Natural Hazards
https://doi.org/10.1007/s11069-022-05404-w

ORIGINAL PAPER

VEC model of water infrastructure in Los Angeles: implications for community resilience and recovery

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Received: 8 November 2021 / Accepted: 12 May 2022

Abstract

Los Angeles is a community that is susceptible to earthquakes, wildfires and other disasters that may cause water utility disruption. This study estimates water production in Los Angeles using a vector autoregressive error correction model (VECM). The model captures the short- and long-run dynamics among water production and elements of the economic system related to the labor market, built environment, energy and transportation networks in the Los Angeles area. We find evidence of a single cointegrating relationship between water production as measured by total monthly potable in gallons, employment, the S&P/Case-Shiller CA-Los Angeles Home Price index, and retail unleaded gasoline prices. VECM results suggest that after a shock that disrupts the equilibrium, such as an earthquake, system moves about 24% toward eliminating the disequilibrium in the first month, with a return to equilibrium in about 4–5 months. The results have implications both domestically and internationally for understanding a community's resilience and recovery to shocks and, thus, may shed light on how natural disasters affect a local economy.

Keywords Vector error correction · Resiliency · Natural disaster · Los Angeles

JEL Classification Q54 · C22

1 Brief introduction and background

Events such as natural disasters (e.g., earthquakes, hurricanes, tornadoes) have the potential to damage critical infrastructure such as a community's water production system. This study utilizes a vector error-correction model (VECM) to examine the relationship among

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Published online: 09 June 2022

water production and several important economic variables. The term water production is used to describe the service or delivery of water that flows through the infrastructure system.[1] We take the approach that the system is initially in equilibrium and we are interested in events that lead to deviations from that equilibrium. Our focus is on Los Angeles, a community that is susceptible to infrastructure failures due to earthquakes, wildfires, age, etc., that may cause water utility disruption (Hofer et al. 2018; Zhang et al. 2018). In particular, while there have been no major earthquakes in our sample period (June 2014–December 2019), the area is known for being on or near several fault lines such as the San Andreas Fault and seismic activity resulting in various degrees of shaking is fairly common. Wildfires in Los Angeles County also occur with some regularity and our sample period includes both the Woolsey Fire (November 2018) and the Sand Fire (July 2016). Nevertheless, understanding the behavior of the data series as a system provides important information regarding disaster preparation to policy makers and regional planners. In our analysis, we treat the disrupting event as a shock to the time series of a multivariate system that includes water production. In addition to water production, the model uses a set of variables that capture elements of the labor market, built environment, energy and transportation networks. This set of other variables is chosen as they correspond to those found in the Hurricane Resiliency Index (HRI) and have been shown to represent an area's resilience to natural hazards and ability to recover following a disaster (Cui et al. 2014, 2016, 2019).

Earthquakes and other natural disasters can be viewed as a severe disruption to the community and the response depends on the level of disturbance. Community resiliency is defined as its ability to rapidly recover from a disaster and return to normal socioeconomic activity (Gilbert 2010). In an area such as Los Angeles, assessment of the resiliency of the community is needed for disaster preparation, recovery, and estimation of potential losses (Baade et al. 2007; Klein et al. 2003; Rose 2007). In fact, a number of studies both domestically and internationally have examined the importance of recovery and resiliency at the city or community level and highlight the importance of this type of work.[2]

Prior work on disaster resilience is frequently focused on social, economic, institutional, and community elements (Bruneau et al. 2003; Cutter et al. 2008; Gunderson 2009; Norris et al. 2008; Rus et al. 2018). Recent work has identified elements with significant impacts on the health of economic enterprises such as individual businesses, industries, and regional economic activities (Ewing et al. 2005; Guimaraes et al. 1993; Taskin and Lodree Jr 2010). The economic effects of an earthquake or other natural disaster include physical damage that may prevent a community from returning to normal economic activity for months or years following the event. For instance, Rose et al. (2012) estimate a computable general equilibrium model for Los Angeles and analyze a scenario in which an earthquake closes the California Aqueduct for 6, 24, or 36 months. The authors find that the 6-month scenario resulted in no economic losses whereas for the 24- and 36-months scenarios economic losses for Los Angeles are predicted to be \$75 billion and \$240 billion, respectively. Job losses for 24- and 36-months scenarios were estimated at 742,000 and 1,315,000 job-years, respectively. Business recovery time is also an important factor to consider (Cremen et al. 2020). Businesses operate in a complex economic environment and challenges to operations in the aftermath of

[1] For consistency we follow the terminology that the Los Angeles Department of Water and Power uses to define the water that is moved through the water system. The term "water production" is not necessarily used to convey a factor demand function is used.

[2] See Asgary et al. (2012); Belasen and Polachek (2008); Chang (2010); Sydnor et al. (2017); Wasileski et al. (2011); Zhang et al. (2009).

a disaster include not only physical damage but also employee injuries, waste management, health and well-being. Including the interaction between engineering and economic indicators are important to consider (Bruneau et al. 2003; Freeman and Hancock 2017; Tierney and Bruneau 2007; Zhang et al. 2018).

Natural disasters such as earthquakes also expose the vulnerability of the built environment (Bosher et al. 2007). The ability of society to meet human needs when elements of the built environment are damaged or destroyed can be severely disrupted (Bartuska and Young 2007). In the aftermath of an earthquake or other natural disaster, a wide range of construction activities such as restoring public services such as water supply, schools, hospitals, power, communications, homes, and other infrastructure are needed (Young 2004). Post-disaster recovery policies also have significant link to household and neighborhood recovery (He et al. 2021). Elements of the built environment may be captured by the housing price index which reflects general construction and restoration activities (Ewing et al. 2007).

Another measure of critical infrastructure and energy use is retail gasoline prices. Gasoline prices are a proxy used to capture the impact of transportation cost on businesses and consumers. Transportation costs are known to fluctuate after a natural disaster (Boin and McConnell 2007; Commission 2006; Deltas 2008; Lewis 2009).

Disruptions to business activity and supply chain can also be a consequence of an earthquake and can result in a redistribution of resources (Chow and Elkind 2005; Comfort and Haase 2006; Kaiser et al. 2009; Sword-Daniels et al. 2015). As a result of the impairment of capacity to produce goods and services, employment may decline (in den Bäumen et al. 2015; Ewing et al. 2009). Employment can rebound in the post-disaster period as affected locales engage in cleanup and redevelopment with the goal of restoring pre-disaster levels of business activities (Burton 2015). There have been various labor market measures studied in the literature; however, a common one is employment (Ewing et al. 2005, 2009; Groen and Polivka 2008; Vigdor 2008).

The VECM provides insight as to both short run and long dynamics among the variables (Engle and Granger 1987). Moreover, the VECM provides a measure of the speed of adjustment from disequilibrium to equilibrium following a shock to the system. The VECM results provide a new look at understanding, measuring, and analyzing the resiliency and recovery process of a community. In addition, the findings shed light on modeling community recovery, measuring and assessing resiliency, and in optimizing the risk management policies and practices of water utility authorities and regulators. The findings complement the recent work of (Davis 2021) which emphasizes water as a basic service lifeline where delivery, quantity, quality, and fire protection are critical elements in the context of resilience and infrastructure performance. As Rojahn, et al. (2019) illustrate, lifeline infrastructure systems such as water and wastewater systems, telecommunications, transportation, and power systems such as natural gas and liquid fuels, are vulnerable to disruptions in many locations. This vulnerability impedes the response and recovery efforts after a natural disaster and thus, the authors advocate for policy, modeling, and research to improve performance post-disaster.

2 Description of data

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. Water is total (natural log) water production (total monthly potable in gallons, served by Los Angeles Department of Water and Power). The natural

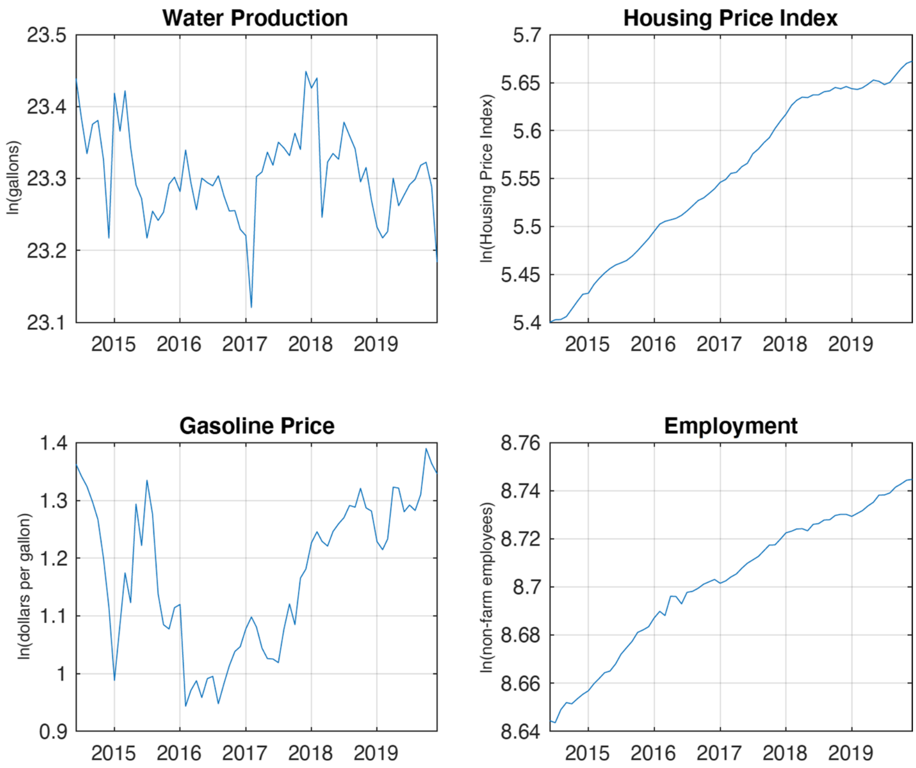

Fig. 1 Graphs of the data series. Water Production is the natural logarithm of the total water production in monthly potable in gallons, served by Los Angeles Department of Water and Power; Housing Price Index (HPI) is the natural logarithm of the S&P/Case-Shiller CA-Los Angeles Home Price Index; Gasoline price is the natural logarithm of US dollars for unleaded regular gasoline per gallon in Los Angeles-Long Beach-Anaheim, CA; Employment is the natural logarithm of total nonfarm employees in Los Angeles-Long Beach-Anaheim, CA (MSA), in thousands of persons

log of the Housing Price Index (HPI) is used to represent the built environment and is the S&P/Case-Shiller CA-Los Angeles Home Price Index. Gasoline price is in US dollars for unleaded regular gasoline per gallon in Los Angeles-Long Beach-Anaheim, CA (CBSA) and captures changes in energy use and transportations costs. Employment is All Employees: Total nonfarm in Los Angeles-Long Beach-Anaheim, CA (MSA), thousands of persons. Water data are from the California Water Board provided to the authors by LADWP while all other series obtained from Federal Reserve Economic Data (FRED) (Fig. 1). All variables are seasonally adjusted. Descriptive statistics are provided in Table 1.

3 Empirical methods

We employ two different tests to check the stationarity properties of the data series. If any data series is nonstationary then there is a time-dependent element to the data generating process. This makes it difficult to represent the data series over a specified interval of time using an econometrics model. On the other hand, if the data is stationary, then the

Table 1 Descriptive statistics

	Mean	Maximum	Minimum	Std. dev	Skewness	Kurtosis
LNWATER	23.307	23.449	23.121	0.064	0.030	3.335
LNGAS	1.173	1.390	0.944	0.128	−0.188	1.719
LNEMP	8.702	8.745	8.644	0.029	−0.442	2.042
LNHPI	5.552	5.673	5.400	0.086	−0.231	1.694

Descriptive statistics. The sample period is from June 2014 until December 2019. Water Production is the natural logarithm of the total water production in monthly potable in gallons, served by Los Angeles Department of Water and Power; Housing Price Index (HPI) is the natural logarithm of the S&P/Case-Shiller CA-Los Angeles Home Price Index; Gasoline price is the natural logarithm of US dollars for unleaded regular gasoline per gallon in Los Angeles-Long Beach-Anaheim, CA; Employment is the natural logarithm of total nonfarm employees in Los Angeles-Long Beach-Anaheim, CA (MSA), in thousands of persons

data generating process can be modeled using a mathematical equation and coefficients can be estimated using past observations of the data (Pindyck and Rubinfeld 1998). Thus, we employ two different statistical tests to determine whether our data series are stationary or nonstationary. The (augmented) Dickey-Fuller (1979) test is based on Eq. (1) and is known as the ADF test.

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

where y_t is the series being examined, Δ 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. The null hypothesis that y_t is a nonstationary time series if $(\rho_1 - 1) < 0$ is rejected based on the finite sample critical values from MacKinnon (1996).

Phillips and Perron (1988) developed a unit root test that allows for weak dependence, heterogeneity in the error term, and is robust to a wide range of serial correlation and time-dependent heteroskedasticity. The Phillips-Perron (PP) test is based on Eq. (2).

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

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_o: $\lambda = 1$) 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.

If any of the data series display evidence of a unit root, then there is a possibility of cointegration between the series. In other words, there may be a common stochastic relationship within the series. This means that there may be a linear combination of the variables that is stationary (Lütkepohl 2005). The presence of cointegration that is not adequately accounted for in the estimation of the model would render the results invalid. Thus, we need to examine whether there is cointegration present in our data. Specifically, we utilize the popular method of testing for cointegration proposed by Johansen and Juselius (1990, 1991). The Johansen-Juselius analysis is based on the following:

$$X_t = \mathbf{\Pi}_1 X_{t-1} + \cdots + \mathbf{\Pi}_k X_{t-k} + \varepsilon_t \quad t = 1, \ldots, T \tag{3}$$

where $\boldsymbol{X}$ is a vector of variables and $\boldsymbol{\varepsilon}$ is a vector of error terms with zero mean and constant variance. Re-writing in first-differences gives:

$$\Delta X_t = \mathbf{\Gamma}_1 \Delta X_{t-1} + \ldots + \mathbf{\Gamma}_{k-1} \Delta \mathbf{\Pi} X_{t-k-1} - \mathbf{\Pi} X_{t-k} + \varepsilon_t \tag{4}$$

where $\mathbf{\Gamma}_i = -\boldsymbol{I} + \mathbf{\Pi}_1 + \ldots + \mathbf{\Pi}_i$, and $\mathbf{\Pi} = \boldsymbol{I} - \mathbf{\Pi}_1 - \ldots - \mathbf{\Pi}_k$

Note that the p x p $\mathbf{\Pi}$ matrix contains information about long-run relations among the variables in the vector. If $\mathbf{\Pi}$ has rank zero, $r=0$, then all elements of $\boldsymbol{X}$ are nonstationary. Thus, there are no cointegrating relations among the variables. If $r=p$ then $\mathbf{\Pi}$ is of full rank which suggests a convergent system of difference equations and that all variables are stationary. For the case where $r<p$ there are r nonzero cointegrating vectors among the elements of $\boldsymbol{X}$ and $p-r$ common stochastic trends. $\mathbf{\Pi}$ can be factored into $\boldsymbol{\alpha\beta'}$ where $\boldsymbol{\alpha}$ is a p x r matrix of the vector error-correction parameters and $\boldsymbol{\beta}$ is a p x r matrix of cointegrating vectors. The cointegration vector can be found as an eigenvector, λ, via a maximum likelihood procedure by solving the following eigenvalue problem:

$$\left| \lambda S_{kk} - S_{k0} S_{00}^{-1} \, S_{0k} \right| = 0 \tag{5}$$

where S_{00} is the residual moment matrix from an ordinary least squares regression of $\boldsymbol{\Delta X_t}$ on $\boldsymbol{\Delta X_{t\text{-}1}}$, …, $\boldsymbol{\Delta X_{t\text{-}k\text{-}1}}$; S_{kk} is the residual moment matrix from an ordinary least squares regression of $\boldsymbol{X_{t\text{-}k}}$ on $\boldsymbol{\Delta X_{t\text{-}k+1}}$; and S_{0k} is the cross-product moment matrix. Following, the number of lags used in the vector autoregression may be chosen based on the evidence provided by AIC (Choudhry 1997) or other choice method such as SBC.[3]

Johansen-Juselius provide two distinct tests to determine the number of cointegrating vectors: the trace test and the maximum eigenvalue test. First, to test the hypothesis that there are at most r cointegrating vectors we use the trace statistic as follows:

$$\lambda_{\text{trace}}(r) = -T \sum_{r+1}^{p} \ln\left(1 - \hat{\lambda}_r\right) \tag{6}$$

where λ_{r+1}, …, λ_p are the $p-r$ smallest eigenvalues (characteristic roots). The null hypothesis is that the number of cointegrating vectors is less than or equal to r against a general alternative. The test statistic λ_{trace} equals zero when all $\lambda_i=0$. The further the eigenvalues are from zero the more negative is ln $(1-\lambda_i)$, thus the larger the λ_{trace} statistic. Second, the maximum eigenvalue test is based on the null hypothesis that the number of cointegrating vectors is r against the alternative of $r+1$ cointegrating vectors, and is given by:

$$\lambda_{\max}(r, r+1) = -T \ln\left(1 - \hat{\lambda}_{r+1}\right) \tag{7}$$

The maximum eigenvalue test $\lambda_{\max}$ equals zero when all $\lambda_i=0$. As in the case of the trace test, the further the eigenvalues are from zero the more negative is ln $(1-\lambda_{r+1})$ thus

[3] For the former, the optimal lag length chosen is the one that minimizes AIC, where AIC = ln det $_k^n+(2d^2k)/T$, and $k=1, 2,\ldots, n$, d is the number of variables in the system, n is the maximum lag length considered, det denotes determinant, and $_k$ is the estimated residual variance–covariance matrix for lag k. An alternative to the AIC method for choosing the model specification is the Schwartz Bayesian Criterion (SBC), where SBC = T ln (residual sum of squares) + n ln (T). The latter places a heavier penalty on additional lag parameters than does AIC, and is asymptotically consistent. In our case, AIC and SBC model selection were identical.

Table 2 Unit root tests

	ADF	PP
LNWATER	– 4.264***	– 4.264***
ΔLNWATER	– 11.0157***	– 13.5276***
LNEMP	– 2.140	– 2.912**
ΔLNEMP	– 3.5595***	– 9.6309***
LNGAS	– 1.880	– 1.915
ΔLNGAS	– 8.3716***	– 8.3716***
LNHPI	– 1.454	– 1.805
ΔLNHPI	– 2.419	– 5.008***

Unit root results for the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP). The null for the ADF and PP tests is a unit root. Δ is the first-difference operator

*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

Table 3 Cointegration analysis

Johansen cointegration tests							
Trace							
None	5% c.v	At most 1	5% c.v	At most 2	5% c.v	At most 3	5% c.v
62.384*	47.856	22.698	29.797	7.511	15.495	2.210	3.842
Max							
None	5% c.v	At most 1	5% c.v	At most 2	5% c.v	At most 3	5% c.v
39.686*	27.584	15.187	21.132	5.300	14.265	2.210	3.842

Johansen cointegration results for model: LNWATERGAL LNHPI LNGAS LNEMP

* denotes statistically significant. Trace refers to the trace statistic; Max refers to the maximum eigenvalue statistic

the larger the $\lambda_{\max}$ statistic. Osterwald-Lenum (1992) provides critical values for both the λ_{trace} and $\lambda_{\max}$ statistics.

Cointegration among the four series, according to the Granger representation theorem (Engle and Granger 1987), implies the existence of an error correction model of the form outlined in Eq. (8). If cointegration is present among the variables under consideration, then we will be interested in examining the following equation from the vector error correction model, where the natural logarithm of the water production series (LNWATER) is the left hand-side variable, LNHPI denotes the natural logarithm of the housing price index, LNGAS denotes natural logarithm of gasoline price, and LNEMP denoted natural logarithm of employment. Given our focus on the water production, we concentrate our discussion only on this particular equation.

$$\Delta \mathrm{LNWATER}_t = a + \sum_{j=1}^{n} b_j \Delta \mathrm{LNWATER}_{t-j} + \sum_{j=1}^{n} c_j \Delta \mathrm{LNHPI}_{t-j} + \sum_{j=1}^{n} d_j \Delta \mathrm{LNGAS}_{t-j} + \sum_{j=1}^{n} f_j \Delta \mathrm{LNEMP}_{t-j} + \eta \mu_{t-1} + e_t \quad (8)$$

where a is a constant; b_j, c_j, d_j, f_j, and η are estimated parameters; Δ is the difference operator representing the first differencing of the respective data series; e_t is the idiosyncratic error term; and u_{t-1} is the error correction term, which is the lagged residual series of the cointegrating vector normalized for LNWATER, LNHPI, LNGAS and LNEMP. The error correction term measures deviations of the series from the long-run equilibrium relation, and $0 < \eta < 1$ in order for the series to converge to the long-run equilibrium relation. Cointegration implies that (not all) of the error correction term(s) coefficients should be zero in the vector autoregression error correction model. From Eq. (8) the null hypothesis that LNHPI (or LNGAS or LNEMP) does not Granger-cause LNWATER is rejected not only if the coefficients on the lagged values of LNHPI (or LNGAS or LNEMP) are jointly significant, but also if the coefficient on the error correction term is significant. Changes in the independent variables may be interpreted as representing the short run causal impact while the error correction term provides the adjustment of changes in them toward their respective long run equilibrium.

4 Results and discussion

The results of the unit root tests are shown in Table 2. The findings suggest that water production may be integrated of order zero, I(0), or stationary while there is some evidence that each of the other variables is I(1).[4] As such, we proceed to examine the cointegrating properties among the variables.

Table 3 presents findings from the cointegration analysis. The results suggest that there is one cointegrating equation and indicate that a long run stable relation among these variables exists. Since we find evidence of a cointegrating relationship, we proceed with estimating a vector error correction model (VECM). The first step is to estimate the error correction term. These terms are presented in Eq. (9), which presents the normalized cointegrating vector equation of the stable water production relation as a function of the LNHPI, LNGAS, and LNEMP with subscripts omitted. The standard errors are in the parenthesis.

$$\begin{array}{l} \mathrm{LNWATERGAL} = -153.834 - \underset{(1.431)}{7.889} * \mathrm{LNHPI} + \underset{(0.153)}{0.711} * \mathrm{LNGAS} + \underset{(4.048)}{19.937} * \mathrm{LNEMP} \end{array} \quad (9)$$

[4] The results and conclusions are robust to the Dickey and Fuller (1981) with GLS detrending, Elliot, Rothenberg, and Stock (1996) point optimal, and Ng and Perron (2001) unit root tests, as well as the Kwiatkowski, Phillips, Schmidt, and Shin (1992) stationarity test. Results not reported for brevity but are available from the authors upon request.

Table 4 Summary of VEC model

	D(LNWATER)$_t$
Error correction$_{t\text{-}1}$	− 0.239
	[− 2.949]
Δ(LNWATER)$_{t\text{-}1}$	− 0.270
	[− 2.130]
Δ(LNWATER)$_{t\text{-}2}$	− 0.037
	[− 0.298]
Δ(LNHPI)$_{t\text{-}1}$	− 0.182
	[− 0.071]
Δ(LNHPI)$_{t\text{-}2}$	− 1.818
	[− 0.728]
Δ(LNGAS)$_{t\text{-}1}$	0.077
	[0.643]
Δ(LNGAS)$_{t\text{-}2}$	− 0.275
	[− 2.329]
Δ(LNEMP)$_{t\text{-}1}$	16.917
	[3.475]
Δ(LNEMP)$_{t\text{-}2}$	5.227
	[1.121]
C	− 0.029
	[− 1.703]
R-squared	0.356
Adj. R-squared	0.248

t-statistics in brackets []. Δ is the first-difference operator

The normalized cointegrating vector can be considered an estimation of the long-run relationship. Following the literature on cointegration we normalize the vector by setting the coefficient on water production at 1 so that the vectors may be interpreted as a water production determination function. All of the variables in the normalized cointegrating equation are statistically significant.

Both gasoline price and employment are positively related to water production. Because of the logarithmic nature of the model gas and employment estimates can be interpreted as elasticities. Energy use, transportation costs, economic activity, and jobs are all positively related to economic activity. Water production is a necessary input for all economic activity and the positive relationship is as expected. A 1% increase in the price of gasoline is associated with a 0.82% increase in water production. A similar increase in employment is associated with a 19% increase in water production.

An increase in the LNHPI is associated with a decrease in water production, albeit a relatively small effect. A possible explanation for the negative effect is that as the LNHPI increases the supply of homes decreases and water consumption declines as a result. Another explanation is that Los Angeles is located in a semi-arid region and is subject to state and local imposed water restrictions. Water consumers could respond with landscaping, water efficient appliances, and other efforts to reduce water consumption. This conservation effort could be responsible for the negative effect that housing prices have on water production.

Table 4 provides a summary of the results from the VECM.[5] For purposes of this analysis, we focus on the disruption of water service disruption and discuss the results corresponding to the water equation. Estimation of the VECM allows for us to further investigate the relation among water production, housing price index, gasoline price, and employment. Note that the vector error correction model includes the lagged residuals from the cointegrating regression as an explanatory variable which is referred to as the error correction term. The VEC model is a system of systems where the system is initially in equilibrium, i.e., the water system is operating normally, and there is an event that disrupts the equilibrium, there is a recovery, and then a return to equilibrium. The VEC model captures both the short-run effects of the shock and the long-run effects of the shock, the latter being captured by the error correction term.

The estimated coefficient on the error-correction term is negative and statistically significant. This indicates that housing price index, gasoline price, and employment establish a long run equilibrium with the water production. However, the size or magnitude of the error-correction coefficient may be interpreted as a measure of the speed at which the series adjust to a change in equilibrium conditions and implies that the movement of the series toward eliminating disequilibrium within one month is about 24 percent. This result implies that the disequilibrium is completely eliminated in about 4–5 months. In terms of the short-run dynamics of water production, we find the second lag of gasoline price to be negative and statistically significant and the first lag of employment to be positive and statistically significant.

As a further check on our results, we examine the impulse responses to LNWATER from a simulated one standard deviation shock to the other variables. This exercise provides guidance as to how long water production takes to recover after a disaster. The shock is fully dissipated when the time path of the series is no longer significantly different from zero as determined by the ± 2 standard error confidence bands. We find that LNWATER stabilizes at a lower level after about 2.5 months in response to a shock to LNGAS. In response to a LNEMP shock, it takes about 2 months for LNWATER to return to the pre-shock level. See Fig. 2. These impulse response functions are in agreement with the error correction estimate of about 4 months for complete elimination of disequilibrium. Moreover, the results were insensitive to a reordering of the variables. However, we report the results for the ordering as shown based on the first two measures being price based, thus the effects would be felt relatively quickly, and the labor market effects more likely occurring with a longer lag. We note that although our results are specific to Los Angeles, they do provide guidance as to how to measure and interpret resiliency with respect to the water supply and thus provide a framework for disaster management.

Finally, we perform Granger causality tests by estimating the VEC model and jointly testing the lags of the right-hand side variables using the Toda-Yamamoto (TY) procedure, which is appropriate when variables of different orders of integration, i.e., I(0) and I(1) (Toda and Yamamoto 1995). If the coefficients on the lagged values of LNHPI (or LNGAS or LNEMP) are jointly significant, then we reject the null that LNHPI (or LNGAS or LNEMP) does not Granger cause LNWATER. Results are presented in Table 5. We reject the null in the LNGAS and LNEMP cases, with LNGAS rejected at the 10% level, but the null is not rejected for LNHPI. These results are consistent with the VECM estimates. Namely, that employment and gasoline prices have predictive content for water production.

[5] For brevity, Table 4 only includes results VECM with LNWATER as the dependent variable. The full VECM results are available from the authors upon request.

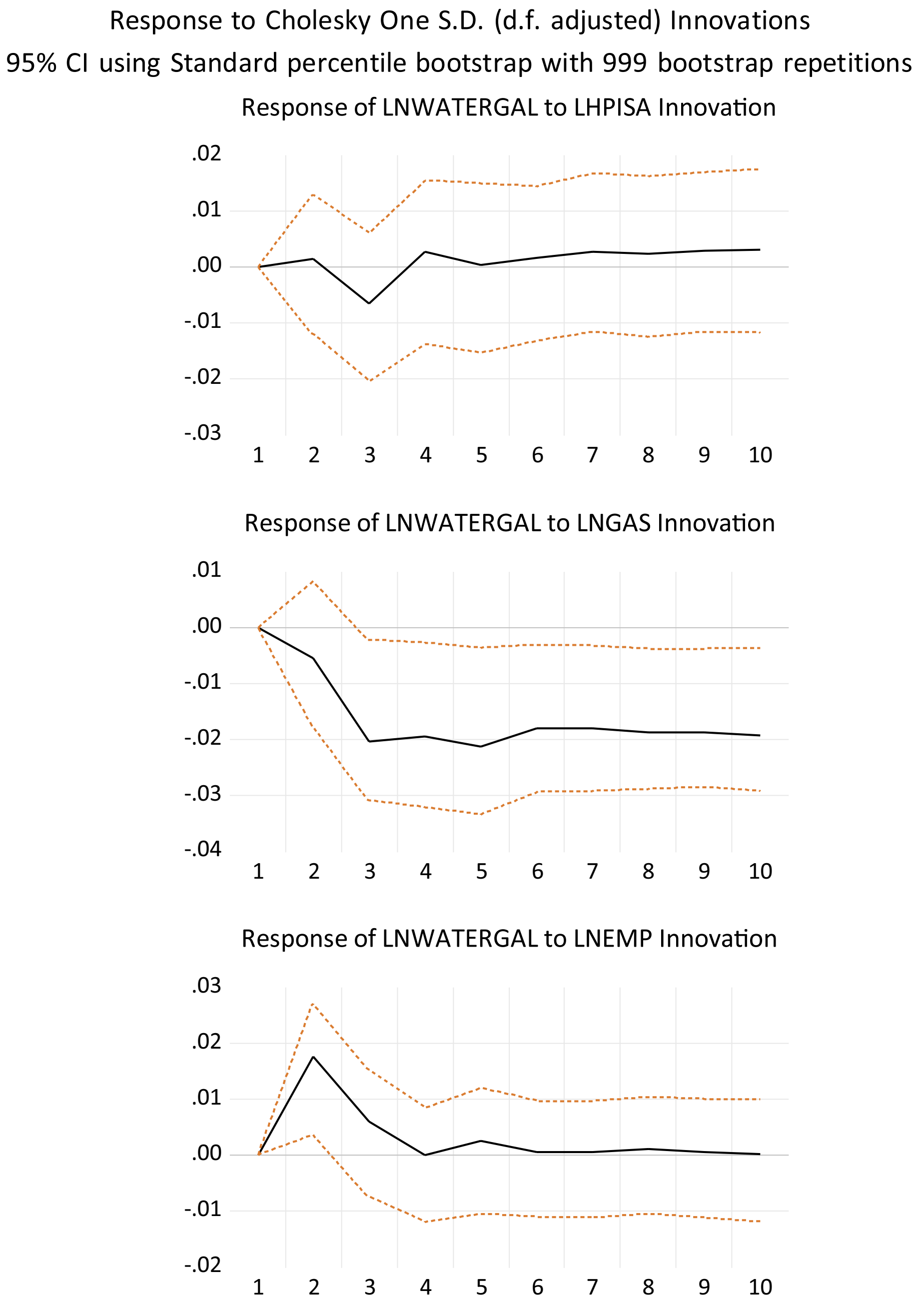

Fig. 2 The vertical axis is measured in relation to standard deviation of the natural log of water measured in monthly potable gallons and the horizontal axis is months since initial shock was imposed. The ± 2 standard error confidence bands are shown as dashed lines

Table 5 Granger causality results

Dependent variable: D(LNWATERGAL)			
Excluded	Chi-sq	d*f*	Prob
D(LNHPI)	1.186	2	0.553
D(LNGAS)	7.767	2	0.021
D(LNEMP)	7.132	2	0.028
All	12.717	6	0.048

Granger Causality test results for Eq. 7 estimated using the Toda-Yamamoto (1995) procedure

5 Conclusions

Using cointegration and error correction modeling techniques, we find that housing prices, gasoline prices, employment, and water production share a long-run cointegrating relation in the community of Los Angeles. Given that these time series establish a long run equilibrium relation we estimate a vector autoregressive error correction model. The results imply that about 24 percent of the disequilibrium is eliminated within the first month. This translates to the "half-life" of the shock being about 4 months and highlights the importance of restoring water production to get the economic conditions, as measured by housing prices, gasoline prices, and employment, back to normal.

The results are an important addition to the literature on the disruptions to systems which include lifeline critical infrastructure components such as a community's water supply. Our results are consistent with others who looked at various regions and found water, housing, and employment important in the resiliency and recovery process (Asgary et al. 2012; Commission 2006; Davis 2021; Ewing et al. 2005; Sydnor et al. 2017). Further, the finding of a cointegrating relation and the subsequent finding that past changes in gasoline price and employment help to explain changes in current water production is an important contribution to the literature on community resilience and recovery (Davis 2021; Rojahn et al. 2019). Further, these results clearly underscore the importance of employment in the process of water production. Local policy makers who want community resiliency with respect to water production could create policies that ensure employment recovery in the event of a natural disaster.

It should be noted that there are several limitations to this study. First, the results are focused on one, large urban community and may not generalize to other cities or to rural areas. In particular, these results are only valid for the Los Angeles region. Second, the empirical analysis is time series based using monthly data. Higher frequency data may be desirable in order capture very short run disruptions. Similarly, data availability limits the analysis such that some variables may not be directly comparable particularly in terms of area covered. Also, the time to recover the equilibrium is not completely independent from the magnitude of the shock. The larger the shock the more likely an extended recovery period would be necessary to recover the pre-disaster equilibrium. Finally, the nature of the vector error correction model only accounts for where the shock is initiated (e.g., in employment) and not the underlying cause of the shock. However, the results may still help domestic and international policy makers model the resilience and recovery process at the city and/or community level based upon a framework that specifically incorporates elements of the built environment, energy and infrastructure, and the labor market. Future research may address these issues and provide further insight into community resilience and recovery.

Author's contribution All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Bradley Ewing and Daniel Pastor. The first draft of the manuscript was written by Bradley Ewing and Daniel Pastor and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding Support for this work comes from the National Science Foundation under CMMI-CRISP Award Number 1735499 "Collaborative Research Type 2: Defining and Optimizing Societal Objectives for the Earthquake Risk Management of Critical Infrastructure" and Colorado State University/National Institute of Standards and Technology Subaward G-99042–14 "Center for Risk-Based Community Resilience Planning". Findings and conclusions or recommendations expressed in this study are those of the author(s) and do not necessarily reflect the views of the National Science Foundation and/or CSU/NIST. The author(s) thank representatives from the Los Angeles Department of Water and Power for helpful discussions and information. An earlier version of this paper was presented at the 2021 Southern Regional Science Association meeting.

Data availability The water data that support the findings of this study were obtained from the Los Angeles Department of Water and Power and restrictions apply to the availability of these data, which were used under agreement for the current research, and so are not publicly available from the authors. Requests for water data should be made directly to the LADWP. All other data are however available from the authors upon reasonable request.

Code availability Not applicable.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interest to disclose.

Consent for publication The authors consent to publication.

Ethical approval Not applicable.

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