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ORIGINAL RESEARCH

A New Approach to Probabilistic County Population Forecasting with an Example Application to West Texas

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Abstract
This paper shows how measures of uncertainty can be applied to existing subnational population forecasts using the 107 counties that make up West Texas as a case study. The measures of forecast uncertainty are relatively easy to calculate and meet several important criteria routinely applied by state and local demographers. We also report the results of two independent comparisons supporting the argument that our approach is valid. The paper concludes it is well-suited for developing probabilistic population forecasts in the United States and elsewhere.

Keywords ARIMA · Bayes · Cohort component method · Error propagation · Espenshade-Tayman method · Evaluation criteria · Superpopulation · Validity

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Introduction

Population forecasts are produced by state demographers and used by state and local governments as an important factor in the planning and budgeting of various governmental programs, services, and infrastructure. Medicaid, education, and transportation form the largest share of state expenditures, and demand for all three is driven by population change (Sigritz, 2023). Major infrastructure may take 20 or 30 years to plan, finance, and be put into place. Thus, it is important to know, with some level of confidence, the size, location, and characteristics of future populations. Given increasing costs for infrastructure and limited fiscal resources, state governments must prioritize which projects get funding. Knowing more about the probability of the state's future population and areas within the state would be useful for such prioritization. In addition, users of the population forecasts may assume more certainty in the forecasts than is warranted. Demographers who produce these forecasts develop reasonable assumptions for each component of population change specified in the model and collect and prepare the data used in the model. However, demographers also know that other factors may ultimately influence the trajectory of any of those factors and the resulting final population.

States have been using and/or producing population forecasts since at least the 1930s[1] and more consistently since the creation of the Federal-State Cooperative for Population Projections (FSCPP) in the early 1980s, a partnership program between the states and the U.S. Census Bureau (U.S. Census Bureau, n.d.). In a survey of members of the FSCPP network, 37 of 43 responding states used the cohort-component method (CCM) approach exclusively or in combination with other methods (You, 2023) to forecast state and county populations. To provide some indications of uncertainty, some producers of state and county population forecasts prepare alternative scenarios, altering the main assumptions (most often limited to different assumptions about migration). Although these alternative scenarios may be useful, they do not provide upper and lower-banded population forecasts like economic forecasts. Wilson and Shalley (2019), in a survey of Australian users of population forecasts, found most users desired measures of uncertainty and had at least a basic understanding of their meaning. Thus, demographers preparing CCM-based population forecasts may consider using probability forecasts as an added enhancement to their final data products.

To date, we are aware of six studies that have presented methods for developing sub-national probabilistic population forecasts (Cameron & Poot, 2011; Tayman et al., 2007; Swanson & Beck, 1994; Swanson & Tayman, 2014; Wilson, 2012; and Yu et al., 2023). Notably, four of these studies link probabilistic uncertainty to the Cohort-Component Method (CCM) approach (Cameron & Poot, 2011; Wilson, 2012; and Yu et al., 2023) or its algebraic equivalent, the Cohort Change Ratio (CCR) approach (Swanson & Tayman, 2014). In addition, Alkema et al. (2015) describe a Bayesian approach that links probabilistic uncertainty to a world population forecast

[1] For instance, the earliest known population forecast for North Carolina was published by the State Planning Board in 1938. It was likely produced by Whelpton and Thompson of the Scripps Foundation, who used the Cohort-Component method for forecasting the population of the nation and states.

based on the Cohort-Component Method (CCM), and a general overview of probabilistic population forecasting can be found in Raftery and Ševčíková (2023).

Adding to this brief body of literature, we describe a method for constructing uncertainty measures that is relatively simple. Importantly, we believe it meets critical evaluation criteria used by state and local demographers (Smith et al., 2013 pp. 301–322): (1) Low production costs (particularly staff time); (2) ease of application and explanation; (3) a high level of face and predictive validity; and (4) be timely and intuitive. In describing the method, we use county population projection data for West Texas prepared by the Texas Demographic Center (Texas Demographic Center 2022). We selected these data for four reasons: (1) they represent a wide range of conditions (population size, economic conditions, etc.) that can affect demographic dynamics; (2) one of the authors is familiar with the area and the data; (3) there is a historical file of annual data available, which is needed to implement the method we propose; and (4) the projections are made using the Cohort Component Method (CCM) by an organization that has a great deal of experience and is known for the high quality of its work.

Our method employs the Auto-Regressive Integrated Moving Average (ARIMA) Time Series method. Using the work of Espenshade and Tayman (1982), we can translate the uncertainty information found in the ARIMA method's forecast to the population forecast provided by the CCM approach.

In the remainder of the paper, we describe the ARIMA approach along with the source data we use in this paper and then show how to translate its uncertainty information to a CCM forecast. We then generate annual ARIMA forecasts from 2021 to 2050 for counties in West Texas (and the region as a whole) and translate the 95% confidence intervals for 2030, 2040, and 2050 to the series of county forecasts (and the region as a whole) generated by the Texas Demographic Center.

Texas County Cohort-Component Forecasts

The Texas Demographic Center uses the CCM approach to forecast the population of Texas and its 254 component counties (Texas Demographic Center, 2022). The Center assumes that migration rates from the most recent past (with the current results referencing the 2010–2020 period) continue for the forecast horizon (known as the 1.0 net migration scenario). The Center also typically prepares at least one alternative scenario (currently the 0.5 net migration scenario that assumes rates of net migration half that of the 2010–2020 period) and a comparative no net migration scenario (0.0 net migration scenario). We selected the 1.0 net migration scenario to use in this example of the process we propose. The results would be slightly different if we used the an alternative scenario in terms of the projected populations but based on research we report later in the validity assessment section of this paper (Swanson & Tayman, 2024, 2025), we believe the uncertainty measures generated by our proposed method will be similar. Regarding total population, a point estimate is produced for each forecast year with no indication of the likelihood of the given result. As will be made clear, the method we propose takes advantage of existing population projections, which, as we note subsequently are based on historical data that our proposed method also uses.

We do not describe the CCM approach (Smith, Tayman, and Swanson, 2013 pp. 155–176) because it is so well known. Instead, we move directly to a brief description of the ARIMA approach. Before doing so, however, we first clarify our use of the term "confidence interval" regarding forecast uncertainty. It is more common to use the term "forecast interval" or "prediction interval" in the context of forecasting because a "confidence interval," strictly speaking, applies to a sample (Swanson & Tayman, 2014 pp. 204). However, underlying the approach we describe herein is the concept of a "superpopulation," which, as discussed later, represents a population that is but one of the infinities of populations that will result by chance from the same underlying social and economic cause systems (Deming & Stephan, 1941).

The ARIMA Model

At its heart, the ARIMA time series model is a regression-like forecast method. It was popularized by Box and Jenkins (1976) and has been used in analyzing and forecasting business, economic, and demographic variables. Examples of its use in demographic forecasting include McNown et al. (1995), Pflaumer (1992), Swanson (2019), Tayman et al. (2007), and Zakria and Muhammad (2009). Many states, including the State of North Carolina, use this method for all or some elements of their official population forecasts (You, 2023; North Carolina Office of State Budget and Management 2023).

As Smith et al., (2001 pp. 172–176) discussed, an ARIMA model attempts to uncover the stochastic processes that generate a historical data series. The mechanism of this stochastic process is described—based on the patterns observed in the data series—and that mechanism forms the basis for developing forecasts. Up to three processes can represent the stochastic mechanism: autoregression, differencing, and moving average.

The autoregressive process has a memory in the sense that it is based on the correlation of each value of a variable with all preceding values. The impact of earlier values is assumed to diminish exponentially over time. The number of preceding values explicitly incorporated into the model determines its "order." For example, in a first-order autoregressive process, the current value is only a function of the immediately preceding value. However, the immediately preceding value is also a function of the one before it, which is a function of the one before it, and so forth. Thus, all preceding values influence current values, albeit with a declining impact. In a second-order autoregressive process, the current value is explicitly a function of the two immediately preceding values; again, all preceding values have an indirect impact. The differencing process creates a stationary time series (i.e., one with constant average and variance over time, which, in turn, implies there is no trend in the series). A stationary time series is essential for the construction of ARIMA models. When a time series is non-stationary, it can often be converted into a stationary time series by calculating differences between values. First differences are usually sufficient, but second differences are occasionally required (i.e., differences between differences). Logarithmic and square root transformations can also convert non-stationary variances to stationary variances. The moving average represents a "shock" to the system or an event with a substantial but short-lived impact on the time series pattern. This impact has a limited duration, and then time series trends return to normal. The order of the moving average process defines the number of time periods affected by the shock.

The most general ARIMA model is usually written as ARIMA (p, d, q), where p is the order of the autoregression, d is the degree of differencing, and q is the order of the moving average. (ARIMA models based on time intervals of less than one year may also require a seasonal component.) The first and most subjective step in developing an ARIMA model is to identify the values of p, d, and q. The d-value must be determined first because a stationary series is required to identify the autoregressive and moving average processes correctly. The value of d is the number of times one has to difference the series to achieve stationarity (usually 0 or 1, but occasionally 2 in data with non-linear growth). The p- and q-values are also relatively small (often 0, 1, or 2). The autocorrelation (ACF) and partial autocorrelation patterns are used to find the correct values for p and q. For example, a first-order autoregressive model [ARIMA (1, 0, 0)] is characterized by an ACF that declines exponentially and quickly and a PACF with a significant spike only at lag 1. Once p, d, and q are determined, maximum likelihood procedures are used to estimate the parameters of the ARIMA model. The final step in the estimation process is model diagnosis. An adequate ARIMA model will have random residuals, no significant values in the ACF, and the smallest possible values for p, d, or q. After a successful diagnosis is completed, the ARIMA model is ready to use.

The patterns of the autocorrelation (ACF) and partial autocorrelation functions (PACF) were used to find the correct values for p and q (Brockwell & Davis, 2016: Chapter 3). Each county's ARIMA model had random residuals and the smallest possible values for p, d, or q, as determined by the Ljung-Box test (1978). Using these criteria, we chose an "adequate" ARIMA model specific to each West Texas county. We note that there may be other versions that also are "adequate" and that further refinement of the selection process can be done (e.g., using the augmented Dickey-Fuller test (Dickey & Fuller, 1979) to identify the amount of differencing required to achieve a stationary time series). Because our aim here is heuristic, not definitive, we did not pursue further refinement of each county's ARIMA model beyond determining it to be adequate. However, we subsequently touch on this issue in the "Two Validity Assessments and ARIMA Model Adequacy" section, where we discuss the effects of varying values of the ARIMA parameter on uncertainty.

Our ARIMA models are based on an annual times series from 1990 to 2020 for the total population. We use the U.S. Census Bureau's intercensal population estimates for 1990–1999 and 2000–2009, the Texas Demographic Center's intercensal population estimates for 2010–2019, and decennial censuses from 1990 through 2020. For this paper, we select 107 counties located in west Texas– equivalent to the Texas State Comptroller's Northwest, Panhandle, West Texas, and Upper Rio Grande Regions (Hegar, 2024)– to implement the ARIMA model and launch the forecasts from 2021. These regions cover the high elevation deserts as well as the mountains around El Paso (the largest city) to the semi-arid areas found in the Texas Panhandle. In addition to El Paso, the region's major cities include Abilene, Amarillo, Lubbock, Midland, Odessa, and Wichita Falls. However, most counties are sparsely populated (with 71 of the 107 counties having populations of 10,000 or less). Oil and gas production, farming and ranching, and international trade are the major industries in the region (See Fig. 1).

ARIMA Forecast Uncertainty Translated to a CCM Total Population Forecast

To illustrate our method of translating ARIMA forecast uncertainty to a total population forecast from a CCM model, we focus on the results for 17 of the 107 West Texas Counties. The subset includes the nine largest counties and eight representative counties selected according to economic type (USDA-ERS 2015). Of the eight, we selected two counties for each economic type: farming, mining, government, and nonspecialized. For each economic type, we show one county with predicted population growth and one with predicted population loss (under the original CCM forecast). The results for all counties are available in Appendices I and II. The uncertainty intervals for 2030, 2040, and 2050 CCM total population forecasts are based on ARIMA models that forecast the uncertainty of population density (total population/land area) for the same horizon years. We use "density" because the Espenshade-

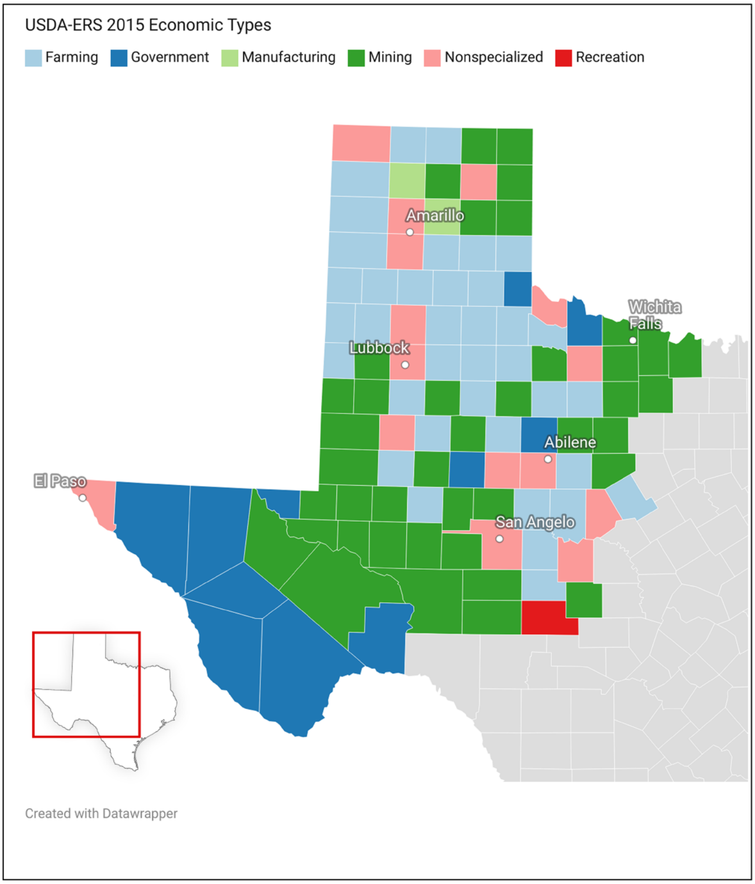

Fig. 1 Economic type, west Texas counties

Tayman (1989) method for translating uncertainty information does so from an estimated "rate," which in this case is the "rate" of population density. Other denominators could be used in developing such a "rate," such as the ratio of population to housing units. However, using the land area as the denominator provides a virtually constant denominator over time, thereby reducing the effort in assembling the "rate" data. It also serves as a stabilizing element regarding the use of ARIMA in that it dampens the effect of short-term population fluctuations more effectively than, say, housing units, which also can fluctuate over time and are not always in concert with population fluctuations. As should be obvious, the data assembled to develop the ARIMA density forecast should encompass the base data used to develop the population projection regarding the total population numbers. The case study we present meets this condition in that the annual ARIMA models cover the period in which the population projections base data are found.

Once the denominator is chosen (and we strongly recommend using a "land area" measure such as square miles), the 95% confidence intervals generated by the ARIMA county "density" forecasts are translated to the county forecasts. Below is an example of this process using the 2050 forecast for Midland County.

Let P = forecasted county population (at time t) obtained from the CCM forecast.

Let D = forecasted county population density obtained from the ARIMA model.

Let A = land area of the county (Midland County = 900.3 sq. miles).

The 2050 ARIMA density forecast shows 259.7, 224.9, and 294.5 for Midland County, the forecasted D, and its 95% Lower and Upper Limits of forecasted D.

The relative width for the 95% Lower and Upper Limits are -0.13397 and 0.13397, respectively. The relative width is the proportionate difference between the Lower and Upper Limits and the forecasted D.

The 2050 forecast for Midland County from the CCM is 293,657.

Multiplying 293,657 × −0.13397 and adding this negative number to 293,657 yields 254,314, the 95% Lower Limit, and adding the product 293,657 × 0.13397 to 293,657 yields 333,000, the 95% Upper Limit of the 2050 Midland County forecast.

Putting it all together, we can state that we are 95% certain that the 2050 population of Midland County will be between 254,314 and 333,000.

Underlying the Espenshade-Tayman method is the idea that a sample is taken from a population of interest. In this case, the ARIMA results represent the sample, and the CCM forecasts represent the population. This interpretation is derived from the idea of a "superpopulation" (Hartley & Sielken, 1975; Sampath, 2005; Swanson & Tayman, 2012 pp. 32–33). This concept can be traced back to Deming and Stephan (1941), who observed that even a complete census describes a population that is but one of the infinite populations that will result by chance from the same underlying social and economic cause systems. It is a theoretical concept that we use to simplify the application of statistical uncertainty to a population forecast that is considered a statistical model in this context. This approach is conceptually and mathematically different from the classical frequentist theory of finite population sampling (Hartley and Sielken (1975), but as pointed out by Ding, Li, and Miratrix (2017), in practical terms, these two approaches result in identical variance estimators. As such, we believe that our approach is on solid statistical ground. Before moving on, we also note that using the Espenshade-Tayman method (1982) here is not new. In addition to being employed by Espenshade and Tayman (1982), it has been used by Swanson (1989) and Roe et al. (1992) in demographic applications.

Table 1 Forecast and 95% uncertainty intervals, selected west Texas Counties[a]

		2020	2030			2040			2050		
County	Economic Type	Census	Forecast	LL95%	UL95%	Forecast	LL95%	UL95%	Forecast	LL95%	UL95%
El Paso	Nonspecialized	865,657	909,933	844,626	975,240	942,242	852,344	1,032,140	953,007	849,611	1,056,403
Lubbock	Nonspecialized	310,639	361,834	342,491	381,177	401,911	373,935	429,887	442,502	407,549	477,455
Midland	Mining	169,983	204,842	185,946	223,738	247,011	217,467	276,555	293,657	254,314	333,000
Ector	Mining	165,171	193,911	174,459	213,363	229,409	198,922	259,896	264,940	224,725	305,155
Taylor	Nonspecialized	143,208	156,945	150,431	163,459	169,708	160,240	179,176	180,699	168,936	192,462
Randall	Nonspecialized	140,753	159,318	154,207	164,429	179,106	171,771	186,441	197,748	188,710	206,786
Wichita	Mining	129,350	126,801	119,178	134,424	122,623	112,197	133,049	116,004	103,924	128,084
Tom Green	Nonspecialized	120,003	132,573	128,586	136,560	145,445	139,592	151,298	156,800	149,468	164,132
Potter	Nonspecialized	118,525	113,747	99,122	128,372	108,367	87,473	129,261	100,779	76,543	125,015
Callahan	Farming	13,708	14,217	13,387	15,047	14,194	13,058	15,330	14,068	12,740	15,396
Comanche	Farming	13,594	13,359	12,571	14,147	12,893	11,817	13,969	12,121	10,882	13,360
Jones	Government	19,663	18,879	15,581	22,177	17,925	13,497	22,353	16,868	11,765	21,971
Mitchell	Government	8,990	9,119	7,444	10,794	9,149	6,772	11,526	9,125	6,222	12,028
Andrews	Mining	18,610	22,997	17,706	28,288	28,993	18,792	39,194	35,825	20,011	51,639
Clay	Mining	10,218	9,600	8,385	10,815	8,801	7,199	10,403	7,970	6,183	9,757
Brown	Nonspecialized	38,095	39,717	37,682	41,752	40,383	37,548	43,218	40,459	37,085	43,833
Hale	Nonspecialized	32,522	29,863	27,422	32,304	27,362	24,200	30,524	24,524	21,053	27,995
West Texas		**2,953,450**	**3,135,639**	**3,024,733**	**3,246,545**	**3,309,067**	**3,144,232**	**3,473,902**	**3,452,751**	**3,248,443**	**3,657,059**

[a]Subset of counties shown for illustrative purpose. Full table available in Appendix I

Table 2 Forecast summary and Forecast half-widths, selected West Texas Counties[a]

				Pct. Change, 2020-2050		Half-Width		
County	Economic Type	2020	2050	Numeric	Percent	2030	2040	2050
El Paso	Nonspecialized	865,657	953,007	87,350	10.1%	7.2%	9.5%	10.8%
Lubbock	Nonspecialized	310,639	442,502	131,863	42.4%	5.3%	7.0%	7.9%
Midland	Mining	169,983	293,657	123,674	72.8%	9.2%	12.0%	13.4%
Ector	Mining	165,171	264,940	99,769	60.4%	10.0%	13.3%	15.2%
Taylor	Nonspecialized	143,208	180,699	37,491	26.2%	4.2%	5.6%	6.5%
Randall	Nonspecialized	140,753	197,748	56,995	40.5%	3.2%	4.1%	4.6%
Wichita	Mining	129,350	116,004	-13,346	-10.3%	6.0%	8.5%	10.4%
Tom Green	Nonspecialized	120,003	156,800	36,797	30.7%	3.0%	4.0%	4.7%
Potter	Nonspecialized	118,525	100,779	-17,746	-15.0%	12.9%	19.3%	24.0%
Callahan	Farming	13,708	14,068	360	2.6%	5.8%	8.0%	9.4%
Comanche	Farming	13,594	12,121	-1,473	-10.8%	5.9%	8.3%	10.2%
Jones	Government	19,663	16,868	-2,795	-14.2%	17.5%	24.7%	30.3%
Mitchell	Government	8,990	9,125	135	1.5%	18.4%	26.0%	31.8%
Andrews	Mining	18,610	35,825	17,215	92.5%	23.0%	35.2%	44.1%
Clay	Mining	10,218	7,970	-2,248	-22.0%	12.7%	18.2%	22.4%
Brown	Nonspecialized	38,095	40,459	2,364	6.2%	5.1%	7.0%	8.3%
Hale	Nonspecialized	32,522	24,524	-7,998	-24.6%	8.2%	11.6%	14.2%
West Texas		2,953,450	3,452,751	499,301	16.9%	3.5%	5.0%	5.9%

[a]Subset of counties shown for illustrative purpose. Full table available in Appendix II

Forecast Uncertainty for 2030, 2040, and 2050

Table 1 provides the CCM forecasts for the selected counties (and West Texas as a whole) for 2030, 2040, and 2050, along with their 95% confidence intervals.

We begin by presenting the range of uncertainty in the selected county forecasts by analyzing half-widths for 10-, 20-, and 30-year forecast horizons, as shown in Table 2. As expected, the half-widths increase for each of the 17 counties and the entire West Texas region as the forecast horizon increases. Among the 107 counties, the maximum half-width in 2030 is found for Loving County (132.2%—in Appendix II), which has a 2020 population of 64 and a 2030 forecasted population of 64.

The same population is forecasted for Loving County in 2040—however, the half-width increases to 166.4%. By 2050, Loving County is still forecasted to have a population of 64, but the half-width increases to 192.6%. The fact that the forecast of Loving County stays constant at 64 people over the 30-year horizon while the half-width increases from 132.2 to 192.6% is consistent with the argument that our proposed approach is well-suited for generating uncertainty measures around population forecasts.

Among the counties shown in Table 2, the maximum half-width for 2030 is found for Andrews County (23.0%), which is forecasted to almost double in size between 2020 and 2050. The half-width for Andrews County will increase to 35.2% in 2040 and 44.1% in 2050. Andrews County is an important oil and gas-producing county. Historically, population change in oil and gas-producing counties is typically volatile following booms and bust cycles of the industry. The larger, nearby Ector and Midland Counties show similar patterns– rapid population growth and larger half-widths relative to counties of comparable sizes. Midland County, at 169,983 in 2020, is forecasted to increase to 293,657 by 2050, a 72.8% gain between 2020 and 2050. In 2030, its half-width is 9.2%, and in 2050 it is 13.4%. Ector County's population is forecasted to increase from 165,171 in 2020 to 264,940 in 2050, a 60.4% gain. Its half-width is 10.0% in 2030, rising to 15.2% in 2050.

The minimum half-with among the 107 counties in 2030 is for Tom Green County, which has a population of 120,003 in 2020. In 2030, its half-width is 3.01%, with a forecasted population of 132,573. In 2040, its half-width is 4.0%, with a forecasted population of 145,445, and by 2050, Tom Green County's half-width is 4.7%, with a forecasted population of 156,800. We believe that this also supports the argument that our proposed system works well in that Tom Green does not have the largest county population (a distinction held by El Paso County, with a 2020 population of 865,657) but is the most stable county in terms of population growth among the 107 counties.

Table 3 contains summary measures of the half-width for all counties and by county economic type and county population size in 2020. The summary measures of the half-widths are consistent with our story. The mean half-with for all counties increases from 16.4% in the 10-year horizon to 24.3% in the 20-year horizon and 32.2% in the 30-year horizon in 2050. The half-width distributions are right skewed as the median half-widths are less than the mean half-widths in all forecast horizons. In the 10-year horizon, 13 counties have half-widths exceeding 25%, while two have half-widths exceeding 50%. In the 20-year horizon, 36 counties have half-widths that exceed 25% and eight that exceed 50%. By 2050, at the 30-year horizon point, 54 counties will have half-widths exceeding 25%, and 14 will have half-widths over 50%. The averages recomputed removing these cases are roughly similar to the median values reported in Table 3.

In addition, the summary measures of uncertainty for counties categorized by population size are consistent with what we know about population forecasts– uncertainty increases as population size decreases. The average half-width for populations under 10,000 is the largest of any population size group in each forecast time point, ranging from 19.9 to 40.2%. The size and range of the half-width lessen consistently with an increase in the population size category. Although population size is an important determinant of forecast uncertainty, the summary measures for counties categorized by economic type are also consistent with what we would expect. Counties more economically tied to a single industry are subject to more volatility in

Table 3 Summary uncertainty measures by county economic type and 2020 population size

Economic Type (N)[a]	2030	2040	2050	2020 Population Size (N)[b]	2030	2040	2050
Farming (37) - Median Pop	3,110	2,928	2,757	<10,000 (71) - Median Pop	3,138	2,951	2,757
Half-Width:				Half-Width:			
Mean	15.7%	23.8%	32.5%	Mean	19.9%	29.8%	40.2%
SD	10.6%	14.9%	20.0%	SD	17.0%	23.3%	33.0%
Median	12.4%	19.4%	26.6%	Median	15.4%	25.0%	32.0%
Number Exceeding 25%	5	13	21	Number Exceeding 25%	13	35	46
Number Exceeding 50%	1	2	6	Number Exceeding 50%	2	8	14
Mining (41) - Median Pop	8,646	8,203	7,576	10,000-50,000 (27) - Median Pop	17,478	17,612	16,496
Half-Width:				Half-Width:			
Mean	15.4%	22.6%	28.8%	Mean	10.3%	14.9%	18.3%
SD	8.1%	12.5%	17.4%	SD	4.9%	7.3%	9.0%
Median	14.5%	21.8%	26.8%	Median	8.7%	12.3%	15.8%
Number Exceeding 25%	3	14	21	Number Exceeding 25%	0	1	8
Number Exceeding 50%	0	2	4	Number Exceeding 50%	0	0	0
Nonspecialized (15) - Median Pop	29,863	27,362	24,524	100,000-200,000 (7) - Median Pop	156,945	169,708	180,699
Half-Width:				Half-Width:			
Mean	9.8%	14.0%	17.6%	Mean	6.9%	9.5%	11.3%
SD	5.0%	7.4%	9.8%	SD	3.8%	5.7%	7.0%
Median	11.3%	17.6%	21.9%	Median	6.0%	8.5%	10.4%
Number Exceeding 25%	0	1	3	Number Exceeding 25%	0	0	0
Number Exceeding 50%	0	0	0	Number Exceeding 50%	0	0	0
Manufacturing (2) - Median Pop	12,698	11,866	11,001	250,000+ (2) - Median Pop	635,884	672,077	697,755
Half-Widths:				Half-Widths:			
Mean	8.3%	11.5%	13.8%	Mean	6.3%	8.3%	9.4%
SD	1.2%	2.0%	2.9%	SD	1.3%	1.8%	2.1%
Median	8.3%	11.5%	13.8%	Median	6.3%	8.3%	9.4%
Number Exceeding 25%	0	0	0	Number Exceeding 25%	0	0	0
Number Exceeding 50%	0	0	0	Number Exceeding 50%	0	0	0
Government (11) - Median Pop	4,460	3,265	2,481	All Counties (107) - Median Pop	5,530	5,493	5,032
Half-Widths:				Half-Widths:			
Mean	33.5%	49.7%	68.7%	Mean	16.4%	24.3%	32.2%
SD	35.3%	46.8%	67.5%	SD	14.9%	20.9%	29.6%
Median	18.9%	26.7%	43.7%	Median	12.9%	19.4%	25.1%
Number Exceeding 25%	5	8	9	Number Exceeding 25%	13	36	54
Number Exceeding 50%	1	4	4	Number Exceeding 50%	2	8	14

[a]Kimble county (recreation) excluded from summaries by economic type

[b]No counties had a 2020 population between 50,000 and 100,000 or between 200, 000 and 250,000

population change, contributing to more error and uncertainty in population forecasts (Smith, Tayman, and Swanson, 2013 pp. 338–342). The average half-width for mining counties is 15.4% in 2030, rising to 28.8% in 2050, while the average half-width for nonspecialized counties is 9.8% in 2030, rising to 17.6% in 2050.

Two Validity Assessments and ARIMA Model "Adequacy"

The first assessment employs data for a world population projection by the U.S. Census Bureau. Using these data, Swanson and Tayman (2025) applied the method described here and compared the "half-widths" (as defined earlier) of the confidence intervals it produced to the half-widths generated from a Bayesian approach for a world population projection done by the United Nations (Alkema et al., 2015; Raftery et al., 2014; United Nations, 2022).

Although the specific 95% confidence intervals are not discussed for years other than 2050 in the 2022 UN report on its probabilistic world population forecasts, they are available in an Excel file (United Nations, 2024), which Swanson and Tayman (2025) used to produce half-widths for the 2030, 2040, 2050, and 2060 UN forecasts. They were, respectively, 0.53%, 1.49%, 2.51%, and 3.76%, while the half widths they constructed for the IDB forecasts for 2030, 2040, 2050, and 2060 were, respectively, 3.35%, 4.94%, and 6.28%. Although the difference narrows between 2030 and 2060, the uncertainty intervals we constructed for the IDB forecasts are wider than those found for the UN forecasts. However, like the UN uncertainty intervals, the ones constructed by Tayman and Swanson (2025) increased between 2030 and 2060.

Swanson and Tayman (2025) concluded that this new approach is well-suited to generate probabilistic world population forecasts and would likely do so at the national and subnational levels, where CCM and CCR methods are routinely used to produce projections. They also noted that there will likely be higher levels of uncertainty at national and sub-national levels due to smaller populations and the presence of migration (which is not present at the world level).

The preceding results lead to the second assessment, which is at the sub-national level and employs data representing the 39 counties of Washington State. Swanson and Tayman (2024) used historical data produced by the Forecasting Division of the Office of Financial Management (Washington, 2024) to implement the ARIMA model, which they then applied to the medium series of the "Growth Management Act" projections produced by the Office of Financial Management (Washington, 2022). Swanson and Tayman (2024) examined the range of uncertainty in the county forecasts by analyzing half-widths and compared the half-widths of their ARIMA-based intervals to half-widths produced using a Bayesian approach by Yu et al., 2023), who discussed their results for the state of Washington and three of its 39 counties, Ferry, King, and Whitman.

The ARIMA-based half widths for Ferry County (a county with a very small population, approximately 7500 in 2024) were wider than those for the Bayes CCM approach at the three horizon lengths of 10, 20, and 30 years. For King County (the county with the highest population, approximately 2.7 million in 2024), the ARIMA-based half-widths were slightly narrower at 10 years than those found for the Bayes CCM approach and substantially narrower at 20 and 30 years. For Whitman County (which has a 2024 population of approximately 48,000 of which 27,000 or so are students at Washington State University), the Bayes CCM produced narrower widths at each of the three horizon lengths. However, Swanson and Tayman (2025) noted that Yu et al. (2023) held the age groups associated with college attendance constant in counties such as Whitman, where these populations have a large impact on the age structure of Whitman County. Considering Washington State as a whole, Swanson and Tayman (2024) found that the half-widths generated by the Bayes CCM were narrower for the 10- and 20-year horizon than the ARIMA-based half-widths, while the latter produced a narrower half-width for the 30-year horizon length. Notably, for all three counties and Washington State, the ARIMA-based half-widths increased over time in a manner that is not inconsistent with the Bayes CCM half-widths.

Swanson and Tayman (2024) concluded that the ARIMA-based approach produces uncertainty measures for county population forecasts that are not dissimilar to those produced by the Bayes CCM approach and that neither approach produced intervals so wide as to be useless, a point brought up by Swanson and Tayman (2016) in an earlier examination of forecast uncertainty.

In regard to the issue of the "adequacy" of a given ARIMA model briefly discussed near the end of the "ARIMA Model" section, Swanson and Tayman (2024) found in their examination of Washington counties that a higher value of the “d” parameter (differencing) causes wider ARIMA intervals and ARIMA intervals that increase more rapidly with lengthening forecast horizons. For example, forecasts from an ARIMA model with first differences follow a linear trend, while forecasts from an ARIMA model with second differences will follow a quadratic trend (Hyndman & Athanasopoulos, 2021: Chapter 9; Tayman et al., 2007). Swanson and Tayman (2024) also found that the average half-width for ARIMA models with first differences was smaller than ARIMA models with second differences in all forecast years. They also found that the gap between them increased with the lengthening of the forecast horizon and that an increase in the variability of the average half-width was much greater for the ARIMA models with second differences. These findings suggest that selecting an ARIMA model must be consistent with the guidelines described here and elsewhere (e.g., Box & Jenkins, 1976; Brockwell & Davis, 2016; Hyndman & Athanasopoulos, 2021; Smith, Tayman, and Swanson, 2013; Swanson & Tayman, 2024).

Discussion

Standard CCM results answer the question, "What will the population look like for a given future time?" However, even within the context of one or more forecast scenarios, we cannot account for the many factors that could ultimately impact that future population's size, characteristics, and distribution, underscoring the need to quantify the uncertainty in a forecast. This study proposes a method for placing confidence intervals around total population point forecasts from a CCM using the quantified uncertainty from an ARIMA model. We illustrate and analyze the results from this method for 107 countries in the West Texas region. This region is the largest cotton and mohair-producing region in the world. It also includes most of the Permian Basin, one of the largest petroleum-producing regions in the world. Climate, weather, and world commodity prices have outsized importance on the economy of this region. Fluctuations in world oil and gas prices influence regional production, which, in turn, can lead to periods of economic booms and busts.

Thus, probability forecasts are useful for counties in this region, showing greater relative uncertainty for counties more influenced by oil and gas production fluctuations. As expected, the prediction intervals for Andrews, Midland, and Ector Counties (heavily influenced by change in oil and gas production) are wider than those for counties with more stable historical population change (such as Brown, Lubbock, and Taylor Counties). These different levels of uncertainty can help decision-makers discuss and negotiate different levels of investment and benefits (e.g., income, revenues) in both the public and private sectors. Given that both investments and benefits are zero-sum processes, it may be the case that both investment levels and expectations concerning benefits may be relatively higher in areas with less uncertainty.

Unlike the approaches found in Swanson (1989) and Swanson and Beck (1994), the method we have described can be linked directly to the CCM method. It is simpler than the methods described by Cameron and Poot (2011) and Wilson (2012) and far simpler than the Bayes CCM approach (Yu et al., 2023).

Green and Armstrong (2015) discuss simple versus complex methods in terms of forecasting, which applies here in that the approach we describe falls more into the simple methodological category rather than the complex category. Green and Armstrong (2015) suggest that while no evidence shows complexity improves accuracy, complexity remains popular among (1) researchers because they are rewarded for publishing in highly ranked journals, which favor complexity; (2) methodologists because complex methods can be used to provide information that supports decision makers' plans; and (3) clients who may be reassured by incomprehensibility. This argument can be applied to Bayesian methods such as found in Yu et al. (2023), a paper that represents the "complex" alternative to our "simple" approach. In this regard, our approach may be preferred because of the argument presented by Green and Armstrong and because applying a Bayesian approach can be complex, opaque, and even counter-intuitive (Goodwin, 2015). Notably, the ARIMA method is widely available on software packages generally used by state and local demographers and is consistent with their existing programming and other skills. They also usually have historical data supporting the construction of county-level ARIMA forecasts, which are embedded in the base data used to develop the CCM projections.

The approach we have described does not produce the uncertainty intervals by age and gender, births, death, and migration as does the Bayes CCM approach described by Yu et al., (2023: 934) and the CCR approach discussed by Swanson and Tayman (2014). Neither the Bayes CCM nor the alternative approach, however, take into account uncertainty in the input data themselves, a similarity also shared with the work by Cameron and Poot (2011), Swanson and Tayman (2014), and Wilson (2012). However, as Yu et al., (2023 pp. 934) implied, these are not likely to be among the most important sources of uncertainty for data in the United States and other countries where subnational population forecasts are routinely produced.

Regarding the method not providing uncertainty intervals by age and gender, Deming's (1950 pp. 127–134) "error propagation" was used to translate uncertainty in age group intervals found in the regression-based CCR forecasts reported by Swanson and Tayman (2014) to the total populations in question. "Error Propagation" refers to a process in which the uncertainty in separate elements of a forecast (e.g., mortality, fertility, and migration) can be brought together to form an uncertainty measure for the forecast of the total population (Alho & Spencer, 2005). In different forms, "error propagation" has been used by Alho and Spencer (2005), Espenshade and Tayman (1982), and Hansen, Hurwitz, and Madow (1953), among others. It may be possible to "reverse-engineer" the "error propagation" approach and develop uncertainty measures by age and gender using our alternative approach, which would be a productive avenue of future research.

Smith et al., (2001 pp. 373) opined that future research would focus increasingly on measuring uncertainty in population forecasts and noted that while such research may not directly improve forecast accuracy, it will enhance our understanding of the uncertainty inherent in population forecasts. They said that this change would imply a shift from "population projections" to "population forecasts," a guideline we have followed in this paper. As such, we believe that this novel application of the Espenshade-Tayman method of translating uncertainty to population forecasts will add to our understanding of the uncertainty in population forecasting.

In closing, we argue that the method described in this paper is well-suited not only to generate probabilistic world population forecasts, but also probabilistic national and subnational population forecasts in the United States and wherever else these forecasts are routinely produced.

Appendix I

Forecast and 95% uncertainty Intervals, West Texas Counties

		2020	2030			2040			2050		
County	Economic Type	Population	Forecast	LL95%	UL95%	Forecast	LL95%	UL95%	Forecast	LL95%	UL95%
Andrews	Mining	18,610	22,997	17,706	28,288	28,993	18,792	39,194	35,825	20,011	51,639
Archer	Mining	8,560	8,073	7,115	9,031	7,462	6,210	8,714	6,853	5,445	8,261
Armstrong	Farming	1,848	1,819	1,575	2,063	1,789	1,449	2,129	1,773	1,361	2,185
Bailey	Farming	6,904	6,602	6,009	7,195	6,324	5,521	7,127	5,945	5,021	6,869
Baylor	Nonspecialized	3,465	3,331	2,954	3,708	3,236	2,665	3,807	3,135	2,378	3,892
Borden	Farming	631	608	455	761	603	389	817	601	340	862
Brewster	Government	9,546	9,811	9,029	10,593	9,354	8,300	10,408	8,866	7,642	10,090
Briscoe	Farming	1,435	1,246	1,027	1,465	1,083	772	1,394	959	559	1,359
Brown	Nonspecialized	38,095	39,717	37,682	41,752	40,383	37,548	43,218	40,459	37,085	43,833
Callahan	Farming	13,708	14,217	13,387	15,047	14,194	13,058	15,330	14,068	12,740	15,396
Carson	Manufacturing	5,807	5,465	4,964	5,966	5,085	4,426	5,744	4,690	3,946	5,434
Castro	Farming	7,371	6,669	6,082	7,256	6,026	5,211	6,841	5,376	4,401	6,351
Childress	Government	6,664	6,697	5,006	8,388	6,659	4,281	9,037	6,424	3,614	9,234
Clay	Mining	10,218	9,600	8,385	10,815	8,801	7,199	10,403	7,970	6,183	9,757
Cochran	Farming	2,547	2,126	1,862	2,390	1,787	1,341	2,233	1,465	618	2,312
Coke	Mining	3,285	3,454	2,793	4,115	3,690	2,691	4,689	3,932	2,628	5,236
Coleman	Farming	7,684	6,825	6,144	7,506	5,835	4,925	6,745	4,890	3,848	5,932
Collingsworth	Farming	2,652	2,349	2,067	2,631	2,082	1,677	2,487	1,795	1,295	2,295
Comanche	Farming	13,594	13,359	12,571	14,147	12,893	11,817	13,969	12,121	10,882	13,360
Concho	Farming	3,303	3,110	1,285	4,935	2,928	498	5,358	2,757	0	5,559
Cottle	Farming	1,380	1,319	1,116	1,522	1,221	865	1,577	1,125	515	1,735
Crane	Mining	4,675	5,027	3,808	6,246	5,493	3,574	7,412	5,887	3,353	8,421
Crockett	Mining	3,098	2,554	1,663	3,445	2,127	1,044	3,210	1,734	642	2,826
Crosby	Farming	5,133	4,402	3,979	4,825	3,724	3,117	4,331	3,081	2,313	3,849
Culberson	Government	2,188	1,935	1,657	2,213	1,660	1,223	2,097	1,410	766	2,054
Dallam	Nonspecialized	7,115	7,155	6,108	8,202	7,309	5,855	8,763	7,455	5,737	9,173
Dawson	Nonspecialized	12,456	11,825	10,026	13,624	11,220	8,806	13,634	10,577	7,790	13,364
Deaf Smith	Farming	18,583	17,478	16,499	18,457	16,437	15,135	17,739	15,211	13,735	16,687
Dickens	Farming	1,770	1,598	951	2,245	1,531	654	2,408	1,406	419	2,393
Donley	Farming	3,258	3,009	2,654	3,364	2,753	2,294	3,212	2,479	1,972	2,986
Eastland	Mining	17,725	17,503	16,306	18,700	16,839	15,211	18,467	15,945	14,057	17,833
Ector	Mining	165,171	193,911	174,459	213,363	229,409	198,922	259,896	264,940	224,725	305,155
El Paso	Nonspecialized	865,657	909,933	844,626	975,240	942,242	852,344	1,032,140	953,007	849,611	1,056,403
Fisher	Farming	3,672	3,464	3,078	3,850	3,278	2,694	3,862	3,108	2,327	3,889
Floyd	Farming	5,402	4,610	3,916	5,304	3,962	2,862	5,062	3,391	1,734	5,048
Foard	Farming	1,095	919	753	1,085	790	516	1,064	688	233	1,143
Gaines	Mining	21,598	25,154	22,323	27,985	30,014	25,334	34,694	34,831	28,580	41,082
Garza	Mining	5,816	5,530	4,301	6,759	5,199	3,544	6,854	4,821	2,934	6,708

		2020	2030			2040			2050		
County	Economic Type	Population	Forecast	LL95%	UL95%	Forecast	LL95%	UL95%	Forecast	LL95%	UL95%
Glasscock	Farming	1,116	1,001	798	1,204	877	626	1,128	815	529	1,101
Gray	Mining	21,227	20,183	17,179	23,187	19,207	14,963	23,451	17,820	12,924	22,716
Hale	Nonspecialized	32,522	29,863	27,422	32,304	27,362	24,200	30,524	24,524	21,053	27,995
Hall	Farming	2,825	2,518	2,186	2,850	2,233	1,747	2,719	1,920	1,306	2,534
Hansford	Farming	5,285	5,071	4,371	5,771	4,927	3,926	5,928	4,748	3,552	5,944
Hardeman	Nonspecialized	3,549	3,131	2,761	3,501	2,757	2,217	3,297	2,435	1,686	3,184
Hartley	Farming	5,382	5,271	3,545	6,997	5,116	2,747	7,485	4,909	2,124	7,694
Haskell	Farming	5,416	5,330	4,882	5,778	5,234	4,550	5,918	5,032	4,137	5,927
Hemphill	Mining	3,382	2,997	2,117	3,877	2,710	1,528	3,892	2,424	1,108	3,740
Hockley	Mining	21,537	20,842	19,037	22,647	20,098	17,481	22,715	19,100	15,901	22,299
Howard	Mining	34,860	36,259	33,099	39,419	37,313	32,715	41,911	37,885	32,167	43,603
Hudspeth	Government	3,202	2,755	1,529	3,981	2,305	796	3,814	1,976	372	3,580
Hutchinson	Mining	20,617	19,324	18,212	20,436	18,048	16,439	19,657	16,496	14,505	18,487
Irion	Mining	1,513	1,427	1,278	1,576	1,346	1,151	1,541	1,305	1,074	1,536
Jack	Mining	8,472	8,002	6,535	9,469	7,522	5,571	9,473	7,004	4,779	9,229
Jeff Davis	Government	1,996	1,747	1,417	2,077	1,470	1,077	1,863	1,186	798	1,574
Jones	Government	19,663	18,879	15,581	22,177	17,925	13,497	22,353	16,868	11,765	21,971
Kent	Farming	753	729	593	865	732	510	954	743	421	1,065
Kimble	Recreation	4,286	4,016	3,614	4,418	3,705	3,180	4,230	3,451	2,852	4,050
King	Farming	265	259	187	331	248	153	343	260	139	381
Knox	Mining	3,353	3,138	2,681	3,595	2,951	2,216	3,686	2,732	1,675	3,789
Lamb	Farming	13,045	12,263	11,585	12,941	11,571	10,616	12,526	10,725	9,577	11,873
Lipscomb	Mining	3,059	2,709	2,331	3,087	2,376	1,907	2,845	2,055	1,558	2,552
Loving	Government	64	64	0	169	64	0	213	64	0	246
Lubbock	Nonspecialized	310,639	361,834	342,491	381,177	401,911	373,935	429,887	442,502	407,549	477,455
Lynn	Farming	5,596	5,425	4,920	5,930	5,148	4,418	5,878	4,918	3,992	5,844
Martin	Farming	5,237	5,543	4,858	6,228	5,896	4,866	6,926	6,311	4,961	7,661
Mason	Mining	3,953	3,821	3,577	4,065	3,708	3,388	4,028	3,666	3,294	4,038
McCulloch	Nonspecialized	7,630	7,260	6,288	8,232	6,746	5,468	8,024	6,177	4,744	7,610
Menard	Farming	1,962	1,753	1,455	2,051	1,581	1,187	1,975	1,423	983	1,863
Midland	Mining	169,983	204,842	185,946	223,738	247,011	217,467	276,555	293,657	254,314	333,000
Mitchell	Government	8,990	9,119	7,444	10,794	9,149	6,772	11,526	9,125	6,222	12,028
Montague	Mining	19,965	20,316	19,373	21,259	20,389	19,107	21,671	20,210	18,715	21,705
Moore	Manufacturing	21,358	19,930	18,438	21,422	18,646	16,769	20,523	17,311	15,278	19,344
Motley	Farming	1,063	987	752	1,222	902	598	1,206	840	494	1,186
Nolan	Nonspecialized	14,738	14,224	12,548	15,900	13,676	11,274	16,078	13,077	10,218	15,936
Ochiltree	Mining	10,015	9,943	8,838	11,048	10,049	8,470	11,628	9,932	8,020	11,844
Oldham	Farming	1,758	1,719	1,512	1,926	1,572	1,272	1,872	1,361	999	1,723

		2020	2030			2040			2050		
County	Economic Type	Population	Forecast	LL95%	UL95%	Forecast	LL95%	UL95%	Forecast	LL95%	UL95%
Parmer	Farming	9,869	9,255	8,605	9,905	8,555	7,705	9,405	7,773	6,827	8,719
Pecos	Mining	15,193	15,176	12,832	17,520	15,306	11,962	18,650	15,275	11,188	19,362
Potter	Nonspecialized	118,525	113,747	99,122	128,372	108,367	87,473	129,261	100,779	76,543	125,015
Presidio	Government	6,131	4,460	2,858	6,062	3,265	1,606	4,924	2,481	937	4,025
Randall	Nonspecialized	140,753	159,318	154,207	164,429	179,106	171,771	186,441	197,748	188,710	206,786
Reagan	Mining	3,385	3,417	2,011	4,823	3,420	1,341	5,499	3,382	830	5,934
Reeves	Mining	14,748	16,015	13,474	18,556	17,702	13,674	21,730	19,284	13,885	24,683
Roberts	Nonspecialized	827	735	594	876	655	477	833	599	400	798
Runnels	Farming	9,900	9,739	8,926	10,552	9,547	8,420	10,674	9,286	7,943	10,629
Schleicher	Mining	2,451	1,758	1,366	2,150	1,249	855	1,643	859	527	1,191
Scurry	Mining	16,932	17,272	14,600	19,944	17,643	13,734	21,552	17,726	12,896	22,556
Shackelford	Mining	3,105	2,806	2,547	3,065	2,508	2,181	2,835	2,214	1,860	2,568
Sherman	Farming	2,782	2,557	2,155	2,959	2,304	1,792	2,816	2,083	1,516	2,650
Stephens	Mining	9,101	8,723	7,668	9,778	8,203	6,800	9,606	7,576	5,989	9,163
Sterling	Mining	1,372	1,704	1,387	2,021	2,226	1,640	2,812	2,923	1,980	3,866
Stonewall	Mining	1,245	1,056	804	1,308	932	512	1,352	792	134	1,450
Sutton	Mining	3,372	2,729	2,199	3,259	2,168	1,572	2,764	1,700	1,128	2,272
Swisher	Farming	6,971	6,301	5,608	6,994	5,684	4,801	6,567	5,049	4,088	6,010
Taylor	Nonspecialized	143,208	156,945	150,431	163,459	169,708	160,240	179,176	180,699	168,936	192,462
Terrell	Government	760	553	299	807	403	0	820	277	0	1,142
Terry	Mining	11,831	11,478	10,699	12,257	11,202	10,127	12,277	10,734	9,472	11,996
Throckmorton	Farming	1,440	1,243	1,006	1,480	1,100	803	1,397	946	633	1,259
Tom Green	Nonspecialized	120,003	132,573	128,586	136,560	145,445	139,592	151,298	156,800	149,468	164,132
Upton	Mining	3,308	3,262	2,652	3,872	3,298	2,306	4,290	3,303	1,891	4,715
Ward	Mining	11,644	12,954	10,843	15,065	14,666	11,225	18,107	16,450	11,695	21,205
Wheeler	Mining	4,990	4,644	3,530	5,758	4,251	2,670	5,832	3,857	2,051	5,663
Wichita	Mining	129,350	126,801	119,178	134,424	122,623	112,197	133,049	116,004	103,924	128,084
Wilbarger	Government	12,887	12,452	11,454	13,450	11,719	10,306	13,132	10,811	9,106	12,516
Winkler	Mining	7,791	8,646	7,269	10,023	9,744	7,549	11,939	10,757	7,789	13,725
Yoakum	Mining	7,694	7,538	6,614	8,462	7,520	6,216	8,824	7,524	5,926	9,122
Young	Mining	17,867	17,857	16,883	18,831	17,612	16,254	18,970	17,023	15,415	18,631
West Texas		**2,953,450**	**3,135,639**	**3,024,733**	**3,246,545**	**3,309,067**	**3,144,232**	**3,473,902**	**3,452,751**	**3,248,443**	**3,657,059**

Appendix II

Forecast summary and forecast half-widths, Texas Counties

				Pct. Change, 2020-2050		Half-Width		
County	Economic Type	2020	2050	Numeric	Percent	2030	2040	2050
Hartley	Farming	5382	4909	-473	-8.8%	32.8%	46.3%	56.7%
Haskell	Farming	5416	5032	-384	-7.1%	8.4%	13.1%	17.8%
Hemphill	Mining	3382	2424	-958	-28.3%	29.4%	43.6%	54.3%
Hockley	Mining	21537	19100	-2437	-11.3%	8.7%	13.0%	16.8%
Howard	Mining	34860	37885	3025	8.7%	8.7%	12.3%	15.1%
Hudspeth	Government	3202	1976	-1226	-38.3%	44.5%	65.5%	81.2%
Hutchinson	Mining	20617	16496	-4121	-20.0%	5.8%	8.9%	12.1%
Irion	Mining	1513	1305	-208	-13.8%	10.4%	14.5%	17.7%
Jack	Mining	8472	7004	-1468	-17.3%	18.3%	25.9%	31.8%
Jeff Davis	Government	1996	1186	-810	-40.6%	18.9%	26.7%	32.7%
Jones	Government	19,663	16,868	-2,795	-14.2%	17.5%	24.7%	30.3%
Kent	Farming	753	743	-10	-1.3%	18.7%	30.3%	43.4%
Kimble	Recreation	4286	3451	-835	-19.5%	10.0%	14.2%	17.4%
King	Farming	265	260	-5	-1.9%	27.8%	38.4%	46.6%
Knox	Mining	3353	2732	-621	-18.5%	14.6%	24.9%	38.7%
Lamb	Farming	13045	10725	-2320	-17.8%	5.5%	8.3%	10.7%
Lipscomb	Mining	3059	2055	-1004	-32.8%	14.0%	19.7%	24.2%
Loving	Government	64	64	0	0.0%	132.3%	166.4%	192.6%
Lubbock	Nonspecialized	310,639	442,502	131,863	42.4%	5.3%	7.0%	7.9%
Lynn	Farming	5596	4918	-678	-12.1%	9.3%	14.2%	18.8%
Martin	Farming	5237	6311	1074	20.5%	12.4%	17.5%	21.4%
Mason	Mining	3953	3666	-287	-7.3%	6.4%	8.6%	10.2%
McCulloch	Nonspecialized	7630	6177	-1453	-19.0%	13.4%	18.9%	23.2%
Menard	Farming	1962	1423	-539	-27.5%	17.0%	24.9%	30.9%
Midland	Mining	169,983	293,657	123,674	72.8%	9.2%	12.0%	13.4%
Mitchell	Government	8,990	9,125	135	1.5%	18.4%	26.0%	31.8%
Montague	Mining	19965	20210	245	1.2%	4.6%	6.3%	7.4%
Moore	Manufacturing	21358	17311	-4047	-19.0%	7.5%	10.1%	11.8%
Motley	Farming	1063	840	-223	-21.0%	23.8%	33.7%	41.2%
Nolan	Nonspecialized	14738	13077	-1661	-11.3%	11.8%	17.6%	21.9%
Ochiltree	Mining	10015	9932	-83	-0.8%	11.1%	15.7%	19.3%
Oldham	Farming	1758	1361	-397	-22.6%	12.0%	19.1%	26.6%
Parmer	Farming	9869	7773	-2096	-21.2%	7.0%	9.9%	12.2%
Pecos	Mining	15193	15275	82	0.5%	15.5%	21.9%	26.8%
Potter	Nonspecialized	118,525	100,779	-17,746	-15.0%	12.9%	19.3%	24.0%
Presidio	Government	6131	2481	-3650	-59.5%	35.9%	50.8%	62.2%
Randall	Nonspecialized	140,753	197,748	56,995	40.5%	3.2%	4.1%	4.6%
Reagan	Mining	3385	3382	-3	-0.1%	41.1%	60.8%	75.5%
Reeves	Mining	14748	19284	4536	30.8%	15.9%	22.8%	28.0%
Roberts	Nonspecialized	827	599	-228	-27.6%	19.2%	27.2%	33.3%
Runnels	Farming	9900	9286	-614	-6.2%	8.4%	11.8%	14.5%
Schleicher	Mining	2451	859	-1592	-65.0%	22.3%	31.5%	38.6%
Scurry	Mining	16932	17726	794	4.7%	15.5%	22.2%	27.3%
Shackelford	Mining	3105	2214	-891	-28.7%	9.2%	13.1%	16.0%

County	Economic Type	2020	2050	Pct. Change, 2020-2050 Numeric	Percent	Half-Width 2030	2040	2050
Sherman	Farming	2782	2083	-699	-25.1%	15.7%	22.2%	27.2%
Stephens	Mining	9101	7576	-1525	-16.8%	12.1%	17.1%	20.9%
Sterling	Mining	1372	2923	1551	113.1%	18.6%	26.3%	32.3%
Stonewall	Mining	1245	792	-453	-36.4%	23.9%	45.1%	83.1%
Sutton	Mining	3372	1700	-1672	-49.6%	19.4%	27.5%	33.7%
Swisher	Farming	6971	5049	-1922	-27.6%	11.0%	15.5%	19.0%
Taylor	Nonspecialized	143,208	180,699	37,491	26.2%	4.2%	5.6%	6.5%
Terrell	Government	760	277	-483	-63.6%	45.9%	101.7%	206.1%
Terry	Mining	11831	10734	-1097	-9.3%	6.8%	9.6%	11.8%
Throckmorton	Farming	1440	946	-494	-34.3%	19.1%	27.0%	33.1%
Tom Green	Nonspecialized	120,003	156,800	36,797	30.7%	3.0%	4.0%	4.7%
Upton	Mining	3308	3303	-5	-0.2%	18.7%	30.1%	42.7%
Ward	Mining	11644	16450	4806	41.3%	16.3%	23.5%	28.9%
Wheeler	Mining	4990	3857	-1133	-22.7%	24.0%	37.2%	46.8%
Wichita	Mining	129,350	116,004	-13,346	-10.3%	6.0%	8.5%	10.4%
Wilbarger	Government	12887	10811	-2076	-16.1%	8.0%	12.1%	15.8%
Winkler	Mining	7791	10757	2966	38.1%	15.9%	22.5%	27.6%
Yoakum	Mining	7694	7524	-170	-2.2%	12.3%	17.3%	21.2%
Young	Mining	17867	17023	-844	-4.7%	5.5%	7.7%	9.4%
West Texas		**2,953,450**	**3,452,751**	**499,301**	**16.9%**	**3.5%**	**5.0%**	**5.9%**

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