are more accurate than the projections based on trend smoothing techniques (either SES or DES).

H5 projections. HP 1-year forecast by different educational attainment levels in 2019

Table 10 listed the results of HP forecasts with different measurements by different educational attainments. Overall, forecasts using HP method for population with Bachelor's degree had smaller forecasting errors than the forecast for population with Associate's degree and Graduate or Professional degree. The total population with Associate's degree, Bachelor's degree, Graduate or Professional degree from ACS estimates were 19,381,937, 45,730,479, 28,771,172, respectively. The APE of forecast with HP Average for Bachelor's degree was 0.03%, and the same forecast for Graduate or Professional degree (APE=1.19%) and Associate's degree (APE=1.32%) had higher APEs.

Measurements in HP method had different accuracy levels in forecasting the three sub-educational attainment levels. For example, the most accurate measurement in the HP method is different for each educational attainment level. Population forecast for Associate's degree had smallest predicting errors using the Single Exponential Smoothing Total (AEP=1.06%) comparing to forecasts with other measurements. Population forecast of Bachelor's prefers using Single Exponential Smoothing Rate with the AEP value of 0.10%, while population forecast for graduate degree or professional degree had smallest APE (0.85%) using the Average Annual Change Difference.

C1, C2, C3, and C4 projections. CCM projections for Associate's degree and above

Table 11 presented the results of CCM forecasts during different perioding time period and by different educational attainments The 1-year CCM forecast of population with Associate's degree and above in 2019 was 93,154,580, and it was under projected 729,008 population comparing to the total population with Associate's degree and above (93,883,588) from 1-year ACS estimates in 2019. The 2-year CCM forecast of population with Associate's degree and above in 2019 was 91,979,738 with APE value of 2.03%, and it was under projected 1,903,850 population comparing to the 1-year ACS estimates. The 4-year CCM forecast of population with Associate's degree and above in 2019 was 89,081,505, and it was under projected 4,802,083 population comparing to the 1-year ACS estimates. The 2-year CCM forecast of population with Associate's degree and above in 2021 was 96,035,766, and it was under projected 3,839,932 population comparing to the total population with Associate's degree and above (99,875,698) from 1-year ACS estimates in 2021.

C5 projections. CCM projections by different educational level

The total number of 1-year population forecast for Associate's degree using CCM method was 19,429,803 in 2019, which over projected by 47,866 compared to the ACS estimated population with Associate's degree (19,381,937). The forecasted population with Bachelor's degree in 2019 was 44,897,626, which was 832,853 of population less than the ACS estimated population with Bachelor's degree. The forecasted population with Graduate or Professional degree was 28,827,151, and it was over projected 55,979 population according to the ACS estimates. The 1-year CCM forecast for Graduate or

Professional degree had smallest APE (0.19%), followed by the forecast for Associate's degree with the APE value of 0.25%, and then the forecast for Bachelor's degree (APE=1.82%).

Table 9. Forecast Results using the HP Method for the Population with Associate's Degree and Above in the United States

Types of Forecasts	Observed Counts (P)	Types of Measurements	Forecasted Population (F)	Difference (DIF)	Percentage Error (PE)	Absolute Percentage Error (APE)
HP 1-year forecast in 2019	93,883,588	HP-Average Annual Change Difference	94,302,760	419,172	0.45%	0.45%
		HP-Average Annual Change Rate	94,627,396	743,808	0.79%	0.79%
		HP-Single Exponential Smoothing Rate	94,601,010	717,422	0.76%	0.76%
		HP-Double Exponential Smoothing Total	94,356,486	472,898	0.50%	0.50%
		HP-Single Exponential Smoothing Total	91,925,733	-1,957,855	-2.09%	2.09%
		HP Average	94,471,913	588,325	0.63%	0.63%
HP 2-year forecast in 2019	93,883,588	HP-Average Annual Change Difference	94,268,253	384,665	0.41%	0.41%
		HP-Average Annual Change Rate	94,849,102	965,514	1.03%	1.03%
		HP-Single Exponential Smoothing Rate	94,765,803	882,215	0.94%	0.94%
		HP-Double Exponential Smoothing Total	95,368,577	1,484,989	1.58%	1.58%
		HP-Single Exponential Smoothing Total	89,523,739	-4,359,849	-4.64%	4.64%
		HP Average	94,812,934	929,346	0.99%	0.99%
HP 4-year forecast in 2019	93,883,588	HP-Average Annual Change Difference	92,942,026	-941,562	-1.00%	1.00%
		HP-Average Annual Change Rate	93,725,436	-158,152	-0.17%	0.17%
		HP-Single Exponential Smoothing Rate	93,572,228	-311,360	-0.33%	0.33%
		HP-Double Exponential Smoothing Total	92,836,443	-1,047,145	-1.12%	1.12%
		HP-Single Exponential Smoothing Total	84,046,109	-9,837,479	-10.48%	10.48%
		HP Average	93,269,033	-614,555	-0.65%	0.65%
HP 2-year forecast in 2021	99,875,698	HP-Average Annual Change Difference	98,539,686	-1,336,012	-1.34%	1.34%
		HP-Average Annual Change Rate	99,228,133	-647,565	-0.65%	0.65%
		HP-Single Exponential Smoothing Rate	99,072,500	-803,198	-0.80%	0.80%
		HP-Double Exponential Smoothing Total	97,818,556	-2,057,142	-2.06%	2.06%
		HP-Single Exponential Smoothing Total	93,881,630	-5,994,068	-6.00%	6.00%
		HP Average	98,664,719	-1,210,979	-1.21%	1.21%

Table 10. Forecast Results using the CCM Method for the Population with Associate’s Degree and Above in the United States

Categories	Associate’s degree and above				1-year forecast 2019 by educational level		
	1-year 2019	2-year 2019	4-year 2019	2-year 2021	Associate’s degree	Bachelor’s degree	Graduate or Professional degree
Observed Counts (P)	93,883,588	93,883,588	93,883,588	99,875,698	19,381,937	45,730,479	28,771,172
Population Base	91,928,137	89,526,674	84,048,303	93,883,588	19,177,676	44,599,186	28,151,275
Components Change							
New graduates	1958043	3,898,417	7,816,788	3,920,699	435,464	604,416	918,163
Immigration	4,732	9,755	20,751	7,135	428	2,399	1,905
Mortality	676456	1,336,756	2,582,413	1,637,310	183,765	308,375	184,316
Forecasted Population (F)	93,214,456	92,098,090	89,303,429	96,174,112	19,429,803	44,897,626	28,887,027
Difference (DIF)	-669,132	-1,785,498	-4,580,159	-3,701,586	47,866	-832,853	115,855
Percentage Error (PE)	-0.71%	-1.90%	-4.88%	-3.71%	0.25%	-1.82%	0.40%
Absolute Percentage Error (APE)	0.71%	1.90%	4.88%	3.71%	0.25%	1.82%	0.40%

Table 11. Forecast Results using the HP Method by Educational Attainment Levels in 2019 in the United States

	Associate's degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	19,381,937	19,634,141	252,204	1.30%	1.30%
HP-Average Annual Change Rate		19,691,217	309,280	1.60%	1.60%
HP-Single Exponential Smoothing Rate		19,629,338	247,401	1.28%	1.28%
HP-Double Exponential Smoothing Total		19,599,395	217,458	1.12%	1.12%
HP-Single Exponential Smoothing Total		19,177,259	-204,678	-1.06%	1.06%
HP Average		19,638,523	256,586	1.32%	1.32%
	Bachelor's degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	45,730,479	45,654,192	-76,287	-0.17%	0.17%
HP-Average Annual Change Rate		45,784,477	53,998	0.12%	0.12%
HP-Single Exponential Smoothing Rate		45,774,627	44,148	0.10%	0.10%
HP-Double Exponential Smoothing Total		45,651,493	-78,986	-0.17%	0.17%
HP-Single Exponential Smoothing Total		44,598,170	-1,132,309	-2.48%	2.48%
HP Average		45,716,197	-14,282	-0.03%	0.03%

	Graduate or Professional degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	28,771,172	29,014,428	243,256	0.85%	0.85%
HP-Average Annual Change Rate		29,159,470	388,298	1.35%	1.35%
HP-Single Exponential Smoothing Rate		29,156,358	385,186	1.34%	1.34%
HP-Double Exponential Smoothing Total		29,121,900	350,728	1.22%	1.22%
HP-Single Exponential Smoothing Total		28,150,304	-620,868	-2.16%	2.16%
HP Average		29,113,039	341,867	1.19%	1.19%

Florida (state level)

H1 projections. HP 1-year forecast in 2019 with different measurements

Table 12 presents the results of H1, H2, H3, and H4 forecasts with different measurements in the state of Florida. The observed population counts with Associate's degree and above from ACS estimates was 6,292,364 in 2019. The forecasted population with Associate's degree and above using Average Annual Change Difference had the most accurate result with the smallest APE (0.78%) and smallest predicting gap (49,150). The forecast using Double Exponential Smoothing Total had relatively small APE (1.08%) with an over projected population of 67,913, followed by forecast with Single Exponential Smoothing Rate (APE=1.22%), and then forecast with Average Annual Change Rate (APE=1.40%). The forecast with Single Exponential Smoothing had the least accurate result with the largest APE (2.48%), and it under projected this population group by 155,799.

H2 projections. HP 2-year forecast in 2019 with different measurements

The accuracies of HP 2-year forecast varied among different measurements. Most of the measurements over projected the population with Associate's degree and above except the Single Exponential Smoothing Total measurement for HP 2-year forecast in 2019. The forecasted population with Associate's degree and above using Average Annual Change Difference had the most accurate result with the smallest APE (1.39%) and smallest predicting difference (87,670), followed by forecasts using Single Exponential Smoothing Rate (APE=2.55%, DIF= 160,328) and forecast with Average Annual Change Rate (APE=2.55%, DIF= 160,350). The forecast using Double Exponential Smoothing Total had a relatively lower accuracy level (APE=3.30%, DIF=

207,560). The forecast with Single Exponential Smoothing had the least accurate forecast (APE =5.26%, DIF=-330,763).

H3 projections. HP 4-year forecast in 2019 with different measurements

The accuracies of HP 4-year forecasts were different among forecasts using different measurements. The forecast with Average Annual Change Difference (APE=0.55%, DIF= -34,578) generated the most accurate results, followed by forecast with Average Annual Change Rate (APE=1.02%, DIF= 64,342), and then the forecast with Single Exponential Smoothing Rate (APE=1.96%, DIF= 123,496). The forecast with Double Exponential Smoothing Total (APE=2.72%, DIF= 171,419) had a relatively less accurate result. Single Exponential Smoothing Total is the measurement created the least accurate result (APE=12.98%, DIF= -816,756).

H4 projections. HP 2-year forecast in 2021 with different measurements

The HP 2-year forecasts in 2021 were under projected with the selected measurements. The total population with Associate's degree and above from ACS estimates was 6,809,350 in the state of Florida in 2021. The forecasts using rates created the most accurate results. The forecasts with Average Annual Rate (APE=0.55%, DIF= -37,644) and Single Exponential Smoothing Rate (APE=0.90%, DIF= -61,315) had relatively small errors than forecasts with other measurements. The forecasts with Average Annual Change Difference (APE=1.74%, DIF= -118,361) and Double Exponential Smoothing Total (APE=2.30%, DIF= -156,556) had larger errors than forecasts using rate measurements. Single Exponential Smoothing Total generated the least accurate result (APE=6.59%, DIF= -449,073).

H5 projections. HP 1-year forecast by different educational attainment levels in 2019

Table 13 listed the results of HP forecasts with different measurements by different educational attainments. Overall, HP forecast for population with Associate's degree had smaller forecasting errors than the forecast for population with Bachelor's degree and Graduate or Professional degree. The total population with Associate's degree, Bachelor's degree, Graduate or Professional degree from ACS estimates were (1,538,727), (2,982,643) (1,770,994). The APE of forecast with HP Average for Associate's degree was 0.67%, and the same forecast for Bachelor's degree (APE=1.39%) and Graduate or Professional degree (APE=2.25%) had higher APEs.

HP 2019 1-year population forecasts for all the three educational attainment levels prefer using the Average Annual Change Difference measurement, and this measurement had the smallest forecast errors compared to the forecasts with other measurements in each educational attainment category. The AEPs for Associate's degree. Bachelor's degree, and Graduate or Professional degree were 0.23%, 1.06% and 1.20%.

C1, C2, C3, and C4 projections. CCM projections for Associate's degree and above

Table 14 presented the results of CCM forecasts during different perioding time period and by different educational attainments The 1-year CCM forecast of population with Associate's degree and above in 2019 was 6,302,220 (APE=0.16%), and it was over projected 9,856 population comparing to the total population with Associate's degree and above (6,292,364) from 1-year ACS estimates in 2019. The 2-year CCM forecast of population with Associate's degree and above in 2019 was 6,288,283 with APE value of 0.06%, and it was under projected 4,081 population comparing to the 1-year ACS estimates. The 4-year CCM forecast of population with Associate's degree and above in 2019 was 6,162,101 (APE=0.16%), and it was under projected 130,263 population comparing to the 1-year ACS estimates. The 2-year CCM forecast of population with Associate's degree and above in 2021 was 6,640,846 (APE=2.47%), and it was under projected 168,504 population comparing to the total population with Associate's degree and above (6,809,350) from 1-year ACS estimates in 2021.

C5 projections. CCM projections by different educational level

The total number of 1-year population forecast for Associate's degree using CCM method was 1,531,340 in 2019, which under projected by 7,387 compared to the ACS estimated population with Associate's degree (1,538,727). The forecasted population with Bachelor's degree in 2019 was 2,988,080, and it was 5,437 of population more than the ACS estimated population with Bachelor's degree. The forecasted population with Graduate or Professional degree was 1,782,091, and it was over projected 11,097 compared to the ACS estimates. The 1-year CCM forecast for Bachelor's degree had smallest APE (0.18%), followed by the forecast for Associate's degree with the APE value of 0.48%, and then the forecast for Graduate or Professional degree (APE=0.63%).

Table 12. Forecast Results using the HP Method for the Population with Associate's Degree and Above in Florida

Types of Forecasts	Observed Counts (P)	Types of Measurements	Forecasted Population (F)	Difference (DIF)	Percentage Error (PE)	Absolute Percentage Error (APE)
HP 1-year forecast in 2019	6,292,364	HP-Average Annual Change Difference	6,341,514	49,150	0.78%	0.78%
		HP-Average Annual Change Rate	6,380,248	87,884	1.40%	1.40%
		HP-Single Exponential Smoothing Rate	6,369,083	76,719	1.22%	1.22%
		HP-Double Exponential Smoothing Total	6,360,277	67,913	1.08%	1.08%
		HP-Single Exponential Smoothing Total	6,136,565	-155,799	-2.48%	2.48%
		HP Average	6,362,781	70,417	1.12%	1.12%
HP 2-year forecast in 2019	6,292,364	HP-Average Annual Change Difference	6,380,034	87,670	1.39%	1.39%
		HP-Average Annual Change Rate	6,452,714	160,350	2.55%	2.55%
		HP-Single Exponential Smoothing Rate	6,452,692	160,328	2.55%	2.55%
		HP-Double Exponential Smoothing Total	6,499,924	207,560	3.30%	3.30%
		HP-Single Exponential Smoothing Total	5,961,601	-330,763	-5.26%	5.26%
		HP Average	6,446,341	153,977	2.45%	2.45%
HP 4-year forecast in 2019	6,292,364	HP-Average Annual Change Difference	6,257,786	-34,578	-0.55%	0.55%
		HP-Average Annual Change Rate	6,356,706	64,342	1.02%	1.02%
		HP-Single Exponential Smoothing Rate	6,415,860	123,496	1.96%	1.96%
		HP-Double Exponential Smoothing Total	6,463,783	171,419	2.72%	2.72%
		HP-Single Exponential Smoothing Total	5,475,608	-816,756	-12.98%	12.98%
		HP Average	6,373,534	81,170	1.29%	1.29%
HP 2-year forecast in 2021	6,809,350	HP-Average Annual Change Difference	6,690,989	-118,361	-1.74%	1.74%
		HP-Average Annual Change Rate	6,771,706	-37,644	-0.55%	0.55%
		HP-Single Exponential Smoothing Rate	6,748,035	-61,315	-0.90%	0.90%
		HP-Double Exponential Smoothing Total	6,652,794	-156,556	-2.30%	2.30%
		HP-Single Exponential Smoothing Total	6,360,277	-449,073	-6.59%	6.59%
		HP Average	6,715,881	-93,469	-1.37%	1.37%

Table 13. Forecast Results using the CCM Method for the Population with Associate's Degree and Above in Florida

Categories	Associate's degree and above				1-year forecast 2019 by educational level		
	1-year 2019	2-year 2019	4-year 2019	2-year 2021	Associate's degree	Bachelor's degree	Graduate or Professional degree
Observed Counts (P)	6,292,364	6,292,364	6,292,364	6,809,350	1,538,727	2,982,643	1,770,994
Population Base	6,136,740	5,961,926	5,475,903	6,292,364	1,489,510	2,920,459	1,726,771
Components Change							
New graduates	116,002	230,321	451,217	230,880	39,533	39,424	37,045
Net Migration	94816	185,453	406,447	231,349	16,886	48,310	29,620
Mortality	45,338	89,417	171,466	113,747	14,589	20,113	11,345
Forecasted Population (F)	6,302,220	6,288,283	6,162,101	6,640,846	1,531,340	2,988,080	1,782,091
Difference (DIF)	9,856	-4,081	-130,263	-168,504	-7,387	5,437	11,097
Percentage Error (PE)	0.16%	-0.06%	-2.07%	-2.47%	-0.48%	0.18%	0.63%
Absolute Percentage Error (APE)	0.16%	0.06%	2.07%	2.47%	0.48%	0.18%	0.63%

Table 14. Forecast Results using the HP Method by Educational Attainment Levels in 2019 in Florida

	Associate's degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	1,538,727	1,535,119	-3,608	-0.23%	0.23%
HP-Average Annual Change Rate		1,543,101	4,374	0.28%	0.28%
HP-Single Exponential Smoothing Rate		1,530,617	-8,110	-0.53%	0.53%
HP-Double Exponential Smoothing Total		1,505,002	-33,725	-2.19%	2.19%
HP-Single Exponential Smoothing Total		1,489,528	-49,199	-3.20%	3.20%
HP Average		1,528,460	-10,267	-0.67%	0.67%
	Bachelor's degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	2,982,643	3,014,165	31,522	1.06%	1.06%
HP-Average Annual Change Rate		3,031,580	48,937	1.64%	1.64%
HP-Single Exponential Smoothing Rate		3,020,205	37,562	1.26%	1.26%
HP-Double Exponential Smoothing Total		3,030,944	48,301	1.62%	1.62%
HP-Single Exponential Smoothing Total		2,920,378	-62,265	-2.09%	2.09%
HP Average		3,024,223	41,580	1.39%	1.39%

	Graduate or Professional degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	1,770,994	1,792,230	21,236	1.20%	1.20%
HP-Average Annual Change Rate		1,806,776	35,782	2.02%	2.02%
HP-Single Exponential Smoothing Rate		1,817,294	46,300	2.61%	2.61%
HP-Double Exponential Smoothing Total		1,827,380	56,386	3.18%	3.18%
HP-Single Exponential Smoothing Total		1,726,659	-44,335	-2.50%	2.50%
HP Average		1,810,920	39,926	2.25%	2.25%

South Dakota (state level)

H1 projections. HP 1-year forecast in 2019 with different measurements

Table 15 presents the results of H1, H2, H3, and H4 forecasts with different measurements in the state of South Dakota. The observed population counts with Associate's degree and above from ACS estimates was 244,615 in 2019. The forecasted population with Associate's degree and above using Double Exponential Smoothing Total had the most accurate result with the smallest APE (0.52%) and smallest predicting gap (1,263). The forecast using Average Annual Change Difference had relatively small APE (1.07%) with an over projected population of 2,619. The forecast using Average Annual Change Rate had larger errors (APE =1.44 %), followed by forecast with Single Exponential Smoothing Rate (APE=1.89%). The forecast with Single Exponential Smoothing had the least accurate result with the largest APE (1.39%), and it under projected this population group by 3,396.

H2 projections. HP 2-year forecast in 2019 with different measurements

The accuracies of HP 2-year forecast varied among different measurements. All of the measurements under projected the population with Associate's degree and above for HP 2-year forecast in 2019. The forecasted population with Associate's degree and above using Average Annual Change Difference had the most accurate result with the smallest APE (4.48%) and smallest predicting difference (-10,970), followed by forecasts using Average Annual Change Difference (APE=4.87%, DIF= -11,905) and forecast with Single Exponential Smoothing Rate (APE=5.23%, DIF=-12,802). The forecast using Double Exponential Smoothing Total had a relatively lower accuracy level (APE=5.38%, DIF=-13,163). The forecast with Single Exponential Smoothing had the least accurate forecast (APE =8.45%, DIF=-20,669).

H3 projections. HP 4-year forecast in 2019 with different measurements

The accuracies of HP 4-year forecast were different among forecasts using different measurements. All of the measurements under projected the population with Associate's degree and above for HP 4-year forecast in 2019.The forecast with Average Annual Change Rate (APE=2.73%, DIF= -6,672) generated the most accurate results, followed by forecast with Average Annual Change Difference (APE=3.39%, DIF=-8,296), and then the forecast with Single Exponential Smoothing Rate (APE=3.96%, DIF= -9,688). Forecasts with Double Exponential Smoothing Total (APE=11.22%, DIF= -27,436) and Single Exponential Smoothing Total (APE=11.22%, DIF= -27,436) created the least accurate results.

H4 projections. HP 2-year forecast in 2021 with different measurements

The total population with Associate's degree and above from ACS estimates was 257,890 in the state of South Dakota in 2021. The forecast with Average Annual Rate (APE=0.03%, DIF= -73) had the most accurate results, followed by Double Exponential Smoothing Total (APE=0.12%, DIF= 300), and then Average Annual Change Difference (APE=0.72%, DIF= -1,861). Forecast with Single Exponential Smoothing Rate (APE=0.87%, DIF= -2,252) had relatively larger errors than forecasts with other measurements, and forecast with Single Exponential Smoothing Total (APE=5.15%, DIF= -13,278) had the largest errors among all the measurements.

H5 projections. HP 1-year forecast by different educational attainment levels in 2019

Table 16 listed the results of HP forecasts with different measurements by different educational attainments. Overall, HP forecast for population with Associate's degree had smaller forecasting errors than the forecast for population with Bachelor's degree and Graduate or Professional degree. The total population with Associate's degree, Bachelor's degree, Graduate or Professional degree from ACS estimates were (69,831), (121,231) (53,553). The APE of forecast with HP Average for Associate's degree was 0.61%, and the same forecast for Bachelor's degree (APE=0.70%) and Graduate or Professional degree (APE=12.56%) had higher APEs.

Different educational attainment levels prefer different measurement in HP method in South Dakota. Population forecast for Associate's degree had smallest predicting errors using Average Annual Change Difference (AEP=0.42%) comparing to forecasts with other measurements. Population forecast of Bachelor's prefers using Average Annual Change Rate with the AEP value of 0.48%, while population forecast for graduate degree or professional degree had smallest APE (9.66%) using Single Exponential Smoothing Rate.

C1, C2, C3, and C4 projections. CCM projections for Associate's degree and above

Table 17 presented the results of CCM forecasts during different perioding time period and by different educational attainments in South Dakota. The 1-year CCM forecast of population with Associate's degree and above in 2019 was 243,727 (APE=0.36%), and it was under projected 888 population comparing to the total population with Associate's degree and above from 1-year ACS estimates (244,615) in 2019. The 2-year CCM forecast of population with Associate's degree and above in 2019 was 232,387 with APE value of 5.00%, and it was under projected 12,282 population comparing to the 1-year ACS estimates. The 4-year CCM forecast of population with associate degree and above in 2019 was 232,087 (APE=5.13%), and it was under projected 12,537 population comparing to the 1-year ACS estimates. The 2-year CCM forecast of population with Associate's degree and above in 2021 was 248,014

(APE=3.83%), and it was under projected 9,876 population comparing to the total population with associate's degree and above from 1-year ACS estimates (257,890) in 2021.

C5 projections. CCM projections by different educational level

The total number of 1-year population forecast for Associate's degree using CCM method was 71,105 in 2019, which over projected by 1,274 compared to the ACS estimated population with Associate's degree (69,831). The forecasted population with Bachelor's degree in 2019 was 118,892, and it under projected 2,339 than the ACS estimated population with Bachelor's degree. The forecasted population with Graduate or Professional degree was 53,671, and it was over projected 118 compared to the ACS estimates. The 1-year CCM forecast for Graduate or Professional degree had smallest APE (0.22%), followed by the forecast for Associate's degree with the APE value of 1.82%, and then the forecast for Bachelor's degree (APE=1.93%).

Table 15. Forecast Results using the HP Method for the Population with Associate's Degree and Above in South Dakota

Types of Forecasts	Observed Counts (P)	Types of Measurements	Forecasted Population (F)	Difference (DIF)	Percentage Error (PE)	Absolute Percentage Error (APE)
HP 1-year forecast in 2019	244,615	HP-Average Annual Change Difference	247,234	2,619	1.07%	1.07%
		HP-Average Annual Change Rate	248,137	3,522	1.44%	1.44%
		HP-Single Exponential Smoothing Rate	249,247	4,632	1.89%	1.89%
		HP-Double Exponential Smoothing Total	245,878	1,263	0.52%	0.52%
		HP-Single Exponential Smoothing Total	241,219	-3,396	-1.39%	1.39%
		HP Average	247,624	3,009	1.23%	1.23%
HP 2-year forecast in 2019	244,615	HP-Average Annual Change Difference	232,710	-11,905	-4.87%	4.87%
		HP-Average Annual Change Rate	233,645	-10,970	-4.48%	4.48%
		HP-Single Exponential Smoothing Rate	231,813	-12,802	-5.23%	5.23%
		HP-Double Exponential Smoothing Total	231,452	-13,163	-5.38%	5.38%
		HP-Single Exponential Smoothing Total	223,946	-20,669	-8.45%	8.45%
		HP Average	232,405	-12,210	-4.99%	4.99%
HP 4-year forecast in 2019	244,615	HP-Average Annual Change Difference	236,319	-8,296	-3.39%	3.39%
		HP-Average Annual Change Rate	237,943	-6,672	-2.73%	2.73%
		HP-Single Exponential Smoothing Rate	234,927	-9,688	-3.96%	3.96%
		HP-Double Exponential Smoothing Total	217,179	-27,436	-11.22%	11.22%
		HP-Single Exponential Smoothing Total	217,179	-27,436	-11.22%	11.22%
		HP Average	231,592	-13,023	-5.32%	5.32%
HP 2-year forecast in 2021	257,890	HP-Average Annual Change Difference	256,029	-1,861	-0.72%	0.72%
		HP-Average Annual Change Rate	257,817	-73	-0.03%	0.03%
		HP-Single Exponential Smoothing Rate	255,638	-2,252	-0.87%	0.87%
		HP-Double Exponential Smoothing Total	258,190	300	0.12%	0.12%
		HP-Single Exponential Smoothing Total	244,612	-13,278	-5.15%	5.15%
		HP Average	256,919	-971	-0.38%	0.38%

Table 16. Forecast Results using the CCM Method for the Population with Associate's Degree and Above in South Dakota

Categories	Associate's degree and above				1-year forecast 2019 by educational level		
	1-year 2019	2-year 2019	4-year 2019	2-year 2021	Associate's degree	Bachelor's degree	Graduate or Professional degree
Observed Counts (P)	93,883,588	93,883,588	93,883,588	99,875,698	19,381,937	45,730,479	28,771,172
Population Base	91,928,137	89,526,674	84,048,303	93,883,588	19,177,676	44,599,186	28,151,275
Components Change							
New graduates	1958043	3,898,417	7,816,788	3,920,699	435,464	604,416	918,163
Immigration	4,732	9,755	20,751	7,135	428	2,399	1,905
Mortality	676456	1,336,756	2,582,413	1,637,310	183,765	308,375	184,316
Forecasted Population (F)	93,214,456	92,098,090	89,303,429	96,174,112	19,429,803	44,897,626	28,887,027
Difference (DIF)	-669,132	-1,785,498	-4,580,159	-3,701,586	47,866	-832,853	115,855
Percentage Error (PE)	-0.71%	-1.90%	-4.88%	-3.71%	0.25%	-1.82%	0.40%
Absolute Percentage Error (APE)	0.71%	1.90%	4.88%	3.71%	0.25%	1.82%	0.40%

Table 17. Forecast Results using the HP Method by Educational Attainment Levels in 2019 in South Dakota

	Associate's degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	69,831	69,539	-292	-0.42%	0.42%
HP-Average Annual Change Rate		70,778	947	1.36%	1.36%
HP-Single Exponential Smoothing Rate		67,556	-2,275	-3.26%	3.26%
HP-Double Exponential Smoothing Total		69,738	-93	-0.13%	0.13%
HP-Single Exponential Smoothing Total		62,294	-7,537	-10.79%	10.79%
HP Average		69,403	-428	-0.61%	0.61%
	Bachelor's degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	121,231	119,794	-1,437	-1.19%	1.19%
HP-Average Annual Change Rate		120,649	-582	-0.48%	0.48%
HP-Single Exponential Smoothing Rate		118,836	-2,395	-1.98%	1.98%
HP-Double Exponential Smoothing Total		122,246	1,015	0.84%	0.84%
HP-Single Exponential Smoothing Total		110,563	-10,668	-8.80%	8.80%
HP Average		120,381	-850	-0.70%	0.70%

	Graduate or Professional degree				
Measurements	**Observed Counts (P)**	**Forecasted Population (F)**	**Difference (DIF)**	**Percentage Error (PE)**	**Absolute Percentage Error (APE)**
HP-Average Annual Change Difference	53,553	46,987	-6,566	-12.26%	12.26%
HP-Average Annual Change Rate		47,237	-6,316	-11.79%	11.79%
HP-Single Exponential Smoothing Rate		48,382	-5,171	-9.66%	9.66%
HP-Double Exponential Smoothing Total		44,695	-8,858	-16.54%	16.54%
HP-Single Exponential Smoothing Total		43,245	-10,308	-19.25%	19.25%
HP Average		46,825	-6,728	-12.56%	12.56%

COMPARISONS AND EVALUATION

Comparing the CCM 1-year forecasts and HP 1-year forecasts with different measurements in 2019

Figure 9 below compared the APE values of CCM 1-year forecast and HP 1-year forecasts with different measurements for population that are 25 years older and with Associate's degree and above in 2019. The HP Average forecast (0.63%) had a smaller APE than the forecast using CCM method (0.71%) at the national level. Figure 10 and figure 11 below compared the APE values of CCM 1-year forecast and HP 1-year forecasts with different measurements for population with Associate's degree and above in 2019 in the state of Florida and South Dakota. In both states, the forecast using CCM method had lower APE than the forecasts with HP Average. This is different from the CCM-HP comparison at the national level where the HP Average forecast had lower APE value than the forecast with CCM method. Moreover, the HP Average forecast performed better at the national level than the HP Average forecast at the state level, but the forecast with CCM method works better for the two states in comparison to the forecast using the CCM method at the national level. This indicates that the CCM method works better than the HP method at the state level for Florida and South Dakota in forecasting population that are 25 years older and with Associate's degree and above, while the HP method works better than the CCM method at the national level. Additionally, Florida had smaller forecasting errors than South Dakota, either using the HP Average method or the CCM method. These comparisons reveal that geography plays a key role in making a choice about the forecasting method because of the geographic differences were found in forecasting accuracy.. For the projections of the U.S. population by educational attainment, the HP method has the advantage in both accuracy and reduced data demands.

For the projections of state populations, the CCM method is still preferred in terms of accuracy.

Why did the HP method work better than the CCM method at national level in predicting population that are 25 years and older and with Associate's degree and above in 2019? The possible reason might be related to the migration component in the CCM method. The migration component at national level only counted the immigrants captured by the ACS, which might be undercounted. such an undercount might affect the accuracy of the CCM method at the national level. The CCM method works better than the HP method in Florida and South Dakota, indicating migration data for computing the migration component at the state level was more reliable than the national level using the ACS data to consider both in-state migration and out-state migration.

Among various sets of results using different measurements in the HP 1-year forecast, the Average Annual Change Difference and the Double Exponential Smoothing Total are the top two accurate measurements for the national forecasts. Although the HP method is less accurate than the CCM method for the state forecasts, the Average Annual Change Difference and the Double Exponential Smoothing Total work better than using other measurements in the HP forecasts. This indicated these two measurements are preferred in forecasting the population with Associate's degree and above at both national level and state level. In South Dakota, the forecast using the HP method with Double Exponential Smoothing Total had smaller predicting errors than the CCM method. This suggests that the HP method with the right measurement can have better performance than the CCM method even when the CCM method is preferred in some context.

Figure 9. APEs Comparison for 1-year forecast in 2019 by Methods and Measurements in the United States

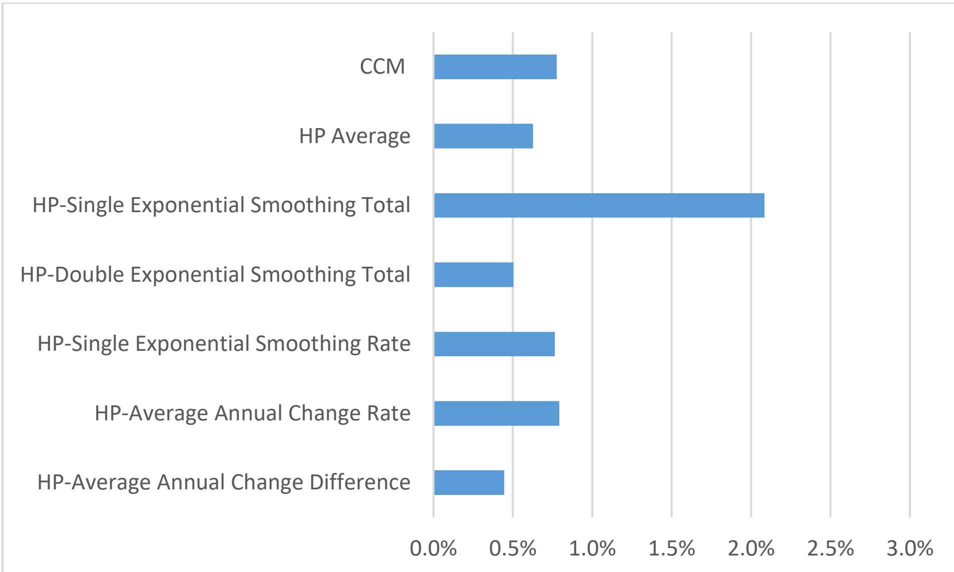


Figure 10. APEs Comparison for 1-year forecast in 2019 by Methods and Measurements in Florida

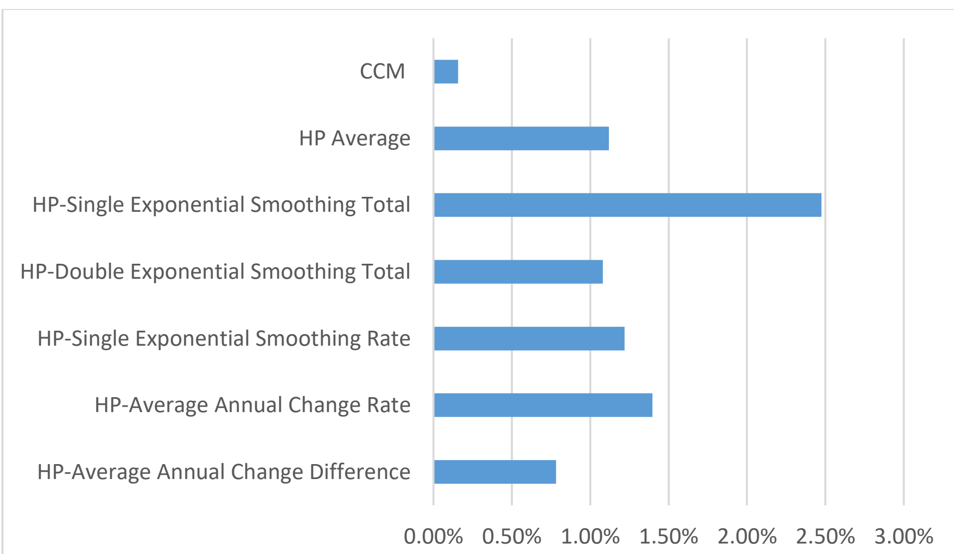
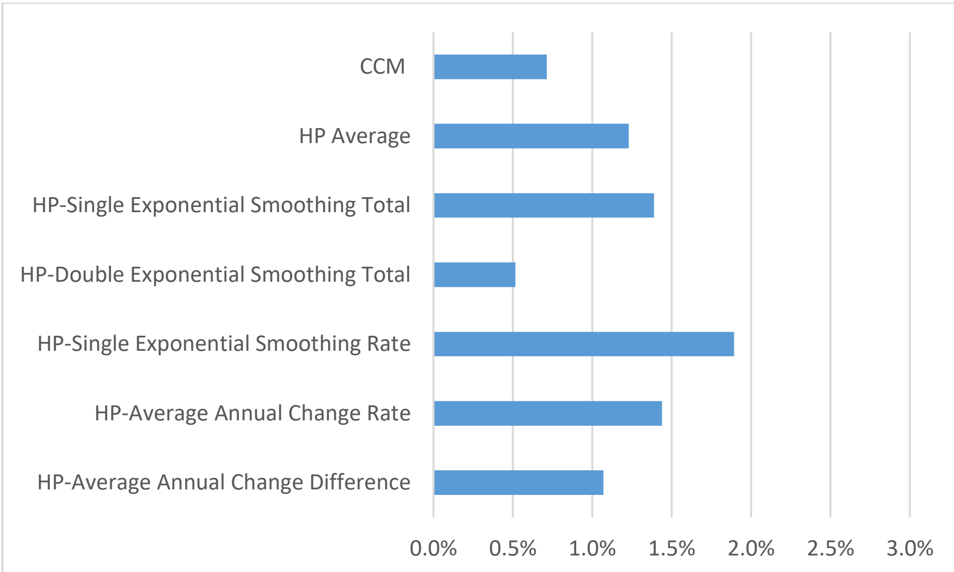


Figure 11. APEs Comparison for 1-year forecast in 2019 by Methods and Measurements in South Dakota



Comparing the CCM 1-year,4-year projections and HP 1-year,4-year projections in 2019

Figure 12 below demonstrated APEs comparison by length of predicting period, methods, and measurements in the United States. The CCM 1-year population forecast for population that are 25 years and older and with Associate's degree and above had smaller APE than that of the CCM 4-year forecasts (0.71% vs 4.88%). On average, the APE value of HP 1-year average forecast (0.63%) was less than the APE value of HP 4-year average forecast (0.65%), but HP 1-year forecast may or may not have smaller APE values than HP 4-year forecast with each measurement. The HP 1-year population forecasts had smaller APE value than the HP 4-year forecasts when using Single Exponential Smoothing Total, Double Exponential Smoothing Total and Average Annual Change Difference as measurement. However, the HP 1-year forecasts had higher APE value than the HP 4-year forecasts when using Average Annual Change Rate and Double Exponential Smoothing Rate measurements.

Figure 13 and Figure 14 below demonstrated APEs comparison by length of predicting period, methods, and measurements in the state of Florida and South Dakota. Similar to the pattern at the national level, the 1-year forecast had smaller APE value than the 4-year forecast using the CCM method and HP method with the Average. In South Dakota, HP 1-year forecasts had smaller APE values than the HP 4-year forecasts with each tested measurement. In Florida, HP 1-year forecasts may or may not have smaller APE values than HP 4-year forecast with each measurement. The HP 1-year population forecasts had smaller APE value than the HP 4-year forecasts when using Single Exponential Smoothing Total, Double Exponential Smoothing Total and Single Exponential Smoothing Rate as measurement. However, the HP 1-year forecasts have higher APE value than the HP 4-year forecasts when using Average Annual Change Rate and Average Annual Change Difference measurements.

Figure 12. APEs Comparison by Length of Projection Period, Methods, and Measurements for the U.S. National Population

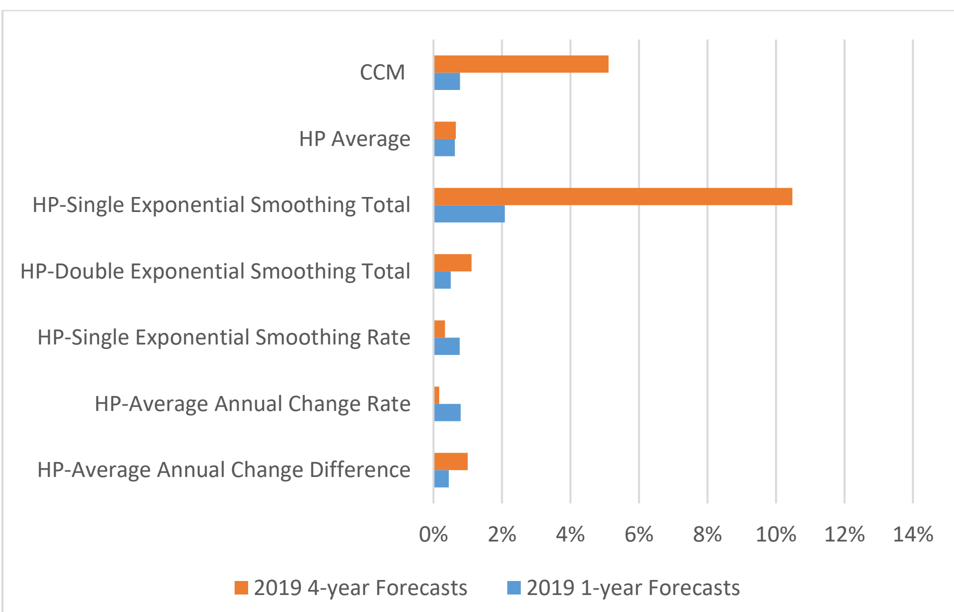


Figure 13. APEs Comparison by Length of Projection Period, Methods, and Measurements for the Population of Florida

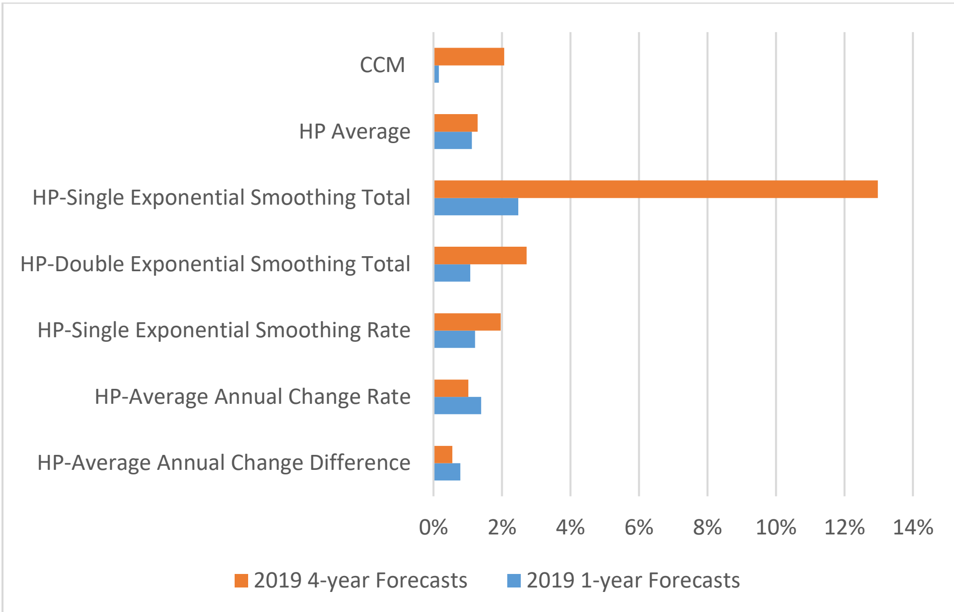
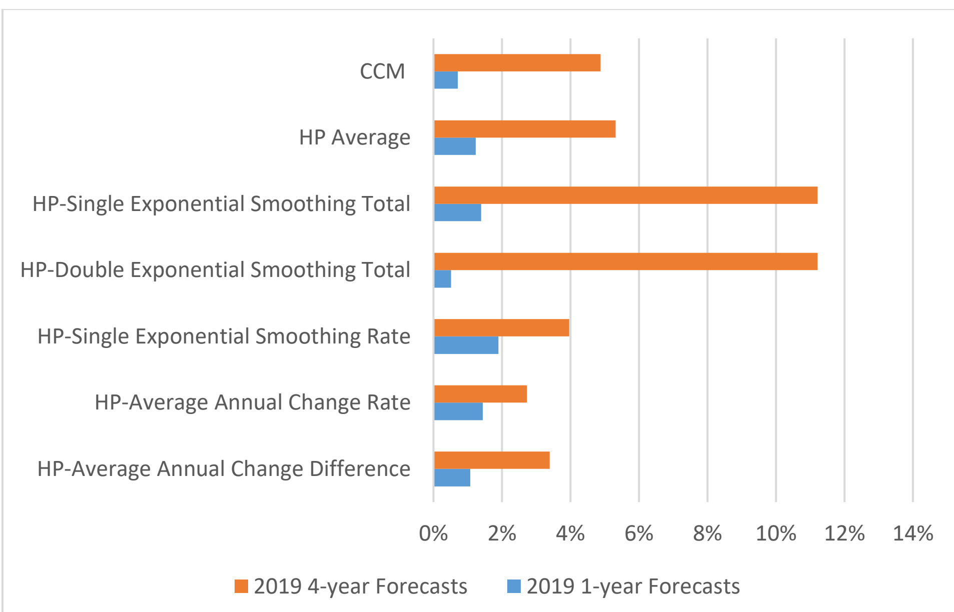


Figure 14. APEs Comparison by Length of Projections Period, Methods, and Measurements for the Population of South Dakota



Comparing the HP 1-year forecast and the CCM 1-year forecast in 2019 by educational attainment level

Figure 15-17 present the comparisons of the APE values using various projection methods and measurements, for the populations by educational attainment in the U.S. and the two chosen states, respectively. Figure 15 below shown the APEs comparison by educational attainment levels, methods, and measurements for 2019 1-year forecasts in the United States. The CCM 1- year forecast in 2019 for Associate's degree and Graduate or Professional degree had lower APE values (0.25% and 0.40%) than the forecast for Bachelor's degree (1.82%). The HP 1-year average forecast in 2019 for Bachelor's degree (0.03%) had lower APE value than the forecasts for Associate's degree and Graduate or Professional degree (1.32% and 1.19%), and this pattern is the same in each HP 1-year forecast with different measurements excluding the Single Exponential Smoothing Total. The CCM method yielded smaller forecasting errors than the HP method in 1- year forecasts for population with Associate's degree and population with Graduate or Professional degree in 2019. The HP method had less forecasting error than the CCM method when forecasting population with Bachelor's degree.

Why HP method works better with Bachelor's degree and CCM method performs better with Associate's degree and Graduate or Professional degree in the U.S.? Bachelor's degree was more popular than Associate's degree and Graduate or Professional degree, and it consisted almost half of the population among people with Associate's degree and above (See Table 5). Bachelor's degree also had more stable growth trend than that of the Associate's degree and Graduate or Professional degree (See figure 2). This may explain why forecasting the population of Bachelor's degree using the HP method had lower APEs in comparison to the CCM method as the HP method takes advantage of stable trend changes. On the other hand, the growth of the Associate's degree and Graduate or Professional degree were less stable (See Figure 2) and thus, the HP method could not catch the growth pattern well enough than the CCM method, which breaks down the changes by component rather than using the trend.

Figure 16 and Figure 17 below shown APEs comparison by educational attainment levels, methods, and measurements for 2019 1-year forecasts in the states of Florida and South Dakota, respectively. In Florida, all three educational levels had smaller APE values in forecast with the CCM method than the HP method in most cases. The HP method using the Average Annual Change Rate and Average Annual Change Difference measurements in forecasting the population with the Associate's degree, in particular, produced more accurate projections than the CCM method, although the improvement is not substantial (0.23% and 0.28% vs. 0.48% APE values).

In South Dakota, the CCM 1-year forecast in 2019 for the Associate's degree and Graduate or Professional degree had lower APE values than the forecast using HP method with the Average, while the HP 1-year average forecast in 2019 for the Bachelor's degree had lower APE values than the forecasts using CCM method. The population with Graduate or Professional degree had relatively large APE values in HP method regardless of which measurement was used in South Dakota, but the forecasting error was relatively low using CCM method. The total population with Graduate or Professional degree are smaller compared to the population with the Associate's degree and Bachelor's degree, so population with Graduate or Professional degree might be sensitive and vulnerable with the change predicted from the overall change with population change measurements. But the CCM method was able to track the change of origins from the new graduates, death, and net migration for this group.

Figure 15. APEs Comparison by Educational Attainment Levels, Methods, and Measurements in the United States

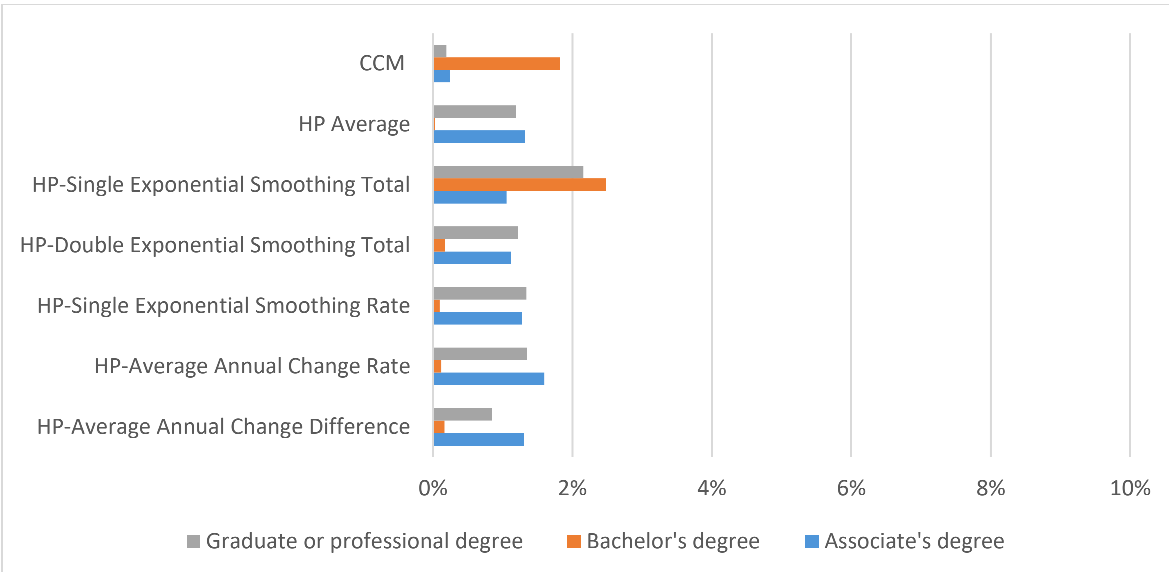


Figure 16. APEs Comparison by Educational Attainment Levels, Methods, and Measurements in Florida

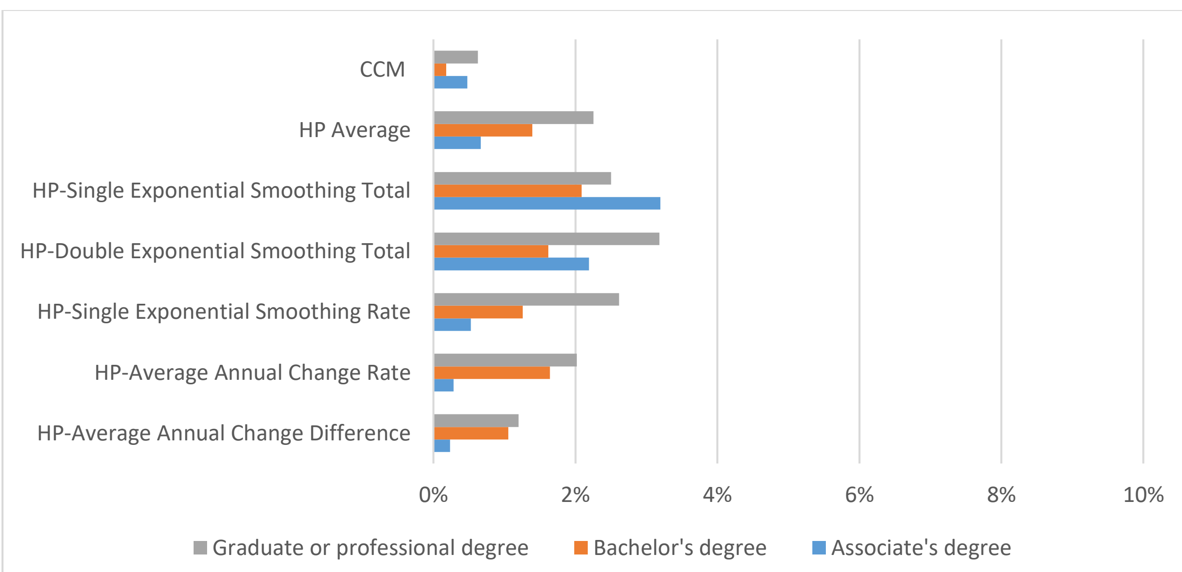
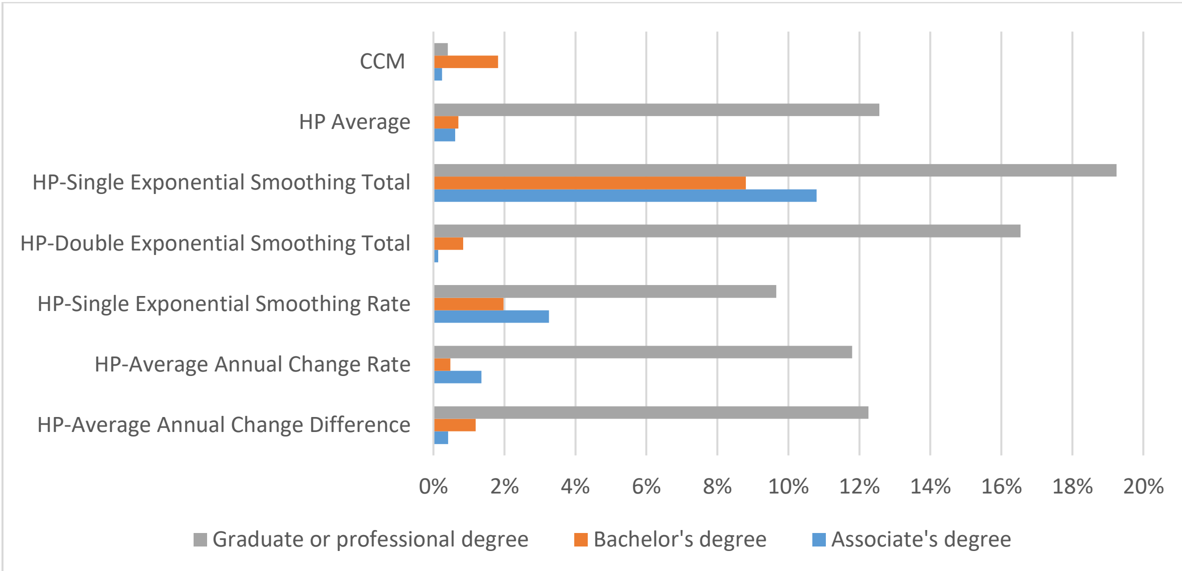


Figure 17. APEs Comparison by Educational Attainment Levels, Methods, and Measurements in South Dakota



Comparing the HP 2-year forecasts in 2019 and 2021 and the CCM 2-year forecasts in 2019 and 2021

Figure 18 below compared the APEs for forecasts made before COVID-19 in 2019 and after COVID-19 happened in 2021 by methods and measurements in the United States. The HP Average 2-year forecast for population that are 25 years and older and with the Associate's degree and above had larger APE value in 2021 (1.21%) than that in the 2019 forecast (0.99%). The forecasts with CCM method had the same pattern, and CCM 2-year forecast in 2021 had greater APE value (3.71%) than the CCM 2-year forecast in 2019 (APE=1.90%). However, the HP 2-year forecast in 2021 had less forecasting error than the HP 2-year forecast in 2019 with the Average Annual Change Rate and the Single exponential Smoothing Rate. When comparing the HP method and CCM method in these 2-year forecasts, the CCM 2-year forecasts in 2019 had larger errors than HP method with each measurement except the Single Exponential Smoothing Total, and CCM 2-year forecasts in 2021 had larger errors than HP method with each measurement except the Single Exponential Smoothing Total. Both HP and CCM methods under forecasted the population that are 25 years and older and with the Associate's degree and above in 2021 2-year forecast.

Figure 19 and figure 20 below compared the APEs for forecasts made before COVID-19 in 2019 and after COVID-19 happened in 2021 by methods and measurements in the state of Florida and South Dakota. In Florida, the CCM 2-year forecast for population that are 25 years and older and with the Associate's degree and above had larger APE value in 2021 (2.47%) than that in the 2019 (0.06%) forecast. However, the HP Average 2-year forecast in 2021 had smaller APE value (1.37%) than the HP 2-year forecast in 2019 (APE=1.39%), although not all the tested measurements in the HP method shared this pattern. The HP 2-year forecasts in 2021 had lower APE values than HP 2-year forecast in 2019 with the Double Exponential Smoothing Total, the Single exponential smoothing Rate, and the Average Annual Change Rate, while the HP 2-year forecasts in 2021 had higher APE values than HP 2-year forecast in 2019 using the Single Exponential Smoothing Total and the Average Annual Change difference. Similar to Florida, the CCM 2-year forecast for South Dakota's population with the Associate's degree and above had larger APE value in 2021 (3.71%) than the 2-year forecast in the 2019 (1.90%); and the HP Average 2-year forecast in 2021 had smaller APE value (0.38%) than the HP 2-year forecast in 2019 (APE=4.99%). Forecast with each measurement in the HP method shared the same pattern that the 2-year forecast in 2021 had lower APE value than the 2-year forecast in 2019.

Both HP and CCM method had larger errors to forecast population ages 25 years and older with the Associate's degree and above in 2021 comparing to the forecast in

2019 at the national level. The pandemic started in 2020, and the health crisis impacted the ACS survey data collection and decreased the response rates (Daily et al. 2021). Moreover, the immigration population with the Associate's degree and above estimates from ACS data might be underestimated and it brought the estimates down in the CCM method in 2021. In HP method, the growth trend of population ages 25 years and older with the Associate's degree and above might change after pandemic happened, so the HP method using the previous growth trend created more bias to the forecast in 2021. However, the 2-year forecasts in 2021 didn't have larger errors than the 2-year forecast in 2019 at state level in Florida and in South Dakota using the HP average but not the CCM method. Also the HP 2-year forecast for 2021 had less forecast errors than the CCM method for 2021 with most tested measurements excluding the Single Exponential Smoothing Total in Florida and South Dakota. Why were the HP 2-year forecasts for 2021 more accurate than the HP 2-year forecasts in 2019? Maybe the population with the Associate's degree and above still had stable growth trend during COVID-19 years in Florida and South Dakota. This indicates that the HP method works well in forecasting populations by educational attainment during the time period with special event such as the COVID-19 public crisis, and forecasting for populations that are 25 years and older and with the Associate's degree and above during the pandemic period are likely to perform better with the HP method than the CCM method at the state level in Florida and South Dakota.

The CCM method created larger errors than the HP method with the Average for 2021 2-year forecasts at both national level and state level (Florida and South Dakota). Why the CCM method with the administrative counts of new graduates and death counts had larger forecasting errors than the HP Average forecast in 2021? One of the reasons might be that the migration data derived from the ACS estimates in 2020 and 2021 did not catch the changes well, and the other reason might be due to the biased ACS 1 year population estimates for the population with the Associate's degree and above that are 25 years and older. The respondents on Current Population Survey Annual Social and Economic Supplement (CPS ASEC) are more likely to be more educated people and this pattern increased in the data collection during COVID-19 pandemic (Rothbaum and Bee, 2021). This finding indicates people with the Associate's degree and above may had higher response rates in the ACS survey than people with higher school degree or less than high school education, so they might overrepresented the population and caused the overestimated 1-year population estimates for people with the Associate's degree and above that are 25 years and older. The false larger error terms might be generated when this study uses this overestimated data for evaluation comparison.

Figure 18. APEs Comparison before and after COVID-19 Years by Methods, and Measurements in the United States

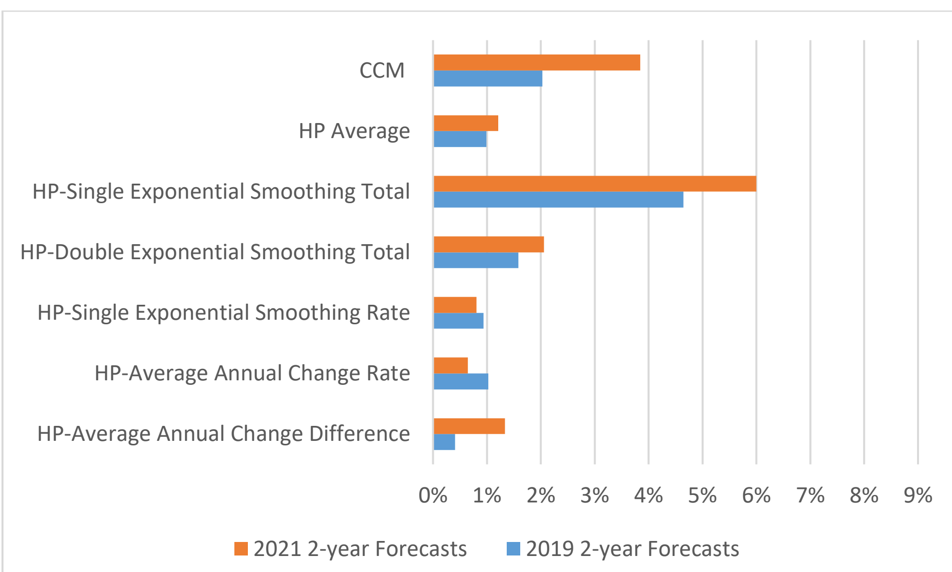


Figure 19. APEs Comparison before and after COVID-19 Years by Methods, and Measurements in Florida

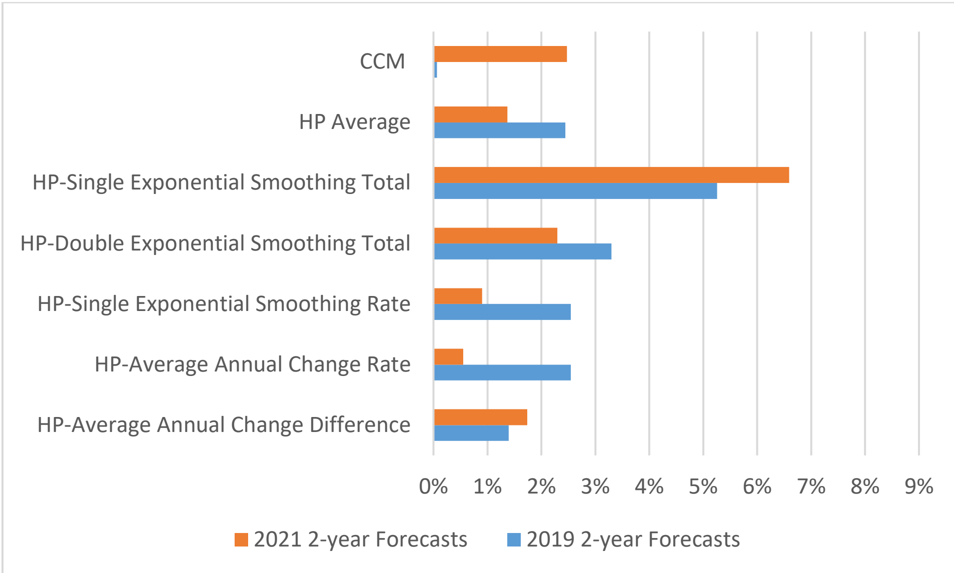
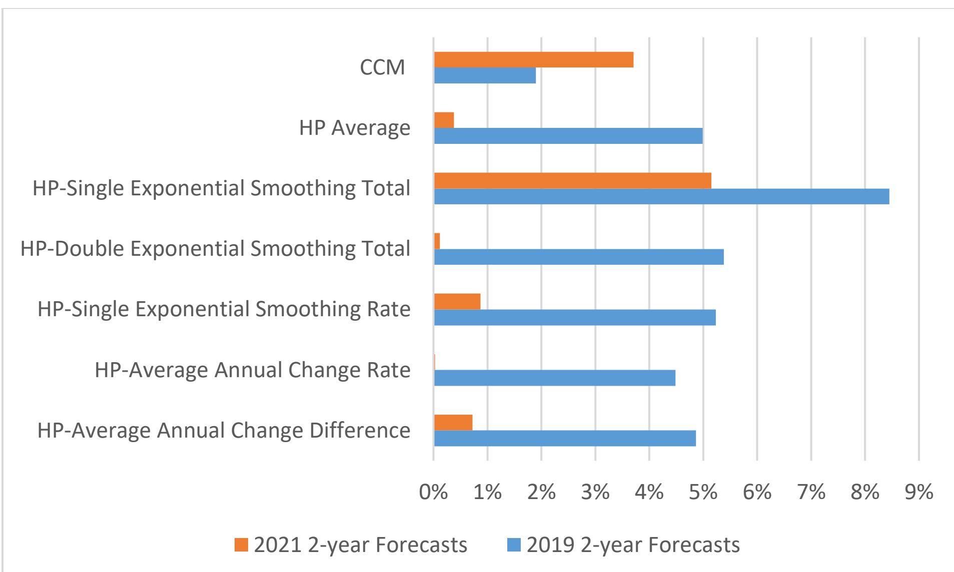


Figure 20. APEs Comparison before and after COVID-19 Years by Methods, and Measurements in South Dakota



CONCLUSION

This dissertation first compared the HP method and CCM method for 1-year population estimates for people ages 25 years and older and with an Associate's degree and above in 2019. Then, this study examined how the length of predicting period, different levels of postsecondary educational levels, and a public health crisis (the COVID-19) influence the accuracy of the HP and CCM methods. The study also compared how those impacts perform by using different measurements and in different types of geographies.

The results indicated the 1-year HP Average method overall created a more accurate forecast than the CCM method for the national population of the United States in 2019. However, CCM method had better performance than the HP Average method at the state level based on the results for Florida and South Dakota. In addition, the 2019 1-year HP Average forecast at national level was more accurate than the 2019 1-year HP Average forecasts at state level in Florida and South Dakota, but the 2019 1-year CCM forecasts in Florida and South Dakota was more accurate than the 2019 1-year CCM forecast at national level. Compared to the CCM methods, however, the measurement choice for the HP method at state level influences the accuracy substantially. For example, forecast using the HP method with Double Exponential Smoothing Total was more accurate than the CCM method applied for South Dakota, when the CCM method had more accurate results than HP Average.

The results also demonstrated that the forecasts generally are more accurate in 1-year forecast than 4-year forecast using both HP and CCM method for predicting population that are 25 years and older with Associate's degree and above in the United

States and state of Florida and South Dakota. However, the HP 4-year forecasts had more accurate results than the 1-year forecasts with some measurements in the United States and South Dakota but not Florida.

The results also suggested that the HP method produced the most accurate results for Bachor's degree while the CCM method was a more reliable method for Associate's degree and Graduate or Professional degree at national level. At the state level, however, it was somewhat reversed. The forecast for people with the Bachor's degree prefers using the CCM method in Florida, the forecast for people with the Associate's degree prefers using the HP method in South Dakota. Moreover, measurements in the HP method can have different patterns.

The results of the 2-year forecasts in 2021 were less accurate than the 2-year forecasts in 2019 using both HP Average and CCM method in the United States. However, 2-year forecasts in 2021 using HP method were more accurate than the 2-year forecasts in 2019 in Florida and South Dakota, while the 2-year forecasts in 2021 using CCM method were more accurate than the 2-year forecasts in 2019 in South Dakota. Moreover, different measurements in HP method shared similar patterns with the HP Average forecast in South Dakota, but not in the United States and Florida.

In summary, to forecast total population that are 25 years and older and with Associate's degree and higher, the HP method is generally more accurate than the CCM method to forecast population 25 years and older and with Associate's degree and above overall at the national level, and the CCM method is more accurate than the HP method at the state level in Florida and South Dakota for 1-year forecast in 2019. Longer predicting period is likely to have less accurate forecasts regardless of choices of tested methods and geographies, but with adjustment of measurements, forecasting for longer predicting period may have comparable accuracy result using HP method. Educational attainment levels had different preferences with the methods depending on the geography. The impact of COVID-19 on forecasting accuracy also depends on the choice of method and measurements in different geographies. Table 18 summarized the evaluation of how main factors (method, length of projection, educational attainment level, public health crisis) impacted and how other factors (measurement and geography) interacted in each comparison group.

Table 18. Summary of Evaluation on How Factors Impacted and Interacted with the Forecasting Accuracy

<table>
<tr><td colspan="4">1. Comparison between H1 and CCM1 (main tested factor: method)</td></tr>
<tr><td>Method * Geography</td><td>Measurement (Top 2) * Geography</td><td>Geography * HP method</td><td>HP Method * Measurement * Geography</td></tr>
<tr><td>Forecasts using HP Average was more accurate than the CCM in the U.S., forecasts using CCM was more accurate than HP Average in state of FL and SD.</td><td>Average Annual Change Difference, Double Exponential Smoothing Total were the top two accurate measurements in HP method among forecasts in all three tested geographies (U.S., FL, SD).</td><td>HP Average forecasts were more accurate at national level compared to state of FL and SD. HP Average forecasts were more accurate in FL (more desirable state) than SD.</td><td>When forecasts using CCM was more accurate than HP Average in SD, forecast using HP method with Double Exponential Smoothing Total was more accurate than CCM in SD.</td></tr>
<tr><td colspan="4">2. Comparison among H3, CCM3, H1, CCM1 (main tested factor: length of projection)</td></tr>
<tr><td>Length of Projection</td><td>Length of Projection * Method * Geography</td><td colspan="2">Length of Projection * Measurement * Geography</td></tr>
<tr><td>Forecasts with longer period were less accurate using both HP Average and CCM in all three tested geographies.</td><td>4-year forecasts had more accurate results using HP Average method than using CCM in the U.S. and FL; 4-year forecasts had more accurate results using CCM than forecasts with HP Average method in SD</td><td colspan="2">HP 4-year forecasts were more accurate than HP 1-year forecasts when using Average Annual Change Rate and Double Exponential Smoothing Rate in the U.S.; HP 4-year forecasts were more accurate than HP 1-year forecasts when using Average Annual Change Rate and Average Annual Change Difference in FL.</td></tr>
<tr><td colspan="4"></td></tr>
</table>

3. Comparison between H5 and CCM5 (main tested factor: educational attainment level)	
Educational attainment level * Method * Geography	**Educational attainment level * Method * Geography * Measurements**
Bachor's degree preferred HP Average method, while Associate's degree and Graduate or Professional degree preferred CCM method in the U.S. All three educational levels preferred CCM method comparing to HP Average in FL; the Associate's degree and Graduate and Professional degree prefers CCM method but the Bachelor's degree prefers HP method in SD.	When all three educational levels prefer CCM method in FL, the HP method using the Average Annual Change Rate and Average Annual Change Difference measurement were more accurate than the CCM method in forecasting the population with the Associate's degree in FL.
4. Comparison among H4, CCM4, H2, CCM2 (main tested factor: public health crisis)	
Public Health Crisis * Method * Geography	**Measurement * Public Health Crisis * Method * Geography**
Forecast for 2021 are less accurate than forecast for 2019 using both method in the U.S. Forecast for 2021 are less accurate than forecast for 2019 using CCM method in all three tested geographies, but forecast for 2021 are more accurate than forecast for 2019 using HP Average in FL and SD.	When forecast for 2021 are less accurate than forecast for 2019 using both HP Average and CCM in the U.S., forecasts for 2021 are more accurate than forecast for 2019 using HP method with the Single exponential smoothing Rate and the Average Annual Change Rate in the U.S. When forecast for 2021 are more accurate than forecast for 2019 using HP Average in FL, forecasts for 2021 are less accurate than forecasts for 2019 using HP method with the Single exponential smoothing total and the Average Annual Change Difference in FL.

DISCUSSION

This dissertation evaluated the accuracy of using two different deterministic methods (HP and CCM) to forecast population that are 25 years old and over and with Associate's degree and above in the U.S., Florida, and South Dakota, and found that differences in methods, lengths of predicting period, educational attainment levels, forecast years (year before COVID-19 and year after), measurements, geography levels and characteristics are related to different levels of forecasting accuracy, and these factors can interact with each other and show different patterns of accuracy. The HP and CCM method have different features. How well the measurement of changes predicted future trends of the changes in the targeted population determines the accuracy of the HP method. Therefore, it is important to select the measurement of change when applying the HP method; and good measurements can create relatively accurate projections that are critical information needed for planning and policy making. Using past trends of the targeted total population to derive the measurement of change for the HP method is useful. According to the past trend on total population that are 25 years and older and with Associate's degree and above, the Single Exponential Smoothing Total is not an appropriate measurement to summarize future changes if this trend stays the same in the future. This study evaluated the forecasting errors using the Single Exponential Smoothing Total and found it created the largest forecasting errors among all the measurements using the HP method in most forecasts. It is consistent with what past data trends suggest.

The advantage of using the HP method to forecast population by educational attainment is more efficient than the CCM method, because it only requires the past population total by educational attainment as the input data. However, the HP method does not consider the fertility, mortality, and migration differentials by educational attainment levels while the CCM method takes into account of these components. Regarding the CCM method, the estimation of growth components (i.e., births, deaths, and migration), especially the migration component, determines the performance of the method. In this dissertation, the population change components in the CCM method are taken from different data sources. New graduates (as the "birth" component) and death counts are obtained from the administrative records. The migration data are derived from the ACS survey estimates which may create bias in migration. This study found that forecasts using the HP method can be more accurate with specified measurements compared to the forecast using the CCM method. Therefore, the HP method can be efficient and accurate with appropriate measurement selection and using past data trends of the targeted total population as indicator to make measurement selection or exclusions in HP method.

It's not easy to conclude which projection method is better without specifying the conditions for making the projections such as how long the predicting period is desired, which population group is forecasted, which year is the forecast, which data are used, and which geography level or location are forecasted, and the assumptions to hold when using past trends. This study informs that length of predicting period, different population groups, and public health crises can all impact the accuracy of the population forecast, despite the projection method to be used. These factors interact with forecasting methods with different measurements of change at different geographies. For example, when 2-year forecast for 2021 was less accurate than 2-year forecast for 2019 using HP method in the U.S., the 2-year forecast for 2021 are more accurate than 2-year forecast for 2019 using HP method with the Single exponential smoothing Rate and the Average Annual Change Rate in the U.S. When 2-year forecast for 2021 was less accurate than 2-year forecast for 2019 using CCM method in the U.S., the 2-year forecast for 2021 was more accurate than forecast for 2019 with CCM method in the state of Florida and South Dakota. Overall, the findings in this study suggest using the HP method at national level, and the CCM method for sub-national level when the population change component data are available. Considering the HP method for forecasts with longer period of forecasting, larger population groups, population group with clear trend patterns; and considering the CCM forecast for smaller population groups, groups with no clear change patterns, when groups in the geography has reliable data sources for estimating population components (Birth, Death, Migration) changes.

There is a famous quote in statistic field says that “All models are wrong, but some models are useful” (Box and Draper 1987:424). It is similar in the demographic field. Researchers analyze the trend based on what we know and what we can observe from the past and current situation to best guess future trends utilizing accessible data and optimized methods and tools. All forecasts are wrong, but some forecasts with certain combinations of elements can be more efficient and accurate than others. Moreover, best guesses are not only based on using methods, models, and tools to predict the future trend and changes, but also requiring the accurate summarized past patterns. How well the past patterns can be observed and represented rely on the quality and availability of the data. The HP methods can be better choices than the CCM methods if the data resource on the components are limited or has quality concerns. But in the real world, researchers can mix using methods and techniques, for example using the HP methods to forecast the components in CCM method when the differential on the three population components need to be considered. An accurate summary of the past pattern is not enough, as special events may happen and change the past pattern. What's more challenging is that special events may not happen often and repeatedly, it not only impacts the data accuracy but also may change the past pattern. It made the forecast even harder to predict. For example, the COVID-19 crisis in 2020. The COVID-19 crisis not only caused more death, but also impacted people's moving intentions, decisions to having children, decisions applying secondary educations, and timing for graduation. The COVID-19 crisis also impacted the data collection which reduced the data quality. With the non-response bias issue increased on the census data during the COVID-19 pandemic (Rothbaum and Bee, 2021), this study still used it as a resource to estimate the observed counts, as it is the data of my best knowledge that can be used to estimate the total population that are 25 years older with Associate's degree and above at different geography levels.

The population forecast by educational attainment levels in this study was limited at national and two states, The state level forecasts in Florida and South Dakota are less accurate than the national level forecast using HP method. It is consistent with the findings from previous study that smaller geographies have less accurate forecast results. However, the state level forecasts are more accurate than the national level forecast using CCM method for population that are 25 years and older and with Associate's degree and above. This indicates that smaller geographies may prefer the CCM method. It might be because the smaller geographies are more vulnerable to changes caused by the new graduates, death and migration. In CCM method, migration data is always a challenge for population estimates or projections. Migration differentials by educational attainment are even harder to estimate and forecast. This study used the ACS data to estimate immigration at national level and in migrants and out migrants at state level. Although the migration components are likely biased, it still provides some guidance on migration trends. Geographic characteristics such as population size and labor force demand may impact the performance of population projection results by educational attainment, because more desirable places, places with adequate employment opportunities; better public transportation infrastructure; higher land development potential; better educated and higher income-level neighboring places, are more likely to have consistent population growth and are easier to make population forecasts (Chi and Wang 2017). As the top state gaining from net migration, Florida had more accurate forecast result in 2019 1-year forecast than South Dakota using both HP and CCM method.

The new graduates, death, migration data in the CCM method have potential data source overlap and gap issues. Each data was captured as a total count annually. The new graduates are the students who graduated from July 1^{st} in the previous year to June 30^{th} of the current year. Death data and migration data are based on each calendar year. Although the counts of new graduates didn't align with the death and migration data during the same period, it is still a good source to estimate the annual graduation counts if the time period has been used consistently each year. The new graduates may overlap with the migrations counts. The new graduates are reported based on the location of the school, and some new graduates may move out from where they get the degree for jobs or family reasons. This study assumes ACS survey tracks the new graduates who moved out, and moved in. But it is not clear how the new graduates are tracked in the ACS survey, and whether the survey represents well for the new graduate's population. Future study can evaluate how well the ACS survey tracks the newly graduated students.

The results may be biased with limited testing samples for testing out the methods and choosing optimal measurements, and each forecast project will have its specific objectives. Depending on the purpose of the projects, forecasts can have different combinations of elements. Elements means the difference choices in methods, predicting period lengths, predicting years, sub population groups, measurements, data sources, locations and so on. Different elements can make each forecasting project unique. The suggestions made here are limited to the specify forecasts tested in this study. This study examined that the choice of methods, predicting period lengths, predicting years with health crisis, subgroups of educational attainment levels, measurements can influence the accuracy of results in forecasting population ages 25 years and older and with Associate's degree and above. This study also summarized that data sources and geography levels or locations may also impact the accuracy of the results. With the uniqueness of the forecasting project, the evaluation process will be suggested for each project. This study emphasized that the different elements combination could impact the accuracy of results in population forecasts for population by educational attainment. To help with the decision-making on method selection with different elements for each unique project, future projects can conduct evaluations to verify whether the methods with those elements tested in this study applies to the field. The findings give future projects a reference to design a similar evaluation process on methods with the elements. Although the knowledge and tools sometimes may not be helpful for forecasting accuracy, they are certainly useful for evaluating forecasting projects (Chi and Wang 2017). However, in real situations, not every element that potentially influences the forecasting accuracy can be tested and evaluated due to data or time limitations, or even the unwillingness from the researchers. If an evaluation process will not be worked out, the HP method with the Average (averaged the results of HP with different measurements) would be a manageable and effective choice for forecasting projects with limited resources.

Due to data and time limitation, this dissertation is limited to evaluate forecasts at the national level and state level in Florida and South Dakota in 2019 and 2021. Indicated by the top net migration population in the nation, Florida state is a more desired state than South Dakota. Florida state also has more population than South Dokota. Using the CCM method, Florida had more accurate forecasting result than South Dakota. It indicates CCM method work better in geographies with more migration flows. Future studies can investigate how CCM and HP method works differently at different types of county level geography.

This dissertation only compared the selected two states and did not do comparisons among all the states in the U.S., as the evaluation process involves a lot of comparisons of the results across different methods, measurements, length of predicting period, population groups, time, geographies. Coding techniques like loops and macro are not enough for the measurement selection and evaluation. With the development of the technology, future applied demography might benefit from trained Machine Learning and Artificial Intelligence techniques and software. Similar evaluation studies may be effectively colonized and automized at different settings by the developed Machine

Learning models to automize from data cleaning, analyze past trend, choose measurement, calculate population changes, make comparisons, and summarize results.

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