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# An Econometric Approach for Modeling Population Change in Arkansas

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# Dedication

I dedicate this thesis to my parents, Abel and Eugenia, and my siblings, Eric and Gabriela.

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by

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## Abstract

This study models population in the state of Arkansas using a small econometric model, and is similar to a previous demographic model developed by Fullerton and Barraza de Anda (2008). The components of population change consist of births, deaths, and net migration. Births minus deaths equal natural increase, and population in the current period is population from the previous period plus natural increase plus net migration. Births and deaths are modeled as functions of a one period autoregressive lag as well as national trends. Net migration is also modeled as a one period lag of itself in addition to relative labor market conditions. Results confirm that births and deaths contain strong inertial components. National trends positively affect births and deaths as well. Net migration also contains a strong inertial component. Additionally, relative labor market conditions also influence migration. Specifically, if employment in Arkansas increases relative to the rest of the country, Arkansas will experience positive net migration. Out of sample simulations are conducted in order to further test model validity. Simulation results are reasonable and follow recent trends. Natural increase and net migration are expected to decrease. Accordingly, population growth is expected to slow down. Experimentation with alternate specifications in addition to using different assumed growth rates for the exogenous variables is suggested. Furthermore, modeling population in nearby regions may assist in confirming, or rejecting, the results obtained in this study.

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# Chapter 1: Introduction

Demographic models and forecasts provide platforms for both private and public sector planning efforts. Examples include infrastructure planning, personnel management, and government case loads. Population modeling is, therefore, an endeavor which receives substantial research attention. Fertility and mortality have historically played important roles for analyzing population change. Many studies in more recent years also devote substantial attention to migratory flows (Booth, 2006).

While the empirical specifications for births and deaths can be relatively simple, modeling migration flows can be more complicated. Numerous studies examine the causes and effects of migration. Harris and Todaro (1970) develop a model in which the economy is divided into 2 sectors – manufacturing and agriculture. In this model, migration continues until the actual rural wage and the expected urban wage converge. This wage, or income, differential framework can be modified to analyze migration between different geographic regions, for example between countries or states.

The objective for this study is to econometrically model population change in Arkansas. Labor market conditions are expected to play important roles in migration. The analysis draws on the regional approach employed by Fullerton and Barraza de Anda (2008). It has been suggested that forecasting population changes in areas with different characteristics and using different techniques can improve forecasts accuracy (Tayman and Swanson, 1996). Subsequent sections include a review of recent literature on the subject; data and methodology; empirical analysis; and concluding remarks. A data appendix is included at the end of the study.

## Chapter 2: Literature Review

Booth (2006) offers a concise review on population and demographic forecasting methods and developments since 1980. Specifically, this review highlights the need to disaggregate and forecast the three components of population change separately, and to combine the separate forecasts in order to model population change. The three components consist of fertility, mortality, and migration. Historically, fertility has been regarded as the main component of population change, but the failure to predict fertility shocks, in addition to a population that lives longer, has led to a shift that includes mortality more prominently. The difference between these two components constitutes natural increase. Migration, although somewhat more difficult to model and forecast, has also gained importance in demographic forecasts. In many regions, migration can rival natural increase as the primary driver for population change.

In addition, Booth (2006) identifies three approaches to forecasting the different components of population change. These include extrapolative methods, expectation-based methods, and structural modeling. Extrapolative methods assume that future observations will depend on past observations. The most common of these extrapolative methods is univariate autoregressive integrated moving average (ARIMA) modeling. Methods based on expectation rely on individuals' own expectations and/or experts' expectations. Structural modeling addresses demographic changes based on some theoretical assumptions, and can sometimes be combined with extrapolative methods in order to help capture all variations (Smith, Tayman, and Swanson, 2001). It is further suggested that model complexity does not necessarily guarantee superior forecasts. Smith (1997) also indicates that more complex population projection models and techniques do not perform better than simpler methods.

Historically, fertility has proven difficult to model. One possible economic predictor of fertility that has been studied extensively is income. Becker (1960) hypothesizes that income and fertility would be positively related, but instead found the relationship to be negative. Becker (1960) indicates that this could be the effect of missing variables, such as the use of contraceptives. A positive relationship between income and births in families that actively engaged in family planning is documented. Some efforts make distinctions between increases in income for men and women (Jones, Schoonbroodt, Tertilt, 2010). Schultz (2005) suggests that if the increase in family income is due an increase in female wages, this will raise the price of children. Schultz (2005) notes that when the price effect dominates the income effect, increases in female incomes will result in lower fertility.

Jones and Tertilt (2006) use microdata from nine different census surveys in order to analyze the relationship between income and lifetime fertility for five-year birth cohorts of women, beginning in the years 1826-1830 and ending in 1956-1960. Jones and Tertilt (2006) use husbands' occupations, as well as education, as proxies for income. The main finding shows a robust inverse relationship between husbands' occupational income with respect to fertility for all available cohorts. An analysis of different subgroups within the cohorts also yields a negative relationship. This implies that lower fertility can result from any rise in income, not just increases in women's wages. Additionally, Jones, Schoonbroodt, and Tertilt (2010) indicate that most data show a robust inverse relationship between income and fertility. In a utility maximization framework, low incomes will cause high birth levels whenever the elasticity of substitution of children, with respect to consumption, is high.

With respect to migration, Harris and Todaro (1970) develop a two-sector model in which manufacturing and agriculture comprise the two sectors. Manufacturing activity takes place in the urban setting while agricultural production occurs in the rural setting. In addition, the model acknowledges that a politically determined urban minimum wage exists, and this minimum wage is assumed to be higher than the agricultural wage. There exists a fixed stock of labor and the model analyzes the allocation of labor. Results indicate that migration from the rural to the urban sector will continue until the actual agricultural real wage equals the expected manufacturing wage. The agricultural real wage is the marginal product of labor in agriculture expressed in terms of the manufactured good, and the urban expected wage equals the real urban minimum wage times the probability of being employed. Unemployment is, thus, consistent with equilibrium.

Corden and Findlay (1975) further extend the low-wage to high-wage sectoral migration model. Among other things, this approach modifies the framework to allow for situations in which a small country is part of a larger world economy in which prices are determined exogenously to the small market. The model also allows for capital mobility.

Plaut (1981) specifies an econometric model for population growth in the State of Texas, and estimates the model using time-series data, while dividing population growth into two components, net migration and natural increase. The components of population growth are modeled separately. Net migration is expected to respond to both relative labor market and relative environmental conditions with respect to Texas and the rest of the country. Labor market conditions are expressed as the ratio of expected incomes, where expected income is a function of the real wage rate and the probability of finding employment. The results indicate that the explanatory powers of the model are high, and out of sample simulations perform well when compared to other, more simple, models.

Other factors can play a part in the decision to migrate. Krieg (1991) examines whether the flow of interstate human capital is statistically different from the flow of interstate migrants. The presence of human capital implies that traditional migration models do not fully capture the costs and benefits that arise due the migration of individuals that possess different levels of human capital. To assess this, four ratios are formulated to measure the human capital of in-migrants relative to the human-capital of out migrants. Proxies for human capital include years of education and expected earnings. The findings indicate that human capital selectivity exists in interstate migration. Accordingly, it may be important to analyze the number of migrants as well as the human capital associated with those migrants.

Clark and Murphy (1996) analyze population and employment changes simultaneously. Changes in employment are modeled as a function of employment and a lag of itself, as well as a vector of predetermined factors that control for a region's fiscal factors, economic and demographic conditions, and amenities. Population change is related to a lag of itself, employment, and a vector including similar factors to those in the employment regression. Although empirical results indicate that changes in employment and population are determined simultaneously, the feedback effects are weak.

Fullerton and Barraza de Anda (2008) develop a population model for the El Paso-Ciudad Juárez border region. Border demographics studies differ from other areas due to the institutional boundary as well as incomplete data, particularly data limitations from Mexico. In spite of these obstacles, this study provides an example of how to model and forecast a region's population using a system of equations for births, deaths, and migration when international labor market conditions vary (Corden and Findlay, 1975).

More recently, Lim (2011) addresses the issue of how much migration is motivated by regional wage differentials and explores the role of regional economic structure on interregional migration. This study calculates the correlation between the wage differential and trade between certain regions. The correlation coefficient is found to be negative and significant. This implies that as the volume of trade increases, the wage differential between regions will decrease. The paper finds evidence that regional trade, specifically intraindustry trade, in addition to similar economic characteristics, undermines the effect the wage differential has on migration. The complementary effect trade plays on wage differentials will be difficult to further explore due to the data limitations.

Hernández-Murillo, Ott, Owyang, and Whalen (2011) look at patterns in interstate migration in the wake of the most recent recession. Specifically, it is contended that it may be preferable to use The Survey of Income and Program Participation (SIPP), as opposed to the Current Population Survey for migration data. The advantage of using the SIPP is that it follows individuals even if they migrate, as opposed to merely tracking physical addresses. These types of panel data can prove more useful in determining the determinants of migration. This study looks at correlations, not causations. Included in its findings are a negative correlation between migration and age, and a positive correlation between education and migration. In addition, migration patterns are different between genders, homeowners, and according to marital status. Life changing events also exhibit correlations with migration. Surprisingly, the study finds that economic conditions between the origin state and the destination state are very similar. Finally, the post-move outcomes show that wages in destination states increase relative to wages in origin states, but the employment rate falls for all movers. This is most likely due to an adjustment period immediately following the move.

Arkansas appears to be an understudied region, particularly when it comes to demographics. Bennett (1970) uses a case study of a mostly agricultural twelve county region in northeastern Arkansas to illustrate population changes and mobility. The case study notes that, after World War II, industrial areas outside of Arkansas created a “pull” factor which served as the primary motive for migration outside of the area of study. In subsequent years, the “push” factor off the farm became the primary motive for migration. The migration patterns uncovered are broadly consistent with the frameworks presented by Harris and Todaro (1970) and Corden and Findlay (1975).

Shbikat and Striffler (2000) study migration trends and population trends for the years 1990 to 2000. The study notes that Arkansas experienced a high degree of migration from Latin America. However, it finds that domestic in-migration was still greater than international in-migration. Not surprisingly, the counties with lower unemployment are also the counties that experienced higher influxes of migrants.

This study seeks to model population changes in Arkansas by employing a methodology similar to Plaut (1981) and Fullerton and Barraza de Anda (2008). Annual frequency data are used to assemble a small econometric system of equations with births, deaths, and migration as the main components of population change. Migration is modeled using a variation of the wage-differential framework set up by Harris and Todaro (1970) and Corden and Findlay (1975). In addition to in-sample fit diagnostics, out of sample simulations are also employed to assess model reliability.

# Chapter 3: Data and Methodology

This study analyzes annual frequency population data for Arkansas using an approach similar to Plaut (1981) and Fullerton and Barraza de Anda (2008). It should be noted that Fullerton and Barraza de Anda (2008) model and forecast population for the El Paso-Ciudad Juárez international border region, but this study will only draw from the specifications for the El Paso region. As observed by Booth (2006), one viable approach for modeling population is to specify the components of population change separately, and then combine these separate equations into one model. Booth (2006) identifies these demographic components as fertility, mortality, and migration. Plaut (1981) and Fullerton and Barraza de Anda (2008) both employ this disaggregation method where births minus deaths constitutes natural increase, and population is the sum of the previous year's population, natural increase, and net migration. Fertility and mortality are notoriously difficult to predict, as many of the determinants of these variables are complex and still not fully understood. Therefore, it is common for simpler specifications to be used instead of more complex ones (Plaut, 1981; Booth, 2006).

Net migration is also an important driver for population growth, and one which can be modeled using economic theory (Booth, 2006). Harris and Todaro (1970) and Corden and Findlay (1975) present a two-sector migration model where labor market conditions, specifically, a wage differential that is defined as the real wage times the probability of being employed, drive migration from one sector to the other. Plaut (1981) and Fullerton and Barraza (2008) both specify the migration equation using a variant of this theory. Plaut (1981) employs a ratio of expected incomes, but allows for the effects of the real wage and probability of employment to have separate and unequal effects, as opposed to combining them into one term. The reasoning behind this is that migrants, being risk averse, will respond more favorably to a higher probability of being employed than to a higher wage rate. Plaut (1981) uses a ratio of employment to vacancies as a proxy for the probability of finding employment. When modeling El Paso domestic migration, Fullerton and Barraza de Anda (2008) use a ratio of local to national employment.

**Table 1: Model Variables**

| *Series* | *Description* | *Units* |
|---|---|---|
| akbir | Arkansas Births | Persons, thousands |
| akdea | Arkansas Deaths | Persons, thousands |
| akni | Arkansas Natural Increase | Persons, thousands |
| aknmig | Arkansas Net Migration | Persons, thousands |
| akpop | Arkansas Population | Persons, thousands |
| akemp | Arkansas Total Full and Part Time Employment | Persons, thousands |
| akpy | Arkansas Personal Income | Dollars, thousands |
| nb | United States Births | Persons, thousands |
| nd | United States Deaths | Persons, thousands |
| npop | United States Population | Persons, thousands |
| usemp | United States Total Full and Part Time Employment | Persons, thousands |
| gdpd | GDP Implicit Price Deflator | Indexed Numbers, 2005 = 100 |
| | **Generated Variables** | |
| akrpy | Arkansas Real Personal Income | *(akpy/gdpd*100)* |
| emp | Employment Ratio | (*akemp/usemp*) |

To model population for Arkansas, a mixture of state and national demographic and economic variables is included. The demographic variables for both the state and national level are comprised of total population, births, deaths, and net migration. Data for Arkansas births and deaths are obtained from the Arkansas Department of Health. Data for births range from 1916 to 2011, while data on deaths are available for 1933 through 2011. Data for United States births and deaths are obtained from The Center for Disease Control and Prevention's National Vital Statistics System, and are available from 1968 up to 2011. Values for the demographic variables of both Arkansas and the United States are included in the Appendix in Table 2 and Table 3, respectively.

The United States Census Bureau provides population estimates as well as for domestic migration and international migration. Data for the latter series begin in 1990 and conclude in the year 2011. Given the relatively few annual observations of the component migration series, it proves more useful to estimate total net migration by subtracting natural increase from population. A drawback of this approach is that domestic and international migration cannot be distinguished from one another; however, internal migration typically outweighs international migration. Additionally, the economic variables included in the model, and obtained from the Bureau of Economic Research (BEA), are employment at the state and national level, and personal income in Arkansas. Employment data are available from 1969 to 2011, and personal income data in Arkansas are available from 1929 through 2011. Table 4 contains values for the economic variables used in the model.

An autoregressive moving average exogenous (ARMAX) approach is used to conduct parameter estimation (Pagan, 1974). There are five equations in the theoretical model. Equation 1, which is an identity, represents natural population increase in Arkansas, which is calculated as resident births in Arkansas minus resident deaths in Arkansas. This study models births and deaths in Arkansas by using an approach similar to Fullerton and Barraza de Anda (2008). The specification for births, represented by Equation 2, includes a one period autoregressive lag, scaled lags of a national birth to population ratio, and real personal income. The scaled lags are comprised of the ratio of national births to national population, and are included because, as noted by Booth (2006) and Fullerton and Barraza (2008), it is important to attempt to capture not only local trends, but national trends as well. The relationship between births and real personal income is expected to be negative (Becker, 1960; Jones and Tertilt, 2006). The specification for deaths includes a one period autoregressive lag as well as a one period scaled lag of a national population ratio, with the scaled national population ratio consisting of the ratio of United States deaths to United States population times the population of Arkansas (Equation 3).

(1) $akni_t = akbir_t - akdea_t$

(2) $akbir_t = \alpha_o + \alpha_1 akbir_{t-1} + \beta_0 akpop_t{*}nb_t/npop_t + \beta_1 akpop_{t-1}{*}nb_{t-1}/npop_{t-1} + \ldots + \beta_n akpop_{t-n}{*}nb_{t-n}/npop_{t-n} + \theta_0 akrpy_t + \theta_1 akrpy_{t-1} + \theta_n akrpy_{t-n} + \varepsilon_t$

(3) $akdea_t = \alpha_o + \alpha_1 akdea_{t-1} + \beta_0\, akpop_t{*}nd_t/npop_t + \beta_2\, akpop_{t-1}{*}nd_{t-1}/npop_{t-1} + \ldots + \beta_n\, akpop_{t-n}{*}nd_{t-n}/npop_{t-n} + u_t$

Some recent literature suggests that several factors, such as the wage differential, human capital, age, marital status, and income may all affect an individual's propensity to migrate (Krieg, 1991; Hernandez-Murillo, Ott, Owyang, and Whalen, 2011). This study, however, will only employ a measure of relative labor market conditions similar to those of Harris and Todaro (1970) and Corden and Findlay (1975). That is because many recent efforts utilize individual survey responses, but this study employs aggregate data. In addition, model complexity does not necessarily guarantee forecast accuracy (Smith, 1997; Booth, 2006).

Equation 4 represents migration, and is specified similar to Plaut (1981) and Fullerton and Barraza de Anda (2008). It is modeled as a function of an autoregressive lag along with relative labor market conditions. In this case, relative labor market conditions are represented as a ratio a ratio of total state to total national employment levels (Plaut, 1981). All else equal, net migration is expected to increase if total full and part time employment in Arkansas increases relative to total employment in the United States. Finally, Equation 5 represents total population in Arkansas. Current population equals the sum of population in period t-1, natural increase in period t, and total net migration in period t. Equation 5 is an identity.

(4) $aknmig_t = \alpha_o + \alpha_1 netmig_{t-1} + \beta_0 emp_t + \beta_1 emp_{t-1} + \ldots + \beta_n emp_{t-n} + w_t$

(5) $akpop_t = akpop_{t-1} + akni_t + aknmig_t$

Demographers typically use panel data as opposed to time series data, but a time series structural model may help capture more variations with respect to population change (Smith, Tayman, and Swanson, 2001). When working with time series data, it is helpful to utilize the stationary component of any series. A series that is stationary has a constant mean and variance over time. A nonstationary variable can be difficult to model. A variety of tests can be utilized to determine whether a series is stationary or not. Stationarity can be induced by differencing the data in question, and by transforming the data using non-linear processes (Pindyck and Rubinfeld, 1998).

The model specification presented in this study can be applied to data in level form as well as to data that have been differenced or transformed. For this study, parameter estimation is conducted using the level form of the data as well as the first difference of the data, and both approaches produce desirable results with respect to the signs and statistical significance of the coefficients. Given that, some sort of model selection tool should be utilized (Pindyck and Rubinfeld, 1998). Spiegelhalter, Best, Carlin, and Van der Linde (2002) develop the Deviance Information Criterion (DIC) as an alternative to the Akaike Information Criterion (AIC) and the Schwarz Information Criterion. This study compares models using level data and models using first differences of the data. Xiao, Zarnikau, and Damien (2007) provide a formula with which to calculate the DIC for linear models, shown in equation 7.

(7) $n \ln 2\pi + 2n \ln \sigma + \left(\frac{1}{\sigma^2}\right) \sum_{i=1}^{n} \varepsilon^2$

In equation 7, $n$ is the number of observations, ε represents the residual term of a particular regression, and σ is the standard deviation of said residuals (Xiao, Zarnikau and Damien, 2007). Similar to the selection rules of the AIC and SIC, the model with the smaller DIC value is the one that is selected.

**Table 5: DIC Results**

| **Dependent Variable** | **DIC for Model Using Level Data** | **DIC for Model Using Differenced Data** |
|---|---|---|
| Births | 89.92 | 91.13 |
| Deaths | 24.75 | 26.15 |
| Net Migration | 308.36 | 298.77 |

Table 5 presents the DIC values for the different model specifications. With respect to the models for births and deaths, the lower DIC values correspond to the models using level data. On the other hand, the net migration model using the first difference of the data has a lower DIC value when compared to the model which uses level data. Given that two of the three comparisons indicate a lower DIC for models using level data, this study opts to conduct parameter estimation using level data (Xiao, Zarnikau and Damien, 2007). Out of sample simulations are also conducted to further assess model reliability. The next section discusses estimation results and model simulation outcomes. Results obtained using differenced data are included in the Appendix.

# Chapter 4: Results

This study employs a methodology in which births, deaths, and net migration constitute the three components of population change. The components are estimated separately and then aggregated in order to model total population. Parameter estimation is conducted using an ARMAX approach (Pagan, 1974). Equations 8 through 12 present the final model specifications. Alternate specifications can be found in the appendix. Equations 8 and 12 are identities, and correspond to natural increase and population at time *t*, respectively, while Equations 9, 10, and 11 represent births, deaths, and net migration. Additionally, given the model selection criteria employed, parameter estimation is conducted using data in level form.

(8) $akni_t = akbir_t - akdea_t$

(9) $akbir_t = \alpha_o + \alpha_1 akbir_{t-1} + \beta_0\, akrpy_t + \beta_1\, akrpy_{t-1} + \theta_0\, akpop_t * nb_t / npop_t + \theta_1\, akpop_{t-1} * nb_{t-1} / npop_{t-1}$

(10) $akdea_t = \alpha_o + \alpha_1\, akdea_{t-1} + \beta_1\, akpop_t * nd_t / npop_t + \beta_2\, akpop_{t-1} * nd_{t-1} / npop_{t-1}$

(11) $aknmig_t = \alpha_o + \alpha_1\, netmig_{t-1} + \beta_0\, emp_t + \beta_1\, emp_{t-1}$

(12) $akpop_t = akpop_{t-1} + akni_t + aknmig_t$

First, births for this sample period in Arkansas are difficult to model. Alternate specifications can be found in the appendix. The current specification, represented by Equation 9, includes a one period lag of the dependent variable, and a contemporaneous and a one period lag of a scaled national births-to-population ratio, and real personal income. Real personal income is included at time *t* as well as at time *t-1*; however, the coefficients for the real personal income variables are not statistically significant at the 5-percent level, and are therefore dropped from the final model.

Table 6, located in Appendix II, depicts the equation for births, and shows good statistical fit, with a coefficient of determination close to 84 percent. Additionally, all three coefficients have t-statistics that are statistically significant at the 5-percent level. Moreover, a high F-statistic allows for rejection of the null hypothesis that none of the explanatory variables explain any of the variation in the dependent variable about its mean. Additionally, the residuals show no sign of serial correlation. Births from the previous period are positively correlated to the number of births in the current period. As noted in Booth (2006), national trends provide useful information when modeling regional births. The coefficients pertaining to the scaled national birth ratios are statistically significant.

Table 7 summarizes output results for deaths (Appendix II). Deaths in Arkansas are modeled as a function of a one period autoregressive lag, a scaled national deaths-to-population ratio, and a one period lag of the same scaled ratio. The equation has a coefficient of determination over 98 percent, indicating good statistical fit. There is no evidence of serial correlation, and all of the coefficients are statistically significant individually as well as jointly. Deaths in the previous period are directly correlated with deaths in the current period. Additionally, an increase in the scaled national death to population ratio at time $t$ produces a disproportionate increase in deaths at the state level, which is offset at period $t-1$.

In Equation 11, net migration is modeled as a function of a one period lag of itself, and a contemporaneous and a one period lag of the ratio of total employment in Arkansas to that in the United States. In Table 8, all of the slope coefficients satisfy the 5-percent criterion, and are also jointly significant at the 5-percent level (Appendix II). Also, the regression shows no indication of serial correlation. Net migration has a fairly strong inertial component associated with it. It also responds to contemporaneous labor market conditions. Specifically, if the employment ratio improves by 0.1 percentage points, implying higher job gains in Arkansas relative to the rest of the country, net migration in Arkansas will increase by close to 6,000 people, all else equal. This result corroborates evidence supported in Davies, Greenwood and Li (2001), as well as in Fullerton and Barraza de Anda (2008).

To further examine the empirical properties of the model, out of sample simulations are conducted for the years 2012 to 2017. Because the simulation period is beyond the historical edge of the sample, some assumptions or forecasts are required for the exogenous variables (Pindyck and Rubinfeld, 1998). Table 9 reports exogenous variable values, in thousands, for the years 2012 to 2017. Forecasts are obtained from IHS Global Insight for economic variables and from the U.S. Census Bureau population projections for national demographic variables (Garg, 2013; Montgomery, 2013; U.S. Census Bureau Population Division, 2012). For the period in question, the national economy is expected to grow more rapidly than that of Arkansas. Personal income in Arkansas is expected to rise regardless of the slow employment growth, most likely due to key service sectors providing most of the job gains (Garg, 2013).

**Table 10: Endogenous Variables (in thousands), 2010 – 2017**

| *Variable* | ***2010*** | ***2011*** | ***2012*** | ***2013*** | ***2014*** | ***2015*** | ***2016*** | ***2017*** |
|---|---|---|---|---|---|---|---|---|
| *AKBIR* | 38.223 | 38.396 | 39.351 | 39.371 | 39.386 | 39.380 | 39.359 | 39.330 |
| *% Change* | -3.7% | 0.5% | 2.49% | 0.05% | 0.04% | -0.01% | -0.06% | -0.07% |
| *AKDEA* | 28.632 | 29.229 | 29.550 | 30.041 | 30.522 | 30.965 | 31.374 | 31.768 |
| *% Change* | -0.1% | 2.1% | 1.1% | 1.7% | 1.6% | 1.5% | 1.3% | 1.3% |
| *AKNI* | 9.591 | 9.167 | 9.802 | 9.330 | 8.864 | 8.415 | 7.985 | 7.562 |
| *% Change* | -13.0% | -4.4% | 6.9% | -4.8% | -5.0% | -5.1% | -5.1% | -5.3% |
| *AKNMIG* | 15.154 | 7.224 | 24.592 | 15.570 | 15.675 | 13.235 | 11.079 | 10.647 |
| *% Change* | 11.0% | -52.3% | 240.4% | -36.7% | 0.7% | -15.6% | -16.3% | -3.9% |
| *AKPOP* | 2,921.588 | 2,937.979 | 2,972.373 | 2,997.273 | 3,021.811 | 3,043.462 | 3,062.526 | 3,080.735 |
| *% Change* | 0.9% | 0.6% | 1.2% | 0.8% | 0.8% | 0.7% | 0.6% | 0.6% |

The Gauss-Seidel solution method is used to simulate the model (Fisher and Hallet, 1988). Table 10 details outcomes of the simulation. Not surprisingly, net migration trends downward in most years. Deaths rise more rapidly than births, causing natural increase to also decline. Given these developments, population growth slows to only 0.6 percent by 2017.

Parameter estimates confirm several of the original hypotheses and the simulation properties of the model seem reasonable. However, experimentation with additional model specifications might prove useful. Also, more simulations with different growth rates for the exogenous variables may yield additional insights.

# Chapter 5: Conclusion

This study models population in Arkansas using annual frequency data. A small econometric model is developed using fertility, mortality, and migration as the components of population change. Births minus deaths equal natural increase, and population in the current period is the sum of the population from the prior period, natural increase, and net migration. For the regression equations, functional form selection is conducted using a Deviance Information Criterion approach.

Births in Arkansas contain a strong inertial component. State birth patterns also follow national demographic trends. Empirical results further indicate that real personal income has no statistically reliable effect on births, so it is dropped from the final model. Arkansas deaths also exhibit strong inertial properties. As with births, deaths at the state level are also correlated with national demographic trends. Net migration is modeled as a function of relative labor market conditions. Similar to natural increase, net migration also has a pronounced inertial component associated with it. The results indicate that when labor market conditions improve in Arkansas relative to the rest of the country, in-migration will increase.

Out of sample simulations are conducted in order to further test model reliability. Several assumptions regarding the independent variables are made to permit simulating the model beyond the end of the sample. National deaths are expected to increase at a faster rate than births. Additionally, labor market conditions in the U.S. are expected to improve relative to labor market conditions in Arkansas. Given these independent variable assumptions, as well as the model's parameters, natural increase in Arkansas is expected to decrease during the simulation period. Additionally, Arkansas net migration is also expected to trend downward. This leads population growth in Arkansas to slow to 0.6 % by the year 2017.

Many public and private entities rely on demographic models and forecasts in order to facilitate planning efforts. Econometric analysis of population trends may help those efforts. Parameter estimation of this model confirms several of the original hypotheses and simulation results seem reasonable and are in line with recent demographic trends in Arkansas. It has been suggested that modeling population growth in different regions, as well as with different techniques, can lead to improvements in forecast accuracy (Tayman and Swanson, 1996.) Accordingly, experimentation with alternate specifications, plus simulations using different growth rates for the exogenous variables, is likely to prove useful. Additional modeling efforts for other nearby states may also help confirm, or overturn, the results obtained for Arkansas.

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# Appendix I: Data

**Table 2: Arkansas Demographic Variables (in thousands), 1969-2011**

| Year | *akbir* | *akdea* | *akni* | *aknmig* | *akpop* |
|---|---|---|---|---|---|
| **1969** | 33.921 | 20.573 | 13.348 | -2.348 | 1,913.000 |
| **1970** | 35.457 | 20.668 | 14.789 | 2.288 | 1,930.077 |
| **1971** | 35.828 | 20.897 | 14.931 | 27.020 | 1,972.028 |
| **1972** | 35.715 | 21.791 | 13.924 | 32.164 | 2,018.116 |
| **1973** | 33.476 | 22.126 | 11.350 | 29.025 | 2,058.491 |
| **1974** | 34.476 | 22.194 | 12.282 | 29.612 | 2,100.385 |
| **1975** | 34.279 | 21.731 | 12.548 | 45.358 | 2,158.291 |
| **1976** | 34.162 | 21.354 | 12.808 | -2.411 | 2,168.688 |
| **1977** | 36.029 | 21.443 | 14.586 | 23.954 | 2,207.228 |
| **1978** | 34.793 | 21.826 | 12.967 | 20.824 | 2,241.019 |
| **1979** | 36.300 | 21.456 | 14.844 | 13.252 | 2,269.115 |
| **1980** | 37.278 | 22.676 | 14.602 | 5.021 | 2,288.738 |
| **1981** | 35.851 | 22.361 | 13.490 | -9.024 | 2,293.204 |
| **1982** | 35.295 | 22.327 | 12.968 | -11.918 | 2,294.254 |
| **1983** | 34.904 | 23.086 | 11.818 | -0.306 | 2,305.766 |
| **1984** | 34.789 | 23.640 | 11.149 | 2.852 | 2,319.767 |
| **1985** | 35.296 | 24.130 | 11.166 | -3.887 | 2,327.046 |
| **1986** | 34.445 | 23.981 | 10.464 | -5.522 | 2,331.988 |
| **1987** | 34.598 | 24.431 | 10.167 | 0.202 | 2,342.357 |
| **1988** | 35.032 | 24.885 | 10.147 | -9.849 | 2,342.655 |
| **1989** | 35.893 | 24.618 | 11.275 | -7.576 | 2,346.354 |
| **1990** | 36.440 | 24.588 | 11.852 | -1.620 | 2,356.586 |
| **1991** | 35.456 | 24.998 | 10.458 | 16.100 | 2,383.144 |
| **1992** | 34.803 | 24.941 | 9.862 | 22.978 | 2,415.984 |
| **1993** | 34.332 | 26.519 | 7.813 | 32.506 | 2,456.303 |
| **1994** | 34.744 | 26.261 | 8.483 | 29.233 | 2,494.019 |
| **1995** | 35.154 | 26.695 | 8.459 | 32.921 | 2,535.399 |
| **1996** | 36.356 | 26.526 | 9.830 | 26.880 | 2,572.109 |
| **1997** | 36.450 | 27.824 | 8.626 | 20.355 | 2,601.090 |
| **1998** | 36.831 | 27.452 | 9.379 | 15.820 | 2,626.289 |
| **1999** | 36.670 | 27.934 | 8.736 | 16.835 | 2,651.860 |
| **2000** | 37.790 | 28.182 | 9.608 | 17.120 | 2,678.588 |
| **2001** | 36.982 | 27.703 | 9.279 | 3.704 | 2,691.571 |
| **2002** | 37.456 | 28.458 | 8.998 | 5.358 | 2,705.927 |
| **2003** | 37.795 | 27.871 | 9.924 | 8.965 | 2,724.816 |
| **2004** | 38.564 | 27.531 | 11.033 | 13.837 | 2,749.686 |
| **2005** | 39.219 | 28.041 | 11.178 | 20.233 | 2,781.097 |
| **2006** | 40.966 | 27.875 | 13.091 | 27.573 | 2,821.761 |
| **2007** | 41.378 | 28.190 | 13.188 | 13.701 | 2,848.650 |
| **2008** | 40.669 | 29.296 | 11.373 | 14.531 | 2,874.554 |
| **2009** | 39.687 | 28.668 | 11.019 | 11.270 | 2,896.843 |
| **2010** | 38.223 | 28.632 | 9.591 | 15.154 | 2,921.588 |
| **2011** | 38.396 | 29.229 | 9.167 | 7.224 | 2,937.979 |

**Table 3: United States Demographic Variables (in thousands), 1969-2011**

| Year | *nb* | *nd* | *npop* |
|---|---|---|---|
| **1969** | 1,800.103 | 1,921.990 | 202,676.946 |
| **1970** | 1,865.693 | 1,921.031 | 205,052.174 |
| **1971** | 1,777.985 | 1,927.542 | 207,660.677 |
| **1972** | 1,745.434 | 1,963.944 | 209,896.021 |
| **1973** | 1,835.088 | 1,973.003 | 211,908.788 |
| **1974** | 2,023.726 | 1,934.388 | 213,853.928 |
| **1975** | 2,227.625 | 1,892.879 | 215,973.199 |
| **1976** | 2,455.749 | 1,909.440 | 218,035.164 |
| **1977** | 2,767.140 | 1,899.597 | 220,239.425 |
| **1978** | 2,861.083 | 1,927.788 | 222,584.545 |
| **1979** | 3,179.428 | 1,913.841 | 225,055.487 |
| **1980** | 3,305.078 | 1,989.841 | 227,224.681 |
| **1981** | 3,313.350 | 1,977.981 | 229,465.714 |
| **1982** | 3,372.317 | 1,974.797 | 231,664.458 |
| **1983** | 3,334.315 | 2,019.201 | 233,791.994 |
| **1984** | 3,356.887 | 2,039.369 | 235,824.902 |
| **1985** | 3,760.561 | 2,086.440 | 237,923.795 |
| **1986** | 3,756.547 | 2,105.361 | 240,132.887 |
| **1987** | 3,809.394 | 2,123.323 | 242,288.918 |
| **1988** | 3,909.510 | 2,167.999 | 244,498.982 |
| **1989** | 4,040.958 | 2,150.466 | 246,819.230 |
| **1990** | 4,158.212 | 2,148.463 | 249,464.396 |
| **1991** | 4,110.907 | 2,169.518 | 252,153.092 |
| **1992** | 4,065.014 | 2,175.613 | 255,029.699 |
| **1993** | 4,000.240 | 2,268.553 | 257,782.608 |
| **1994** | 3,952.767 | 2,278.994 | 260,327.021 |
| **1995** | 3,899.589 | 2,312.132 | 262,803.276 |
| **1996** | 3,891.494 | 2,314.690 | 265,228.572 |
| **1997** | 3,880.894 | 2,314.245 | 267,783.607 |
| **1998** | 3,941.553 | 2,337.256 | 270,248.003 |
| **1999** | 3,959.417 | 2,391.399 | 277,840.888 |
| **2000** | 4,058.814 | 2,403.351 | 282,171.957 |
| **2001** | 4,025.933 | 2,416.425 | 285,049.647 |
| **2002** | 4,021.726 | 2,443.387 | 287,745.630 |
| **2003** | 4,089.950 | 2,448.288 | 290,242.027 |
| **2004** | 4,112.052 | 2,397.615 | 292,936.109 |
| **2005** | 4,138.349 | 2,448.017 | 295,618.454 |
| **2006** | 4,265.555 | 2,426.264 | 298,431.771 |
| **2007** | 4,316.233 | 2,423.712 | 301,393.632 |
| **2008** | 4,247.694 | 2,471.984 | 304,177.401 |
| **2009** | 4,130.665 | 2,437.163 | 306,656.290 |
| **2010** | 3,999.386 | 2,468.435 | 309,330.219 |
| **2011** | 3,953.593 | 2,513.171 | 311,591.917 |

### Table 4: Economic Variables (in thousands), 1969-2011

| **Year** | ***gdpd*** | ***akpy*** | ***akrpy*** | ***akemp*** | ***usemp*** | ***emp*** |
|---|---|---|---|---|---|---|
| **1969** | 23.119 | 5,005,258 | 21,649,976 | 799.917 | 79,850.000 | 0.010018 |
| **1970** | 24.338 | 5,482,180 | 22,525,187 | 805.274 | 79,750.000 | 0.010097 |
| **1971** | 25.554 | 6,089,663 | 23,830,567 | 830.624 | 79,554.000 | 0.010441 |
| **1972** | 26.657 | 6,880,585 | 25,811,550 | 867.240 | 81,583.000 | 0.010630 |
| **1973** | 28.136 | 8,188,566 | 29,103,519 | 901.673 | 85,202.000 | 0.010583 |
| **1974** | 30.69 | 9,174,337 | 29,893,571 | 927.399 | 86,573.000 | 0.010712 |
| **1975** | 33.591 | 10,075,261 | 29,993,930 | 904.885 | 85,044.000 | 0.010640 |
| **1976** | 35.519 | 11,184,577 | 31,488,997 | 941.116 | 87,402.000 | 0.010768 |
| **1977** | 37.783 | 12,486,268 | 33,047,318 | 981.263 | 90,421.000 | 0.010852 |
| **1978** | 40.435 | 14,496,074 | 35,850,313 | 1,021.156 | 94,777.000 | 0.010774 |
| **1979** | 43.798 | 15,929,916 | 36,371,332 | 1,031.309 | 98,017.000 | 0.010522 |
| **1980** | 47.791 | 17,213,787 | 36,018,888 | 1,032.439 | 98,370.000 | 0.010495 |
| **1981** | 52.27 | 19,509,866 | 37,325,169 | 1,026.248 | 99,225.000 | 0.010343 |
| **1982** | 55.459 | 20,525,912 | 37,010,967 | 1,010.727 | 97,305.000 | 0.010387 |
| **1983** | 57.652 | 21,818,603 | 37,845,353 | 1,039.399 | 98,041.000 | 0.010602 |
| **1984** | 59.817 | 24,325,474 | 40,666,489 | 1,079.236 | 102,458.000 | 0.010533 |
| **1985** | 61.628 | 25,895,775 | 42,019,496 | 1,098.411 | 104,987.000 | 0.010462 |
| **1986** | 62.991 | 27,108,232 | 43,035,088 | 1,110.294 | 106,873.000 | 0.010389 |
| **1987** | 64.819 | 28,161,393 | 43,446,201 | 1,136.620 | 109,754.000 | 0.010356 |
| **1988** | 67.046 | 30,113,776 | 44,915,097 | 1,169.911 | 112,864.000 | 0.010366 |
| **1989** | 69.577 | 32,207,901 | 46,291,017 | 1,189.148 | 115,501.000 | 0.010296 |
| **1990** | 72.262 | 33,938,706 | 46,966,187 | 1,203.622 | 116,964.000 | 0.010291 |
| **1991** | 74.824 | 35,993,605 | 48,104,358 | 1,230.169 | 115,525.000 | 0.010649 |
| **1992** | 76.598 | 39,148,520 | 51,109,063 | 1,255.030 | 115,968.000 | 0.010822 |
| **1993** | 78.29 | 41,001,582 | 52,371,417 | 1,301.238 | 117,604.000 | 0.011065 |
| **1994** | 79.94 | 43,634,403 | 54,583,942 | 1,329.036 | 120,379.000 | 0.011040 |
| **1995** | 81.606 | 46,297,028 | 56,732,382 | 1,382.418 | 123,236.000 | 0.011218 |
| **1996** | 83.159 | 49,308,500 | 59,294,244 | 1,405.330 | 125,461.000 | 0.011201 |
| **1997** | 84.628 | 51,620,980 | 60,997,519 | 1,427.163 | 128,316.000 | 0.011122 |
| **1998** | 85.584 | 54,622,677 | 63,823,468 | 1,453.311 | 131,563.000 | 0.011047 |
| **1999** | 86.842 | 57,163,803 | 65,825,065 | 1,470.837 | 134,350.000 | 0.010948 |
| **2000** | 88.723 | 60,467,596 | 68,153,236 | 1,493.267 | 137,228.000 | 0.010882 |
| **2001** | 90.727 | 64,232,708 | 70,797,787 | 1,482.678 | 136,890.000 | 0.010831 |
| **2002** | 92.196 | 65,646,579 | 71,203,283 | 1,477.823 | 135,937.000 | 0.010871 |
| **2003** | 94.135 | 69,230,717 | 73,544,077 | 1,480.228 | 135,602.000 | 0.010916 |
| **2004** | 96.786 | 73,719,848 | 76,167,884 | 1,500.992 | 137,067.000 | 0.010951 |
| **2005** | 100 | 77,475,378 | 77,475,378 | 1,531.355 | 139,006.000 | 0.011016 |
| **2006** | 103.231 | 82,918,067 | 80,322,836 | 1,565.130 | 141,440.000 | 0.011066 |
| **2007** | 106.227 | 89,312,492 | 84,077,016 | 1,582.366 | 142,928.000 | 0.011071 |
| **2008** | 108.582 | 94,460,843 | 86,994,937 | 1,581.061 | 142,000.000 | 0.011134 |
| **2009** | 109.529 | 91,793,885 | 83,807,836 | 1,546.619 | 136,170.000 | 0.011358 |
| **2010** | 110.993 | 94,581,100 | 85,213,572 | 1,545.593 | 135,545.000 | 0.011403 |
| **2011** | 113.359 | 99,127,035 | 87,445,227 | 1,552.597 | 137,056.000 | 0.011328 |

# Appendix II: Arkansas Population Equations

### Table 6: Arkansas Births Equation

Dependent Variable: AKBIR
Method: Least Squares
Sample (adjusted): 1970 2011
Included observations: 42 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 1.402028 | 2.678373 | 0.523463 | 0.6037 |
| AKBIR(-1) | 0.929380 | 0.078592 | 11.82543 | 0.0000 |
| AKPOP*NB/NPOP | 0.419294 | 0.125517 | 3.340533 | 0.0019 |
| AKPOP(-1)*NB(-1)/NPOP(-1) | -0.387438 | 0.121583 | -3.186626 | 0.0029 |

| | | | |
|---|---|---|---|
| R-squared | 0.839515 | Mean dependent var | 36.38707 |
| Adjusted R-squared | 0.826846 | S.D. dependent var | 1.950078 |
| S.E. of regression | 0.811463 | Akaike info criterion | 2.510438 |
| Sum squared resid | 25.02197 | Schwarz criterion | 2.675930 |
| Log likelihood | -48.71919 | Hannan-Quinn criter. | 2.571097 |
| F-statistic | 66.26092 | Durbin-Watson stat | 1.671197 |
| Prob(F-statistic) | 0.000000 | | |

**Table 7: Arkansas Deaths Equation**

Dependent Variable: AKDEA
Method: Least Squares
Sample (adjusted): 1970 2011
Included observations: 42 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -3.437790 | 1.340762 | -2.564056 | 0.0144 |
| AKDEA(-1) | 0.612681 | 0.129173 | 4.743104 | 0.0000 |
| AKPOP*ND/NPOP | 1.393259 | 0.183034 | 7.612031 | 0.0000 |
| AKPOP(-1)*ND(-1)/NPOP(-1) | -0.767218 | 0.258489 | -2.968087 | 0.0052 |

| | | | |
|---|---|---|---|
| R-squared | 0.985914 | Mean dependent var | 25.11988 |
| Adjusted R-squared | 0.984802 | S.D. dependent var | 2.769947 |
| S.E. of regression | 0.341485 | Akaike info criterion | 0.779366 |
| Sum squared resid | 4.431252 | Schwarz criterion | 0.944858 |
| Log likelihood | -12.36668 | Hannan-Quinn criter. | 0.840025 |
| F-statistic | 886.5463 | Durbin-Watson stat | 2.289088 |
| Prob(F-statistic) | 0.000000 | | |

**Table 8: Arkansas Net Migration Equation**

Dependent Variable: AKNMIG
Method: Least Squares
Sample (adjusted): 1970 2011
Included observations: 42 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -58.71673 | 60.24860 | -0.974574 | 0.3359 |
| AKNMIG(-1) | 0.579873 | 0.132821 | 4.365819 | 0.0001 |
| EMP | 37273.75 | 12557.58 | 2.968226 | 0.0052 |
| EMP(-1) | -31389.87 | 12382.36 | -2.535047 | 0.0155 |

| | | | |
|---|---|---|---|
| R-squared | 0.524663 | Mean dependent var | 13.13707 |
| Adjusted R-squared | 0.487136 | S.D. dependent var | 13.95457 |
| S.E. of regression | 9.993495 | Akaike info criterion | 7.532139 |
| Sum squared resid | 3795.058 | Schwarz criterion | 7.697631 |
| Log likelihood | -154.1749 | Hannan-Quinn criter. | 7.592798 |
| F-statistic | 13.98110 | Durbin-Watson stat | 2.503309 |
| Prob(F-statistic) | 0.000003 | | |

# Appendix III: Exogenous Variable Forecasts

**Table 9: Exogenous Variable Forecasts (in thousands)**

| | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|
| *AKPY* | 102,400,000 | 105,200,000 | 110,000,000 | 114,900,000 | 120,415,200 | 126,556,375 |
| *% Change* | 3.3% | 2.7% | 4.6% | 4.5% | 4.8% | 5.1% |
| *AKRPY* | 88,735,249 | 89,902,962 | 92,433,627 | 95,124,261 | 97,882,864 | 100,819,350 |
| *% Change* | 1.5% | 1.3% | 2.8% | 2.9% | 2.9% | 3.0% |
| *AKEMP* | 1,559.295 | 1,552.473 | 1,570.581 | 1,586.953 | 1,602.347 | 1,615.165 |
| *% Change* | 0.4% | -0.4% | 1.2% | 1.0% | 1.0% | 0.8% |
| *USEMP* | 133,700 | 135,800 | 138,000 | 140,800 | 143,600 | 145,700 |
| *% Change* | -2.4% | 1.6% | 1.6% | 2.0% | 2.0% | 1.5% |
| *EMP* | 0.01166 | 0.01143 | 0.01138 | 0.01127 | 0.01116 | 0.01109 |
| *% Change* | 3.0% | -2.0% | -0.4% | -1.0% | -1.0% | -0.7% |
| *NB* | 4,209.571 | 4,238.995 | 4,265.811 | 4,290.077 | 4,312.261 | 4,332.538 |
| *% Change* | 6.5% | 0.7% | 0.6% | 0.6% | 0.5% | 0.5% |
| *ND* | 2,521.852 | 2,552.865 | 2,583.281 | 2,613.406 | 2,643.433 | 2,673.485 |
| *% Change* | 0.3% | 1.2% | 1.2% | 1.2% | 1.1% | 1.1% |
| *NPOP* | 314,004.465 | 316,438.601 | 318,892.103 | 321,362.789 | 323,848.670 | 326,347.810 |
| *% Change* | 0.8% | 0.8% | 0.8% | 0.8% | 0.8% | 0.8% |
| *PGDP* | 115.4 | 117.0 | 119.0 | 120.8 | 122.7 | 124.6 |
| *% Change* | 1.8% | 1.4% | 1.7% | 1.5% | 1.6% | 1.5% |

## Appendix IV: Endogenous Variable Graphs

**Figure 1: Arkansas Births (in thousands), 1969-2017**

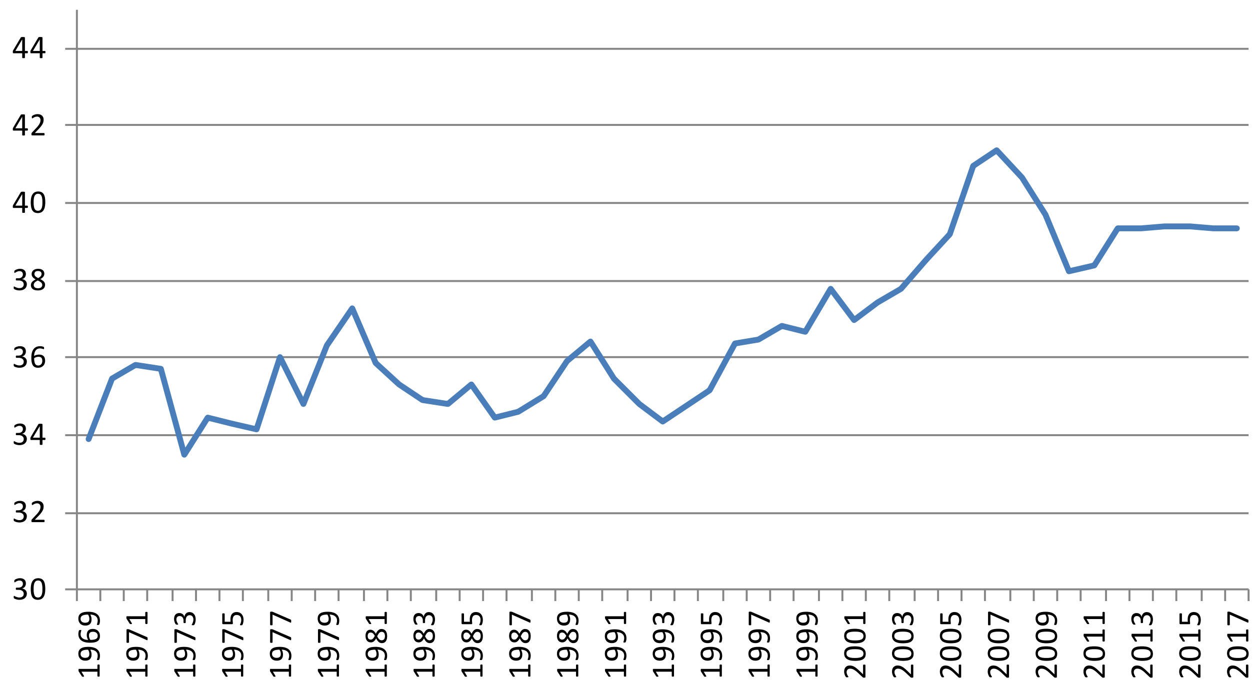


**Figure 2: Arkansas Deaths (in thousands), 1969-2017**

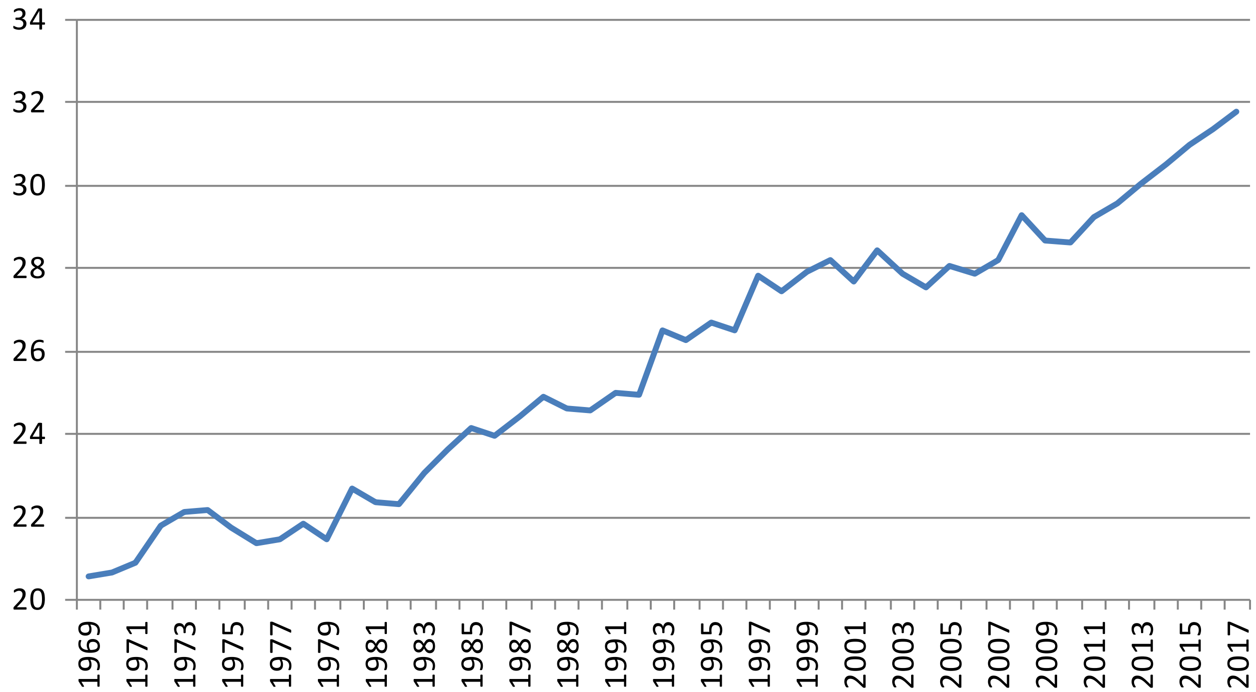


**Figure 3: Arkansas Natural Increase (in thousands), 1969-2017**

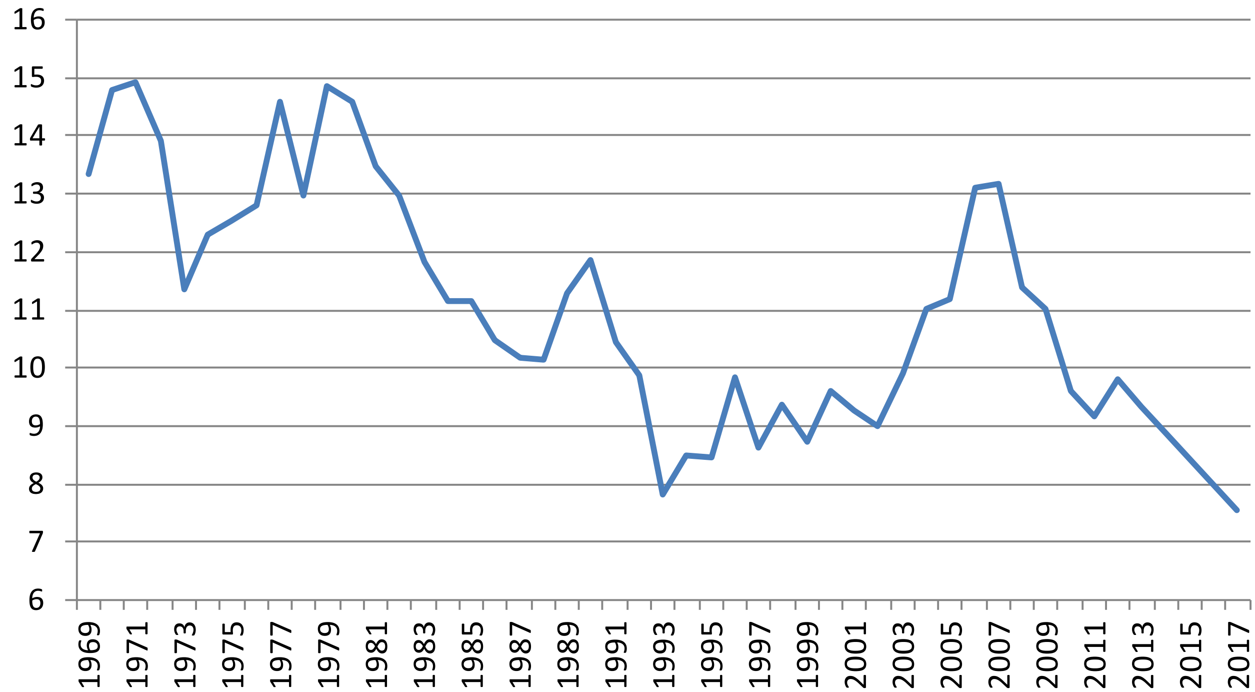


**Figure 4: Arkansas Net Migration (in thousands), 1969-2017**

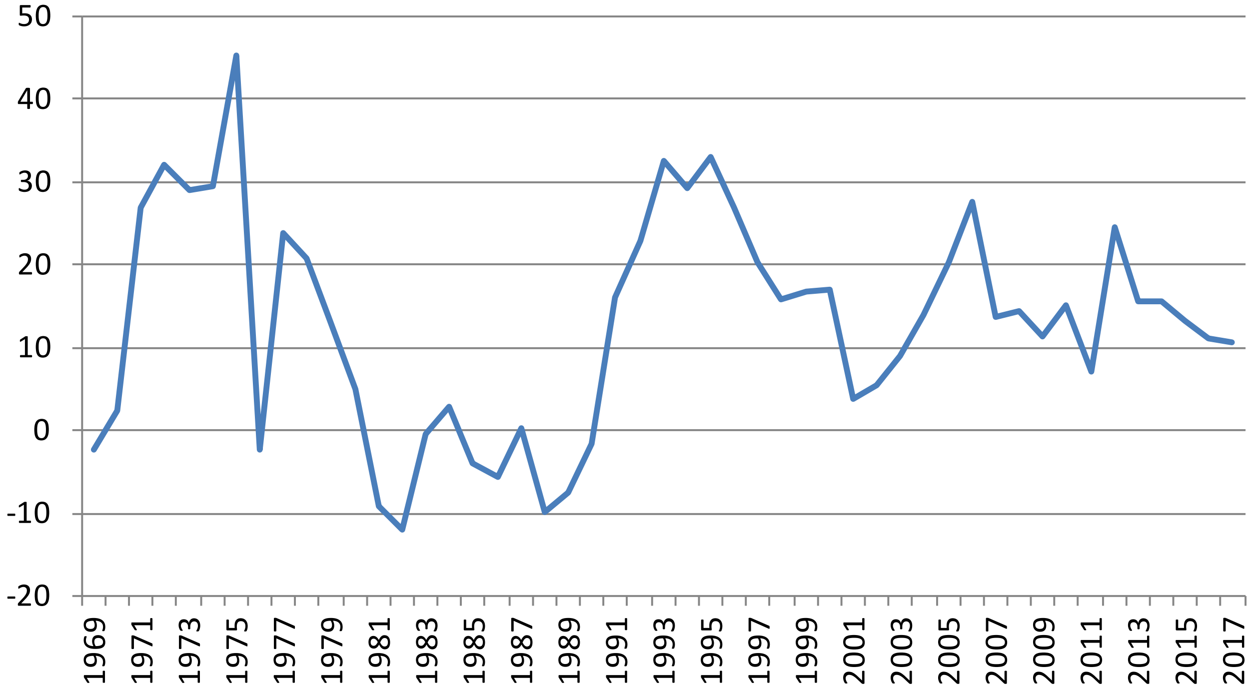
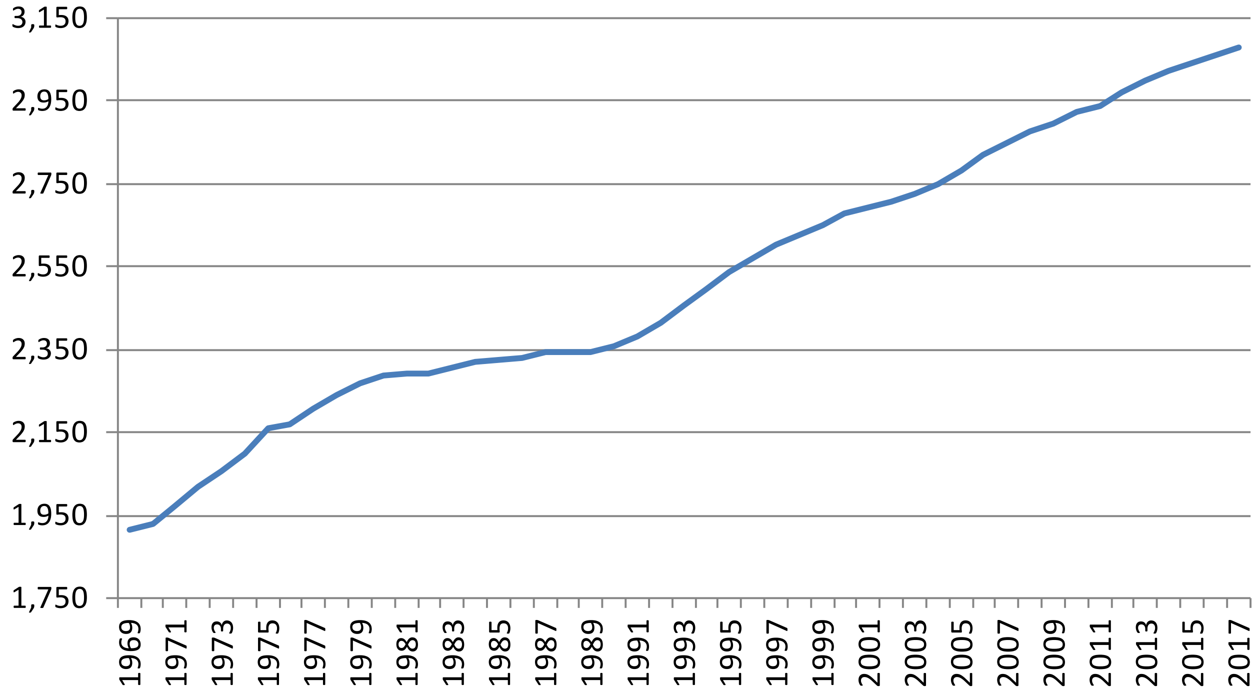


**Figure 5: Arkansas Population (in thousands), 1969-2017**



# Appendix V: Alternate Equations

### Table 11: Arkansas Birth Equation with 2 lags of Personal Income

Dependent Variable: AKBIR
Method: Least Squares
Sample (adjusted): 1970 2011
Included observations: 42 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 9.667049 | 3.999448 | 2.417096 | 0.0208 |
| AKBIR(-1) | 0.692858 | 0.115674 | 5.989765 | 0.0000 |
| AKRPY | -2.24E-08 | 9.71E-08 | -0.231044 | 0.8186 |
| AKRPY(-1) | 6.37E-08 | 9.99E-08 | 0.637695 | 0.5277 |
| AKPOP*NB/NPOP | 0.397073 | 0.118234 | 3.358370 | 0.0019 |
| AKPOP(-1)*NB(-1)/NPOP(-1) | -0.417478 | 0.114784 | -3.637066 | 0.0009 |

| | | | |
|---|---|---|---|
| R-squared | 0.865852 | Mean dependent var | 36.38707 |
| Adjusted R-squared | 0.847220 | S.D. dependent var | 1.950078 |
| S.E. of regression | 0.762229 | Akaike info criterion | 2.426423 |
| Sum squared resid | 20.91573 | Schwarz criterion | 2.674662 |
| Log likelihood | -44.95489 | Hannan-Quinn criter. | 2.517412 |
| F-statistic | 46.47196 | Durbin-Watson stat | 1.505988 |
| Prob(F-statistic) | 0.000000 | | |

**Table 12: Arkansas Birth Equation with 2 Dependent Variable Lags**

Dependent Variable: AKBIR
Method: Least Squares
Sample (adjusted): 1971 2011
Included observations: 41 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.407726 | 2.651282 | 0.153785 | 0.8786 |
| AKBIR(-1) | 0.953396 | 0.138018 | 6.907764 | 0.0000 |
| AKBIR(-2) | -0.013603 | 0.134828 | -0.100893 | 0.9202 |
| AKPOP*NB/NPOP | 0.470526 | 0.121063 | 3.886611 | 0.0004 |
| AKPOP(-1)*NB(-1)/NPOP(-1) | -0.422485 | 0.116489 | -3.626826 | 0.0009 |

| | | | |
|---|---|---|---|
| R-squared | 0.862174 | Mean dependent var | 36.40976 |
| Adjusted R-squared | 0.846860 | S.D. dependent var | 1.968685 |
| S.E. of regression | 0.770407 | Akaike info criterion | 2.430053 |
| Sum squared resid | 21.36695 | Schwarz criterion | 2.639025 |
| Log likelihood | -44.81608 | Hannan-Quinn criter. | 2.506149 |
| F-statistic | 56.29991 | Durbin-Watson stat | 1.942260 |
| Prob(F-statistic) | 0.000000 | | |

# Appendix VI: Differenced Equations

## Table 13: Arkansas Births with Personal Income

Dependent Variable: D(AKBIR)
Method: Least Squares
Sample (adjusted): 1971 2011
Included observations: 41 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.201641 | 0.271167 | -0.743604 | 0.4621 |
| D(AKBIR(-1)) | 0.138136 | 0.175351 | 0.787770 | 0.4361 |
| D(AKRPY) | -2.53E-08 | 1.09E-07 | -0.232316 | 0.8176 |
| D(AKRPY(-1)) | 1.24E-07 | 1.03E-07 | 1.208399 | 0.2350 |
| D(AKPOP*NB/NPOP) | 0.451063 | 0.126507 | 3.565527 | 0.0011 |
| D(AKPOP(-1)*NB(-1)/NPOP(-1)) | -0.217406 | 0.149191 | -1.457233 | 0.1540 |

| | | | |
|---|---|---|---|
| R-squared | 0.322521 | Mean dependent var | 0.071683 |
| Adjusted R-squared | 0.225738 | S.D. dependent var | 0.904153 |
| S.E. of regression | 0.795584 | Akaike info criterion | 2.514977 |
| Sum squared resid | 22.15336 | Schwarz criterion | 2.765744 |
| Log likelihood | -45.55703 | Hannan-Quinn criter. | 2.606292 |
| F-statistic | 3.332420 | Durbin-Watson stat | 2.074518 |
| Prob(F-statistic) | 0.014482 | | |

**Table 14: Arkansas Births Differenced Equation without Personal Income**

Dependent Variable: D(AKBIR)
Method: Least Squares
Sample (adjusted): 1971 2011
Included observations: 41 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.056160 | 0.138351 | -0.405926 | 0.6871 |
| D(AKBIR(-1)) | 0.136372 | 0.161393 | 0.844971 | 0.4036 |
| D(AKPOP*NB/NPOP) | 0.476804 | 0.122411 | 3.895113 | 0.0004 |
| D(AKPOP(-1)*NB(-1)/NPOP(-1)) | -0.228372 | 0.141276 | -1.616499 | 0.1145 |

| | | | |
|---|---|---|---|
| R-squared | 0.293569 | Mean dependent var | 0.071683 |
| Adjusted R-squared | 0.236291 | S.D. dependent var | 0.904153 |
| S.E. of regression | 0.790143 | Akaike info criterion | 2.459263 |
| Sum squared resid | 23.10008 | Schwarz criterion | 2.626441 |
| Log likelihood | -46.41489 | Hannan-Quinn criter. | 2.520140 |
| F-statistic | 5.125317 | Durbin-Watson stat | 2.086696 |
| Prob(F-statistic) | 0.004582 | | |

**Table 15: Arkansas Deaths Differenced Equation**

Dependent Variable: D(AKDEA)
Method: Least Squares
Sample (adjusted): 1971 2011
Included observations: 41 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.067667 | 0.066985 | 1.010181 | 0.3190 |
| D(AKDEA(-1)) | -0.385733 | 0.149863 | -2.573908 | 0.0142 |
| D(AKPOP*ND/NPOP) | 1.279144 | 0.189077 | 6.765216 | 0.0000 |
| D(AKPOP(-1)*ND(-1)/NPOP(-1)) | 0.331217 | 0.272718 | 1.214500 | 0.2323 |

| | | | |
|---|---|---|---|
| R-squared | 0.612619 | Mean dependent var | 0.208805 |
| Adjusted R-squared | 0.581210 | S.D. dependent var | 0.541470 |
| S.E. of regression | 0.350407 | Akaike info criterion | 0.833026 |
| Sum squared resid | 4.543050 | Schwarz criterion | 1.000203 |
| Log likelihood | -13.07703 | Hannan-Quinn criter. | 0.893903 |
| F-statistic | 19.50442 | Durbin-Watson stat | 2.009447 |
| Prob(F-statistic) | 0.000000 | | |

**Table 16: Arkansas Net Migration Differenced Equation**

Dependent Variable: D(AKNMIG)
Method: Least Squares
Sample (adjusted): 1971 2011
Included observations: 41 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -1.906137 | 1.596674 | -1.193817 | 0.2401 |
| D(AKNMIG(-1)) | -0.470037 | 0.139901 | -3.359796 | 0.0018 |
| D(EMP) | 31550.85 | 12345.36 | 2.555685 | 0.0148 |
| D(EMP(-1)) | 37893.08 | 13347.14 | 2.839042 | 0.0073 |

| | | | |
|---|---|---|---|
| R-squared | 0.390513 | Mean dependent var | 0.120390 |
| Adjusted R-squared | 0.341095 | S.D. dependent var | 11.99337 |
| S.E. of regression | 9.735374 | Akaike info criterion | 7.481877 |
| Sum squared resid | 3506.768 | Schwarz criterion | 7.649055 |
| Log likelihood | -149.3785 | Hannan-Quinn criter. | 7.542754 |
| F-statistic | 7.902263 | Durbin-Watson stat | 1.997960 |
| Prob(F-statistic) | 0.000338 | | |

# Vita

David Ramirez was born and raised in El Paso, Texas, and is the eldest son of Abel and Eugenia Ramirez. He graduated from Montwood High School in 2004, and subsequently attended the University of Texas at El Paso (UTEP), where he received a B.B.A. in Economics in 2008. After completing his undergraduate degree, he worked for an equity research analyst before enrolling in the Master of Science in Economics program at UTEP. During this time he worked as a graduate research assistant at the Institute for Policy and Economic Development (IPED), and is currently the Research Associate at IPED.

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