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Forecasting Water Demand in Phoenix

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FORECASTING WATER DEMAND IN PHOENIX

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Chapter 1: Introduction

Short-term forecasts can facilitate decision-making at operational and managerial planning levels (Jain and Lindell, 2002; Herrera et al., 2010; House-Peters and Chang, 2011). Water demand forecasting helps utilities operate treatment plants and wells appropriately, develop new water sources, and/or expand current ones. Forecasts are also important for accurately quantifying the risk of water shortages and revenue shortfalls (Donkor et al., 2014).

Recent trends in North American water demand highlight the importance of accurate forecasts. Business cycle fluctuations, new water-conserving appliances, and changing demographics have contributed to stagnant or declining water sales at utilities across the continent (Rockaway et al., 2011; Qi and Chang, 2011). Demand erosion complicates utility financial planning processes because the large fixed costs of infrastructure will have to be recovered from a shrinking base (Sang, 1982; Beecher, 2010). Over-prediction of water sales can result in water requirements overestimation and the development of needlessly expensive projects (DeOreo and Mayer, 2012). In regions where seasonal demands consistently outstrip historical raw water sources, accurate forecasts of monthly consumption are of added importance (Fullerton and Elías, 2004).

The main objective of this paper is to analyze short-term water demand behavior in Phoenix, Arizona. Located in a semi-arid region, residential water consumption in Phoenix peaks during the summer. More than 40 percent of annual use occurs from June to September (Wentz and Gober, 2007). The average annual rainfall during the last three decades is eight inches, which is insufficient to supply local needs (NOAA, 2014). Historically, severe droughts have affected this region. Although total water produced in Phoenix during 2013 was the lowest

since 1995, water conservation is a dominant issue and alternative sources of water have been developed at high costs (City of Phoenix, 2014). The high cost of maintaining an adequate water supply in this region underscores the need for better demand forecasting.

Monthly data for 2008 to 2014 are used to model and forecast single-family and multi-family residential, as well as nonresidential, water demand. Because most economic research on water demand has been conducted for residential usage, one contribution of this study is examination and prediction of nonresidential consumption patterns (Boland, 1983). Previously, mixed forecast accuracy results have been found across different municipal customer categories (Fullerton and Molina, 2010). In this effort, various assessments are used to evaluate different dimensions of forecast accuracy across the three customer classes analyzed. The paper is organized in the following manner. A brief literature review regarding water demand forecasting follows this section. Data and methodology are described in Section 3. Section 4 contains a summary of empirical results. Finally, conclusions and suggestions for future research are presented in Section 5.

Chapter 2: Literature Review

A large volume of literature analyzes factors that affect residential water demand. Key determinants of residential water consumption include price, income, and climatic variables. Supporting standard economic theory, much water demand research indicates an inverse relationship between price and quantity (Pint, 1999; Gaudin, 2006). In a survey of empirical work, Worthington and Hoffman (2008) report price elasticity estimates between zero and -0.5 in the short-run, and -0.5 to -1.0 in the long-run.

Several factors help to explain why water demand is usually estimated to be price-inelastic. First, because the water bill typically represents a small proportion of family income, consumers are not likely to invest a large amount of time in understanding water rate structures, which can be quite complex. Consequently, reactions to changes in the rate structure may be muted. Second, no substitutes exist for basic uses of water, such as personal hygiene, cleaning, and food. Given that, customers may not drastically adjust consumption in response to price changes (Chicoine and Ramamurthy, 1986; Arbués, García-Valiñas, and Martínez-Espiñeira 2003; Arbués and Villanúa, 2006).

Higher water prices can encourage greater conservation, especially during summer months when the price elasticity may be higher due to increased discretionary use (Moncur, 1987; Espey, Espey, and Shaw, 1997; Olmstead and Stavins, 2009). Factors such as household size and socioeconomic characteristics can also affect the price elasticity of consumption and should be considered in the rate design process (Arbués, Villanúa, and Barberán, 2010). Renwick and Archibald (1998) find that low income households are more than five times as price responsive than wealthier utility customers. That suggests that such households may

account for a disproportionately large share of any reduction in demand induced by higher prices. Non-price measures such as education, public information, and ordinances have also helped to achieve significant reductions in resource demand (Michelsen, McGuckin, and Stumpf, 1999; Martinez-Espiñeira, and Nauges, 2004).

Another important variable affecting metropolitan water demand is income. Per capita income for a given region or the assessed value of property are often utilized for household-level and aggregate studies, respectively (Dandy, Nguyen, and Davies, 1997; Musolesi and Nosvelli, 2011). Monthly frequency studies have also utilized employment and industrial production as proxies for income (Fullerton and Elias, 2004; Fullerton, Tinajero, and Barraza, 2006; Fullerton, Tinajero, and Mendoza-Cota, 2007). The relationship between income and water demand tends to be direct and inelastic (Kulshreshtha, 1996; Renwick and Green, 2000). Approximately 90 percent of the 162 income elasticity estimates analyzed by Dalhuisen et al. (2003) are less than unity.

In general, water can be regarded as a normal good because its consumption increases with higher income levels (Martinez-Espiñeira, 2002; Schleich and Hillerbrand, 2009). The income elasticity of water demand may vary over time due to changes in the structural relationship between the quantity of water consumed and income. It also tends to vary in response to seasonal weather changes. The long-run income elasticity may also differ from the short-run elasticity because changes in the stock of water-using durable equipment, such as dishwashers, clothes washers, and bathtubs may only be possible over the long-run (Nauges and Thomas, 2003; Polebitski and Palmer, 2010; Woo et al., 2012).

Climatic variables, such as temperature and precipitation, significantly affect monthly consumption. Gato et al. (2007) conclude that there is a reduction of roughly 0.08ML in water

use per millimeter of rainfall in an Australian community. Praskievicz and Chang (2009) find that daily water consumption in July increases up to 4 liters per person in Seoul, Korea, for every one degree increase in maximum temperatures. Several authors suggest that water demand is better correlated with rainfall occurrence than with the amount of rainfall itself (Jain, Varshney, and Joshi, 2001; Martinez-Espiñeira, 2002). In general, forecast accuracy is improved by including information on weather variables when modeling water usage (Fildes, Randall, and Stubs, 1997).

The foregoing discussion focusses on the determinants of residential water use. Water use patterns also differ across customer categories. While residential use is mainly for direct consumption, industrial and commercial customers generally use water as an input to production (Hussain, Thrikawala, and Barker, 2002). Beyond that, some apartment complexes use common metering and this does not provide a strong incentive to renters to change their water usage behavior in response to price signals (Agthe and Billings, 2002). As a consequence of the diversity in water consumption patterns across customer classes, different specifications are often employed to model demand in the various categories.

The number of active customers (connections) per class has been used as an explanatory variable to predict aggregate water use for various customer categories (Williams and Suh, 1986). Determinants of multi-family residential water demand may include assessed property value per bedroom, number of bedrooms, vacancy, age of the complex, presence of indoor water-saving devices (Agthe and Billings, 2002), and the presence of pools, dishwashers, and washer-dryers (Wentz et al., 2014). Swimming pool areas, in-unit dishwashers, and in-unit washer-dryers collectively explain nearly 50 percent of the total variation in the summer time water consumption across complexes (Wentz et al., 2014). A few studies also suggest that urban

design influences resource usage in multi-family housing (Zhang and Brown, 2005; Mayer et al., 2006; Randolph and Troy, 2008).

In a study for Brisbane, Australia, Hoffman, Worthington and Higgs (2006) find the price elasticity of demand in owner-occupied households to be greater than in rental-unit households. This is in large part because rental tenants are entitled to a free allocation of a reasonable amount of water under local legislation. Even if some apartment residents regard water as a free good, as a consequence of common metering, apartment complex owners react significantly to price increases by investing in water-saving capital such as low-flow showerheads and faucets (Agthe and Billings, 1996). Water conservation initiatives including price increases and non-price strategies (such as programs to replace aging plumbing fixtures) can have important impacts on multi-family residential water demand (Agthe and Billings, 2002).

Commercial usage and industrial demand have been modeled as functions of the respective employment figures for each of those sectors (Metzner, 1989). Value added in manufacturing and the level of industrial output have also been used to predict industrial water demand (Williams and Suh, 1986; Renzetti 1988). In a model developed for Zaragoza, Spain, Arbués, García-Valiñas, and Villanúa (2010) models service and industrial demand as a function of a constructed proxy for levels of output, firm surface area (proxy for size), and numbers of workers. Additionally, categories such as government and school water usage have been analyzed as functions of total employment (Metzner, 1989) or resident population per account (Schneider and Whitlatch, 1991).

Most of the industrial sector consists of manufacturers. Several studies conclude that the price elasticity of water demand is higher for the industrial sector than for the residential (Arbués, García-Valiñas, and Villanúa, 2010) and commercial sectors (Williams and Suh, 1986).

Some authors report a significant price elasticity of industrial water demand with a mean value of -1.0 (Wang and Lall, 1999; Feres and Reynaud, 2005; Kumar, 2006). Hussain, Thrikawala, and Barker (2002) conclude that a 10 percent increase in the price of water will reduce manufacturing water demand by more than 13 percent, indicating that industrial water demand is fairly price elastic. Several studies suggest that industrial customers, unlike residential users, can often respond to significant price increases by recycling water used in production (Williams and Suh, 1986; Renzetti 1988; Arbués, García-Valiñas, and Villanúa, 2010). Water recirculation is a substitute for water intake and water discharge (Renzetti, 1992; Dupont and Renzetti, 2001). Pricing policies to improve water management may have greater effects on industrial usage due to the higher sensitivity of manufacturers to water price increases.

The Southwest region of the United States has been the object of extensive analysis regarding water demand. The South and West may be more sensitive to price changes than the rest of the country due to greater public awareness of the scarcity of water (Nieswiadomy, 1992). Residential water consumption in Phoenix, Arizona, has been found to be significantly affected by household characteristics, urban design features, and landscaping practices (Wentz and Gober, 2007). Also, given the high heat absorption of its urban built structures, water demand in this metropolitan area is affected by the Urban Heat Island effect (Guhathakurta and Gober, 2007; Aggarwal et al., 2012). In this context, Guhathakurta and Gober (2007) report that increasing daily low temperatures by one degree Fahrenheit is associated with an average monthly increase in single-family water use of 290 gallons.

However, the sensitivity of water demand to variations in climate differs within Phoenix. Balling, Gober, and Jones (2008) report that greater weather sensitivity occurs in census tracts with large lots, pools, and wealthier residents. That suggests that more affluent neighborhoods

will be disproportionately affected by increasing temperatures. Simulation results under varying future climate scenarios indicate that only additional groundwater mining can support current levels of per capita water consumption in Phoenix.

Groundwater mining refers to a prolonged and progressive decrease in the amount of water stored in a groundwater system, as may occur in heavily pumped aquifers (Alley, Reilly, and Franke, 1999). In addition to reducing the available supply of water, extensive groundwater mining may cause subsidence. Land subsidence is a sudden sinking or gradual settling of the Earth's surface due to subsurface movement of earth materials (USGS, 2000). Over the long-run, additional groundwater mining is unsustainable if it exceeds natural recharge. Fortunately, even the most pessimistic climate change scenarios can be weathered if feasible reductions in residential water demand are attained (Gober et al., 2010).

Lee, Wentz, and Gober (2010) utilize a Bayesian Maximun Entropy approach to forecast residential water demand in Phoenix. Results indicate that water use peaks between 2012 and 2017 and gradually decreases afterward. This curved growth trajectory can be explained by the interplay between demographic expansion and water conservation. The initial increase in projected water consumption is a consequence of expected rapid population growth. The subsequent reduction in total demand occurs because per capita water use is expected to fall and this decline is predicted to outweigh the effect of continuing demographic growth in the latter part of the forecast period.

This study extends previous research on Phoenix area water demand by modeling and forecasting consumption for three customer classes: single-family residential, multi-family residential, and nonresidential. As discussed above, patterns of water demand often vary across customer categories and water demand modeling efforts may benefit by explicitly accounting for

this heterogeneity. A variety of assessment methods are used to evaluate the accuracy of the forecasts.

Chapter 3: Data and Methodology

Monthly frequency time series data from January 2008 to December 2014 are utilized for the investigation of short-term water demand dynamics in Phoenix. Water consumption is divided into three broadly defined rate classes: single-family residential, multi-family residential, and nonresidential. The strategy followed to model water consumption in Phoenix involves decomposing demand in each of the three customer classes into demand per account and number of accounts (Fullerton and Schauer, 2001). Thus, a total of six regression equations are estimated.

Per-customer water usage in each customer category is obtained by dividing water billed by the number of customers in the corresponding category. Consumption is modeled as a function of average price, cooling degree days, number of days per month with rainfall, an economic conditions index, the rental vacancy rate, and the unemployment rate. The number of customer accounts is modeled as a function of economic variables (Fullerton, Tinajero, and Barraza, 2006; Fullerton, Tinajero, and Mendoza-Cota, 2007). Total employment and multi-family housing starts are the explanatory variables in the customer base equations. Data constraints do not allow multi-family housing stock to be utilized.

The monthly total bill is equal to the monthly water bill plus the monthly sewer bill. The water rate schedule is fairly straightforward. There is a single fixed price per hundred cubic feet in excess of a base fee allowance. However, the sewer rate schedule is much more complex, with different flat and volumetric fees for various sub-categories of customers. Because the data necessary to assign appropriate weights to fees in each sub-category are not available over the

course of the sample period, calculation of monthly marginal sewer rates for the three major customer categories is not feasible.

Furthermore, complete time series data on water demand are not available for each of the various sub-categories. Therefore, this study employs an average price measure. Previously, the same approach has been shown to yield reliable econometric results when it is difficult or not possible to obtain detailed public utility tariff information (Shin, 1985; Nieswiadomy and Molina, 1991). Average price is calculated by dividing monthly total revenues over total water consumption in the city of Phoenix. In order to obtain real values, the average price figures are deflated using the consumer price index (CPI).

Data on water billed, total water and sewer revenue, and the number of accounts by category are provided by the City of Phoenix (COP). Total cooling degree days and the number of days with rainfall occurrence are retrieved from the National Oceanic and Atmospheric Administration (NOAA). Cooling degree days reflect the personal preferences of people who work or live in a building, and are calculated with a generally accepted base temperature (Stathopoulou, Cartalis, and Chrysoulakis, 2006). In this study, temperatures above 65 Fahrenheit degrees generate cooling degree days.

Given data constraints regarding monthly personal income at the regional level, either an economic conditions index, rental vacancy rate, or the unemployment rate are used as a proxy for economic conditions. The unemployment rate and CPI are collected from the Bureau of Labor Statistics (BLS). The former represents the number unemployed as a percentage of the labor force. The economic conditions index is available from a publication by the Federal Reserve Bank of St. Louis (Arias, Gascon, and Rapach, 2015). It measures the average (positive or negative) economic growth in the metropolitan area over the previous three months.

The source for data on the rental vacancy rate and multi-family housing starts is the Census Bureau. The former indicates the proportion of the rental inventory which is vacant for rent. Unfortunately, it is only available on a quarterly basis. To create a monthly series, a local quadratic interpolation is performed in which the average of the high frequency matches the low frequency data actually observed. Total nonfarm employment data are available from the Office of Employment and Population Statistics at the Arizona Department of Administration (ADOA-EPS).

The City of Phoenix Water Services Department serves the entire Phoenix incorporated area (546 square miles) and approximately 1.4 million customers (Aggarwal et al., 2012). For the variables unemployment rate, total employment, and multi-family housing starts, data for Maricopa County are utilized. Since no county level data are available regarding the rental vacancy rate and the economic conditions index, MSA level data are utilized instead. The Phoenix-Mesa-Scottsdale Metropolitan Statistical Area (MSA) as defined by the Office of Management and Budget (OMB) includes Maricopa and Pinal counties. Table 1 lists the variables, definitions, units of measure, and sources.

The variables utilized exhibit different orders of integration. First differencing is applied to the customer base, price, and economic conditions index variables to achieve stationarity. In addition to first differencing, seasonal differencing is necessary for the consumption, total cooling degree days, unemployment rate, total employment, and multi-family housing starts variables. Second order differencing is applied to the rental vacancy rate variable, and the variable that accounts for the number of days with rainfall appears in level form. Table 2 reports summary statistics for the sample data.

Table 1. Variables

Variable	Definition	Units	Source
SFUSE	Single-family residential per customer water usage	Hundred cubic feet	COP
MFUSE	Multi-family residential per customer water usage	Hundred cubic feet	COP
NRUSE	Nonresidential per customer water usage	Hundred cubic feet	COP
SFCUST	Number of single-family residential customers	Water accounts	COP
MFCUST	Number of multi-family residential customers	Water accounts	COP
NRCUST	Number of nonresidential customers	Water accounts	COP
PRICE	Real average price	Dollars per hundred cubic feet	COP
TCDD	Total cooling degree days	Cooling degree days	NOAA
NODR	Number of days rainfall	Days	NOAA
ECI	Economic conditions index	Percentage	St. Louis Fed
RVR	Rental vacancy rate	Percentage	Census Bureau
UNEMP	Unemployment rate	Percentage	BLS
TOTEMP	Total nonfarm employment	Thousands	ADOA-EPS/BLS
MFHS	Multi-family housing starts	Units	Census Bureau

In this study, the linear transfer function (LTF) modeling approach is utilized. LTF is an extension of the univariate ARIMA method (Box and Jenkins, 1976). Previously, this approach has been successfully utilized by several authors to analyze and forecast the demand for residential natural gas, electricity, and regional employment (Liu and Lin, 1991; Tserkezos, 1992; Trívez and Mur, 1999). In the context of water demand forecasting, Donkor et al. (2014) emphasize the potential value of this type of approach in which demand is modeled as a function

of appropriate lags of explanatory variables and autocorrelation functions are used to select autoregressive (AR) and moving average (MA) parameters.

Table 2. Summary statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	No.
SFUSE	14.465	3.244	9.007	21.036	84
MFUSE	96.236	11.626	75.411	120.111	84
NRUSE	100.614	30.776	53.766	157.056	84
SFCUST	353,054	4,489	339,531	361,617	84
MFCUST	15,670	183	15,269	16,216	84
NRCUST	33,875	254	33,087	34,348	84
PRICE	1.94	0.14	1.55	2.19	84
TCDD	409	367	0	1,039	84
NODR	2	2	0	12	84
ECI	0.51	5.27	-12.50	6.45	81
RVR	12.9	3.8	7.6	20.1	84
UNEMP	7.5	1.6	3.9	10.3	84
TOTEMP	1,721.2	70.5	1,597.3	1,858.7	84
MFHS	315	364	0	1,586	84

In order to determine the potential lag structures of the explanatory variables, the cross correlation functions (CCFs) between the stationary components of the dependent and independent variables are plotted and inspected. Then, AR and MA terms are introduced into the multiple input transfer function to account for any systematic movement in the dependent variable remaining unexplained (Wei, 2006). Significant residual autocorrelation and partial autocorrelation coefficients allow potential ARMA structures to be identified.

The specifications for modeling each category of water consumption per customer are shown in equations (1), (2), and (3), respectively. The hypothesized relationships between the regressors and the dependent variable appear in the parentheses above each of the explanatory variables. With the exception of the number of days with rainfall, all variables are transformed to ensure stationarity.

$$\begin{aligned} &\qquad\qquad\quad (-) \qquad\qquad\qquad (+) \qquad\qquad\qquad (-) \qquad\qquad\qquad (+) \qquad\qquad\qquad \textbf{(1)} \\ SFUSE_t &= \theta_0 + \sum_{a=1}^{A} \beta_a\, PRICE_{t-a} + \sum_{b=1}^{B} \beta_b TCDD_{t-b} + \sum_{c=1}^{C} \beta_c NODR_{t-c} + \sum_{d=1}^{D} \beta_d ECI_{t-d} + \sum_{i=1}^{p} \phi_i SFUSE_{t-i} \\ &\quad + \sum_{j=1}^{q} \theta_j u_{t-j} + u_t \end{aligned}$$

$$\begin{aligned} &\qquad\qquad\quad (-) \qquad\qquad\qquad (+) \qquad\qquad\qquad (-) \qquad\qquad\qquad\qquad\qquad\qquad\quad \textbf{(2)} \\ MFUSE_t &= \theta_0 + \sum_{a=1}^{A} \beta_a\, PRICE_{t-a} + \sum_{b=1}^{B} \beta_b TCDD_{t-b} + \sum_{c=1}^{C} \beta_c RVR_{t-c} + \sum_{i=1}^{p} \phi_i MFUSE_{t-i} + \sum_{j=1}^{q} \theta_j u_{t-j} + u_t \end{aligned}$$

$$\begin{aligned} &\qquad\qquad\quad (-) \qquad\qquad\qquad (+) \qquad\qquad\qquad (-) \qquad\qquad\qquad (-) \qquad\qquad\qquad \textbf{(3)} \\ NRUSE_t &= \theta_0 + \sum_{a=1}^{A} \beta_a\, PRICE_{t-a} + \sum_{b=1}^{B} \beta_b TCDD_{t-b} + \sum_{c=1}^{C} \beta_c NODR_{t-c} + \sum_{d=1}^{D} \beta_d UNEMP_{t-d} + \sum_{i=1}^{p} \phi_i NRUSE_{t-i} \\ &\quad + \sum_{j=1}^{q} \theta_j u_{t-j} + u_t \end{aligned}$$

Water consumption is expected to vary inversely with prices. In other words, an increase in the price of water would generate a decrease in the per customer water demand. A larger number of cooling degree days, reflective of warmer temperatures, is expected to increase water consumption. This is congruent with the historical peak in water demand during the summer in

Phoenix. An increase in the number of days with rainfall is expected to have a negative relationship with water demand because less watering is required for gardens and other outdoor water uses.

An improvement in economic activity is expected to increase water usage. Therefore, the economic conditions index is expected to be positively correlated with water demand. For similar reasons, the rental vacancy rate and unemployment rate are expected to have an inverse relationship with water usage.

The specifications for the number of COP customers by category are given by the equations (4), (5), and (6). All variables are expressed as stationary components of the original data series. The hypothesized relationships between the regressors and the dependent variables appear in the parentheses above each explanatory variables. Total employment and multi-family housing starts are both expected to be positively correlated with the customer base.

$$SFCUST_t = \theta_0 + \sum_{a=1}^{A} \overset{(+)}{\beta_a\, TOTEMP_{t-a}} + \sum_{i=1}^{p} \phi_i SFCUST_{t-i} + \sum_{j=1}^{q} \theta_j v_{t-j} + v_t \tag{4}$$

$$MFCUST_t = \theta_0 + \sum_{a=1}^{A} \overset{(+)}{\beta_a\, MFHS_{t-a}} + \sum_{i=1}^{p} \phi_i MFCUST_{t-i} + \sum_{j=1}^{q} \theta_j v_{t-j} + v_t \tag{5}$$

$$NRCUST_t = \theta_0 + \sum_{a=1}^{A} \overset{(+)}{\beta_a\, TOTEMP_{t-a}} + \sum_{i=1}^{p} \phi_i NRCUST_{t-i} + \sum_{j=1}^{q} \theta_j v_{t-j} + v_t \tag{6}$$

Water consumption appears on the left-hand sides of regression equations (1), (2), and (3) and as the denominator in the average price variable on the right-hand sides of those same equations. Consequently, it is important to test for endogeneity (Fullerton et al., 2013). An artificial regression test is utilized for this purpose (Davidson and MacKinnon, 1989). The artificial regression procedure evaluates the null hypothesis that average price is uncorrelated with the error term in each equation. The instrument used to conduct the test is the national capital stock deflator for water systems, which is obtained from the Bureau of Economic Analysis (BEA). The capital stock deflator is an adequate instrument because national-level fluctuations in infrastructure costs are likely to be correlated with local water rates but are not affected by changes in Phoenix area water consumption.

Because good in-sample statistical traits do not guarantee out-of-sample simulation accuracy, forecasting performance is also analyzed (Leamer, 1983). After the parameters of each equation have been estimated, *ex-post* forecasts are conducted over the course of a 36 month period. Initially, a subsample estimation period is defined from January 2008 to December 2011, with the period covered by the forecast running from January 2012 to December 2012.

Then, the estimation period is expanded by one month to January 2012 and the forecast period is rolled forward by one month to cover the period from February 2012 through January 2013. This process is repeated until the subsample estimation period extends through November 2014. The results are 36 one-month forecasts, 35 two-month forecasts, 34 three-month forecasts and so on.

Simulation accuracy is investigated utilizing random walk forecasts as benchmarks. For the per customer water consumption series, which exhibit a high degree of seasonality, a random walk (RW) prediction is defined as the observed value of demand in the same month of the

previous year. The customer base, by contrast, tends to move in a non-seasonal pattern. The RW forecast of customer accounts is simply the last historical observation in that series.

The latest available change is the random walk with drift (RWD) prediction for all months beyond the sample estimation range. Previous research indicates that such benchmark extrapolations are competitive with econometric forecasts in other regions (Fullerton and Elias, 2004; Fullerton, Tinajero, and Barraza, 2006). The LTF, RW, and RWD forecasts are compared against the actual COP water utility data for January 2012 through December 2014.

Descriptive measures of accuracy, such as root mean square errors (RMSE) and Theil (1961) inequality *U*-statistics are then estimated. Additionally, two formal tests are performed. The first is the forecast error differential test proposed by Ashley, Granger, and Schmalensee (1980). The second is a non-parametric test for directional accuracy (Henriksson and Merton, 1981). The *U*-statistic, which is based on the RMSE, measures forecast accuracy and can assume values ranging from zero to one. When *U*=0 it means that a perfect fit is obtained. Alternatively, if *U*=1, the predictive performance of the forecast is as bad as it can possibly be (Pindyck and Rubinfield, 1998). The Theil inequality coefficient is given by equation (7):

$$U = \frac{\sqrt{\frac{1}{n}\sum(Y_t^s - Y_t^a)^2}}{\sqrt{\frac{1}{n}\sum(Y_t^s)^2} + \sqrt{\frac{1}{n}\sum(Y_t^a)^2}} \qquad \textbf{(7)}$$

where Y_t^s represents the forecasted value and Y_t^a the actual observation. In order to extract additional information about forecast accuracy, the second moment of the *U*-statistic can be further decomposed into the following three proportions of inequality: bias (U_M), variance (U_S), and covariance (U_C). The bias proportion measures the systematic divergence between the means of actual and predicted values. The variance proportion reflects the forecast's ability to replicate the degree of variability in the variable of interest. The covariance proportion

represents unsystematic error. The inequality components can be written as shown in the following equations:

$$U_M = \frac{(\bar{Y}^s - \bar{Y}^a)^2}{\frac{1}{n}\sum(Y_t^s - Y_t^a)^2} \quad \textbf{(8)}$$

$$U_S = \frac{(\sigma_s - \sigma_a)^2}{\frac{1}{n}\sum(Y_t^s - Y_t^a)^2} \quad \textbf{(9)}$$

$$U_C = \frac{2(1-\rho)\sigma_s\sigma_a}{\frac{1}{n}\sum(Y_t^s - Y_t^a)^2} \quad \textbf{(10)}$$

where $\bar{Y}^s$ and $\bar{Y}^a$ are the means, and σ_s and σ_a are standard deviations of the series Y_t^s and Y_t^a, respectively, and ρ is their correlation coefficient. The ideal distribution of the three inequality proportions is $U_M = U_S = 0$ and $U_C = 1$ (Pindyck and Rubinfield, 1998).

The error differential regression test determines whether the difference between the errors from two competing forecasts is statistically significant. The LTF predictions are first compared with a RW benchmark and then with a RWD benchmark. By defining the two variables shown below in equations (11) and (12), the null hypothesis of the test can be expressed as equation (13):

$$\Delta_t = e_{1t} - e_{2t} \quad \textbf{(11)}$$

$$\Sigma_t = e_{1t} + e_{2t} \quad \textbf{(12)}$$

$$\mathrm{H}_0\text{: } MSE(e_1) - MSE(e_2) = [\mu(e_1)^2 - \mu(e_2)^2] + \mathrm{cov}(\Delta, \Sigma) = 0 \quad \textbf{(13)}$$

The first two equations represent sums and differences of the forecast errors generated by the two models at each time period *t*, respectively. In equation (13), MSE stands for mean squared error while μ denotes the mean and cov denotes the covariance. Assuming the means of both sets of errors have the same sign, a test of $\mathrm{cov}(\Delta,\Sigma) = \mu(\Delta) = 0$ can be used to evaluate the null hypothesis as follows:

$$\Delta_t = \beta_1 + \beta_2[\Sigma_t - \mu(\Sigma_t)] + u_t \quad \textbf{(14)}$$

where u_t is a randomly distributed error term. The following equation is utilized when the error means have opposite signs:

$$\Sigma_t = \beta_1 + \beta_2[\Delta_t - \mu(\Delta_t)] + u_t \qquad \textbf{(15)}$$

A positive value for β_2 indicates that the model associated with e_{2t} outperforms the model associated with e_{1t}. The interpretation of β_1 depends on the sign of the mean of e_1. If β_1 has the same sign as the mean of e_1, this indicates that the forecasts that generated e_{2t} outperform the forecasts associated with e_{1t}. Ashley, Granger, and Schmalensee (1980) provide guidelines for evaluating the *t*- and *F*-statistics associated with the regression equations in order to establish whether one model outperforms the competing model by a statistically significant margin.

An alternative approach is utilized to assess whether a forecast can accurately predict the direction of change in the series of interest. In this context, Henriksson and Merton (1981) propose a test for forecasting ability that involves probabilities calculated from a contingency table, such as Table 3 below.

Table 3. Contingency table

		Forecast		
		Increase	Decrease	Total
Actual	Increase	n_{11}	n_{12}	n_{10}
	Decrease	n_{21}	n_{22}	n_{20}
	Total	n_{01}	n_{02}	N

In Table 3, the total number of forecasts sum to N. The diagonal elements, n_{11} and n_{22} represent correct predictions of directional change while n_{12} and n_{21} represent incorrect change

forecasts. By dividing the values of n_{ij} by the row totals, probabilities are obtained. For example, $p_1 = E(n_{11}/n_{10})$, where E is the expectation operator. The null hypothesis, stated in equation (16), is that forecasts of directional change are independent of the directional changes actually observed. In other words, the set of forecasts provides no useful information for a given variable's directional change.

$$\mathrm{H}_0: p_1 + p_2 = 1 \qquad \textbf{(16)}$$

For a forecast with a perfect direction of change prediction, $p_1 = 1$, $p_2 = 1$, and $p_1 + p_2 = 2$. On the other hand, if a model always forecasts incorrectly, $p_1 + p_2 = 0$. A one-tailed test of H_0: $p_1 + p_2 \leq 1$ against H_a: $p_1 + p_2 > 1$ is recommended because it does not seem highly probable that forecasts would systematically predict the wrong direction of change. The null hypothesis can be rejected if $n_{11} \geq x^*(c)$, where n_{11} has a hypergeometric distribution, c is the confidence level, and $x^*(c)$ is obtained from equation (17).

$$1 - c = \sum_{x=x^*}^{\bar{n}_{11}} \frac{\binom{n_{10}}{x}\binom{n_{20}}{n_{01}-x}}{\binom{N}{n_{01}}} \qquad \textbf{(17)}$$

In the following section, empirical results are reported and forecasting accuracy comparisons are conducted. Forecasts generated using the LTF ARIMA methodology are compared against random walk and the random walk with drift benchmark forecasts. In order to determine if the LTF model exhibits better out-of-sample properties compared to the benchmarks, Theil inequality coefficients, an error differential regression test, and a non-parametric directional accuracy test are employed.

Chapter 4: Empirical Results

Tables 4, 5, and 6 show LTF ARIMA estimation results for single-family residential, multi-family residential, and nonresidential per customer water usage equations, respectively. In order to induce stationarity, the price variable and the economic conditions index are first-differenced. Consumption, total cooling degree days, and the unemployment rate are first- and seasonally-differenced. Second order differencing is applied to the rental vacancy rate variable. The variable that accounts for the number of days with rainfall appears in level form.

The independent variables affect demand with different lags. The estimated coefficients associated with each of the explanatory variables are significant at the 95 percent confidence level. Also, all of the coefficient signs are as hypothesized. Two autoregressive parameters are included to correct for serial correlation in the single-family residential demand equation. For the multi-family residential and nonresidential demand equations, autoregressive and moving average parameters are included for the same purpose.

The intercept terms in Tables 4 and 6 are positive, but only the latter intercept is statistically significant. Because the data are differenced prior to estimation, this result indicates the presence of a deterministic upward trend in nonresidential water consumption for the sample period analyzed. The intercept term for Table 5 is negative and not significant. These results are not surprising because water conservation efforts have helped restrain consumption growth in Phoenix. The total volume of water produced by COP in 2013 was the lowest since 1995 in spite of a 30 percent increase in population during the same period (City of Phoenix, 2014).

Table 4. ARIMA LTF single-family residential per customer water usage

Dependent Variable: SFUSE
Method: Least Squares
Sample (adjusted): 2009M11 2014M12
Included observations: 62 after adjustments
Convergence achieved after 9 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.188023	0.129714	1.449518	0.1529
PRICE	-2.699224	1.248223	-2.162453	0.0349
TCDD(-1)	0.005285	0.001571	3.363783	0.0014
NODR	-0.099038	0.046196	-2.143868	0.0365
ECI(-11)	0.226773	0.091371	2.481890	0.0162
AR(1)	-0.593101	0.110920	-5.347089	0.0000
AR(8)	-0.342149	0.112670	-3.036723	0.0037

R-squared	0.595262	Mean dependent var	0.014597
Adjusted R-squared	0.551109	S.D. dependent var	1.574545
S.E. of regression	1.054935	Akaike info criterion	3.050840
Sum squared resid	61.20880	Schwarz criterion	3.291000
Log likelihood	-87.57604	Hannan-Quinn criter.	3.145133
F-statistic	13.48172	Durbin-Watson stat	2.116557
Prob(F-statistic)	0.000000		

Inverted AR Roots	.75-.33i	.75+.33i	.27-.79i	.27+.79i
	-.41-.78i	-.41+.78i	-.91-.32i	-.91+.32i

Tables 4 through 6 show contemporaneous negative relationships between movements in the real average price and water usage. Previous research reports evidence that residential (Ruijs, Zimmermann, and van den Berg, 2008), commercial, and industrial (Hussain, Thrikawala, and Barker, 2002) consumers respond to contemporaneous values of average prices. The significant impacts of the contemporaneous lag of price point to potential forward-looking expectations behavior by the COP customer base (Fullerton and Elias, 2004; Fullerton, Tinajero, and Barraza de Anda, 2006).

The price elasticity for the single-family usage category is -0.36. It is calculated by multiplying the price coefficient in Table 4 by the ratio of mean price to mean usage in that category. It is smaller in magnitude than the average price elasticity estimate reported by Worthington and Hoffman (2008) of -0.5. The price elasticity for the multi-family usage

category is -0.31, and it is calculated analogously. Again, it is smaller in magnitude than the price elasticity for multi-family water demand estimated by Agthe and Billings (2002) and the price elasticity for renter-occupied households reported by Hoffman, Worthington and Higgs (2006).

Table 5. ARIMA LTF multi-family residential per customer water usage

Dependent Variable: MFUSE
Method: Least Squares
Sample (adjusted): 2010M03 2014M12
Included observations: 58 after adjustments
Convergence achieved after 16 iterations
MA Backcast: 2010M02

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.010475	0.031440	-0.333188	0.7403
PRICE	-15.29766	7.460086	-2.050600	0.0454
TCDD(-1)	0.036991	0.010753	3.440086	0.0012
RVR(-11)	-1.509119	0.629779	-2.396267	0.0202
AR(12)	-0.354100	0.130667	-2.709945	0.0091
MA(1)	-0.980975	0.028286	-34.68014	0.0000

R-squared	0.691417	Mean dependent var	-0.046500
Adjusted R-squared	0.661745	S.D. dependent var	8.636699
S.E. of regression	5.023077	Akaike info criterion	6.163660
Sum squared resid	1312.028	Schwarz criterion	6.376809
Log likelihood	-172.7461	Hannan-Quinn criter.	6.246686
F-statistic	23.30239	Durbin-Watson stat	2.163745
Prob(F-statistic)	0.000000		

Inverted AR Roots	.89+.24i	.89-.24i	.65+.65i	.65-.65i
	.24+.89i	.24-.89i	-.24-.89i	-.24+.89i
	-.65+.65i	-.65+.65i	-.89-.24i	-.89+.24i
Inverted MA Roots	.98			

Utilizing the same calculation procedure, the price elasticity for the nonresidential usage category is -0.75. That is in between the elasticity estimates reported for the commercial and industrial sectors by Hussain, Thrikawala, and Barker (2002), -0.17 and -1.15, respectively. In addition, it is in line with a study that concludes that the price elasticity of water demand is higher for the industrial sector than for the residential sector (Arbués, García-Valiñas, and Villanúa, 2010).

Table 6. ARIMA LTF nonresidential per customer water usage

Dependent Variable: NRUSE
Method: Least Squares
Sample (adjusted): 2010M06 2014M12
Included observations: 55 after adjustments
Convergence achieved after 11 iterations
MA Backcast: 2010M02 2010M05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.067299	0.900612	3.405795	0.0013
PRICE	-39.14598	10.66549	-3.670341	0.0006
TCDD(-1)	0.062207	0.013504	4.606663	0.0000
NODR	-1.562528	0.362709	-4.307935	0.0001
UNEMP(-15)	-6.063227	2.406502	-2.519519	0.0151
AR(1)	-0.480628	0.143462	-3.350221	0.0016
MA(4)	-0.580557	0.109539	-5.299988	0.0000

R-squared	0.572459	Mean dependent var	0.318655
Adjusted R-squared	0.519016	S.D. dependent var	11.24641
S.E. of regression	7.799721	Akaike info criterion	7.064466
Sum squared resid	2920.111	Schwarz criterion	7.319945
Log likelihood	-187.2728	Hannan-Quinn criter.	7.163262
F-statistic	10.71164	Durbin-Watson stat	1.996908
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.48			
Inverted MA Roots	.87	-.00+.87i	-.00-.87i	-.87

It is important to test the price variable for endogeneity given that total water consumption is utilized to calculate average price and it is also used to compute the dependent variables, per customer usage in each category, in Tables 4, 5, and 6. The results obtained utilizing an artificial regression test for this purpose indicate that there is no feedback between water usage and contemporary values of average price (Davidson and MacKinnon, 1989). Some prior studies also report evidence that average water price variables are exogenous (Nieswiadomy, 1992; Nauges and Thomas, 2000; Mylopoulos, Mentes, and Theodossiou, 2004).

Regardless of the category analyzed, higher temperatures are associated with higher water usage with a one month lag. This is not surprising given that Phoenix water consumption exhibits a strong seasonal pattern and reaches peak levels during the summer months. An increase in the number of days in a month with rainfall negatively impacts water usage in the

same month. Several research papers document that water demand in other regions responds to weather conditions in ways similar to those described above (Jain, Varshney, and Joshi, 2001; Martinez-Espiñeira, 2002; Fullerton et al., 2013).

It is noteworthy that none of the variables related to rainfall turn out to be relevant for predicting multi-family residential water usage (Table 5). Multi-family water usage is somewhat less seasonal than the other categories shown in Figure 1. Water usage in this category cannot, however, be reliably linked to variations in rainfall.

Automatic irrigation systems are often used by multi-family complexes, which can preclude water savings during non-dry days. Also, outdoor water usage per apartment varies considerably from one complex to another, with some complexes having little or no vegetation coverage and limited outdoor water usage (Agthe and Billings, 2002). Total precipitation and the number of days when the temperature exceeds 90° Fahrenheit were not found to exert statistically significant impacts on any category of demand and, in consequence, are not included in the model.

The economic conditions index positively impacts single-family residential water usage with a lag of eleven months (Table 4). The coefficient indicates that a 1 percentage point increase in ECI is expected to increase per-customer water demand by 22.7 cubic feet within eleven months. The rental vacancy rate negatively impacts multi-family residential water usage, also with a lag of eleven months (Table 5).

That coefficient indicates that a 1 percentage point increase in RVR is expected to decrease water usage by 151 cubic feet within the same time frame. This result is in line with previous research which finds that the vacancy rate is a significant factor in apartment complex water use (Agthe and Billings, 2002). These results suggest that business cycle fluctuations

affect the intensity of water use by both classes of residential consumers (Bithas and Stoforos, 2006).

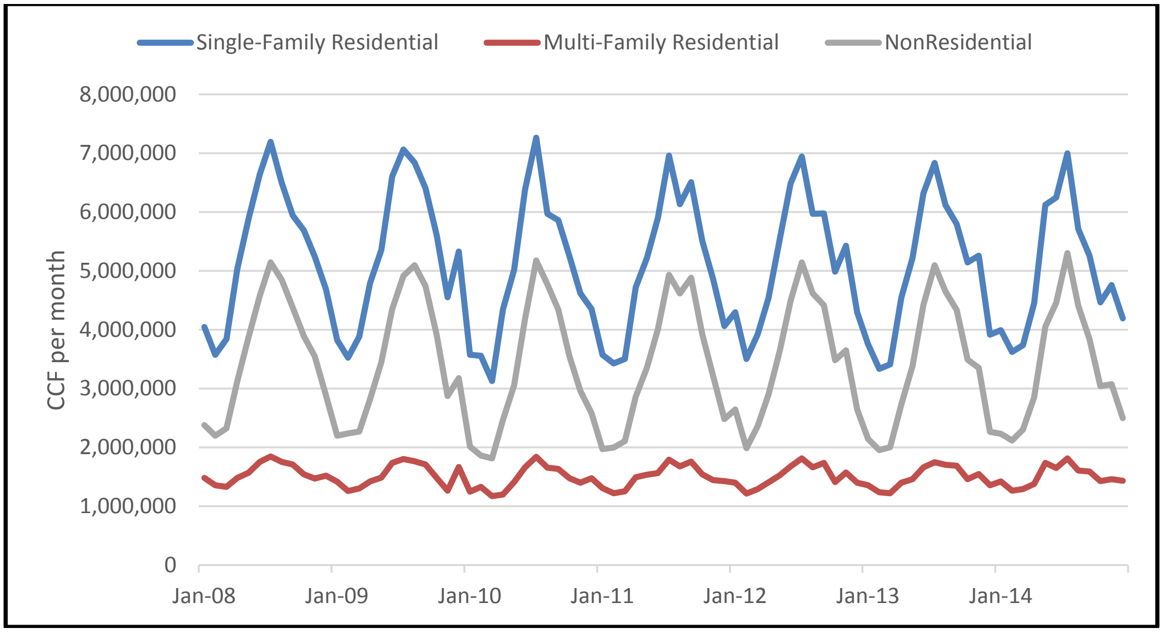

Figure 1. COP actual monthly water use by customer category

The unemployment rate negatively impacts nonresidential water usage with a lag of fifteen months (Table 6). The coefficient indicates that a 1 percentage point increase in UNEMP is expected to decrease water usage by 606 cubic feet within fifteen months. The size and timing of the economic impacts on water demand documented in Tables 4 through 6 are congruent with previous studies utilizing similar economic indicators for other regions (Fullerton, Tinajero, and Barraza de Anda, 2006; Fullerton, Tinajero, and Mendoza-Cota, 2007).

Tables 7, 8, and 9 show LTF ARIMA estimation results for the single-family residential, multi-family residential, and nonresidential customer base equations, respectively. In order to induce stationarity, the series corresponding to the customer base in each category are first differenced. In addition to first differencing, total nonfarm employment and multi-family housing starts are seasonally differenced.

With the exception of the parameter corresponding to total employment in the single-family regression, all other estimated slope coefficients associated with each of the explanatory variables satisfy the 5-percent significance criterion. All of the slope coefficients have the hypothesized arithmetic signs. In order to correct for residual serial correlation, ARMA terms are introduced in the single-family and multi-family customer equations.

Table 7. ARIMA LTF number of single-family residential customers

Dependent Variable: SFCUST
Method: Least Squares
Sample (adjusted): 2010M01 2014M12
Included observations: 60 after adjustments
Convergence achieved after 11 iterations
MA Backcast: 2009M12

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	46.19510	131.3079	0.351808	0.7263
TOTEMP(-11)	38.12193	20.04694	1.901633	0.0623
MA(1)	-0.511923	0.110963	-4.613450	0.0000

R-squared	0.173375	Mean dependent var	155.3667
Adjusted R-squared	0.144370	S.D. dependent var	1916.464
S.E. of regression	1772.734	Akaike info criterion	17.84714
Sum squared resid	1.79E+08	Schwarz criterion	17.95186
Log likelihood	-532.4142	Hannan-Quinn criter.	17.88810
F-statistic	5.977530	Durbin-Watson stat	1.876944
Prob(F-statistic)	0.004398		

Inverted MA Roots	.51

Table 8. ARIMA LTF number of multi-family residential customers

Dependent Variable: MFCUST
Method: Least Squares
Sample (adjusted): 2010M07 2014M12
Included observations: 54 after adjustments
Convergence achieved after 19 iterations
MA Backcast: 2010M05 2010M06

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12.89101	11.24420	1.146459	0.2571
MFHS(-15)	0.064271	0.022176	2.898233	0.0056
AR(2)	-0.549329	0.137597	-3.992288	0.0002
MA(2)	0.804975	0.134506	5.984684	0.0000

R-squared	0.322503	Mean dependent var	11.44444
Adjusted R-squared	0.281853	S.D. dependent var	84.05112

S.E. of regression	71.22791	Akaike info criterion	11.44083
Sum squared resid	253670.8	Schwarz criterion	11.58817
Log likelihood	-304.9025	Hannan-Quinn criter.	11.49765
F-statistic	7.933678	Durbin-Watson stat	2.115532
Prob(F-statistic)	0.000200		
Inverted AR Roots	-.00+.74i	-.00-.74i	
Inverted MA Roots	-.00+.90i	-.00-.90i	

Table 9. ARIMA LTF number of nonresidential customers

Dependent Variable: NRCUST
Method: Least Squares
Sample (adjusted): 2010M04 2014M12
Included observations: 57 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-20.23715	31.69315	-0.638534	0.5258
TOTEMP(-14)	7.926378	3.627461	2.185103	0.0332

R-squared	0.079878	Mean dependent var	4.473684
Adjusted R-squared	0.063148	S.D. dependent var	230.9376
S.E. of regression	223.5270	Akaike info criterion	13.69140
Sum squared resid	2748039.	Schwarz criterion	13.76309
Log likelihood	-388.2049	Hannan-Quinn criter.	13.71926
F-statistic	4.774677	Durbin-Watson stat	2.108623
Prob(F-statistic)	0.033159		

Total nonfarm employment positively impacts the number of single-family residential and nonresidential customers, with lags of eleven and fourteen months, respectively. That suggests that it takes around a year for changes in employment to affect the customer bases in those categories. The employment coefficient in Table 7 indicates that for every one thousand new nonfarm jobs, approximately 38 new single-family residential water customers are added to the system within 11 months.

Also, multi-family housing starts positively impact the number of multi-family residential customers. The coefficient in Table 8 indicates that for every one hundred new multi-family housing starts, approximately 6 new multi-family water customers are added to the system within fifteen months. Previous work documents similar time lags in the response of the customer base

to changes in economic conditions (Fullerton, Tinajero, and Barraza de Anda, 2006; Fullerton, Tinajero, and Mendoza-Cota, 2007).

Multiple sets of forecasts for each category of per customer water usage and the customer base are generated for the January 2012 – December 2014 period. Tables 10 through 15 report root-mean squared errors, Theil inequality coefficients, and second moment decompositions for each forecasted variable. The tables include comparative forecast accuracy results for the LTF, RW, and RWD models at each step length. Figures shown in bold highlight the most accurate forecasts.

Table 10 presents descriptive accuracy results for the single-family residential per customer water usage forecasts. The LTF forecasts have the smallest RMSE for seven out of the twelve forecast periods. However, the RW has the smallest RMSE for five forecast periods. On one hand, this implies that the LTF forecasts outperform the benchmarks over the majority of step-lengths considered.

On the other hand, this implies that RW extrapolations are fairly competitive with LTF forecasts, especially for six- to twelve-month-ahead forecasts. Conclusions regarding relative forecast accuracy are the same for the U-statistics as for the RMSE with one exception, the RW forecast nine months ahead. This discrepancy is due to higher forecasts values for the RW benchmark relative to the LTF at this particular step-length.

The second moment decompositions for the LTF forecast errors in Table 10 exhibit good characteristics. The bias and variance proportions of the U-statistic are low for each set of the forecast step-lengths. Consequently, the covariance proportion remains above the seventy five percent mark for all step-lengths considered. The LTF out-of-sample forecasts provide good approximations of the systematic movements in single-family residential demand.

Table 11 presents the descriptive accuracy results for the multi-family residential per customer water usage forecasts. The LTF has the smallest RMSE for eleven out of the twelve forecast periods. The RW has the smallest RMSE only for forecasts of eleven months ahead. This implies that the LTF forecast are superior to the benchmarks across almost all step-lengths. The U-statistics follow similar patterns.

Again, the LTF second moment decompositions exhibit good characteristics. The bias and variance proportions of the U-statistic are low for each set of the forecast step-lengths. The covariance proportion remains above the ninety percent mark for all step-lengths. The LTF out-of-sample forecasts apparently provide good approximations of the systematic movements in the multi-family residential category, also.

Table 12 reports descriptive accuracy results for the nonresidential per customer water usage forecasts. The LTF has the smallest RMSE and U-statistics across all forecast step-lengths. This implies that the LTF forecasts are superior to the benchmarks across all forecast periods. The second moment decompositions of the LTF exhibit good characteristics. The bias and variance proportions of the U-statistic are low for each set of the forecast step-lengths. Consequently, the covariance proportion remains above the sixty percent mark for all the periods considered. The LTF out-of-sample forecasts also provide good approximations of the systematic movements in this category.

The results for the single-family residential customer base forecasts are summarized in Table 13, and indicate that the RWD forecasts outperform those of the LTF and RW at all step lengths. The U-statistics indicate, however, that the LTF, RW, and RWD forecasts are very close to one another, in terms of accuracy, for each of the twelve step lengths. The covariance proportion decreases as the step-length increases for the LTF and RW. Also, the bias proportion

increases rapidly for the LTF and RW forecast errors as the horizon increases and, after six months, it accounts for more than half of the out-of-sample errors. Thus, the errors in the LTF and RW forecasts are not primarily random in nature and the systematic movements in the number of single-family residential customers are only partially replicated by either approach.

On balance, the prediction errors for the RWD single-family customer forecasts are more random in nature than those of the alternatives. This, combined with the smaller average size of the RWD errors as measured by RMSE, indicates the LTF model, in its current form, is relatively unsuccessful at predicting the number of single-family residential customers (Pindyck and Rubinfield, 1998). The strong performance of the RWD model in comparison to the LTF and RW models implies that previous trends in the number of single-family residential customers serve as relatively reliable indicators of subsequent movements in this category of the customer base in Phoenix.

Table 14 summarizes the results for the multi-family residential customer base forecasts. It indicates that the LTF outperforms the benchmarks at all step lengths. The U-statistics indicate the covariance proportions for the LTF forecasts decrease as the step-length increases. At the same time, the variance proportion increases rapidly for the LTF forecast errors as the horizon increases and, after eight months, it accounts for more than half of the out-of-sample errors. The large variance proportion indicates that deviation between the actual and predicted variability of the series constitutes a disproportionate share of the forecast errors. While the LTF predictions are more accurate, overall, than the alternatives, the existence of discernible patterns in the forecast error series suggests that the LTF model would benefit from further refinement.

Table 15 shows the results for the nonresidential customer base forecasts. Those results indicate that the LTF outperforms the benchmarks for the last six step lengths. However, the

RW outperforms both the LTF and RWD across the first six step lengths. The second moment decompositions of the LTF and RW exhibit good characteristics. The bias and variance proportions of the U-statistic are low for each set of the forecast step-lengths. The covariance proportions for LTF and RW remain above the eighty and seventy percent marks, respectively, for all the periods considered.

Table 10. RMSE, *U*-statistics, and proportions of inequality – single-family residential per customer water usage

Horizon	Forecast Name	RMSE	U-Stat	U-bias	U-var	U-cov
	LTF	**0.95431**	**0.03308**	0.00281	0.02889	0.96830
One Month Ahead	RW	1.11108	0.03821	0.03198	0.01447	0.95356
	RWD	1.14846	0.03950	0.02681	0.01462	0.95857
	LTF	**0.88172**	**0.03039**	0.00004	0.03551	0.96445
Two Months Ahead	RW	1.07620	0.03680	0.05873	0.00494	0.93633
	RWD	1.11651	0.03819	0.04993	0.00539	0.94468
	LTF	**0.93458**	**0.03194**	0.00003	0.08310	0.91688
Three Months Ahead	RW	1.09172	0.03704	0.06208	0.00324	0.93468
	RWD	1.13249	0.03843	0.05329	0.00357	0.94314
	LTF	**1.04551**	**0.03546**	0.00024	0.13555	0.86421
Four Months Ahead	RW	1.09263	0.03680	0.08176	0.00009	0.91815
	RWD	1.13694	0.03831	0.06910	0.00034	0.93056
	LTF	**1.04731**	**0.03539**	0.00001	0.20800	0.79199
Five Months Ahead	RW	1.10379	0.03705	0.07495	0.00020	0.92485
	RWD	1.14793	0.03855	0.06223	0.00056	0.93722
	LTF	1.15491	0.03912	0.00058	0.22588	0.77353
Six Months Ahead	RW	**1.11301**	**0.03740**	0.09146	0.00048	0.90806
	RWD	1.15905	0.03896	0.07570	0.00096	0.92334
	LTF	1.10707	0.03790	0.00328	0.23159	0.76513
Seven Months Ahead	RW	**1.09761**	**0.03713**	0.13144	0.00666	0.86190
	RWD	1.14020	0.03859	0.11327	0.00829	0.87844
	LTF	1.11995	0.03904	0.01738	0.16814	0.81448
Eight Months Ahead	RW	**1.11545**	**0.03826**	0.13066	0.00910	0.86025
	RWD	1.15934	0.03978	0.11415	0.01192	0.87393
	LTF	**1.11400**	0.03917	0.02679	0.12277	0.85044
Nine Months Ahead	RW	1.12817	**0.03898**	0.12183	0.00791	0.87027
	RWD	1.17262	0.04053	0.10558	0.01045	0.88397
	LTF	**1.05421**	**0.03752**	0.06441	0.03426	0.90134
Ten Months Ahead	RW	1.09433	0.03818	0.09712	0.00107	0.90181
	RWD	1.13315	0.03956	0.08106	0.00176	0.91718
	LTF	1.07447	0.03834	0.09626	0.01377	0.88996
Eleven Months Ahead	RW	**1.06778**	**0.03732**	0.07431	0.00037	0.92532
	RWD	1.10640	0.03869	0.05964	0.00080	0.93956
	LTF	1.08130	0.03870	0.08905	0.01045	0.90050
Twelve Months Ahead	RW	**1.05096**	**0.03676**	0.11716	0.00115	0.88170
	RWD	1.09368	0.03828	0.09465	0.00183	0.90352

Table 11. RMSE, *U*-statistics, and proportions of inequality – multi-family residential per customer water usage

Horizon	Forecast Name	RMSE	U-Stat	U-bias	U-var	U-cov
One Month Ahead	LTF	**4.67688**	**0.02437**	0.01465	0.00381	0.98155
	RW	5.08617	0.02646	0.02888	0.01340	0.95772
	RWD	5.24268	0.02727	0.02774	0.01528	0.95698
Two Months Ahead	LTF	**4.68101**	**0.02433**	0.02293	0.00196	0.97511
	RW	5.06062	0.02626	0.04371	0.00778	0.94851
	RWD	5.23391	0.02715	0.04074	0.00982	0.94943
Three Months Ahead	LTF	**4.74143**	**0.02453**	0.01946	0.00450	0.97604
	RW	5.13396	0.02650	0.04395	0.00734	0.94871
	RWD	5.31022	0.02741	0.04237	0.00834	0.94930
Four Months Ahead	LTF	**4.83341**	**0.02490**	0.02018	0.00466	0.97516
	RW	5.19459	0.02670	0.05171	0.00353	0.94477
	RWD	5.37903	0.02764	0.04863	0.00484	0.94653
Five Months Ahead	LTF	**4.89436**	**0.02516**	0.02075	0.00500	0.97424
	RW	5.18254	0.02660	0.04059	0.00494	0.95447
	RWD	5.32068	0.02731	0.03566	0.00667	0.95768
Six Months Ahead	LTF	**4.96592**	**0.02554**	0.01818	0.00522	0.97660
	RW	5.26465	0.02703	0.04063	0.00499	0.95438
	RWD	5.40184	0.02774	0.03426	0.00667	0.95907
Seven Months Ahead	LTF	**5.01808**	**0.02590**	0.02110	0.00686	0.97204
	RW	5.18469	0.02668	0.06667	0.01177	0.92156
	RWD	5.30309	0.02729	0.05948	0.01440	0.92612
Eight Months Ahead	LTF	**5.05154**	**0.02629**	0.01518	0.00169	0.98313
	RW	5.27191	0.02732	0.07128	0.01939	0.90932
	RWD	5.39023	0.02794	0.06499	0.02390	0.91112
Nine Months Ahead	LTF	**5.12566**	**0.02678**	0.01886	0.00256	0.97859
	RW	5.35437	0.02787	0.06772	0.01947	0.91281
	RWD	5.47368	0.02849	0.06126	0.02380	0.91494
Ten Months Ahead	LTF	**5.20025**	**0.02733**	0.02317	0.00514	0.97170
	RW	5.39171	0.02826	0.05711	0.01303	0.92986
	RWD	5.48950	0.02878	0.04929	0.01450	0.93621
Eleven Months Ahead	LTF	5.24163	0.02751	0.01811	0.00513	0.97677
	RW	**5.20868**	**0.02729**	0.03650	0.01486	0.94864
	RWD	5.29885	0.02778	0.02975	0.01634	0.95391
Twelve Months Ahead	LTF	**4.91467**	**0.02580**	0.05607	0.00735	0.93658
	RW	5.05266	0.02649	0.07274	0.02038	0.90688
	RWD	5.15904	0.02706	0.06079	0.02210	0.91710

Table 12. RMSE, *U*-statistics, and proportions of inequality – nonresidential per customer water usage

Horizon	Forecast Name	RMSE	U-Stat	U-bias	U-var	U-cov
	LTF	**7.43274**	**0.03564**	0.00088	0.04481	0.95431
One Month Ahead	RW	9.41401	0.04513	0.00005	0.00775	0.99221
	RWD	9.78116	0.04688	0.00010	0.00834	0.99156
	LTF	**7.67355**	**0.03647**	0.00064	0.08330	0.91606
Two Months Ahead	RW	8.92541	0.04245	0.00512	0.00062	0.99426
	RWD	9.31752	0.04430	0.00528	0.00094	0.99378
	LTF	**7.48299**	**0.03514**	0.00129	0.21709	0.78162
Three Months Ahead	RW	9.05563	0.04264	0.00517	0.00056	0.99428
	RWD	9.45323	0.04450	0.00523	0.00093	0.99384
	LTF	**8.61158**	**0.04002**	0.00102	0.30204	0.69694
Four Months Ahead	RW	9.09660	0.04243	0.00980	0.00012	0.99008
	RWD	9.51959	0.04440	0.00922	0.00000	0.99078
	LTF	**8.57893**	**0.03968**	0.00000	0.33750	0.66250
Five Months Ahead	RW	9.23584	0.04283	0.01082	0.00024	0.98894
	RWD	9.66711	0.04483	0.00966	0.00000	0.99034
	LTF	**8.46245**	**0.03920**	0.00277	0.36247	0.63476
Six Months Ahead	RW	9.25807	0.04287	0.01871	0.00028	0.98101
	RWD	9.72047	0.04501	0.01610	0.00001	0.98389
	LTF	**8.19253**	**0.03838**	0.01301	0.32197	0.66502
Seven Months Ahead	RW	9.05092	0.04215	0.03865	0.00053	0.96081
	RWD	9.51601	0.04431	0.03422	0.00133	0.96445
	LTF	**8.00665**	**0.03830**	0.03108	0.25585	0.71307
Eight Months Ahead	RW	9.14971	0.04330	0.04918	0.00471	0.94611
	RWD	9.61178	0.04548	0.04470	0.00704	0.94826
	LTF	**7.82408**	**0.03796**	0.04348	0.20648	0.75004
Nine Months Ahead	RW	9.30580	0.04458	0.04801	0.00517	0.94682
	RWD	9.77808	0.04683	0.04408	0.00789	0.94803
	LTF	**7.47226**	**0.03678**	0.08077	0.14511	0.77412
Ten Months Ahead	RW	8.84238	0.04298	0.02721	0.00016	0.97263
	RWD	9.23841	0.04490	0.02342	0.00000	0.97658
	LTF	**7.48120**	**0.03691**	0.11578	0.10657	0.77765
Eleven Months Ahead	RW	8.54676	0.04165	0.01248	0.00130	0.98621
	RWD	8.91704	0.04346	0.00965	0.00058	0.98977
	LTF	**7.60022**	**0.03752**	0.08429	0.09123	0.82448
Twelve Months Ahead	RW	8.38988	0.04087	0.03051	0.00097	0.96852
	RWD	8.81249	0.04294	0.02381	0.00034	0.97585

Table 13. RMSE, *U*-statistics, and proportions of inequality – number of single-family residential customers

Horizon	Forecast Name	RMSE	U-Stat	U-bias	U-var	U-cov
	LTF	848.03437	0.00119	0.21404	0.01713	0.76883
One Month Ahead	RW	664.67490	0.00093	0.20614	0.00143	0.79243
	RWD	**626.07170**	**0.00088**	0.00031	0.00029	0.99940
	LTF	1085.46417	0.00152	0.26149	0.05061	0.68789
Two Months Ahead	RW	1020.36862	0.00143	0.29734	0.02202	0.68064
	RWD	**907.00890**	**0.00127**	0.00195	0.01156	0.98650
	LTF	1217.11519	0.00171	0.31488	0.07639	0.60873
Three Months Ahead	RW	1199.06282	0.00168	0.39987	0.04718	0.55294
	RWD	**957.89154**	**0.00134**	0.02854	0.04320	0.92826
	LTF	1341.00579	0.00188	0.37048	0.08979	0.53973
Four Months Ahead	RW	1347.27328	0.00189	0.50080	0.06723	0.43197
	RWD	**950.05372**	**0.00133**	0.10534	0.09467	0.79998
	LTF	1474.33685	0.00207	0.42825	0.08469	0.48706
Five Months Ahead	RW	1567.18682	0.00220	0.57183	0.07119	0.35698
	RWD	**1066.57672**	**0.00149**	0.15564	0.12584	0.71852
	LTF	1635.37325	0.00229	0.47767	0.08053	0.44181
Six Months Ahead	RW	1848.12756	0.00259	0.61376	0.06884	0.31741
	RWD	**1266.04988**	**0.00177**	0.15947	0.13954	0.70099
	LTF	1783.18046	0.00250	0.52539	0.07718	0.39743
Seven Months Ahead	RW	2106.67551	0.00295	0.65070	0.06990	0.27940
	RWD	**1445.99083**	**0.00202**	0.18347	0.16597	0.65056
	LTF	1975.60002	0.00277	0.57677	0.08702	0.33621
Eight Months Ahead	RW	2385.87864	0.00335	0.68346	0.07887	0.23767
	RWD	**1655.45042**	**0.00231**	0.18650	0.20639	0.60711
	LTF	2179.69221	0.00305	0.64741	0.11119	0.24140
Nine Months Ahead	RW	2657.76339	0.00373	0.73370	0.09591	0.17040
	RWD	**1701.12625**	**0.00237**	0.21782	0.32830	0.45388
	LTF	2381.52008	0.00334	0.69494	0.10378	0.20128
Ten Months Ahead	RW	2946.67663	0.00413	0.77177	0.08777	0.14046
	RWD	**1798.84849**	**0.00251**	0.21257	0.35206	0.43538
	LTF	2611.54566	0.00366	0.73462	0.10403	0.16135
Eleven Months Ahead	RW	3268.26610	0.00458	0.80232	0.08361	0.11407
	RWD	**1907.11349**	**0.00266**	0.18451	0.36812	0.44737
	LTF	2813.75963	0.00394	0.76268	0.09548	0.14184
Twelve Months Ahead	RW	3550.58210	0.00498	0.82899	0.07634	0.09467
	RWD	**1986.83568**	**0.00277**	0.19156	0.40103	0.40740

Table 14. RMSE, *U*-statistics, and proportions of inequality – number of multi-family residential customers

Horizon	Forecast Name	RMSE	U-Stat	U-bias	U-var	U-cov
	LTF	**50.14586**	**0.00159**	0.01341	0.02866	0.95793
One Month Ahead	RW	54.81788	0.00174	0.11253	0.03874	0.84873
	RWD	52.93009	0.00168	0.01312	0.00029	0.98659
	LTF	**75.06084**	**0.00238**	0.01887	0.04118	0.93994
Two Months Ahead	RW	84.08839	0.00267	0.15966	0.04061	0.79972
	RWD	82.78898	0.00262	0.01473	0.00065	0.98462
	LTF	**91.02024**	**0.00288**	0.01411	0.05814	0.92775
Three Months Ahead	RW	102.61421	0.00325	0.21005	0.04605	0.74390
	RWD	100.41363	0.00318	0.01650	0.00395	0.97956
	LTF	**108.61432**	**0.00344**	0.01150	0.06769	0.92081
Four Months Ahead	RW	122.64435	0.00389	0.25406	0.04991	0.69603
	RWD	119.21000	0.00377	0.02378	0.00594	0.97028
	LTF	**117.79217**	**0.00373**	0.01402	0.08552	0.90047
Five Months Ahead	RW	142.31413	0.00451	0.31255	0.06761	0.61984
	RWD	136.25250	0.00431	0.04434	0.00152	0.95414
	LTF	**122.13288**	**0.00386**	0.02321	0.16153	0.81526
Six Months Ahead	RW	160.65240	0.00509	0.37187	0.10438	0.52375
	RWD	147.38205	0.00467	0.07763	0.00151	0.92086
	LTF	**128.89778**	**0.00408**	0.03898	0.30673	0.65429
Seven Months Ahead	RW	176.54055	0.00560	0.44198	0.16780	0.39022
	RWD	153.38576	0.00486	0.13394	0.02753	0.83853
	LTF	**133.90884**	**0.00423**	0.05772	0.43282	0.50946
Eight Months Ahead	RW	190.62583	0.00605	0.51365	0.21692	0.26943
	RWD	156.29391	0.00495	0.20857	0.06685	0.72457
	LTF	**137.17853**	**0.00434**	0.07488	0.57724	0.34788
Nine Months Ahead	RW	205.65036	0.00653	0.57122	0.26882	0.15996
	RWD	163.36636	0.00517	0.28635	0.12991	0.58374
	LTF	**148.21220**	**0.00468**	0.07950	0.66722	0.25327
Ten Months Ahead	RW	225.66954	0.00716	0.59501	0.35541	0.04958
	RWD	179.82777	0.00569	0.34173	0.26470	0.39357
	LTF	**151.95790**	**0.00480**	0.08047	0.67205	0.24749
Eleven Months Ahead	RW	235.27455	0.00747	0.62215	0.34362	0.03423
	RWD	190.75545	0.00604	0.34536	0.22808	0.42655
	LTF	**144.57073**	**0.00456**	0.08530	0.69336	0.22134
Twelve Months Ahead	RW	241.00440	0.00765	0.67170	0.31234	0.01596
	RWD	188.99926	0.00598	0.37930	0.18182	0.43887

Table 15. RMSE, *U*-statistics, and proportions of inequality – number of nonresidential customers

Horizon	Forecast Name	RMSE	U-Stat	U-bias	U-var	U-cov
	LTF	126.96031	0.00187	0.01271	0.00238	0.98491
One Month Ahead	RW	**125.67164**	**0.00185**	0.00193	0.00017	0.99789
	RWD	129.21187	0.00190	0.00466	0.03664	0.95870
	LTF	171.58285	0.00253	0.00911	0.00001	0.99088
Two Months Ahead	RW	**168.74943**	**0.00249**	0.00028	0.00267	0.99705
	RWD	178.25185	0.00263	0.00019	0.04854	0.95127
	LTF	192.40911	0.00283	0.00151	0.01078	0.98771
Three Months Ahead	RW	**189.77905**	**0.00279**	0.01319	0.02387	0.96294
	RWD	208.44247	0.00307	0.00696	0.04264	0.95040
	LTF	215.50918	0.00317	0.00000	0.02555	0.97445
Four Months Ahead	RW	**210.75801**	**0.00310**	0.03478	0.05017	0.91506
	RWD	230.47535	0.00339	0.03070	0.03634	0.93295
	LTF	241.52398	0.00356	0.00005	0.02911	0.97084
Five Months Ahead	RW	**235.21426**	**0.00346**	0.05018	0.06149	0.88833
	RWD	259.24726	0.00382	0.05681	0.03860	0.90460
	LTF	255.40638	0.00376	0.00003	0.03636	0.96361
Six Months Ahead	RW	**254.92826**	**0.00375**	0.06045	0.06397	0.87558
	RWD	285.80974	0.00421	0.08186	0.04942	0.86872
	LTF	**263.78191**	**0.00389**	0.00084	0.03067	0.96849
Seven Months Ahead	RW	264.31042	0.00389	0.09085	0.06544	0.84371
	RWD	302.27638	0.00445	0.14332	0.05645	0.80024
	LTF	**274.54582**	**0.00405**	0.00046	0.03605	0.96349
Eight Months Ahead	RW	284.06586	0.00418	0.09380	0.06648	0.83972
	RWD	330.71420	0.00486	0.17625	0.05729	0.76646
	LTF	**275.68780**	**0.00406**	0.00195	0.05988	0.93817
Nine Months Ahead	RW	297.55414	0.00438	0.11513	0.07900	0.80587
	RWD	352.71330	0.00518	0.24655	0.04253	0.71093
	LTF	**284.57412**	**0.00419**	0.00323	0.08461	0.91217
Ten Months Ahead	RW	315.38008	0.00464	0.12998	0.08390	0.78612
	RWD	392.05996	0.00576	0.28859	0.03398	0.67743
	LTF	**290.15931**	**0.00428**	0.00635	0.12017	0.87348
Eleven Months Ahead	RW	332.94005	0.00490	0.15391	0.09148	0.75461
	RWD	442.30270	0.00650	0.32217	0.02606	0.65177
	LTF	**304.07796**	**0.00448**	0.00727	0.14222	0.85051
Twelve Months Ahead	RW	353.06606	0.00519	0.17392	0.10175	0.72434
	RWD	499.21186	0.00733	0.34892	0.01621	0.63487

In order to formally test whether the difference between forecast errors from two models is statistically significant, an error differential equation is utilized (Ashley, Granger, and Schmalensee, 1980). This test can only be used to compare two sets of forecasts at a time. Therefore, the LTF forecasts are compared sequentially against RW and RWD benchmarks. The RW-LTF and RWD-LTF results are presented side-by-side for each of the six equations analyzed. Rejection of the null hypothesis implies that the LTF model represents a significant improvement over the benchmark forecast.

Tables 16, 17, and 18 summarize results for the single-family residential, multi-family-residential, and nonresidential per customer water usage, respectively. With one exception, those results do not indicate that the difference between the LTF and either benchmark is statistically significant. The lone exception is the one month ahead nonresidential LTF forecast, which represents a statistically significant improvement over the corresponding RWD forecast. Failure to reject the null hypothesis of prediction error equality for the large majority of per-customer demand forecasts indicates that the differences in accuracy documented in Tables 10 through 12 are relatively insignificant.

Tables 19, 20, and 21 show the results for the single-family residential, multi-family residential, and nonresidential customer base. Regarding the number of single-family residential customers (Table 19), the LTF represents a significant improvement over the RW for the last seven step-lengths and also outperforms the eight-month-ahead RWD forecast by a statistically significant margin.

With regard to the number of multi-family residential customers (Table 20), the LTF represents a significant improvement over the RW across all step-lengths and the margin of improvement over the RWD is statistically significant for the last seven step-lengths. For the

number of nonresidential customers (Table 21), the null hypothesis is rejected in the case of both the RW and the RWD forecasts for the last eight step-lengths.

Table 16. Error differential regression test results – single-family residential per customer water usage

Horizon	Benchmark Forecast	Benchmark Error Mean	*t*-Statistic (H$_0$: β_1=0)	*t*-Statistic (H$_0$: β_2=0)	*F*-Statistic (H$_0$: β_1=β_2=0)	Conclusion
One	RW	Positive	0.4914	0.9336	0.5565	-
Month	RWD	Positive	0.4507	1.1710	0.7942	-
Two	RW	Positive	1.4493	1.0868	1.6407	-
Months	RWD	Positive	1.3622	1.3578	1.8495	-
Three	RW	Positive	1.4593	0.7858	1.3735	-
Months	RWD	Positive	1.3663	1.0466	1.4809	-
Four	RW	Positive	1.5461	0.0101	1.1952	-
Months	RWD	Positive	1.4281	0.3032	1.0657	-
Five	RW	Positive	0.8993	0.0852	0.4080	-
Months	RWD	Positive	0.8394	0.3689	0.4203	-
Six	RW	Positive	0.8529	-0.5519	0.5160	-
Months	RWD	Positive	0.7851	-0.2291	0.3344	-
Seven	RW	Positive	0.9104	-0.5656	0.5743	-
Months	RWD	Positive	0.8493	-0.2087	0.3825	-
Eight	RW	Positive	0.6674	-0.4964	0.3459	-
Months	RWD	Positive	0.6219	-0.1279	0.2016	-
Nine	RW	Positive	0.5433	-0.2758	0.1856	-
Months	RWD	Positive	0.5004	0.0633	0.1272	-
Ten	RW	Positive	0.1928	0.1384	0.0282	-
Months	RWD	Positive	0.1427	0.4380	0.1061	-
Eleven	RW	Positive	-0.1080	0.0427	0.0067	-
Months	RWD	Positive	-0.1591	0.3562	0.0761	-
Twelve	RW	Positive	0.0926	-0.3672	0.0717	-
Months	RWD	Positive	0.0337	0.0698	0.0030	-

The null hypothesis tested is that of mean squared error equality.
Rejection of the null hypothesis indicates that the LTF forecasts are most accurate.

Table 17. Error differential regression test results – multi-family residential per customer water usage

Horizon	Benchmark Forecast	Benchmark Error Mean	*t*-Statistic (H_0: β_1=0)	*t*-Statistic (H_0: β_2=0)	*F*-Statistic (H_0: β_1=β_2=0)	Conclusion
One	RW	Positive	0.4920	0.6552	0.3357	-
Month	RWD	Positive	0.4730	0.8800	0.4990	-
Two	RW	Positive	0.5618	0.5579	0.3135	-
Months	RWD	Positive	0.5212	0.8142	0.4673	-
Three	RW	Positive	0.6543	0.5513	0.3660	-
Months	RWD	Positive	0.6360	0.8018	0.5237	-
Four	RW	Positive	0.7600	0.4529	0.3914	-
Months	RWD	Positive	0.7147	0.7175	0.5128	-
Five	RW	Positive	0.5196	0.3826	0.2082	-
Months	RWD	Positive	0.4324	0.5948	0.2704	-
Six	RW	Positive	0.5826	0.3763	0.2406	-
Months	RWD	Positive	0.4615	0.5852	0.2777	-
Seven	RW	Positive	0.9363	0.0720	0.4409	-
Months	RWD	Positive	0.8118	0.2751	0.3674	-
Eight	RW	Positive	1.2120	0.1104	0.7406	-
Months	RWD	Positive	1.0868	0.3075	0.6379	-
Nine	RW	Positive	1.0373	0.1479	0.5489	-
Months	RWD	Positive	0.9173	0.3404	0.4786	-
Ten	RW	Positive	0.7526	0.1531	0.2949	-
Months	RWD	Positive	0.6107	0.3230	0.2387	-
Eleven	RW	Positive	0.4412	-0.1298	0.1058	-
Months	RWD	Positive	0.2993	0.0386	0.0455	-
Twelve	RW	Positive	0.2937	0.1419	0.0532	-
Months	RWD	Positive	0.1512	0.3355	0.0677	-

The null hypothesis tested is that of mean squared error equality.
Rejection of the null hypothesis indicates that the LTF forecasts are most accurate.

Table 18. Error differential regression test results – nonresidential per customer water usage

Horizon	Benchmark Forecast	Benchmark Error Mean	t-Statistic (H$_0$: β_1=0)	t-Statistic (H$_0$: β_2=0)	F-Statistic (H$_0$: β_1=β_2=0)	Conclusion
One	RW	Positive	-0.0676	1.4918	1.1150	-
Month	RWD	Positive	-0.0517	1.7376	1.5109	Reject
Two	RW	Positive	0.2505	0.8828	0.4210	-
Months	RWD	Positive	0.2674	1.1400	0.6856	-
Three	RW	Positive	0.2079	1.0938	0.6198	-
Months	RWD	Positive	0.2225	1.3476	0.9327	-
Four	RW	Positive	0.3272	0.2917	0.0961	-
Months	RWD	Positive	0.3270	0.5570	0.2086	-
Five	RW	Positive	0.3647	0.3911	0.1430	-
Months	RWD	Positive	0.3543	0.6550	0.2773	-
Six	RW	Positive	0.3075	0.4692	0.1573	-
Months	RWD	Positive	0.2904	0.7537	0.3262	-
Seven	RW	Positive	0.3046	0.5302	0.1869	-
Months	RWD	Positive	0.2933	0.8434	0.3987	-
Eight	RW	Positive	0.2157	0.8112	0.3523	-
Months	RWD	Positive	0.2139	1.1389	0.6714	-
Nine	RW	Positive	0.1421	1.0887	0.6027	-
Months	RWD	Positive	0.1455	1.4042	0.9965	-
Ten	RW	Positive	-0.2422	1.2120	0.7638	-
Months	RWD	Positive	-0.2565	1.4807	1.1291	-
Eleven	RW	Positive	-0.5787	1.1412	0.8187	-
Months	RWD	Positive	-0.6020	1.3997	1.1608	-
Twelve	RW	Positive	-0.2592	0.7632	0.3248	-
Months	RWD	Positive	-0.2916	1.0768	0.6223	-

The null hypothesis tested is that of mean squared error equality.
Rejection of the null hypothesis indicates that the LTF forecasts are most accurate.

Table 19. Error differential regression test results – number of single-family residential customers

Horizon	Benchmark Forecast	Benchmark Error Mean	t-Statistic (H_0: β_1=0)	t-Statistic (H_0: β_2=0)	F-Statistic (H_0: β_1=β_2=0)	Conclusion
One	RW	Negative	1.6656	-3.0220	5.9534	-
Month	RWD	Negative	5.5780	-1.9240	17.4077	-
Two	RW	Negative	-0.0211	-1.2531	0.7854	-
Months	RWD	Positive	-1.6791	-0.3089	1.4573	-
Three	RW	Negative	-1.1836	-1.2571	1.4906	-
Months	RWD	Positive	-1.5892	-0.6617	1.4817	-
Four	RW	Negative	-2.5339	-2.0937	5.4021	-
Months	RWD	Positive	-1.5736	-1.8134	2.8823	-
Five	RW	Negative	-4.4915	-1.8358	11.7720	-
Months	RWD	Positive	-1.5212	-1.3893	2.1222	-
Six	RW	Negative	-5.9639	-0.6309	17.9831	Reject
Months	RWD	Positive	-1.4956	-0.1829	1.1351	-
Seven	RW	Negative	-7.7683	0.3193	30.2242	Reject
Months	RWD	Positive	-1.4667	0.6461	1.2843	-
Eight	RW	Negative	-9.7604	1.1857	48.3354	Reject
Months	RWD	Positive	-1.5987	1.8822	3.0493	Reject
Nine	RW	Negative	-10.8662	1.6127	60.3375	Reject
Months	RWD	Positive	-1.8985	1.7654	3.3606	-
Ten	RW	Negative	-13.6457	2.0960	95.2986	Reject
Months	RWD	Positive	-2.2365	2.2889	5.1204	-
Eleven	RW	Negative	-15.3989	2.4158	121.4810	Reject
Months	RWD	Positive	-2.7009	2.9231	7.9195	-
Twelve	RW	Negative	-13.6568	1.7262	94.7445	Reject
Months	RWD	Positive	-2.8681	2.7773	7.9697	-

The null hypothesis tested is that of mean squared error equality.
Rejection of the null hypothesis indicates that the LTF forecasts are most accurate.

Table 20. Error differential regression test results – number of multi-family residential customers

Horizon	Benchmark Forecast	Benchmark Error Mean	t-Statistic (H_0: β_1=0)	t-Statistic (H_0: β_2=0)	F-Statistic (H_0: β_1=β_2=0)	Conclusion
One	RW	Negative	-2.3292	0.3570	2.7762	Reject
Month	RWD	Negative	-0.0457	0.5225	0.1375	-
Two	RW	Negative	-3.6243	0.4388	6.6640	Reject
Months	RWD	Negative	0.0348	1.0727	0.5760	-
Three	RW	Negative	-5.8314	0.1357	17.0117	Reject
Months	RWD	Negative	-0.2357	1.0783	0.6091	-
Four	RW	Negative	-8.7799	-0.3651	38.6102	Reject
Months	RWD	Negative	-0.6866	1.0287	0.7648	-
Five	RW	Negative	-10.7364	0.1707	57.6498	Reject
Months	RWD	Negative	-1.3872	1.5708	2.1958	-
Six	RW	Negative	-13.8280	1.1621	96.2822	Reject
Months	RWD	Negative	-1.8902	1.8089	3.4225	Reject
Seven	RW	Negative	-16.3684	0.9891	134.4511	Reject
Months	RWD	Negative	-2.3880	1.3180	3.7199	Reject
Eight	RW	Negative	-15.5926	0.4447	121.6634	Reject
Months	RWD	Negative	-2.8430	0.6812	4.2734	Reject
Nine	RW	Negative	-18.8214	0.4374	177.2172	Reject
Months	RWD	Negative	-3.3123	0.4202	5.5738	Reject
Ten	RW	Negative	-20.8729	0.2247	217.8635	Reject
Months	RWD	Negative	-4.4996	0.2713	10.1602	Reject
Eleven	RW	Negative	-20.4770	-0.1584	209.6671	Reject
Months	RWD	Negative	-4.3282	0.5603	9.5235	Reject
Twelve	RW	Negative	-22.1733	-0.0254	245.8289	Reject
Months	RWD	Negative	-4.1828	0.6279	8.9451	Reject

The null hypothesis tested is that of mean squared error equality.
Rejection of the null hypothesis indicates that the LTF forecasts are most accurate.

Table 21. Error differential regression test results – number of nonresidential customers

Horizon	Benchmark Forecast	Benchmark Error Mean	t-Statistic (H_0: β_1=0)	t-Statistic (H_0: β_2=0)	F-Statistic (H_0: β_1=β_2=0)	Conclusion
One	RW	Negative	1.2673	-0.0877	0.8068	-
Month	RWD	Negative	0.7307	0.3726	0.3364	-
Two	RW	Positive	-0.2322	-0.2304	0.0535	-
Months	RWD	Negative	1.2627	0.6864	1.0327	-
Three	RW	Positive	0.2158	-0.3645	0.0897	-
Months	RWD	Positive	0.1462	1.0142	0.5250	-
Four	RW	Positive	0.5252	-0.8179	0.4724	-
Months	RWD	Positive	0.5242	0.6037	0.3196	-
Five	RW	Positive	5.2719	-1.2764	14.7109	Reject
Months	RWD	Positive	2.5879	0.4568	3.4530	Reject
Six	RW	Positive	6.0575	-0.8245	18.6866	Reject
Months	RWD	Positive	2.8846	0.6904	4.3988	Reject
Seven	RW	Positive	6.9589	-1.1321	24.8543	Reject
Months	RWD	Positive	3.3753	0.5351	5.8393	Reject
Eight	RW	Positive	7.2816	-0.3672	26.5783	Reject
Months	RWD	Positive	3.6876	0.7535	7.0830	Reject
Nine	RW	Positive	8.0911	0.4105	32.8175	Reject
Months	RWD	Positive	4.1432	0.8328	8.9298	Reject
Ten	RW	Positive	8.1093	0.8406	33.2336	Reject
Months	RWD	Positive	4.5585	1.1645	11.0682	Reject
Eleven	RW	Positive	9.2347	1.4683	43.7174	Reject
Months	RWD	Positive	5.2671	1.8317	15.5486	Reject
Twelve	RW	Positive	11.0781	1.6429	62.7117	Reject
Months	RWD	Positive	6.0176	2.3473	20.8604	Reject

The null hypothesis tested is that of mean squared error equality.
Rejection of the null hypothesis indicates that the LTF forecasts are most accurate.

The ability of a model to accurately predict the direction of change in a variable of interest is determined using directional forecast evaluations. Table 22 shows the directional accuracy test for the per customer water usage and the customer base in the three categories, respectively. In the first three columns, the null hypothesis states that the forecast fails to predict directional changes in demand per customer (Henriksson and Merton, 1981). Rejection of the null implies that the model successfully predicts the direction of the movements in water usage.

In the first column, for the single-family residential category, the null is rejected at six step-lengths. In the second column, for the multi-family residential category, the null is rejected at four step-lengths. In the third column, for the nonresidential category, the null is rejected at six step-lengths. These results are consistent with the results presented in Tables 10, 11, and 12.

In the last three columns, the null hypothesis states that the forecast fails to predict directional changes in the number of customers (Henriksson and Merton, 1981). Analogously, rejection of the null implies that the model successfully predicts the direction of the movements in the customer base. For all categories of customer base forecasts, it is not possible to reject the null hypothesis that actual and predicted directional changes are distributed independently of one another.

Table 22. Directional Accuracy Tests. LTF Forecasts of per customer water usage and number of customer by category

Horizon	SFUSE HM Test	MFUSE HM Test	NRUSE HM Test	SFCUST HM Test	MFCUST HM Test	NRCUST HM Test
One Month	0.0016**	0.0429**	0.0034**	0.9545	0.9659	0.7604
Two Months	0.1479	0.1017	0.1202	0.9471	0.7964	0.9065
Three Months	0.0050**	0.0785*	0.0399**	0.9201	0.4095	0.9550
Four Months	0.0546*	0.0684*	0.0252**	0.8406	0.9107	0.4369
Five Months	0.3200	0.1367	0.0396**	0.9151	0.7667	0.8615
Six Months	0.4231	0.1056	0.3435	0.7186	0.5316	0.5781
Seven Months	0.4397	0.0927*	0.5786	0.6201	0.1810	0.2395
Eight Months	0.3638	0.1402	0.2952	0.8952	0.4628	0.7088
Nine Months	7.62E-08**	0.1667	0.0934*	0.9159	0.2693	0.6376
Ten Months	0.0473*	0.1988	0.1101	0.9067	0.7411	0.5847
Eleven Months	0.0549*	0.2375	0.0612*	0.7846	0.5476	0.5000
Twelve Months	0.2870	0.1628	0.1016	0.7687	0.3374	0.5704

** $p < .05$
* $p < 0.10$

In summary, the LTF ARIMA estimation results indicate that per customer water usage in Phoenix is affected by variations in prices, economic conditions, and weather patterns. The price elasticities calculated for each per customer water usage category analyzed are in the neighborhood of previous research findings. All of the independent variables in the water usage equations have statistically significant effects. The same holds true for the customer base explanatory variables, with the exception of total employment in the single-family category.

The descriptive accuracy results corresponding to per customer water usage forecasts in most cases favor the LTF model. However, the improvement in accuracy over the benchmark models is also statistically insignificant in most cases. Directional accuracy results indicate that the LTF model successfully predicts the direction of movement in water usage around forty percent of the time.

Analysis of the LTF customer base forecasts yields mixed descriptive accuracy results. For the single-family residential and nonresidential categories, benchmark forecasts of customer accounts perform well relative to the LTF in most cases. Although the LTF generates the smallest forecast errors for the multi-family residential customer category, a relatively large proportion of those errors is systematic rather than random. Also, the LTF model is relatively unsuccessful at predicting the direction of movements in the customer base. Overall, the random walk and random walk with drift benchmark forecasts are competitive with the LTF customer base forecasts.

Chapter 5: Conclusion

This study applies a linear transfer function approach in order to model water demand for single-family residential, multi-family residential, and nonresidential customer categories in Phoenix, Arizona. A total of six LTF regression equations are estimated. Demand for each of the three customer classes is decomposed into demand per account and the number of accounts. LTF simulations are compared to random-walk and random-walk with drift benchmarks using tests of out-of-sample forecast accuracy.

Monthly frequency time series for average price, cooling degree days, number of days per month with rainfall, an economic conditions index, the rental vacancy rate, and the unemployment rate are used as independent variables to explain variations in per-customer water consumption. Total employment and multi-family housing starts are the explanatory variables for the customer base equations. There are contemporaneous negative relationships between movements in real average price and water usage. The price elasticities for the single-family residential, multi-family residential, and nonresidential usage categories are -0.36, -0.31, and -0.75, respectively. Those results are close to those reported in prior studies for various regions.

Statistically significant impacts are found between climatic conditions and water demand. Higher temperatures are associated with higher water usage, and an increase in the number of days in a month with rainfall reduces municipal water usage. In addition, an improvement in economic activity increases water usage. A one percentage point increase in the economic conditions index is associated with an increase of 22.7 cubic feet in per-customer water demand for the single-family residential category. One percentage point increases in the rental vacancy rate and the unemployment rate are associated with decreases of 151 and 606 cubic feet in per-customer water demand for the multi-family residential and nonresidential categories,

respectively. The customer base equations confirm that positive relationships exist between the number of customers and both employment and multi-family housing starts.

In order to generate ex-post forecasts at different step-lengths from January 2012 to December 2014, an expanding-regression approach is utilized. The descriptive accuracy results corresponding to per customer water usage forecasts in most cases favor the LTF model. Nonetheless, in most cases the improvement in accuracy over the benchmark models is not statistically significant. The LTF model successfully predicts the direction of movement in water usage around forty percent of the time, as indicated by directional accuracy test results.

Mixed descriptive accuracy results are obtained from an analysis of the LTF customer base forecasts. For the single-family residential and nonresidential categories, benchmark forecasts of customer accounts perform well relative to the LTF in most cases. In addition, the direction of movements in the customer base is relatively unsuccessfully predicted by the LTF model. Overall, the random walk and random walk with drift benchmark forecasts are competitive with the LTF customer base forecasts.

More research on per capita water demand and customer base forecasting appears warranted for this metropolitan economy. Future efforts may attempt to increase forecast accuracy by constructing a composite forecast using LTF, RW, and RWD models. Also, if serial correlation issues can be resolved, employing a seemingly unrelated regression method appears promising. Additional explanatory variables such as foreclosure rate and housing stock per category, if available, might potentially improve out-of-sample simulation results for the customer base. Similar efforts conducted for other regional water utilities would also be helpful in determining whether these results are unique to Phoenix.

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Appendix: Historical Data

Date	SFCUST	MFCUST	NRCUST	SFUSE	MFUSE	NRUSE	PRICE	TCDD	NODR	UNEMP
Jan-08	355,051	15,677	33,606	11.397	94.457	70.820	1.64	0	6	4.1
Feb-08	354,783	15,696	33,423	10.075	86.487	65.831	1.71	11	4	3.9
Mar-08	355,219	15,747	33,689	10.818	84.433	69.054	1.79	108	0	4.2
Apr-08	354,816	15,742	33,660	14.201	94.216	92.985	1.83	277	0	4.1
May-08	354,828	15,741	33,871	16.588	99.837	114.358	1.56	429	3	4.5
Jun-08	354,207	15,703	33,842	18.752	111.632	135.108	1.74	852	0	5.3
Jul-08	353,699	15,659	33,878	20.347	117.877	151.947	1.64	935	5	5.7
Aug-08	353,695	15,652	34,043	18.359	112.065	142.424	1.68	873	12	6.2
Sep-08	353,279	15,643	34,014	16.821	109.213	128.780	1.70	752	0	6.3
Oct-08	353,039	15,629	33,949	16.108	98.707	114.561	1.85	412	0	6.4
Nov-08	352,206	15,579	33,773	14.893	94.426	104.967	1.55	104	2	6.6
Dec-08	352,634	15,616	34,035	13.293	97.492	84.756	1.71	0	7	7.1
Jan-09	352,191	15,602	34,042	10.864	90.712	64.604	1.85	9	3	7.8
Feb-09	351,720	15,580	33,996	10.027	80.876	65.866	1.75	33	4	8.0
Mar-09	351,692	15,553	33,962	11.040	83.721	66.766	2.00	108	0	8.2
Apr-09	352,334	15,553	34,025	13.616	91.464	83.072	2.03	222	1	8.1
May-09	352,982	15,593	34,060	15.177	95.300	101.204	1.74	663	3	8.5
Jun-09	353,269	15,598	34,059	18.710	111.296	127.696	1.92	718	1	9.3
Jul-09	353,154	15,611	33,992	19.999	115.305	144.571	1.86	1038	4	9.6
Aug-09	353,119	15,608	34,035	19.369	113.181	149.734	1.86	946	2	10.0
Sep-09	353,190	15,698	34,082	18.146	109.055	139.128	1.87	757	1	10.1
Oct-09	352,796	15,719	34,071	15.891	94.202	114.828	2.10	321	0	10.1
Nov-09	352,761	15,716	33,873	12.908	80.289	84.883	1.69	125	1	9.8
Dec-09	352,295	15,665	33,696	15.136	106.352	94.262	1.68	0	2	9.8
Jan-10	353,238	15,731	34,083	10.120	79.424	59.059	1.98	0	6	10.3
Feb-10	346,137	15,482	33,399	10.279	85.757	55.812	2.00	1	8	10.0
Mar-10	347,076	15,539	33,722	9.007	75.411	53.766	2.18	42	4	9.7
Apr-10	339,531	15,269	33,087	12.794	78.578	74.576	2.19	192	1	9.3
May-10	347,902	15,590	33,883	14.429	90.556	90.300	2.01	417	0	9.2
Jun-10	347,726	15,598	34,066	18.339	106.484	122.722	2.02	794	0	9.5
Jul-10	345,337	15,336	33,620	21.036	120.111	154.007	2.00	990	3	9.7
Aug-10	345,051	15,514	33,795	17.311	106.818	141.109	2.03	907	5	9.8
Sep-10	344,178	15,539	33,804	17.034	105.318	128.334	2.06	800	1	9.5
Oct-10	345,396	15,347	33,285	15.197	96.375	106.589	1.97	400	4	9.1
Nov-10	344,085	15,402	33,526	13.423	90.793	88.304	2.07	81	1	9.1
Dec-10	345,674	15,432	33,586	12.586	95.710	76.813	1.92	4	5	8.8
Jan-11	347,763	15,567	33,920	10.280	83.864	58.061	2.13	0	2	9.2
Feb-11	348,306	15,605	34,072	9.834	78.296	58.596	2.09	0	4	8.8
Mar-11	348,597	15,628	34,126	10.056	80.258	61.756	2.05	120	1	8.5
Apr-11	349,417	15,617	34,014	13.512	95.705	84.199	2.08	310	1	8.2

Date	SFCUST	MFCUST	NRCUST	SFUSE	MFUSE	NRUSE	PRICE	TCDD	NODR	UNEMP
May-11	349,633	15,617	34,076	14.930	98.213	98.501	1.93	434	1	8.2
Jun-11	349,417	15,634	34,135	16.868	100.026	117.291	2.08	783	0	9.4
Jul-11	349,407	15,520	33,767	19.927	115.400	146.074	2.00	942	7	9.3
Aug-11	348,652	15,504	33,561	17.598	108.150	137.534	2.03	1039	1	9.0
Sep-11	347,932	15,297	33,129	18.716	114.971	147.469	2.01	800	1	8.7
Oct-11	349,816	15,530	33,632	15.742	99.097	116.688	1.96	436	3	8.3
Nov-11	350,011	15,554	33,669	13.882	92.659	95.402	2.01	33	6	7.7
Dec-11	350,753	15,554	33,778	11.586	91.728	73.432	1.92	0	6	7.6
Jan-12	350,807	15,585	33,826	12.256	89.776	78.117	1.77	3	0	7.9
Feb-12	351,968	15,620	34,055	9.954	77.860	58.377	2.08	9	0	7.6
Mar-12	352,611	15,603	34,052	11.117	82.643	69.337	1.96	109	1	7.4
Apr-12	352,725	15,592	34,024	12.872	90.139	85.232	2.01	319	2	7.0
May-12	352,663	15,628	34,010	15.695	97.697	107.019	1.86	612	1	7.2
Jun-12	353,076	15,643	34,191	18.371	107.291	131.415	2.01	869	0	7.7
Jul-12	352,806	15,611	33,938	19.682	116.056	151.530	1.94	903	7	7.9
Aug-12	352,603	15,624	34,026	16.931	106.345	135.786	1.96	948	6	7.7
Sep-12	353,688	15,663	34,030	16.898	110.748	129.758	1.96	719	3	7.1
Oct-12	353,626	15,655	34,088	14.102	90.180	102.134	2.05	437	0	6.9
Nov-12	354,593	15,598	34,049	15.307	100.854	107.212	2.04	137	1	6.5
Dec-12	355,452	15,618	34,031	12.096	89.586	77.646	2.00	5	6	6.6
Jan-13	355,588	15,655	34,039	10.559	86.545	62.977	2.06	5	6	7.0
Feb-13	355,371	15,630	34,038	9.391	79.209	57.482	2.12	3	2	6.6
Mar-13	355,952	15,706	34,158	9.583	77.766	58.652	2.11	180	2	6.6
Apr-13	356,876	15,715	34,236	12.736	89.096	79.759	2.10	316	1	6.3
May-13	356,677	15,741	34,272	14.643	92.818	98.754	2.03	594	0	6.4
Jun-13	357,308	15,748	34,348	17.692	105.627	128.790	1.91	902	0	7.0
Jul-13	357,407	15,740	34,238	19.123	110.993	148.828	1.90	959	5	6.9
Aug-13	357,600	15,705	34,227	17.106	108.475	135.865	1.91	929	3	7.1
Sep-13	358,082	15,702	34,202	16.190	107.625	126.740	1.93	719	2	6.7
Oct-13	358,157	15,739	33,927	14.371	92.599	103.027	2.01	305	0	6.5
Nov-13	359,058	15,720	33,838	14.652	98.294	98.976	2.01	111	4	6.0
Dec-13	359,108	15,732	33,855	10.911	86.095	66.837	2.01	0	2	6.0
Jan-14	359,298	15,711	33,764	11.118	90.453	66.115	1.98	4	0	6.2
Feb-14	359,846	15,780	33,762	10.072	80.268	62.758	2.05	58	0	6.0
Mar-14	359,839	16,011	33,787	10.391	80.834	68.218	1.99	137	2	6.1
Apr-14	359,145	16,014	33,722	12.385	86.118	84.620	2.04	306	0	5.4
May-14	359,026	16,052	33,805	17.062	108.142	119.895	1.72	570	0	5.7
Jun-14	359,173	16,127	33,744	17.404	102.251	132.202	1.94	855	0	6.1
Jul-14	359,624	16,119	33,753	19.468	112.341	157.056	1.86	984	3	6.2
Aug-14	359,185	16,098	33,635	15.902	99.704	131.065	1.91	831	4	6.3
Sep-14	358,294	16,044	33,496	14.678	99.206	114.609	1.93	728	5	5.9

Date	SFCUST	MFCUST	NRCUST	SFUSE	MFUSE	NRUSE	PRICE	TCDD	NODR	UNEMP
Oct-14	358,274	16,043	33,413	12.463	88.849	90.983	2.04	471	2	5.7
Nov-14	359,417	16,099	33,528	13.235	90.804	91.730	2.03	92	0	5.5
Dec-14	361,617	16,216	33,977	11.599	88.279	73.459	1.98	10	6	5.4

Date	TOTEMP	MFHS	RVR	ECI
Jan-08	1,847.9	840	13.0	-4.21
Feb-08	1,858.7	309	12.2	-3.65
Mar-08	1,855.3	367	11.8	-4.21
Apr-08	1,846.4	846	11.8	-4.84
May-08	1,839.5	578	12.2	-4.72
Jun-08	1,800.9	925	13.0	-5.04
Jul-08	1,768.6	558	14.8	-5.43
Aug-08	1,799.1	310	15.9	-5.20
Sep-08	1,803.3	659	17.0	-5.07
Oct-08	1,797.7	397	18.5	-6.23
Nov-08	1,794.8	202	19.1	-9.00
Dec-08	1,783.0	16	19.4	-10.54
Jan-09	1,723.9	174	18.6	-11.49
Feb-09	1,718.8	315	18.6	-12.50
Mar-09	1,712.0	88	18.7	-12.45
Apr-09	1,699.0	9	19.5	-11.58
May-09	1,687.5	6	19.4	-9.35
Jun-09	1,644.8	0	19.0	-7.94
Jul-09	1,622.2	10	17.6	-7.09
Aug-09	1,633.8	10	17.2	-6.15
Sep-09	1,645.2	51	17.1	-5.45
Oct-09	1,652.4	3	17.5	-3.73
Nov-09	1,664.1	33	17.9	-2.27
Dec-09	1,664.1	28	18.3	-1.51
Jan-10	1,625.7	187	20.1	-1.64
Feb-10	1,636.5	23	20.0	-1.05
Mar-10	1,646.7	172	19.3	0.15
Apr-10	1,652.0	35	16.3	2.92
May-10	1,657.1	35	15.3	2.44
Jun-10	1,614.4	39	14.7	2.03
Jul-10	1,597.3	36	14.9	0.66
Aug-10	1,619.7	49	14.9	0.85
Sep-10	1,630.4	91	14.9	1.54
Oct-10	1,654.1	101	15.8	4.15
Nov-10	1,671.0	108	15.6	5.30

Date	TOTEMP	MFHS	RVR	ECI
Dec-10	1,675.7	69	15.1	5.88
Jan-11	1,643.0	15	13.9	3.73
Feb-11	1,655.6	21	12.9	3.01
Mar-11	1,665.5	171	11.9	2.70
Apr-11	1,674.1	33	10.1	4.73
May-11	1,671.3	0	9.4	5.73
Jun-11	1,629.4	47	9.3	5.33
Jul-11	1,614.8	602	10.2	4.90
Aug-11	1,650.8	383	10.4	4.56
Sep-11	1,672.1	200	10.6	5.56
Oct-11	1,685.5	129	10.5	3.97
Nov-11	1,704.4	382	10.8	4.53
Dec-11	1,707.5	0	11.4	4.89
Jan-12	1,677.4	3	13.5	6.44
Feb-12	1,690.1	666	13.5	6.26
Mar-12	1,702.2	70	12.6	6.45
Apr-12	1,704.3	8	9.0	5.61
May-12	1,702.1	70	8.0	5.42
Jun-12	1,672.2	10	7.6	5.22
Jul-12	1,654.2	245	8.5	4.86
Aug-12	1,694.0	620	8.8	5.98
Sep-12	1,713.2	203	9.4	5.91
Oct-12	1,729.3	244	10.7	6.27
Nov-12	1,751.8	145	11.1	4.96
Dec-12	1,759.1	1271	11.1	3.90
Jan-13	1,722.3	335	10.5	2.92
Feb-13	1,739.2	247	10.1	3.95
Mar-13	1,748.5	82	9.7	4.16
Apr-13	1,754.9	580	8.8	4.50
May-13	1,753.5	810	8.4	3.72
Jun-13	1,721.3	106	8.3	4.26
Jul-13	1,709.0	530	8.2	4.37
Aug-13	1,746.6	177	8.5	3.84
Sep-13	1,762.0	22	9.2	2.77
Oct-13	1,783.0	121	11.2	1.09
Nov-13	1,808.5	40	11.7	1.81
Dec-13	1,813.2	1291	11.6	2.78
Jan-14	1,772.0	354	10.5	4.42
Feb-14	1,785.0	1042	9.9	4.00
Mar-14	1,791.7	1586	9.3	3.33
Apr-14	1,798.3	966	8.0	2.34
May-14	1,787.3	757	7.8	1.89

Date	TOTEMP	MFHS	RVR	ECI
Jun-14	1,761.1	316	8.2	0.22
Jul-14	1,745.5	648	10.1	0.06
Aug-14	1,785.3	669	10.6	-0.07
Sep-14	1,800.1	191	10.8	0.61
Oct-14	1,825.6	558	10.7	NA
Nov-14	1,847.7	412	10.3	NA
Dec-14	1,854.1	1377	9.6	NA

SFCUST: Number of single-family residential customers
Units: Water accounts — Source: City of Phoenix

MFCUST: Number of multi-family residential customers
Units: Water accounts — Source: City of Phoenix

NRCUST: Number of nonresidential customers
Units: Water accounts — Source: City of Phoenix

SFUSE: Single-family residential per customer water usage
Units: Hundred cubic feet — Source: City of Phoenix

MFUSE: Multi-family residential per customer water usage
Units: Hundred cubic feet — Source: City of Phoenix

NRUSE: Nonresidential per customer water usage
Units: Hundred cubic feet — Source: City of Phoenix

PRICE: Real average price
Units: Dollars per hundred cubic feet — Source: City of Phoenix

TCDD: Total cooling degree days
Units: Cooling degree days — Source: National Oceanic and Atmospheric Administration

NODR: Number of days rainfall
Units: Days — Source: National Oceanic and Atmospheric Administration

UNEMP: Unemployment rate
Units: Percentage — Source: Bureau of Labor Statistics

TOTEMP: Total nonfarm employment
Units: Thousands — Source: Office of Employment and Population Statistics at the Arizona Department of Administration - Bureau of Labor Statistics

MFHS: Multi-family housing starts
Units: Units — Source: Census Bureau

RVR:	Rental vacancy rate	
	Units: Percentage	Source: Census Bureau
ECI:	Economic conditions index	
	Units: Percentage	Source: Federal Reserve Bank of St. Louis

Vita

Juan P. Cardenas was born in El Paso, Texas, to Jose M. Cardenas and Adriana M. Ramirez. He enrolled at the University of Texas at El Paso in August 2005. In the fall of 2010, he received a Bachelor of Business Administration degree with double major in Economics and Finance. After working for Robert BOSCH in the automotive industry, he joined the Master of Science in Economics program in August 2013. During his time as a graduate student he worked as a teaching and research assistant at the Border Region Modeling Project.

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