

# **Dynamics of Power Prices and Water Production in Los Angeles: Implications for Earthquake Resilience and Recovery<sup>\*</sup>**

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**Abstract:** This study examines the time-series properties of electric power prices and water production in Los Angeles, an area that is susceptible to earthquakes that may cause utility disruption. We focus on underlying stochastic properties of series that capture potential trends and cycles of critical infrastructure as measured by power price and water production. Specifically, the analysis utilizes a battery of time series-based unit root tests to determine whether or not average monthly electricity price and water production are stationary or nonstationary. The findings have implications regarding model specification and use of these series for modeling regional recovery, measuring and assessing resiliency, and in optimizing the risk management policies and practices of local utility authorities. The findings are discussed in the context of earthquakes but may provide some general insight for other natural disasters, as well.

**Keywords:** Electric Power Prices, Water Production, Earthquake Resilience, Los Angeles

## **1. Introduction**

Earthquakes can wreak havoc on a region's critical infrastructure such as power and water (Hofer, et al., 2018). This study examines the time-series properties of electric

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power prices and water production in Los Angeles, an area that is susceptible to earthquakes<sup>1</sup> that may cause utility disruption (Zhang, et al., 2018). Attempts to make cities resilient to disasters and to speed up the recovery process need to be evidence and data-based.

There are a number of practical models that examine an area's vulnerability as well as studies that focus on pre- and post-disaster comparisons. These models, which include a variety of simulations, CGE (Computable General Equilibrium), and economic event studies, provide much useful information to policy and decision makers (Botzen et al, 2019; Ewing, et al., 2004 and 2005; Cochrane, 2004; Shaughnessy et al., 2010; *among others*). However, we depart from these traditional methods of disaster analysis to focus on underlying stochastic properties of series that capture potential trends and cycles of critical infrastructure as measured by power price and water production. Specifically, the analysis utilizes a battery of time series-based unit root tests to determine whether or not average monthly electricity price and water production are stationary or nonstationary. Knowledge of these times series properties can aid in forecasting the magnitude and extent of disaster-induced perturbations (or shocks) to the series. Further, the findings will shed light on whether these effects are permanent or transitory in nature. For example, if X is a non-stationary process (i.e., contains a unit root), then unexpected changes in X will result in a permanent impact on the series. On the other hand, if X is stationary, then unexpected changes (i.e., shocks) will be temporary, or transitory in nature, and the series will revert back to some long-run mean. In the context of an earthquake-induced disaster, mean reversion is suggestive of resilient behavior as the series will return to normalcy after some time. The findings have implications regarding the proper specification and use of these series for modeling regional recovery, measuring and assessing resiliency, and in optimizing the risk management policies and practices of local utility authorities. In this sense, our goal is a step in the direction of providing data-based measures of community resiliency utilizing readily available and repeatedly sampled data. The findings are discussed in the context of earthquakes but may provide some general insight for other natural disasters, as well.

## **2. Time Series Properties of Power and Water in Los Angeles**

Data are for the city of Los Angeles and correspond to the area covered by the LA Department of Water and Power. The sample period contains monthly observations covering June 2014 through December 2019. Power is (natural log) electricity price

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<sup>1</sup> Holden, et al. (2011) illustrate the extent of earthquake exposure focusing on businesses and employment in areas including Los Angeles, California.

in US cents per kwh and Water is total (natural log) water supplied in AF (acre-feet). All variables are seasonally adjusted. Figure 1 provides a graph of the two series. The Water series exhibits what appear to be large swings in value although without a clear upward or downward trend. Some of the movements appear to be autocorrelated. The Power series exhibits regular volatility with a possible downward shift almost midway through the sample. It is not clear from casual observation whether either of these series is stationary or nonstationary and thus further investigation is required to make a determination.

In order to check the stationarity properties of the Water and Power data series, we employ unit root tests proposed by Dickey-Fuller (1979), Elliot et al. (1996), Phillips and Perron (1988), Kwiatkowski et al. (1992), and the Variance Ratio test. In addition, where applicable, we perform a break point unit root test, i.e., we allow for an endogenously determined break in the data generating process of the series. Equation (1) forms the basis for the augmented Dickey-Fuller (ADF) test.

$$\Delta y_t = \rho_0 + (\rho_1 - 1)y_{t-1} + \rho_2 t + \sum_{k=1}^m \delta_k \Delta y_{t-k} + e_t \tag{1}$$

where  $y_t$  is the series being investigated,  $\Delta$  is the first-difference operator;  $t$  represents a linear time trend,  $e_t$  is a covariance stationary random error and the number of lags  $m$  is determined by Schwarz information criterion to ensure serially uncorrelated residuals. We reject the null hypothesis that  $y_t$  is a nonstationary time series if  $(\rho_1 - 1) < 0$  and statistically significant based on finite sample critical values from MacKinnon (1996). The Dickey and Fuller Generalized Least Squares (DF-GLS) unit root test of Elliot et al. (1996) estimates the standard ADF equation (1) where the GLS detrended series,  $\tilde{y}_t^j$  is substituted for  $y_t^j$ .<sup>2</sup> Critical values are provided by Elliot et al. (1996). The Phillips and Perron (1988) unit root test allows for weak dependence, heterogeneity in the error term, and is robust to a wide range of serial correlation and time-dependent heteroskedasticity. Equation (2) forms the basis for the Phillips-Perron (PP) test.

$$y_t = \eta_0 + \eta_1(t - T/2) + \lambda y_{t-1} + v_t \tag{2}$$

where  $(t - T/2)$  is the time trend,  $T$  represents the sample size, and  $v_t$  is the error term. The null hypothesis of a unit root ( $H_0: \lambda = 1$ ) is tested against the alternative hypothesis that the series  $y_t$  is stationary around a deterministic trend ( $H_a: \lambda < 1$ ) where statistical significance is determined using MacKinnon (1996) critical values.

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<sup>2</sup> Elliot et al. (1996) provide details on the detrending procedure.

The stationarity test developed by Kwiatkowski et al. (KPSS, 1992) differs from the ADF, DF-GLS, and PP unit root tests in that the series is assumed to be (trend) stationary under the null hypothesis. The KPSS statistic may be obtained from the residuals by regressing  $y_t$  on a constant and a trend, and is defined as the Lagrange multiplier (LM) statistic:

$$KPSS = \left( T^{-2} \sum_{t=1}^T \hat{S}_t^2 \right) / \hat{\lambda}^2 \quad (3)$$

where  $\hat{S}_t$  is the sum of residuals from the regression,  $\hat{\lambda}^2$  is a consistent estimate of the long-run variance, and  $T$  represents sample size. Kwiatkowski et al. (1992) provides critical values from the asymptotic distributions for the KPSS test statistic. We may reject the null hypothesis of stationarity if the KPSS test statistic exceeds the respective critical value. Along with the ADF, DF-GLS, PP and KPSS tests, we employed the Variance Ratio (VR) test. The variance of a  $q$ -period difference should be  $q$  times the variance of the one-period difference if a series follows a random walk. The variance ratio test developed by Lo and MacKinlay (1988, 1989) allows for general forms of heteroscedasticity and dependence, the hypothesis of which is referred to as the martingale null. The variance ratio,  $VR(q)$ , is computed as the ratio of the variance estimator at difference  $q$  to the variance of the first difference. A  $z$ -statistic is proposed that is asymptotically normal with a mean of zero and a variance equal to one. Chow and Denning (1993) noted that the variance ratio restriction holds for  $q > 1$ , and thus developed a joint variance ratio test that examines a set of multiple variance ratios statistics. In our analysis, we examine the variance ratios over 2, 4, and 8 months.

The results of the unit root tests for Water and Power series are shown in Table 1. For the three tests that have a null hypothesis that the series has a unit root (i.e., ADF, DF-GLS, PP) indicate that Water is integrated of order zero,  $I(0)$ , or stationary, i.e., we fail to reject the null that Water has a unit root. The variance ratio test rejects the null that Water is a martingale while the KPSS test does not reject the null that Water is stationary. However, the ADF, DF-GLS, and PP do not reject the null of a unit root when examining the (natural log) level of electricity price while the variance ratio does not reject that Power is a martingale and KPSS rejects the null of stationarity. Further, the results suggest that Power requires first-differencing to render the series stationary.

Perron (1989) and others note that conventional unit root tests are biased toward a false unit root null when the data are (trend) stationary with a structural break. Accordingly, we estimate the break point unit root test developed and used by Perron

(1989), Vogelsang and Perron (1998), Zivot and Andrews (1992), Banerjee et al. (1992) in which the break date is estimated or endogenously determined. Further, we examine several scenarios or models with a one-time break for trending data (though results are robust to nontrending as well) where there is a change in level, a change in both level and trend, and a change in trend. Ultimately, the result was robust to variations in model specification and we report only the change in level findings in Table 2. The break date for the Power series is estimated to be 2016M10 using an innovational outlier model and 2016M11 using an additive outlier model. The break point unit root test(s) indicate that Power is stationary around a breaking trend in either October or November of 2016. Interestingly, this roughly corresponds to the time following the drop in average wholesale electricity prices in California as well as at major trading hubs (U.S. Energy Information Administration, Energy Today, <https://www.eia.gov/todayinenergy>, 1/11/17). The finding of stationarity with a structural break is important and contradicts the previous unit root test results that did not allow for a break point and indicated that Power was non-stationary. Allowing for the break, our results suggest that Power is indeed stationary.

### **3. Implications of Results & Concluding Remarks**

Generally speaking, the unit root test results shown in Table 1 indicate that Water is stationary while Power is non-stationary. However, allowing for a structural break in the latter series we find that Power is stationary. Given that Los Angeles is subject to earthquakes that appear in stochastic fashion and are short-lived, the utility disruption to electric power prices and water supply may be thought of as an exogenous shock to the series. Indeed, some shocks may even disrupt the trend (i.e., intercept or trend) but the finding of stationary non-unit root behavior in Power and Water suggests that the impact of innovations is transitory in nature as opposed to being permanently felt. The mean-reverting nature of the Power and Water series provides evidence of an inherent resiliency in Los Angeles electric power prices and water supply that may be exploited to mitigate and manage utility-related disruptions. This is important as these utility-related, critical infrastructure disruptions may lead to business discontinuity and adverse residential and community outcomes. Specifically, following an earthquake where the built environment may be damaged including structures, roads, networks, etc., authorities may orchestrate recovery efforts to not only institutions and areas that are considered essential but to allocate resources to areas based on whether or not transitory or permanent effects of shocks exist.

Finally, since Power and Water are found to be stationary when properly accounting for potential structural breaks, the use of historical averages for forecasting or predicting recovery would be deemed appropriate from a statistical point of view.

That is, the application of an historical average of the stationary series depends on how long the effects of unexpected changes and disruptions (i.e., shocks) last. Moreover, disaster management personnel, urban planners, utility managers, etc. may be interested in the time horizon for which Power and Water take to fully dissipate a shock as the length of time for mean-reversion may be thought of as a measure of resiliency. A shorter the horizon corresponds to more resilient power prices or water production and this might provide a way in which policies geared towards resiliency may be evaluated. We address this important aspect of resiliency by estimating an autoregressive (AR) model for both Power and Water. We used standard Box-Jenkins techniques and various lag length criteria techniques such as Schwartz Information Criterion, Final Prediction Error and Akaike Information Criterion, as described in Mills (1999) to determine the order of the autoregressive models and in both cases the chosen models were AR(1) and where a dichotomous variable equal to one (zero otherwise) is included at the endogenously determined break date in the case of Power. We simulated a one standard deviation shock to each series and measure the response from the series long-run historical average to produce an impulse response function. Initially, the shock raises Water (or Power) creating a deviation from the long run mean. Given the mean reverting behavior of the series, this allows us to examine the impulse response to see how long it takes for the shock to fully dissipate and thus provides guidance as to how long either Water or Power takes to recover or return to normalcy, i.e., a measure of community resiliency. Full dissipation of the shock and thus mean reversion occurs when the time path of the series is no longer significantly different from zero as determined by the +/- 2 standard error confidence bands. In both cases, the mean reversion process took up to 3 months. Accordingly, we interpret these impulse response functions as evidence that both Water and Power are, in effect, self-stabilizing in about 3 months following a one standard deviation shock. It should be noted that our results are specific to the case of Los Angeles and while they may not generalize to other cities or regions, they do provide guidance as to how to measure and interpret resiliency with respect to electric power prices and water supply. Further, the methodology and analysis may be extended in two important ways. First, future research will consider other cities or regions at risk of disasters to determine if electric power prices and water production follow similar time series dynamics. Second, the future research will consider other variables that represent various types of critical infrastructure and may include, for example, natural gas or energy prices, road and transportation networks, and information technology.

**Table 1: Unit Root Tests**

	ADF	DF-GLS	PP	VR	KPSS
<i>Water</i>	-4.4468***	-3.7256***	-4.4468***	2.2204*	0.1070
$\Delta$ <i>Water</i>	----	----	----	----	----
<i>Power</i>	-2.2390	-2.0350	-2.0798	1.7394	0.1684**
$\Delta$ <i>Power</i>	-10.5580***	-8.3836***	-10.6169***	----	0.0569

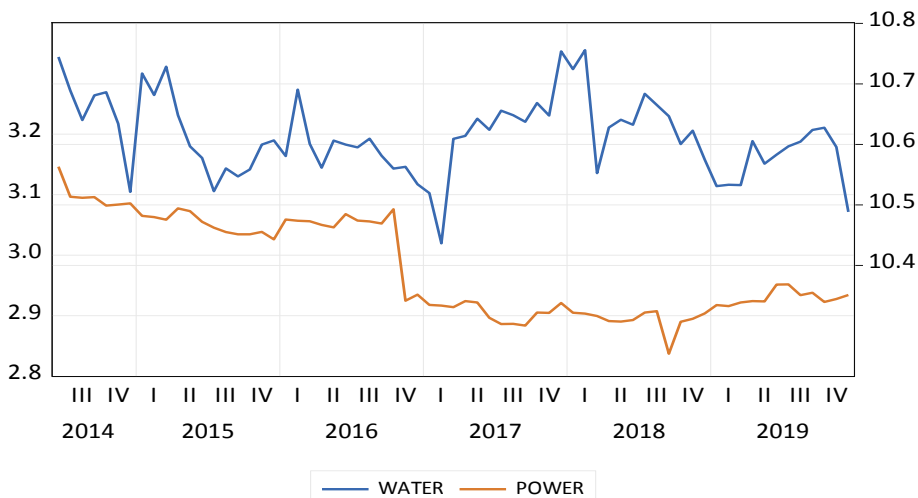
Notes: The sample period contains monthly observations covering June 2014 through December 2019. Power is (natural log) electricity price in cents per kwh; Water is (natural log) total water supplied in AF (acre-feet); All variables are seasonally adjusted.  $\Delta$  denotes the first difference operator. Lag lengths were selected based on Schwarz information criterion. \*\*\*, \*\* and \* indicate significance at the 1%, 5%, and 10% levels, respectively.

**Table 2: Breakpoint Unit Root Test**

	t-statistic	Break Date
<i>Power</i>	-8.7446***	2016M10

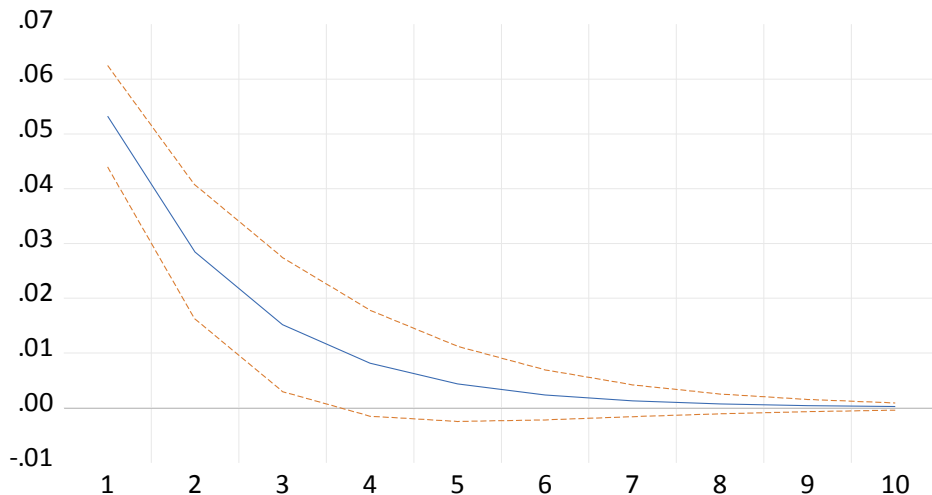
Notes: The sample period contains monthly observations covering June 2014 through December 2019. Power is (natural log) electricity price in cents per kwh and is seasonally adjusted. Lag length selected based on Schwarz information criterion. \*\*\*, \*\* and \* indicate significance based on Vogelsang and Perron (1998) asymptotic one-sided p-values at the 1%, 5%, and 10% levels, respectively. Break Date is estimated for the change in intercept and innovational outlier model.

**Figure 1: Los Angeles Electric Power Price and Water Production**

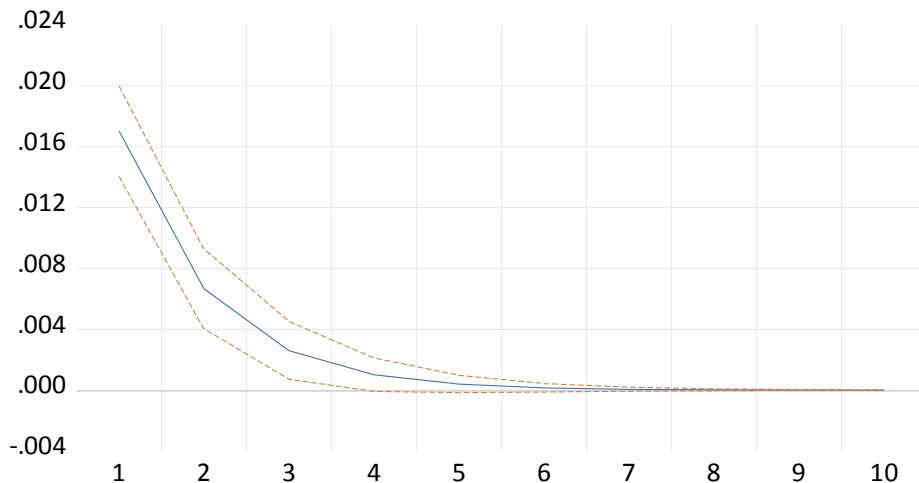


Note: The sample period contains monthly observations covering June 2014 through December 2019. Power is (natural log) electricity price in cents per kwh; Water is (natural log) total water supplied in AF (acre-feet); All variables are seasonally adjusted.

**Figure 2: Impulse Response of WATER to WATER Innovation using Diagonal One S.D. Factors**



**Figure 3: Impulse Response of POWER to POWER Innovation using Diagonal One S.D. Factors**



Note: The vertical axis is measure in relation to standard deviation and the horizontal axis is months since initial shock was imposed. The +/- 2 standard error confidence bands are shown as dashed lines.



**References**

- Banerjee, A., Lumsdaine, R. and Stock J., 1992, Recursive and Sequential Tests of the Unit-Root and Trend-Break Hypotheses: Theory and International Evidence, *Journal of Business and Economic Statistics*, 10(3), 271-287.
- Botzen, W., Deschenes, O. and Sanders, M., 2019, The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies, *Review of Environmental Economics and Policy*, 13(2), 167-188.
- Box, G. and Jenkins, G., 1976, *Time Series Analysis, Forecasting, and Control*. San Francisco, Holden-Day.
- Chow, V. and Denning, K., 1993, A simple multiple variance ratio test. *Journal of Econometrics*, 58, 385-401.
- Cochrane, H., 2004, Economic Loss: Myth and Measurement, *Disaster Prevention and Management*, 13(4), 290-296.
- Dickey, D. and Fuller, W., 1979, Distribution of the estimators for autoregressive time series with a unit root. *Journal of American Statistical Association*. 74, 427-431.
- Elliott, G., Rothenberg, T., and Stock, J., 1996, Efficient tests for an autoregressive unit root. *Econometrica*, 64, 813-836.
- Ewing, B., Kruse, J. and Thompson, M., 2004, Employment Dynamics and the Nashville Tornado, *Journal of Regional Analysis and Policy*, Mid-Continent Regional Science Association, 34(4), 1-14.
- Ewing, B., Kruse, J., Ozdemir, O. and Ewing, B., 2005, Disaster Losses in the Developing World: Evidence from the August 1999 Earthquake in Turkey, *Economic Development: Issues and Policies*, Ed. N. Narayana, Serials Publications, 2, 1017-1033.
- Hofer, L., Zanini, M., Faleschini, F. and Pellegrino, C., 2018, Profitability Analysis for Assessing the Optimal Seismic Retrofit Strategy of Industrial Productive Processes with Business-Interruption Consequence, *Journal of Structural Engineering*, 144(2), 04017205.
- Kwiatkowski, D., Phillips, P., Schmidt, P., and Shin, Y., 1992, Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? *Journal of Econometrics*. 54, 159-178.
- Lo, A. and MacKinlay, A.C., 1988, Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies*, 1, 41-66.

Lo, A. and MacKinlay, A.C., 1989, The size and power of the variance ratio test in finite samples. *Journal of Econometrics*, 40, 203-238.

MacKinnon, J., 1996, Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*. 11, 601-618.

Perron, P., 1989, The Great Crash, the Oil Price Shock and the Unit Root Hypothesis, *Econometrica*, 57, 1361-1401.

Phillips, P. and Perron, P., 1988, Testing for a unit root in time series regression. *Biometrika*. 75, 335-346.

Shaughnessy, T., White, M. and Brendler, M., 2010, The Income Distribution Effect of Natural Disasters: An Analysis of Hurricane Katrina, *Journal of Regional Analysis and Policy*, Mid-Continent Regional Science Association, 40(1), 1-12.

Vogelsang, T.J., and Perron. P., 1998, Additional Tests for a Unit Root Allowing for a Break in the Trend Function at an Unknown Time. *International Economic Review*, 39, 4, 1073–1100.

Zhang, W., Lin, P., Wang, N., Nicholson, C. and Xue, X., 2018, Probabilistic Prediction of Postdisaster Functionality Loss of Community Building Portfolios Considering Utility Disruptions. *Journal of Structural Engineering*, 144(4), 04018015.

Zivot, E. and Andrews, D., 1992, Further Evidence of the Great Crash, the Oil-price Shock and the Unit-root Hypothesis. *Journal of Business and Economic Statistics*, 10, 251-270.