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Municipal Water Consumption and Urban Economic Growth in El Paso

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Abstract: This study investigates the nexus between municipal water consumption and economic growth for El Paso, TX, USA. Located in the semi-arid southwestern United States, El Paso water consumption has been the subject of prior economic studies. However, the relationship between water consumption and economic growth has not been previously analyzed for El Paso or any other metropolitan economies in the region. Empirical results indicate that municipal water usage and real personal income are integrated of order one, but are not co-integrated. Given that, a vector autoregression model is estimated and a Granger causality test is performed. Estimation results show unidirectional causation from real income growth to water consumption, indicating that water conservation policies will not inhibit economic growth in this urban economy.

1. Introduction

Water is required for urban economic development. In spite of that, relatively few studies examine the nexus between water consumption and metropolitan economic growth. This study analyzes data for El Paso, TX, USA, an urban economy located in a semi-arid region of the southwestern United States. Reflective of the latter, El Paso Water, the metropolitan water service utility, frequently imposes seasonal usage restrictions. Conservation efforts have helped lower per capita consumption substantially since 1990 [1].

As an important input into economic development, understanding the relationship between water consumption and income may have implications for future growth [2]. From planning urban development to water conservation policies, local entities need regional data to implement policies that can support economic growth. Because water conditions vary considerably across regions, the details of the relationship between water consumption and economic growth are likely to be of interest to local governments and businesses [3].

Determining whether the relationship between water consumption and regional economic growth is causal is relevant for effective resource management. If there is evidence for a causal link, a poorly designed water conservation policy could have negative impacts on economic growth [4–6]. This study examines the water-growth nexus by estimating a vector autoregression and performing Granger causality testing on water consumption and real personal income per capita for El Paso from 1976 to 2018.

The remainder of the study is organized as follows. A brief review of prior research on the water-growth nexus is presented next. The third segment discusses data and methodology. Empirical results are then discussed. The closing section provides policy implications and concluding remarks.

Previous Research

The water economics literature regarding aggregate demand is voluminous [7]. There are many fewer studies, however, that analyze potential linkages between water consumption and economic growth. Given the wide-ranging debates over water conservation and other policy issues, that gap in the literature is surprising.

There have been a number of research efforts that investigate the nexus between electricity and different aspects of economic performance, such as output or income growth. In fact, that branch of energy economics is internationally extensive [8,9]. Studies in this area were initially oriented toward national data samples but, given widespread economic heterogeneity within national economies, have recently become more focused on regional and urban economies [10,11].

Causal links between water consumption and economic growth have implications for water conservation policies and economic development objectives. When the direction of causality runs from economic growth to water consumption, this suggests that metropolitan economies can implement water conservation strategies without jeopardizing economic growth. Conversely, if causality runs from water consumption to economic growth, there may be a tradeoff between economic growth and conservation goals. Despite these practical implications, there has been relatively little attention devoted to the analysis of directional causality between water consumption and urban economic growth.

At the country level, studies tend to focus on the environmental Kuznets curve (EKC). An EKC illustrates the relationship between an environmental quality indicator and per capita income. Evidence of an inverted U-shape, similar to what exists between economic growth and income inequality [12], between water and income is a common finding. Grossman and Krueger (1991) [13,14] posit a potential inverted U-shape relationship between income and the environmental effects under the North American Trade Agreement (NAFTA). A follow up study in 1995 confirmed such a relationship following NAFTA implementation [14].

A variety of studies report evidence of inverted U-shaped relationships between incomes and water usage. Many of these studies are cross-sectional and involve 65 or more countries. The latter include Rock (1998) [15], Barbier (2004) [16], and Duarte et al. (2013) [17]. Similar results are also reported using panel data in Cole (2004) [18] and Duarte et al. (2014) [19]. Although Scott et al. (2011) [20] discuss the water-energy nexus in the United States, the relationship between income and water consumption is not examined. Katz (2015) [21] cautions, however, that EKC estimates may not be reliable enough to inform water planning efforts and/or policy design.

Many EKC studies ignore cointegration, but that can be an important feature of some time series [22]. Ignoring cointegration between variables can result in spurious regression results and erroneous interpretations. For example, standard *t* and *F* statistics will be invalid. The EKC method, usually estimated with panel data, is unable to disentangle the long-run relationships between variables from spurious results [23]. Misunderstanding the relationship between the variables could lead to policy mistakes and/or subpar/inefficient water resource management.

A vector autoregression (VAR) is preferable for the type of analysis conducted herein because examination of the direction of causality between water consumption and real income is the study objective. Granger causality testing is straightforward when using a VAR. The VAR provides a good alternative to an EKC analysis because the VAR methodology can accommodate cointegration if it is present among the data. Beyond that, VAR models can also provide information about long-term and short-term dynamics associated with the variables.

Given its prominence as a growing metropolitan economy located in a semi-arid desert setting, El Paso water consumption has been dissected in a number of empirical studies. Among the topics examined in these efforts are short-range consumption reactions to weather and economic stimuli [24], surface usage rights transfers [25], long-term historical forecast accuracy [26], and short-term consumption prediction accuracy during business cycle downturns [27]. Of course, El Paso still faces important policy questions regarding the provision of municipal water services.

In response to looming water supply limitations elsewhere, a growing number of regional studies analyze links between income and usage. Recent work includes Barnett et al. (2020) [28], which analyzes residential water use in Northern Utah. Results in that study indicate that lower income residents are more responsive to prices than higher income households. Li, Yi, et al. (2017) [29] find decoupling between growth in China's textile industry and water usage from 2002 until 2014, but do not address causality. Hussien et al. (2016) [30] investigate data for 407 homes in Iraq and document a positive relationship with water consumption and household income. Romano et al. (2014) [31] also report a direct correlation between per capita incomes and water consumption. Domene and Saurí (2006) [32] documents a relatively small positive relationship between water consumption and household income for Barcelona, Spain. Yoo (2007) [33] reports unidirectional causality from regional economic growth to water consumption in a data sample for Taejon, Korea. This study employs the augmented VAR approach of Toda and Yamamoto (1995) [34] to examine causality between income and water usage for El Paso. That aspect of the role played by water in this urban economy located in a semi-arid, water-constrained region has not previously been analyzed.

2. Materials and Methods

Vector autoregression (VAR) models are often used to examine Granger causality among variables. A VAR can answer the question of how useful some variables are for forecasting others. In this case, we are interested in the relationship between economic growth and water consumption. A VAR is an extension of a univariate time series model to multiple equations. Each equation includes lagged values of all of the regressors in each equation. The VAR allows for the joint testing of restrictions across all of the equations. For instance, testing whether the coefficients on all regressors of lag p are zero. VAR models are appropriate when the interaction of the variables in the model have implications for estimation and interpretation of the model's equations. In situations where there are multiple channels of influence among variables, VAR can be used to estimate the model.

VAR models provide a method to investigate the dynamic structure of a model using the data. When estimating a VAR, only the number of variables and the largest number of lags needed to capture the effects those variables have on each other need to be specified. There needs to be a sufficient number of lags for each variable to describe the system, but each additional lag increases the number of parameters to be estimated and reduces degrees of freedom [35].

If the variables are integrated of order one, I(1), and not cointegrated, a VAR in first-differences can be estimated. However, if there exists a cointegrating relationship, the variables share a common long-term trend and differencing will obscure that trend. Under that circumstance, an error correction model (ECM) must be estimated. ECMs are estimated using methods that preserve the long-term relationship between the variables [36]. Hence, testing the variables for stationarity and cointegration is performed prior to estimation. Toda (1995) [37] shows that tests for cointegration ranks in some types of ECM models are sensitive to the values of the nuisance parameters in finite samples. Thus, ECM causality inference can sometimes suffer from pre-test bias.

Toda and Yamamoto (1995) [34], hereafter TY, propose an augmented VAR approach that has practical appeal because it can be applied for any arbitrary level of integration. The TY procedure has high power for moderate to large sample sizes [38]. It also generates small size distortions, limiting the likelihood of Type I errors [39]. If there is any ambiguity surrounding the order of integration of the variables, the TY procedure can be employed for parameter estimation.

The first step in applying the TY procedure is testing the logarithmically transformed variables for unit roots. Because time series data are employed, the sample data need to be tested for stationarity. A data series is stationary if the mean and autocovariances are time independent. A data series that is not stationary is referred to as nonstationary. If nonstationary data are used in a multivariate framework the results can be spurious. A common solution to a nonstationary data series is to take the first difference of the series. If the resulting data are stationary, the series is considered difference stationary and is integrated of order d, where d is the order of integration, or simply the number of

times the series must be differenced before it is stationary [36]. For example, a first-differenced series that is stationary is integrated of order 1, or I(1), and is said to have a unit root. Similarly, a stationary series is denoted I(0).

In order to avoid spurious results, and to apply standard hypothesis testing and inference to a data series, the data must be stationary. Therefore, it is important to test the data for evidence of unit roots. In this study three different tests are used to determine the order of integration for the two data series that comprise the sample. The first is the Augmented Dickey–Fuller (ADF) test. The ADF test is an autoregression-type test used to determine whether the data series in question are stationary. The null hypothesis is that the data are not stationary, while the alternative is that the data are stationary [35].

A shortcoming of the ADF test is that it can be sensitive to serial correlation and heteroskedasticity. Thus, we also employ the Phillips–Peron (PP) unit root test. The PP is another regression-based test but modifies the test statistic to account for serial correlation and heteroskedasticity. The null and alternative hypotheses for the PP test are the same as for the ADF test [36].

A third test is deployed as a check against the unit-root tests. It is known as the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The KPSS null hypothesis is that the data are stationary around a trend while the alternative is that the data are nonstationary. By comparing the results of the unit root tests with the KPSS tests results, data series that appear to have a unit root, appear to be stationary, or do not have enough information to form a conclusion can be identified [36].

The next step is to determine the maximal order of integration, *d*, of the variables included in the sample. For example, if there are two time series and one is I(1) and the other is I(0), then *d* = 1. The optimal lag length, *p*, of a VAR is then obtained by minimizing the Akaike information criterion (AIC). Unlike the unit root tests, the AIC procedure is descriptive, only, and has no underlying distribution associated with it [35].

Wald tests are used for joint hypothesis tests that involve multiple coefficient restrictions, such as when two or more coefficients are constrained to equal zero. The test statistic follows a chi-squared distribution. The null is that all of the coefficients are equal to zero while the alternative is that at least one coefficient is nonzero [35]. If a Wald test is used to test restrictions on parameters of a VAR model and some of the data contain unit roots, then the test statistic does not follow the usual asymptotic chi-squared distribution. In fact, the test statistic asymptotic distribution involves unobservable nuisance parameters that make the distribution non-standard [40,41]. Toda (1995) [37] finds that, in finite samples, tests for cointegration in Johansen-type ECM models are sensitive to the values of nuisance parameters. Because of the presence of unit roots in the ECM system, causality inference may be biased.

If the data have the same order of integration, the Johansen [42,43] trace and maximum eigenvalue tests are used to assess the cointegrating rank. The Johansen test is a sequential procedure for determining the number of cointegrating relationships, *r*, between time series variables. The test moves from *r* = 0 to *r* = *k* − 1. The null and alternative hypotheses are different for the trace and maximum eigenvalue statistics. The null for the trace is *r* cointegrating relationships against the alternative of *k* cointegrating relationships, with *k* being the number of endogenous variables for *r* = 0, 1, 2, ... , *k* − 1. The null for the maximum eigenvalue statistic is *r* cointegrating relationships against the alternative of *r* + 1 relationships [42,43].

If cointegration is not detected, a standard VAR model can be used. To determine the number of lags for cointegration testing, AIC minimization is employed. Under this approach, the model with the smallest AIC statistic is the preferred model. The AIC statistic is based on the goodness-of-fit of the model and penalizes over-fitting, or in this case, including too many lags [36]. It should be noted that, from a practical perspective, using the TY method allows properly completing causality testing even if data series have differing orders of integration and are possibly cointegrated.

The next step is estimation of a lag-augmented VAR(*p* + *d*) model in levels:

$$V_t = \alpha + \beta_1 V_{t-1} + \beta_2 V_{t-2} + \cdots + \beta_p V_{t-p} + \cdots + \beta_{p+d} V_{t-p-d} + \varepsilon_t \tag{1}$$

where α is a vector of constants, β_t is the coefficient matrix, and ε_t are white noise residuals. Robustness checks of the augmented VAR($p + d$) model are performed to verify stability of the model. Three different stability checks are utilized. The first is known as a Lagrange Multiplier (LM) test. The LM test is a post-estimation residual diagnostic test used to determine whether the residuals of the VAR contain serial correlation. If serial correlation is present then inference and hypothesis testing may be invalid. The LM null hypothesis is that there is no serial correlation. Rejection of the LM null implies that serial correlation is present [35].

The second diagnostic test is the White (1980) [44] heteroskedasticity test. The presence of heteroskedasticity means that the standard errors of the parameter estimates are invalid. The White test is also a post-estimation residual test and tests for the presence of heteroskedasticity in the residuals. The null hypothesis is no heteroskedasticity and rejecting the null means that heteroskedasticity is present.

The third stability check is whether the characteristic equation roots lie inside the unit circle. If the characteristic roots are within the unit circle, it means that the estimated VAR is stable and the process is stationary. Characteristic roots fall outside the unit circle if the model is unstable. [36].

Finally, a Wald test is conducted only on the first p parameters instead of all the parameters in the VAR($p + d$) model. The TY procedure ensures that the Wald statistic follows an asymptotic Chi-squared distribution with p degrees of freedom [34,38]. The null hypothesis tested is that the row i, column j element in β_k equals zero for $k = 1, 2, \ldots , p$. The jth element of V_t does not Granger cause the ith element of V_t if and only if the null hypothesis is true.

Granger causality is tested by estimating the following VAR model:

$$y_t = \alpha_1 + \sum_{i=1}^{p+d} \alpha_{1i} y_{t-i} + \sum_{i=1}^{p+d} \beta_{1i} w_{t-i} + \mu_t \tag{2}$$

$$w_t = \alpha_2 + \sum_{i=1}^{p+d} \alpha_{2i} y_{t-i} + \sum_{i=1}^{p+d} \beta_{2i} w_{t-i} + v_t \tag{3}$$

where y and w are the natural logarithms of real personal income and water consumption, respectively, and μ_t and v_t are serially uncorrelated error terms. The first hypothesis test is $H_{01} : \beta_{11} = \beta_{12} = \cdots = \beta_{1p} = 0$ against the alternative of *Not* H_{01}, that is, at least one $\beta_{1i} \neq 0$. The second hypothesis test is $H_{02} : \alpha_{21} = \alpha_{22} = \cdots = \alpha_{2p} = 0$ against the alternative of *Not* H_{02}.

To conclude that w_t Granger causes y_t, or vice versa, two conditions must be met. First, changes in w_t should help predict changes in y_t, and H_{01} should be rejected. Second, y_t should not help predict w_t and H_{02} fails to be rejected. The procedure is repeated to test whether y_t Granger causes w_t.

There are four possible outcomes to the causality tests. One is that w_t Granger causes y_t. The second is that y_t Granger causes w_t. The third is bi-directional causality between w_t and y_t. The fourth is that lags of w_t do not help explain fluctuations in y_t and lags of y_t do not help explain movements in w_t [35].

To test the hypothesis that water consumption and economic growth are causally related, data on water consumption and personal income are collected for El Paso, TX, USA. Table 1 provides descriptions and units of measure for the variables. Data on personal income and the gross domestic product (GDP) deflator are from the U.S. Bureau of Economic Analysis. Data on total municipal water consumption in billions of gallons per year are collected from El Paso Water, the water provider for the city of El Paso, TX, USA.

Real personal income in millions of 2012 dollars is used to quantify economic growth [45]. El Paso real personal income is calculated by deflating personal income using the GDP deflator. Per capita income is then calculated by dividing that result by the population of El Paso. A total of 44 years of data are used in the analysis. Summary statistics for the non-log transformed variables are presented in Table 2. The compound annual growth rate for real per capita personal income is 1.7% over the entire sample period. For total water consumption, the compound annual growth rate during the sample period is approximately 0.83%.

Table 1. Mnemonics and variable definitions.

Variable	Definition	Units
Y	Real per capita personal income	Millions of 2012 dollars
W	Water consumption	Billions of gallons

Note: Sample data period: 1976–2019.

Table 2. Descriptive statistics.

Variable	Y	W
Mean	23,631	32.826
Standard Deviation	5372	2.852
Maximum	33,392	36.997
Minimum	15,557	24.089
Coef. of Variation	0.227	0.087
Skewness	0.218	−0.971
Kurtosis	1.788	3.609
Observations	44	44

Note: Sample data period: 1976–2019.

As would be expected, real personal income is right-skewed, while aggregate urban water usage is left-skewed. Relative to a Gaussian distribution, real per capita income is platykurtic, while municipal water consumption is leptokurtic. With the thicker tails associated with income, it is not surprising that the coefficient of variation for that variable is nearly 0.3. Water usage has plateaued in recent years, partially contributing to the relatively small coefficient of variation of less than 0.1.

Figure 1 depicts the water consumption and real per capita personal income for El Paso over the sample period. While water consumption appears to be relatively stable, there are some periods of elevated consumption in 1988, 1994, and 2011. Consumption also decreases from 2002 to 2004, remaining at a lower level until starting to increase again in 2008. Real per capita personal income steadily increases, with the exception of the period from 2012 to 2013, from $15,557 in 1976 to $33,595 in 2019.
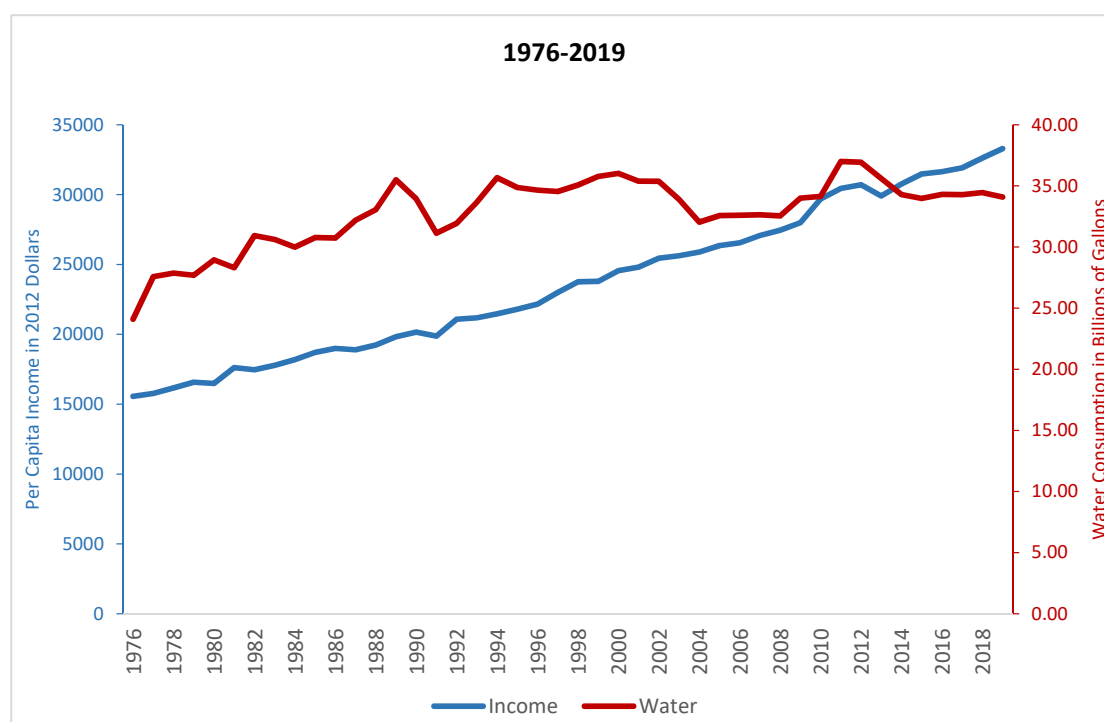
Figure 1. Water Consumption and Per Capita Personal Income.

3. Results and Discussion

The first step in applying the TY method is testing the logarithmically transformed variables for unit roots. The sample contains amount data that only have positive values. Transformation using natural logarithms helps ensure that the normality assumption is satisfied [46]. Table 3 presents the results of three different unit-root tests: Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS). The ADF and PP tests have unit root null hypotheses, while the KPSS test has stationarity as the null hypothesis.

Table 3. Unit root test results.

	ADF Test Results		Phillips-Peron Test Results		KPSS Test Results	
	t-Statistic	5% Critical Values	*t*-Statistic	5% Critical Values	*t*-Statistic	5% Critical Values
w	−2.341	−2.933	−4.239 *	−2.933	0.596 *	0.463
y	−0.612	−2.931	−1.663	−2.931	0.844 *	0.463
Δw	−6.799 *	−2.935	−7.974 *	−2.935	0.400	0.463
Δy	−8.909 *	−2.933	−14.857 *	−2.933	0.500 *	0.463

Note: Lower case variables y and w represent the natural log transformed variables Y and W, respectively. * indicates rejection of the null hypothesis using a 5% significance level.

For water consumption in level form, the ADF test fails to reject the presence of a unit root, but the PP test rejects the presence of a unit root. This occurs because the computed *t*-statistic is smaller than the critical value for the ADF statistic, yet the computed *t*-statistic for the PP test is larger than the corresponding critical value. The KPSS test rejects the stationarity null hypothesis because the water consumption computed *t*-statistic exceeds the corresponding critical value for it. The first-differenced water consumption variable rejects the null meaning that according to the KPSS test, water consumption is first-difference stationary. However, income does not appear to be first-difference stationary according to the KPSS test, since both the level and first differenced values of income reject the null of stationarity. Given the agreement between the ADF and KPSS tests, it is likely that water consumption is integrated of order one whereas income is likely I(1) according to ADF and PP tests, but not according to the KPSS test. Fortunately, the TY procedure is appropriate for data series that exhibit ambiguous orders of integration.

The next step in applying the TY method is to determine the maximal order of integration (*d*) of the variables. Because the unit root tests show the variables are likely I(1), the maximal order of integration is set at *d* = 1.

Because the variables are integrated of the same order, cointegration testing is performed. The lag length is determined by estimating a vector autoregressive model in levels of the two sample variables. The minimum value of the Akaike information criterion (AIC) is achieved with a lag length of 2. This lag order is used in both the Johansen test and the TY procedure. The Johansen test results are presented in Table 4. For the trace and maximum eigenvalue tests, neither test statistic exceeds the corresponding 5% critical values necessary for the rejection of the null hypothesis. Both test statistics indicate that there is no cointegration between personal income and municipal water consumption in El Paso.

Table 4. Johansen Cointegration Test results.

Hypothesized Number of Cointegrating Equations	None	At Most One
Trace	7.157	0.153
5% critical value	15.494	3.841
p-value	0.559	0.696
Maximum eigenvalue statistic	7.004	0.153
5% critical value	14.264	3.841
p-value	0.489	0.696

Note: The null hypothesis fails to be rejected using trace and maximum eigenvalue statistics indicating there is no cointegration.

The maximal order of integration is calculated to be one. The TY procedure is applied using $p + d = 3$ and a VAR(3) model is estimated. Diagnostics tests are performed to ensure stability of the estimates. A Lagrange multiplier test indicates there is no serial correlation in the residuals and the White heteroskedasticity test cannot reject the null hypothesis of no heteroskedasticity. The VAR is stable with all the unit roots within the unit circle. Granger causality tests are conducted, next.

Table 5 reports the results of the Granger causality tests. Results indicate that there is unidirectional causality running from income to water. This is evident due to the rejection of the null hypothesis that water non-Granger causes income whereas the hypothesis that income non-Granger causes water consumption is not rejected. Thus, an increase in income will result in an increase in water consumption, but not vice versa. That result implies that City of El Paso efforts to encourage water conservation will not inhibit regional economic growth. This result is consistent with Yoo (2007) [33], who documents similar patterns for South Korea. From a general resource stewardship perspective, it is also consistent with what is reported for electricity and growth in El Paso by Walke and Fullerton (2019) [11].

Table 5. Granger Causality Test Results.

	Chi-Square Statistics	
Left-Hand Side Variable	y	w
y	-	6.914 *
	-	(0.0315)
w	3.100	-
	(0.2122)	-

Note: The values in the parenthesis are *p*-values. * indicates null hypothesis rejection at a 5% significance level.

While this result is not entirely surprising, it has not previously been formally quantified. The City of El Paso began implementing water conservation measures in 1990. Those mechanisms include enacting a city ordinance that made wasting water a crime, implementing water conservation and beautification requirements for commercial properties in 1995, adding irrigation guidelines along with tougher enforcement language to the building requirements in 2001, and substantially higher usage tariffs.

El Paso Water has also provided various incentive and rebate programs to encourage low water use landscapes and the adoption of more water efficient appliances. Such efforts have resulted in a 33% reduction in per capita water consumption since 1989 [1]. During the same period, real personal income increased by nearly 143% in aggregate terms and by nearly 68% in per capita terms [47].

4. Conclusions

This study investigates water consumption and economic growth for the metropolitan economy of El Paso, Texas. The sample contains 44 annual frequency observations of municipal water consumption and real personal income from 1976 through 2019. Those data are used to investigate the previously unanalyzed water and income growth nexus for this growing urban economy located in a semi-arid region of the border with Mexico. The sample data are integrated of order one, but not co-integrated. Given that, a vector autoregression model is then estimated using a procedure that allows for that possibility. Empirical testing is also conducted to investigate which hypothesis regarding water-income causality is prevalent in El Paso.

The results for El Paso indicate there is a unidirectional causality running from real income growth to water consumption. This means that income growth leads to higher water consumption, but not the converse. Given that El Paso is situated in a semi-arid region of the southwestern United States, water conservation is an ever-present aspect of local public policy. These results suggest that El Paso will not sacrifice economic growth as a consequence of continuing to implement water conservation efforts.

The approach utilized in this study can be applied to other regional and metropolitan economies. Specifically, urban areas such as Phoenix or Tijuana that experience seemingly perpetual, long-term water issues can benefit from the application of the methods used here. Internationally, developing countries that have concerns regarding the potential trade-offs between growth and conservation could also be a focus of future research. Finally, because data requirements are not very extensive, the methods employed for this study can apply to any country or municipality without concern over potential informational constraints. Doing so may yield valuable information for policy analysts concerned about the potential impacts of resource conservation measures on economic growth. While water conservation does not appear to hamper economic expansion in El Paso, there is no guarantee that the same result will also characterize other regional and urban economies. More empirical research on the water growth nexus is warranted.

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