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Estimating hydrogen demand function: A structural time series model

Mohammad Sharif Karimi [a,*], Saleh Ghavidel Doostkouei [b], Babak Naysary [c], Mir Hossein Mousavi [d]

[a] Department of Econometrics and Business Statistics, School of Business, Monash University Malaysia, Subang Jaya, Selangor, Malaysia
[b] Department of Economics, Firoozkooh Branch, Islamic Azad University, Firoozkooh, Iran
[c] School of Business, Birmingham City University, UK
[d] Department of Economics, Faculty of Social Sciences and Economics, Alzahra University, Tehran, Iran

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A B S T R A C T

This paper utilizes a Structural Time Series Model (STM) with an underlying component to estimate the global hydrogen demand function. This approach allows for the discernment of the ongoing impact of technology and the dynamic changes in consumer behavior that affect hydrogen demand over time. To estimate the hydrogen demand function, the analysis incorporates key variables, including hydrogen price, natural gas price, oil price, and GDP (Gross Domestic Product) per capita. The study utilizes quarterly global data from the first quarter of 2009 to the fourth quarter of 2021. In comparing the underlying components influencing hydrogen demand, the study suggests that advancements in production technology, organizational technology, and changes in consumer behavior collectively contribute to a gradual leftward shift in the global hydrogen demand curve over time. The study uncovered that, in the short term, global hydrogen demand demonstrates high inelasticity. Furthermore, the results reveal.

a complementary relationship between natural gas and hydrogen, although this complementarity diminishes significantly over time. Additionally, the findings suggest that oil.

can function as a substitute for hydrogen, with the substitution effect intensifying in the long term. Interestingly, hydrogen is initially perceived as a luxury commodity, yet over the long term, it transitions to behaving as a normal commodity.

1. Introduction

Hydrogen is emerging as a promising energy carrier due to its clean combustion properties, high energy content, and versatility. With the world increasingly shifting towards a more sustainable future, the demand for hydrogen as an alternative energy source is experiencing rapid growth. Policymakers, industries, and investors are all captivated by the ability of hydrogen to reduce greenhouse gas emissions and improve air quality. The development of renewable energy such as hydrogen have garnered significant attention in the energy sector due to their potential to enhance energy security, minimize harmful emissions, and alleviate the impacts of climate change (Moghaddam et al., 2019).

Hydrogen is considered highly promising as an energy carrier for various applications, including stationary fuel cell systems and electromobility. The demand for hydrogen as an alternative energy source has surged recently, making it a focal point for policymakers, industries, and investors. The significant driver behind its growing popularity lies in hydrogen's potential to lower greenhouse gas emissions, improve air quality, and achievement to climate change mitigation (Abid et al., 2023a, 2023b). Notably, the demand for hydrogen has increased more than threefold since 1975 (International Energy Agency (IEA) , International Energy Agency, 2021). Moreover, its high energy density, along with ease of storage and transportation, has positioned hydrogen as a preferred clean energy carrier (Dutta, 2014). Numerous processes exist for hydrogen production, utilizing both conventional and alternative energy resources, including natural gas, coal, nuclear, biomass, solar, and wind (Nikolaidis and Poullikkas, 2017). According to recent studies (Weger et al., 2021), hydrogen is being considered as a potential replacement for gasoline and diesel in vehicle fueling.

Despite these advantages, there are significant challenges to the widespread use of hydrogen. One of the main issues is the high cost of production and distribution, which still renders it more expensive than

* Corresponding author.
E-mail addresses: mohammadsharif.karimi@monash.edu (M.S. Karimi), saleh.ghavidel@iau.ac.ir (S.G. Doostkouei), babak.naysary@bcu.ac.uk (B. Naysary), hmousavi@alzahra.ac.ir (M.H. Mousavi).

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traditional fossil fuels. Additionally, the infrastructure for hydrogen production, storage, and distribution is currently limited, posing difficulties in scaling up hydrogen production. The assessment of hydrogen as a clean energy source involves weighing its advantages and disadvantages. Consequently, estimating hydrogen demand and identifying the factors influencing it becomes crucial for investors, politicians, and stakeholders.

Estimating hydrogen demand is crucial for guiding the emerging hydrogen economy. While global hydrogen use is increasing, demand remains concentrated in traditional applications within refining and the chemical industry, with the majority of production still relying on unabated fossil fuels (International Energy Agency, 2023). Estimating demand provides essential insights for planning infrastructure, aligning policies, and attracting investments. Accurate forecasts support the transition to a low-carbon economy, unlocking hydrogen's potential in sustainable energy solutions and addressing climate change challenges.

Analyzing the factors influencing hydrogen demand is essential for accurate demand forecasting. The primary factor is the production and pricing of fossil fuels, with particular emphasis on oil. In the petroleum refining industry, hydrogen consumption is intricately linked to raw materials and processing technology; for instance, in China, refineries are major users of hydrogen (Xuesong, 2003). Simultaneously, the demand for hydrogen can be impacted by the availability and cost of oil as a fuel alternative. The second crucial factor is natural gas, extensively employed in industries, transportation, electricity generation, notably, hydrogen production. The production methods and global pricing trends of natural gas also play a pivotal role in influencing hydrogen demand. According to the IEA report, depending on regional gas prices, the levelized cost of hydrogen production from natural gas varies from USD 0.5 to USD 1.7 per kg. The integration of Carbon Capture, Utilization and Storage (CCUS) technologies to mitigate CO2 emissions increases the production cost to approximately USD 1 to USD 2 per kg, while utilizing renewable electricity for hydrogen production ranges from USD 3 to USD 8 per kg (IEA, 2017, International Energy Agency, 2021).

One of the critical factors in the demand function is consumer income. Given that this paper focuses on estimating the global demand function for hydrogen, global per capita income becomes a significant determinant. While there is limited research specifically addressing the impact of consumer income on hydrogen demand, some studies have explored the influence of per capita income on the demand for renewable energy. For instance, Sadorsky (2009a, 2009b) demonstrates that over the long term, a 1% rise in real income per capita correlates with an approximately 3.5% increase in per capita consumption of renewable energy in emerging economies.

This study acknowledges that changes in technology and consumer behavior (taste) are among the important factors affecting hydrogen demand, despite being neglected in research due to their unobservability. Consequently, an extension of the analysis beyond traditional factors—such as price of hydrogen, per capita income, and the cost of alternative fuels—is made to encompass the impact of technology and consumer preferences on hydrogen demand. To achieve this, the Structural Time Series Modeling (STM) is applied to observe the underlying trend. By employing this method, we can control for unobserved factors like technological advancements and changes in consumer behavior (Harvey, 1990).

This paper presents three distinct contributions setting it apart from similar studies. Firstly, it investigates the determinants of hydrogen demand, incorporating variables such as hydrogen price, natural gas price, oil price, and GDP per capita. The analysis of quarterly global data spanning from 2009 to 2021 illuminates the dynamic nature of hydrogen demand and its interplay with key economic factors. Secondly, it identifies various factors influencing hydrogen demand, including advancements in production technology, organizational technology, and changes in consumer behavior—factors that are inherently unobservable and challenging to measure. Thirdly, it employs the STM method to estimate the hydrogen demand function. This method offers four distinct advantages: (i) These models can account for the complex interrelationships among various economic factors that influence energy demand. This allows for a more accurate and comprehensive understanding of the underlying drivers of energy demand (Commandeur and Koopman, 2007). This model provides valuable insights into how technology, laws and regulations, and consumer preferences have influenced hydrogen demand over time. (ii) The STM can capture both short-term and long-term trends in energy demand, which is crucial for forecasting future demand and planning energy infrastructure investments. (iii) These models can handle irregularities and missing data in the time series data, which is common in energy demand data due to factors such as weather patterns and changes in consumer behavior. Overall, the use of STM for estimating energy demand can lead to more accurate and reliable predictions, which can inform energy policy decisions and facilitate the transition to a more sustainable (Box et al., 2008) and efficient energy system (Houghton, 2019). (iv) This method splits the time series of hydrogen demand into five components, The trend component, the seasonal component, the cyclical component, the first-order autoregressive component, and the irregular time series component. With this segmentation, our understanding of the behavior of time series increases.

The reason for estimating the global hydrogen demand function in this research is as follows: The global demand function provides a comprehensive perspective on the overall market dynamics and trends. This broader view allows researchers, policymakers, and industry stakeholders to understand the interdependencies between different markets and identify emerging patterns that may not be evident when examining individual countries in isolation. Global demand analysis enables the examination of interactions and dependencies between different countries and regions. It helps in identifying potential opportunities for international collaboration, trade, and investment in hydrogen production, distribution, and infrastructure for use. The reason for choosing to estimate the demand function for hydrogen stems from the fact that while many studies have estimated the demand function for other renewable energies, there has been no estimation for hydrogen's demand function thus far. By estimating the demand function for hydrogen and identifying the factors influencing it, we can forecast future hydrogen demand and address potential obstacles preemptively. Overall, estimating hydrogen demand supports the transition to a sustainable energy future, drives economic development, and fosters technological innovation, positioning hydrogen as a key player in the global energy landscape.

The remainder of the paper is organized as follows. The first section is introduction. The second section is a literature review of energy demand in various studies. In the third section, we elaborate on the STM model. The empirical model will be presented in section four. Section five provides an interpretation of the data. The results of the estimation are presented in the sixth section. Finally, concluding remarks and policy recommendations will be presented in the seventh section.

2. Understanding energy demand: A comprehensive literature review

Research on estimating energy demand is typically divided into two primary categories: renewable energy and nonrenewable energy. In this paper, the literature on energy demand is examined in two separate groups, with a particular emphasis on the demand for hydrogen in the second group.

2.1. Nonrenewable energy demand

Numerous studies investigate the complicated dynamics of nonrenewable energy demand, focusing primarily on the elasticity of price and income while also exploring nuanced factors such as technology and consumer preferences (Alarenan et al., 2020). Modeling energy consumption demand has gained prominence in recent years, with researchers employing a variety of time series analysis techniques tailored to different energy sources. These models can be categorized based on the specific methods utilized, including Ordinary Least Squares (OLS), Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR), Vector Error Correction Model (VECM), or structural time series models. For instance, Hunt and Lynk (1995) utilized cointegration approaches to analyze industrial energy demand in the UK. Among the prevailing trends, researchers consistently find that nonrenewable energy sources like gasoline and diesel tend to exhibit price inelasticity, while income elasticity often hovers around one, shaping consumption patterns and market behavior (Mousavi and Ghavidel, 2019). Empirical investigations across various countries and regions yield invaluable insights into the determinants of energy demand. While income, energy prices, and population remain core factors, the influence of urbanization, climate conditions, technological advancements, consumer preferences, and government policies cannot be understated. For instance, studies like Amarawickrama and Hunt (2008) on electricity demand in Sri Lanka, Dilaver and Hunt (2011) on industrial electricity demand in Turkey, and Filippini and Hunt, 2012 on residential energy demand in the United States shed light on the intricate interplay of these variables, particularly emphasizing the role of energy efficiency and conservation efforts.

Moreover, the scholarly discourse proposes advanced frameworks and methodologies to enhance energy demand modeling accuracy and effectiveness. Hunt and Ryan (2015) advocate for a more comprehensive approach that accounts for the heterogeneity of energy-consuming activities and the interrelationships between energy services and efficiency improvements, as evidenced in their study of UK households. Similarly, Salisu and Ayinde's (2016) comprehensive analysis underscores the importance of integrating evolving policy landscapes and technological advancements into energy demand models to enable robust forecasting and informed policy formulation. Jointly, innovative approaches like that of McGookin et al. (2021) for estimating local energy demand and supply in Ireland underscore the ongoing pursuit of holistic solutions that consider diverse variables, from population density to building infrastructure, in shaping energy transitions at a community level.

2.2. Renewable energy demand

Scientists widely agree on the urgent need to transition to renewable energy as a pivotal strategy to mitigate climate change (Ma et al., 2023). Consequently, the analysis and estimation of renewable energy demand are gaining momentum, although there are fewer studies compared to those focusing on non-renewable energy sources. The majority of investigations tend to approach renewable energy as a whole entity rather than dissecting its components. These studies span various countries and regions, examining regional disparities and employing diverse analytical methods, including panel data analysis, to estimate the elasticity of price and income in renewable energy demand over both short and long terms (Sadorsky, 2009a,b). Additionally, some studies incorporate factors such as the prices of other fossil fuels, such as oil and natural gas, which can act as related commodities in the demand for renewable energy (Ackah and Kizys, 2015). A few go further to consider changes in technology and consumer behavior within the demand function for renewable energy.

Numerous factors intricately shape the consumption and production of renewable energy. For instance, Wei et al. (2023) illustrate how financial inclusion influences production and consumption within China's renewable energy sector. In Sadorsky's (2009a) research, a model estimating renewable energy consumption in G7 countries reveals that real GDP per capita and CO2 emissions are significant drivers of per capita renewable energy consumption. The study also finds a negative impact of oil prices on renewable energy consumption. Moreover, high-income elasticities of renewable energy consumption suggest that high-income countries are better positioned to invest in and produce renewable energy. Ackah and Kizys (2015) delve into factors influencing renewable energy demand in African countries, revealing that real income per capita, energy resource depletion, carbon emissions, and energy prices are primary drivers.

Further studies explore specific facets of renewable energy dynamics. Jiang et al. (2021) investigate the demand response potential of flexible electric water heaters with high renewable energy penetration, while Shang et al. (2022) analyze the influence of climate policy uncertainty on renewable and non-renewable energy demand in the United States. In a recent study, Weng et al. (2023) investigated the asymmetric adjustment of clean energy demand in OECD countries, elucidating how clean energy consumption responds differentially to variations in energy prices and income growth. Employing an Autoregressive Distributed Lag (ARDL) model, they discovered that clean energy demand exhibits greater responsiveness to price decreases than increases and is more sensitive to negative income changes than positive ones. Collectively, these studies deepen our understanding of renewable energy demand dynamics and inform policy decisions crucial for achieving sustainable energy transitions.

2.2.1. Hydrogen demand

It's important to mention that there is very little research and estimation specifically focused on the demand for hydrogen. Some studies have explored the demand for hydrogen in specific industries through case studies (Ni et al., 2005). Here is a brief overview of notable previous studies on estimating the hydrogen demand function:

Ball and Wietschel (2009) review hydrogen's potential as an energy carrier, emphasizing its high energy density, low emissions, and ability to enhance energy security. Rahmouni et al. (2016) analyze hydrogen demand in Algeria's road transport sector, considering population density, vehicle density, and fuel consumption to estimate demand across different regions.

Nagasawa et al. (2019) examined the impact of wind-based renewable hydrogen production on transportation fuel demand, highlighting its potential to notably cut greenhouse gas emissions. Hassan et al. (2023) assess Saudi Arabia's green hydrogen potential, stressing its importance in climate change mitigation. Despite strides in renewable energy, including solar, meeting green hydrogen demand remains challenging. Saudi Arabia seeks alliances with efficient green hydrogen producers, aiming to establish energy hubs generating 5 GW of hydrogen by 2025. However, solar-derived hydrogen storage may not match battery cost-effectiveness until around 2035.

In their 2010 study, Ma & Chen examined China's future hydrogen and renewable energy demand, considering economic development. They proposed two scenarios based on China's economic growth rate, emphasizing initial investment in hydrogen research and government support for manufacturing over transportation. China's evolving hydrogen demand is influenced by various factors beyond economic growth, necessitating further exploration. Huang et al. (2022) discuss China's policies to stimulate green hydrogen and fuel cell demand, analyzing hydrogen demand dynamics using a system model. Factors like environmental conditions, hydrogen supply, and facility construction affect demand, with predictions made until 2030 across different scenarios.

South Korea stands out as a leading country in the field of hydrogen operation, attracting numerous studies on the subject, such as the one conducted by Park et al. (2022). This study employs diverse forecasting techniques, including the Bass, logistic, and Gompertz models, in addition to the analogy method, to project the demand for Hydrogen fuel cell vehicles (HFCV). By adjusting the diffusion rate, the study provides projections for HFCV demand in 2040 under three scenarios, and it also forecasts annual hydrogen demand and daily hydrogen demand per charging station. The findings reveal a significant increase, with the daily hydrogen demand per hydrogen station expected to range from 1 to 2.3 tons by 2040. Another study points to the barriers to hydrogen consumption and production in South Korea (Lee et al., 2022). They find and classify the obstacles holding back the growth of hydrogen fuel cell energy in South Korea. Using expert Delphi surveys, the research identifies five key factors. The results point out that institutional and political factors are the most significant barriers, alongside challenges related to the cost of the unit and fuel cell infrastructure.

Several studies address challenges related to hydrogen demand. Yusaf et al. (2022) present a conceptual model for hydrogen energy, focusing on pathways and unintended consequences, notably the risk of increased NOx emissions from combustion. Global hydrogen demand forecasts range from 73 to 158 Mt by 2030. Brändle et al. (2021) advocate for natural gas reforming with carbon capture as the most cost-efficient low-carbon hydrogen production method in the medium term. Cost predictions suggest production costs could drop below $1/kg by 2050 in specific regions. Chen et al. (2023) demonstrate a 12.90% reduction in carbon emissions with electrolysis for hydrogen production and a 1.543% emissions reduction with adjustable thermal-electric demand response, alongside a 5.24% cost decrease. These studies underscore technology's impact on energy consumption and production.

Finally, as outlined by the World Energy Council in 2021, various scenarios exploring the future demand for hydrogen are investigated. The expected demand for hydrogen will fluctuate depending on the degree to which upcoming infrastructure integrates hydrogenation. Specifically, to meet the goal of restraining global warming to below 1.8 °C, it is imperative to attain a target of 600 MT (Million Tons) in hydrogen demand by the year 2050 (World Bank Group, 2022).

2.3. Summary of literature review

The summary of previous studies indicates a prevalent focus on estimating the demand function for energy, primarily centered around non-renewable sources like fossil fuels. The similarity between the studies estimating the demand function for fossil fuels and those for clean energy lies in the observation that the price elasticity of energy demand is generally smaller than unity. However, there is a slight difference in income elasticity: the income elasticity for clean energy is higher than that for fossil energy. Other factors mentioned in the studies include financial inclusion, the rate of urbanization, and the prices of alternative energy sources. Notably, studies specific to estimating the demand function for hydrogen were notably absent. Hence, this research's endeavor to estimate the demand function for hydrogen and identify its influencing factors presents a valuable contribution to the energy demand field. While this study shares similarities with previous research in selecting energy demand factors based on microeconomic rationale—such as energy prices and consumer income—it also diverges in two significant aspects. Firstly, it addresses the demand function for hydrogen as a clean fuel, a topic largely overlooked in prior studies. Secondly, it examines the role of technology in the clean energy demand function, an area seldom explored in existing literature. These distinctions highlight the novelty and significance of the present research in advancing our understanding of energy demand dynamics, particularly in the context of hydrogen as a clean energy source.

3. Material and methods

In this section, we outline the methodology employed for estimating hydrogen demand and provide details regarding the data and materials utilized in the estimation process.

3.1. Structural time series models (STM)

Structural time series models were introduced into econometrics and statistics by Harvey (1990). This model considers time series as a combination of unobserved components such as trend, cycle, seasonal, and irregular components. A univariate structure time series model is represented by Eq. (1):

$$y_t = \mu_t + \gamma_t + \psi_t + r_t + \varepsilon_t \tag{1}$$

The variable μ_t represents a trend component, γ_t denotes a seasonal component, ψ_t signifies a cyclical component, r_t stands for a first-order autoregressive component, and ε_t represents an irregular time series component. Each of these components can exhibit deterministic and stochastic behavior. The trend component consists of two parts: the level and the slope; this component is also referred to as the underlying trend (Mousavi and Ghavidel, 2019). In general, the trend component follows Eqs. (2) and (3). Eq. (2) indicates the level of the trend, and Eq. (3) indicates changes in the level or slope of the trend. This component reflects the long-term behavioral characteristics of the time series.

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \quad \eta_t \sim N\left(0, \sigma_\eta^2\right) \tag{2}$$

$$\beta_t = \beta_{t-1} + \xi_t \quad \xi_t \sim N\left(0, \sigma_\xi^2\right) \tag{3}$$

In most economic time series, seasonal effects are present. The seasonal component may take the form of a dummy variable or a trigonometric function. The seasonal component, in the case of stochastic and deterministic dummy variables, will be represented by Eqs. (4) and (5), respectively. The parameter 's' denotes the number of seasonal frequencies in a specific period. For example, for monthly data (s = 12), quarterly data (s = 4), and six-month data (s = 2).

$$\sum_{i=1}^{s-1} \gamma_{t-i} = \omega_t \quad \omega_t \sim N\left(0, \sigma_\omega^2\right) \tag{4}$$

$$\sum_{i=1}^{s-1} \gamma_{t-i} = 0 \tag{5}$$

In Eq. (4), the sum of seasonal effects has a zero mean, although due to its stochastic, they are sometimes formed slowly (when the variance is small) and sometimes quickly (when the variance is large). Eq. (5) is the case where the variance is zero. In this case, seasonal effects are constant over time.

The cyclic component can be shown in two ways, deterministic and stochastic trigonometric cycles. A deterministic cycle with the period λ $(0 < \lambda < \pi)$ is expressed in the form of Eq. (6).

$$\psi_t = \alpha \cos(\lambda t) + \beta \sin(\lambda t) \tag{6}$$

If time (t) is continuous, then ψ_t is a periodic function with periodicity $\left(\frac{2\pi}{\lambda}\right)$ and oscillation amplitude $\sqrt{\alpha^2 + \beta^2}$. If time is discrete, ψ_t will not be exactly a periodic function unless for some values where j and k are integers $\left(\lambda = \frac{2j\pi}{k}\right)$. Regrettably, cycles in economic time series data are seldom systematic enough to be represented by a specific periodic function, as in Eq. (6). Nevertheless, through Fourier analysis, we understand that complex cyclic data can be expressed as the sum of a limited number of sinusoidal functions, exemplified in Eq. (6). As an alternative method for identifying one or more specific cycles that depend on a large number of parameters, a stochastic cycle can be represented in the form of Eq. (7).

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} \cos(\lambda) & \sin(\lambda) \\ -\sin(\lambda) & \cos(\lambda) \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} v_t \\ v_t^* \end{bmatrix} \tag{7}$$

Where (ρ) indicates the cycle adjustment factor and is between zero and one. If this parameter is less than one, the cycle is stationary and if it is equal to one, the cycle is nonstationary. (λ) shows the periodic cycle in radians. The v_t, v_t^* represent the error terms that show the stochastic of cycles and have independent and identical distribution with zero mean and common variance σ_v^2. If the variance is zero, the cycle converts to a specific cycle. This model can depict quite complex cyclical patterns in economic time series without introducing additional parameters. Rather than modeling the cyclical nature of a time series through a deterministic cyclical model (Eq. (6)) or a stochastic cyclical model (Eq. (7)), we can directly express it using Eq. (8)

$$r_t = \rho r_{t-1} + \upsilon_t \quad \upsilon_t \sim N(0, \sigma_\upsilon^2) \tag{8}$$

where r_t is an unobserved autoregressive component which follows a first-order autoregressive process with $-1 < \rho < +1$. This unobserved autoregressive component, despite its simplicity, can capture many of the movements in the time series data that indicate the inertia of business cycles and are present in many economic time series.

Beyond structural modeling of univariate time series, a regression can be developed by adding explanatory variables as well as lag values of y_t on the right side for more accurate forecasting of y_t series. The general form of the structural time series regression model is as Eq. (9).

$$y_t = \mu_t + \gamma_t + \psi_t + r_t + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j_1=0}^{J_1} \beta_{1j_1} x_{1t-j_1} + \ldots.. + \sum_{j_n=0}^{J_n} \beta_{kj_n} x_{kt-j_n} + \varepsilon_t \tag{9}$$

3.2. Experimental model

Based on the theoretical literature concerning factors influencing hydrogen demand and following the methodology of structural time series regression, the empirical model for estimating the global demand function of hydrogen is as follows:

$$q_t^h = \theta_t + \sum_{i=1}^{I} \alpha_i q_{t-i}^h + \sum_{j=0}^{J} \beta_j p_{t-j}^h + \sum_{k=0}^{K} \delta_k p_{t-k}^{ng} + \sum_{l=0}^{L} \varphi_l p_{t-l}^{oil} + \sum_{m=0}^{M} \varphi_m gdp_{t-m}^{per} + w_t \lambda + \varepsilon_t$$
$$\theta_t = \mu_t + \gamma_t + \psi_t + r_t \tag{10}$$

In Eq. (10) variables $q_t^h, p_t^h, p_t^{ng}, p_t^{oil}$, and gdp_t^{per} represent hydrogen demand, hydrogen price, natural gas price, oil price, and per capita income, respectively. All variables are in logarithms. w_t is the vector of intervention variables. Intervention variables can appear in the form of unexpected events as dummy variables in the model. If the unexpected event occurring at time τ has a pulse effect, the intervention variable is defined in Eq. (11).

$$w_t = \begin{cases} 1 & for \quad t = \tau \\ 0 & for \quad t \neq \tau \end{cases} \tag{11}$$

If the unexpected event that happens at the time τ leads to a change in the slope or changes in the trend, in this case, the dummy variable is defined in Eq. (12).

$$w_t = \begin{cases} t - \tau & for \quad t > \tau \\ 0 & for \quad t \leq \tau \end{cases} \tag{12}$$

In Eq. (10), the variances related to μ_t, γ_t, ψ_t, and r_t are introduced as hyperparameters, which can be zero or positive. Depending on whether these variances are zero or non-zero, the unobservable components of the time series of hydrogen demand can be stochastic or fix, which is shown in Table 1.

The critical component is represented by μ in Eq. (10). This component is estimated through the Kalman Filter process depicted in Diagram 1. The Kalman filter is a recursive mathematical algorithm used to estimate the state of a dynamic system from a sequence of noisy measurements. It operates by generating an optimal estimate of the system's current state, considering its previous state and the latest observation, while also accounting for the uncertainty associated with both the system dynamics and the measurements. In the following, the estimation of μ for each year is calculated and plotted. Through this method, we ascertain the dynamic impact of technology and consumer preferences on hydrogen demand. Estimation of other parameters in Eq. (10) is performed by the Maximum Likelihood Estimator in regression.

Table 1
Hyperparameters and character of components.

Character components	Components and hyperparameters				
	Trend level	Trend slope	Seasonal	Cyclical	Unobserved Autoregressive component
Stochastic	$\sigma_\eta^2 > 0$	$\sigma_\xi^2 > 0$	$\sigma_\omega^2 > 0$	$\sigma_\nu^2 > 0$	$\sigma_\upsilon^2 > 0$
Fixed	$\sigma_\eta^2 = 0$	$\sigma_\xi^2 = 0$	$\sigma_\omega^2 = 0$	$\sigma_\nu^2 = 0$	$\sigma_\upsilon^2 = 0$

3.3. Data analysis

The period used in the current research is the first quarter of 2009 to the fourth quarter of 2021. Table 2 describes the characteristics of the logarithm of data. Due to the lack of access to global hydrogen demand data, the total value of hydrogen imports by all countries, which was extracted from the World Integrated Trade Solution (WITS) website, was used. In order to obtain the real value of the demand for hydrogen, the nominal value of the import is divided by the price index of the producer of hydrogen and argon gas manufacturing to the base price of 2009, and this variable is a proxy for the global demand of hydrogen in the current paper.

The mean and median indicators show that the data are normally distributed. It is also confirmed by using the Jarque–Bera test, except for the oil price variable. The indicators of the maximum, minimum, and standard deviation of the variables show that except for the logarithm of natural gas price (LNGP) and logarithm of oil price (LOP), the rest of the variables have less volatility. The values of the upper and lower bounds of the variables obtained by using the first, second, and third quartiles show that the variables did not have outlier data.[1]

By using the HEGY[2] method and considering the seasonality of the variables, all the variables with zero frequency are nonstationary at level, but they are stationary in the first difference. In other words, the variables are I(1). According to Johansen's cointegration test and effect and maximum eigenvalue statistics in the cases of no deterministic trend in data, linear deterministic in data, and quadratic deterministic in data, there are at least two cointegration vectors between these variables. Therefore, it is possible to use the level of these variables in the regression model.

The scatterplots between the logarithm of global hydrogen demand and the logarithm of hydrogen price, logarithm of natural gas price, logarithm of oil price, and logarithm of per capita income are shown in

[1] To accomplish this, the first quantile (Q1), second quantile (Q2), and third quantile (Q3) are calculated for a given time series. Subsequently, upper and lower bounds are determined using the formulas (Q3 + 1.5 * Q2) and (Q1 - 1.5 * Q2). If the maximum value in the time series is less than (Q3 + 1.5 * Q2), and the minimum value is greater than (Q1 - 1.5 * Q2), then none of the data in the time series are considered outliers. For example, consider the variable LHQ with a maximum value of 7.834 and a minimum value of 7.121. The upper and lower bounds are calculated as 18.65547 and −3.91028, respectively (Table 2). Since the data fall within this range, there are no outliers.

[2] - Hylleberg, Engle, Granger, and Yoo (HEGY) test statistics for the null hypothesis seasonal unit roots.

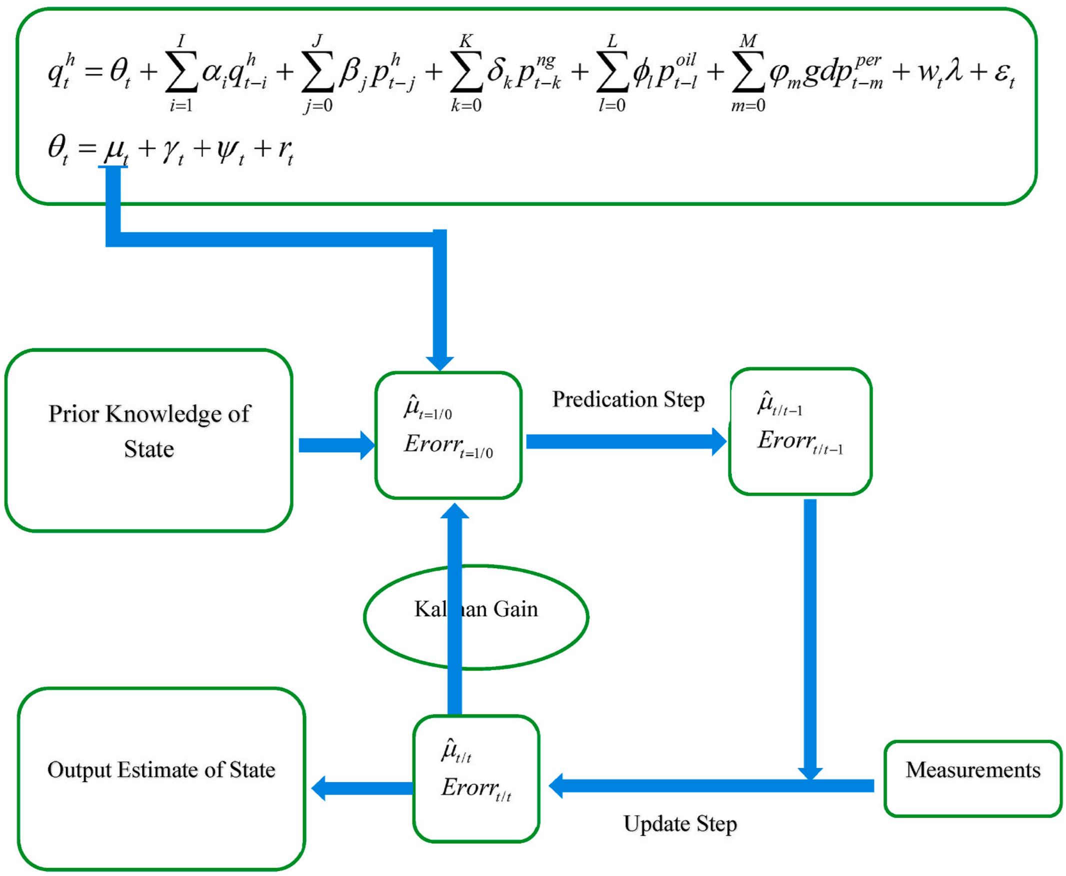

Diagram 1. Methodology of STM and Kalman filter to estimate Hydrogen demand.

Table 2
Data description.

Notation:	LHQ	LHP	LNGP	LOP	LPERGDP
Variable:	Logarithm of Hydrogen demand	Logarithm of Hydrogen price	Logarithm of Natural Gas Price	Logarithm of Oil price	Logarithm of Per capita income
Unit:	Trade Value 1000USD	Producer Price Index by manufacturing: Index Jun 2009 = 100	Global price of Natural gas, U.S. Dollars per Million Metric British Thermal Unit	Brent - Europe, Dollars per Barrel	GDP per capita, PPP (constant 2017 international $)
Source:	(WITS)	Federal Reserve Economic Data	Federal Reserve Economic Data	Federal Reserve Economic Data	World Development Indicators
Observations	52	52	52	52	52
Mean	7.402	4.618	2.017	4.237	9.637
Median	7.431	4.648	2.099	4.228	9.644
Maximum	7.834	4.729	3.451	4.816	9.777
Minimum	7.121	4.456	0.548	2.698	9.483
Std. Dev.	0.166	0.083	0.503	0.401	0.075
Skewness	0.208	−0.467	−0.311	−1.043	−0.251
Kurtosis	2.280	1.859	3.970	5.322	2.036
Jarque-Bera (Prob)	1.496 (0.473)	4.707 (0.095)	2.878 (0.237)	21.114 (0.000)	2.559 (0.278)
Quantile 1 (Q1)	7.236697	4.542719	1.724867	3.962119	9.576218
Quantile 2 (Q2)	7.431321	4.647606	2.099207	4.22776	9.644279
Quantile 3 (Q3)	7.508485	4.691623	2.390807	4.609923	9.698524
LOWER BOUND (Q1-1.5*Q2)	−3.91028	−2.42869	−1.42394	−2.37952	−4.8902
UPPER BOUND (Q3+1.5*Q2)	18.65547	11.66303	5.539618	10.95156	24.16494
Unit Root Test (HEGY)	I(1) Frequency 0	I(1) Frequency 0	I(1) Frequency 0	I(1) Frequency 0	I(1) Frequency 0

Fig. 1. Based on the statistical facts in Fig. 1, there is a negative correlation between the global demand for hydrogen and its price index at levels of the logarithm of the price index above 4.523. It should be noted that most of the observations of hydrogen price and demand are at levels higher than 4.523.

The scatter plot between the price of natural gas and the global demand for hydrogen, as well as the price of oil and the global demand for hydrogen, shows that there is a positive correlation between these variables, which can indicate that natural gas and oil are substitutes for hydrogen. The scatter diagram between per capita income and global

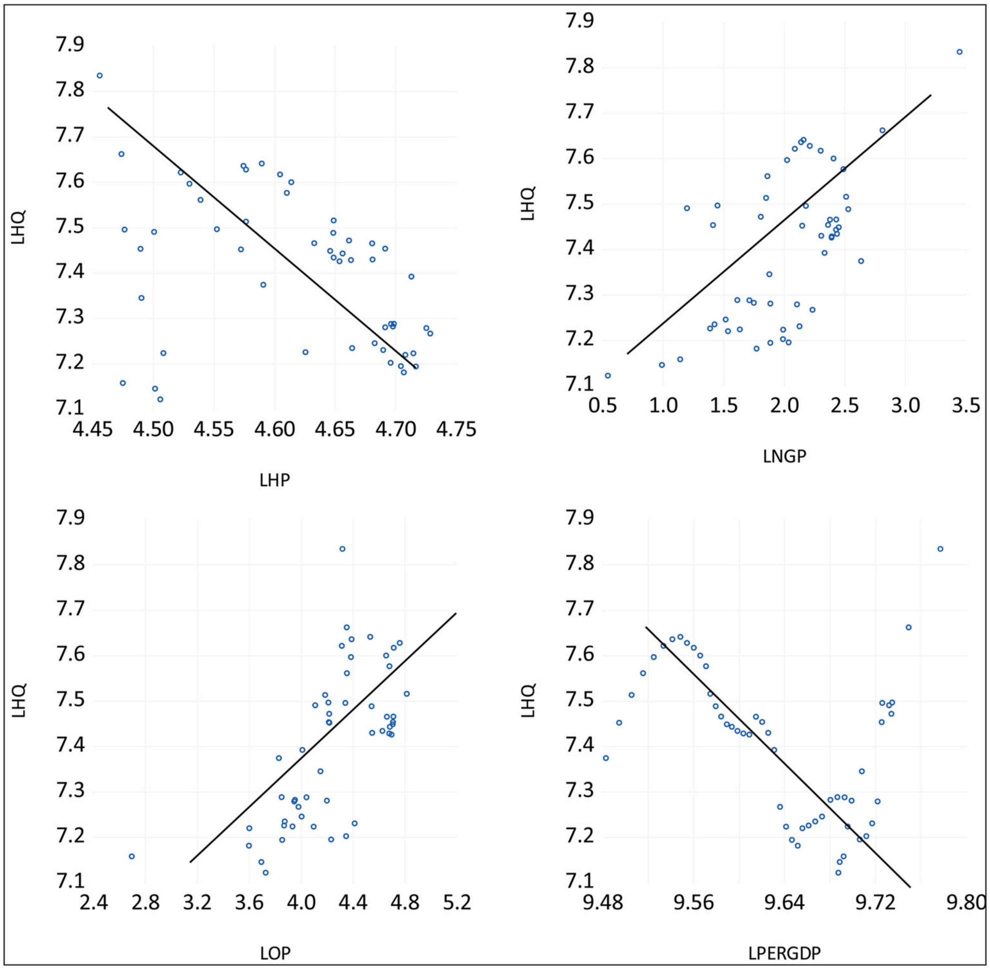

Fig. 1. Correlation between the logarithm of global hydrogen demand and logarithm of hydrogen price, logarithm of natural gas price, logarithm of oil price, and logarithm of per capita income.

hydrogen demand shows that in the range of logarithm of per capita income between 9.549 and 9.688, there is a negative correlation between these two variables, which means that as per capita income increases, global hydrogen demand has decreased.

In order to accurately analyze the behavior of global hydrogen demand, we analyze its trend, seasonal, cyclical, and irregular components. These components are shown in Eq. (1) and are derived using the STM. The component of trend of global hydrogen demand shows its long-term volatility due to changes in technology or changes in consumer taste. The seasonal component of global hydrogen demand indicates its periodic pattern, in other words, it indicates the calendar effects. Changes in this component are usually due to factors such as weather conditions and customs. The cyclical component of global hydrogen demand represents repeated upward or downward movements around the trend. These fluctuations around the trend can be related to short-term (4 years), medium-term (10 years), and long-term (20 years) periods. This means that repeated movements are measured from one through point to another through point or from one peak point to another peak point. Cyclical changes are not necessarily caused by economic factors. The irregular component of the global hydrogen demand represents the movements of this time series that do not follow a regular pattern. In other words, this component represents a part of global hydrogen demand that is not explained by the trend, seasonal, and cyclical components. These are caused by unusual events that cannot be predicted, such as natural disasters, mass strikes, and manipulation of data intentionally or unintentionally.

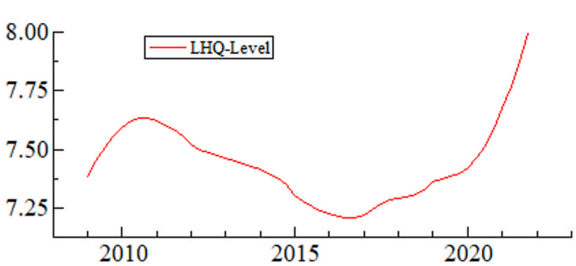

Fig. 2. Trend-level component of global hydrogen demand.

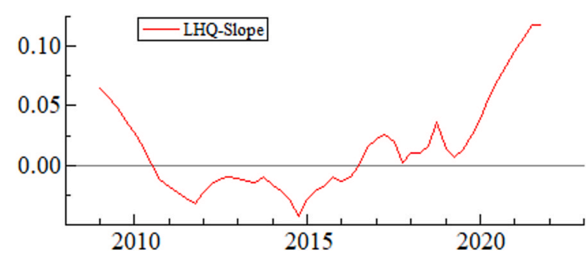

Fig. 3. Slope-trend component of global hydrogen demand.

Figs. 2 and 3 show the behavior of the trend component of global hydrogen demand. A change in the trend component of global hydrogen demand can be due to a change in the level or slope (changes in the level) of the series. The long-term behavior of the global demand for hydrogen shows that the consumption of this fuel has decreased between 2010 and 2017, but since 2017, the desire to consume this fuel has increased sharply. The slope of the trend shows the change in willingness to consume in the long term. It can be seen that the intensity of changes in the desire to use hydrogen fuel has increased since 2015, which can be due to changes in technology in the production of this fuel or changes in the taste and preferences of consumers towards this fuel (Fig. 3). To understand the cause of this phenomenon (prompted change in behavior and technological advancement), we must examine the events that transpired in 2015. One of the most significant environmental events of that year was the Paris Agreement. Unlike previous agreements, which were based on Intended Nationally Determined Contributions (INDC), the Paris Agreement changed the concept of INDC. According to paragraph 2 of Article 4 of the agreement, countries are required to prepare and subsequently implement their INDC. The use of the term "shall" in this paragraph imparts a mandatory legal obligation, indicating that, unlike past decisions regarding INDC submissions, which were non-binding, INDCs are entirely binding programs.

Fig. 4 shows the seasonal component of global hydrogen demand. The movement pattern of this component is determined based on Eqs. (4) and (5). It can be seen that hydrogen demand has reached its maximum and minimum value in the first and third seasons of each year from 2009 to 2021, and this behavior is repeated every year. In other words, global hydrogen consumption reaches its maximum amount in January, February, and March and its minimum amount in July, August, and September. The primary consumption of hydrogen occurs in the chemical and refinery sectors (International Energy Agency, 2023). Within the chemical sector, it is predominantly used for ammonia production, a key component in chemical fertilizers for agricultural purposes. Notably, the demand for chemical fertilizers typically peaks during the spring season. Conversely, in the refinery sector, the consumption of oil derivatives like gasoline and diesel experiences a surge in demand during spring, coinciding with the onset of vacations and increased travel. These factors significantly contribute to the seasonal fluctuations observed in hydrogen demand.

Fig. 5 shows the cyclic component behavior of the global demand for hydrogen. This pattern is determined based on Eqs. (6) and (7). The cyclical behavior of global hydrogen demand indicates that it takes three years to reach one maximum consumption amount to another maximum consumption amount. For example, a peak of global hydrogen demand was in the second quarter of 2011, and three years later, or 12 seasons, in the second quarter of 2014, we reached another peak. The important point is the asymmetry of the cycles in terms of the cycle depth, which means that the depth of the cycles has increased over time, and this has indicated the increase in fluctuations in the global demand for hydrogen in recent years. The recent deepening of the cycle may be linked to key events in the energy sector. These events, both positive and negative, include the Paris Agreement in 2015, Covid-19 in 2020, and the Ukraine War in 2021.

Fig. 6 shows the irregular component of global hydrogen demand. This component represents that part of the global hydrogen demand that is not explained by the trend, season, and cycle components and is affected by unknown factors. As shown in Fig. 6, apart from the first season of 2015, 2018, and 2019, the movement behavior of this component has had little fluctuations. It is to be emphasized that this represents an unidentified component within the time series. In other words, any factor affecting the demand for hydrogen beyond technological advancements, changes in consumer behavior, cyclic fluctuations, and seasonal variations is concealed within this component. Among these factors, we can point out shifts in international trade, including the trade tensions between China and the United States in 2018. Additionally, recent developments in the energy sector, such as a significant increase in the installation of solar and wind power plants, a decline in the cost of solar and wind energy production, and a rise in the adoption of electric cars, contribute to this component.

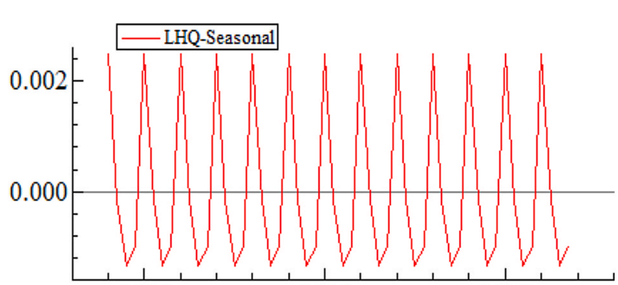

Fig. 4. Seasonal component of global hydrogen demand.

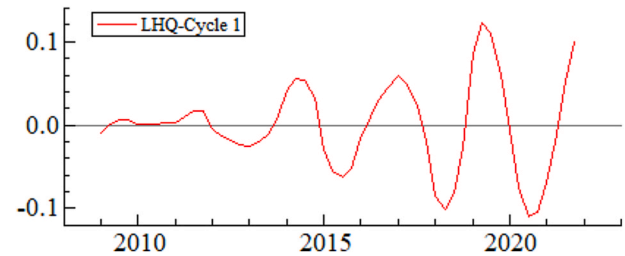

Fig. 5. Cyclical component of global hydrogen demand.

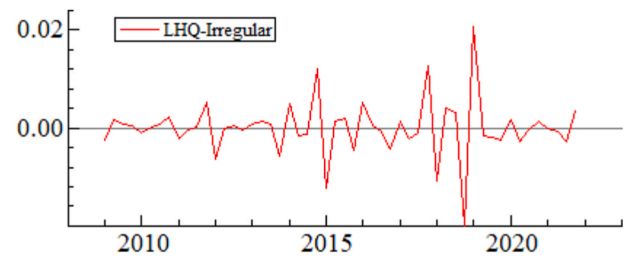

Fig. 6. Irregular component of global hydrogen demand.

4. Results and discussion

In this part, the demand function for hydrogen is estimated using the STM.[3] Based on the assumptions for the hyperparameters, Eq. (10) has been estimated in five cases, and the results are reported in Table 3. In order to find the optimal lags in Eq. (10), it was used Akaike Information Criterion (AIC), the Hannan-Quinn Information Criterion (HQIC), and the Schwarz Criterion (SC) in the Autoregressive Distributed Lag (ARDL) estimation. The coefficients represent the elasticity because the variables are logarithmic. In the first case, the assumption is made that unobserved factors comprise trends and seasonal components, with the trend component characterized by a stochastic level and slope. The second case is similar to the first case, except that the slope of the trend is fixed. In the third case, the cycle component is also considered in unobserved factors. The fourth case is the same as the third case, but the slope of trend is stochastic. Finally, in the fifth case, the unobserved factors including all the components are defined in Table 1. Furthermore, in all instances, intervention variables represented as unexpected events in the form of dummy variables have been controlled for. There is a pulse in the data for the first quarter of 2015, 2018, and 2019.

The first variable that must be interpreted in any demand function is the price. In the short term, the demand for global hydrogen is very inelastic. The coefficient of LHP is small and statistically insignificant in

[3] For estimating the hydrogen demand function, the software OxMetrics 7 is used.

Table 3
Estimation of global hydrogen demand function.

	The assumption of hyperparameters				
	Case 1	Case 2	Case 3	Case 4	Case 5
Explanatory variables	$\sigma_\eta^2 > 0$ $\sigma_\xi^2 > 0$ $\sigma_\omega^2 > 0$	$\sigma_\eta^2 > 0$ $\sigma_\xi^2 = 0$ $\sigma_\omega^2 > 0$	$\sigma_\eta^2 > 0$ $\sigma_\xi^2 = 0$ $\sigma_\omega^2 > 0$ $\sigma_\nu^2 > 0$	$\sigma_\eta^2 > 0$ $\sigma_\xi^2 > 0$ $\sigma_\omega^2 > 0$ $\sigma_\upsilon^2 > 0$	$\sigma_\eta^2 > 0$ $\sigma_\xi^2 > 0$ $\sigma_\omega^2 > 0$ $\sigma_\nu^2 > 0$ $\sigma_\upsilon^2 > 0$
LHQ(-1)	0.984*** (0.000)	0.972*** (0.000)	0.984*** (0.000)	0.984*** (0.000)	0.983*** (0.000)
LHQ(-2)	−0.175*** (0.005)	−0.183** (0.084)	−0.176*** (0.005)	−0.176*** (0.006)	−0.179*** (0.006)
LHQ(-3)	−0.022 (0.558)	−0.005 (0.934)	−0.023 (0.542)	−0.022 (0.563)	−0.019 (0.612)
LHP	−0.105* (0.219)	−0.031 (0.823)	−0.107 (0.203)	−0.107 (0.211)	−0.108 (0.212)
LHP(-1)	0.096 (0.393)	−0.279* (0.111)	−0.099 (0.378)	−0.098 (0.389)	−0.105 (0.376)
LHP(-2)	−0.155** (0.094)	−0.093 (0.514)	−0.157** (0.090)	−0.156* (0.094)	−0.158** (0.099)
LNGP	−0.118*** (0.000)	−0.074*** (0.017)	−0.115*** (0.000)	−0.118*** (0.000)	−0.118*** (0.000)
LNGP(-1)	0.082*** (0.000)	0.041** (0.100)	0.079*** (0.000)	0.082*** (0.000)	0.082*** (0.000)
LOP	0.025*** (0.018)	0.025** (0.092)	0.024*** (0.024)	0.025*** (0.018)	0.025*** (0.016)
LOP(-1)	0.046*** (0.008)	0.022 (0.214)	0.044*** (0.011)	0.047*** (0.008)	0.047*** (0.008)
LPERGDP	8.785*** (0.000)	8.860*** (0.000)	8.809*** (0.000)	8.792*** (0.000)	8.791*** (0.000)
LPERGDP(-1)	−8.539*** (0.000)	−8.08*** (0.000)	−8.542*** (0.000)	−8.547*** (0.000)	−8.522*** (0.000)
Outlier_2015 (1)	−0.112*** (0.000)	−0.083*** (0.000)	−0.113*** (0.000)	−0.112*** (0.000)	−0.111*** (0.000)
Outlier_2018 (1)	−0.111*** (0.000)	−0.111*** (0.000)	−0.111*** (0.000)	−0.111*** (0.000)	−0.110*** (0.000)
Outlier_2019 (1)	0.086*** (0.000)	0.088*** (0.000)	0.085*** (0.000)	0.087*** (0.000)	0.087*** (0.000)
-2LOGL	−246.242	−233.695	−246.164	−246.218	−245.517
R^2	0.984	0.976	0.984	0.984	0.984
DW	1.58	1.64	1.55	1.57	1.51
Obs	50	50	50	50	50
μ_2021(4)	−0.561	−4.332	0.412	0.576	0.500
β_2021(4)	−0.001	−0.004	−0.001	−0.001	−0.001
ω_2021(4)	5.440	3.820	4.922	5.413	5.302
Cycle_2021 (4)	–	–	0.002	–	0.0003
AR coefficient	–	–	–	0.903	0.889

all cases. The price elasticity of demand is statistically significant in the long term, although its value is less than one unit. This coefficient is the sum of LHP and its statistically significant lags (LHP (−1), LHP(-2)). The price elasticity of demand for hydrogen is about 0.15 in the long term. As a result, the demand for hydrogen in the world is less sensitive to price changes. This is consistent with the results of most studies such as Rao and Rao (2009), and Espey (1998) who found low price elasticity in the case of gasoline and diesel. Most studies on the demand for renewable and non-renewable energy believe that the price elasticity of energy is less than unity (e.g., Hunt and Ryan, 2015). Economically, this is favorable for hydrogen because if the price rises for any reason, like an increase in production costs, the demand for hydrogen will decrease insignificantly. A 100% increase in the price of hydrogen results in just a 15% decrease in the demand amount.

In the short term, the increase in the logarithm of natural gas price (LNGP) leads to a decrease in the demand for hydrogen. In other words, natural gas and hydrogen are two complementary fuels in the short term which is in line with the findings of Kani et al. (2014). Of course, this cross-elasticity is small and about −0.1, which means that a one percent increase in the price of natural gas, in the short term, reduces the demand for hydrogen by 0.1 percent. The important thing is that the complementarity of these two fuels will be greatly reduced in the long run because the coefficient of LNGP (−1) is positive. Both LNGP and LNGP (−1) coefficients are statistically significant, and the LNGP coefficient is larger than LNGP (−1). The cross elasticity of natural gas price decreases from −0.1 in the short term to −0.02 in the long term. The main reason for the complementarity of natural gas and hydrogen is that hydrogen is produced from natural gas. Fortunately, the cost of natural gas experienced a significant decrease from 2010 to 2020, halving in price according to Federal Reserve Economic Data. Although there was a rise in 2021 and 2022, the overall long-term trend suggests a declining trajectory. The reduced cost of natural gas fosters optimism for future mass production of hydrogen. Importantly, the inelastic demand for hydrogen to natural gas prices implies that even an increase in natural gas costs is unlikely to pose a significant threat to reducing hydrogen demand.

The coefficients for LOP and LOP (−1) indicate that oil acts as a substitute for hydrogen. The substitution effect intensifies in the long term, such that a one percent increase in the price of oil immediately boosts the demand for hydrogen by 0.02. However, in the long term, this effect reaches 0.06 (the sum of LOP and LOP (−1) coefficients), effectively tripling the impact. This confirms the results of Abada et al. (2013) who found the interfuel substitution at different fuel prices. This result is indicative of the fact that the drop in oil prices could threaten the global demand for hydrogen, which is a clean fuel, as the increase in the price of oil can boost the hydrogen market. Given the historical volatility of oil prices, predicting their future decrease or increase based solely on past trends remains challenging. While any potential rise in oil prices poses a threat to the demand for hydrogen, the relatively low elasticity of hydrogen demand concerning oil prices suggests that this threat is not of significant concern.

Based on the LPERGDP coefficient, hydrogen is identified as a luxury commodity. The income elasticity for hydrogen is substantial, indicating that, in the short term, a one percent increase in income can lead to an 8.8 percent increase in hydrogen demand. However, this elasticity undergoes adjustments over time, as reflected by the negative coefficient of LPERGDP (−1). In essence, hydrogen exhibits immediate luxury status for consumers, but in the long run, it transitions to being considered a normal commodity. The income elasticity for hydrogen demand in the long term is approximately 0.3, calculated as the sum of the LPERGDP and LPERGDP (−1) coefficients. The positive news is that the world's per capita income is steadily increasing, promising a favorable outlook for the future surge in demand for hydrogen. In contrast, nonrenewable energy sources such as gasoline and diesel are considered normal goods, as their income elasticity remains less than one even in the short run.

Hydrogen demand has faced an unexpected shock in the form of a negative pulse in the first quarter of 2015 and 2018, and a positive pulse in the first quarter of 2019. These pulses are controlled by dummy variables Outlier_2015 (1), Outlier_2018 (1), and Outlier_2019 (1). The coefficients of these dummy variables are statistically significant.

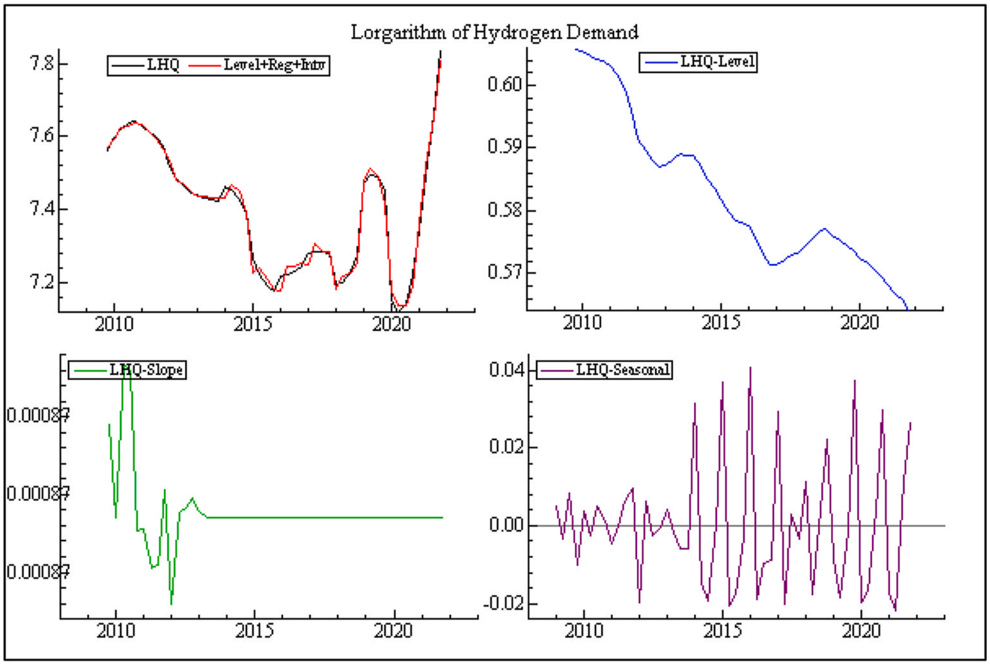

Fig. 7. Case 1 – Stochastic Level and Slope for Underlying Trend (Logarithm of Hydrogen demand, 1000$).

4.1. Analysis of unobserved components

As mentioned in the model section, the unobserved components include the underlying trend along with the level and slope, seasonal, cyclical, unobserved autoregression, and an irregular component. In case 1, the results of which are shown in Tables 3 and it is assumed that the unobserved components include the underlying trend and the seasonal component. In addition, it is assumed that the underlying trend has a stochastic level and slope. Fig. 7 shows the level and slope of the underlying trend as well as the seasonal component. It can be seen that the level trend of global demand for hydrogen from 2009 to 2021 has been downward with an almost constant slope, that is, the intercept of the hydrogen demand function has shifted downward over time. Underlying trends often reflect changes in technology and consumer preferences over time. As a result, technology and consumer preferences and tastes have changed over time in such a way that the demand for hydrogen has decreased. This trend shows that technology has not helped to increase the demand for hydrogen in terms of production and consumption. The reasons for this outcome can vary; some of them are outlined below.

While technology often drives innovation and growth, advancements in alternative energy sources or storage technologies may have outpaced those related to hydrogen. If competing technologies offer superior efficiency, cost-effectiveness, or environmental benefits, consumers may opt for alternatives, leading to a decrease in hydrogen demand. Changes in consumer preferences play a pivotal role in shaping market trends. If consumers prioritize energy sources that align with specific values, such as sustainability, affordability, or ease of use, this can influence the demand for hydrogen. If hydrogen-based solutions do not resonate with current consumer preferences, it can contribute to a decline in demand.

Consumer perceptions of the value offered by hydrogen technologies compared to alternatives are crucial. If competing technologies are perceived as more reliable, accessible, or suitable for their needs, consumers are likely to favor them over hydrogen-based options. Consumer choices are often influenced by the convenience and accessibility of energy solutions. If alternative technologies are more readily available or easier to integrate into existing infrastructure, they may gain preference over hydrogen, contributing to a decline in demand. Lack of awareness or understanding about the benefits of hydrogen technologies could also impact consumer choices. Effective education and communication strategies are essential to highlight the advantages of hydrogen and address any misconceptions that may contribute to decreased demand.

The movement pattern of the seasonal component shows that until 2013, the seasonal effects were negligible. From 2014 to 2017, the peak of demand was in the spring season and the bottom was in the summer. From 2017 onwards, the calendar effect has changed so that the autumn season has the peak demand and the spring season has the lowest demand. The shift in the peak hydrogen demand from spring to autumn and the lowest demand from spring to summer could be influenced by several factors, including changes in industrial processes, regulatory shifts, and market dynamics. The demand for hydrogen can be heavily influenced by industrial processes, such as refining, chemical manufacturing, and energy production. Changes in these industries, including shifts in production schedules or the adoption of new technologies, could lead to fluctuations in demand throughout the year. Hydrogen is used in various sectors, including energy production and transportation. Changes in seasonal energy usage patterns, such as increased heating demands in autumn or changes in transportation needs, could affect the timing and magnitude of hydrogen demand. Changes in market dynamics, including fluctuations in the prices of alternative energy sources or disruptions in the supply chain, can influence the demand for hydrogen. Additionally, the availability of infrastructure for hydrogen production, distribution, and storage may impact seasonal demand patterns. In Fig. 7, the fitness of the estimate of the demand function is also plotted (first curve on the left side). It can be seen that the estimation is very close to the real value so the R^2 is about 98%. This demonstrates that the model exhibits high validity when compared to actual hydrogen demand data.

In the second case, it is assumed that the trend slope is fixed and not stochastic, and the rest of the assumptions are the same as in the first case. The results of the level and slope of the trend are almost the same as in the first case, the level of the downtrend with a constant slope (Fig. 8). Seasonal effects are slightly different, with a peak of demand in winter and a trough in spring. It should be noted that the irregular component is present in all cases, this component represents that part of the global hydrogen demand that is affected by unknown factors, so it cannot be interpreted.

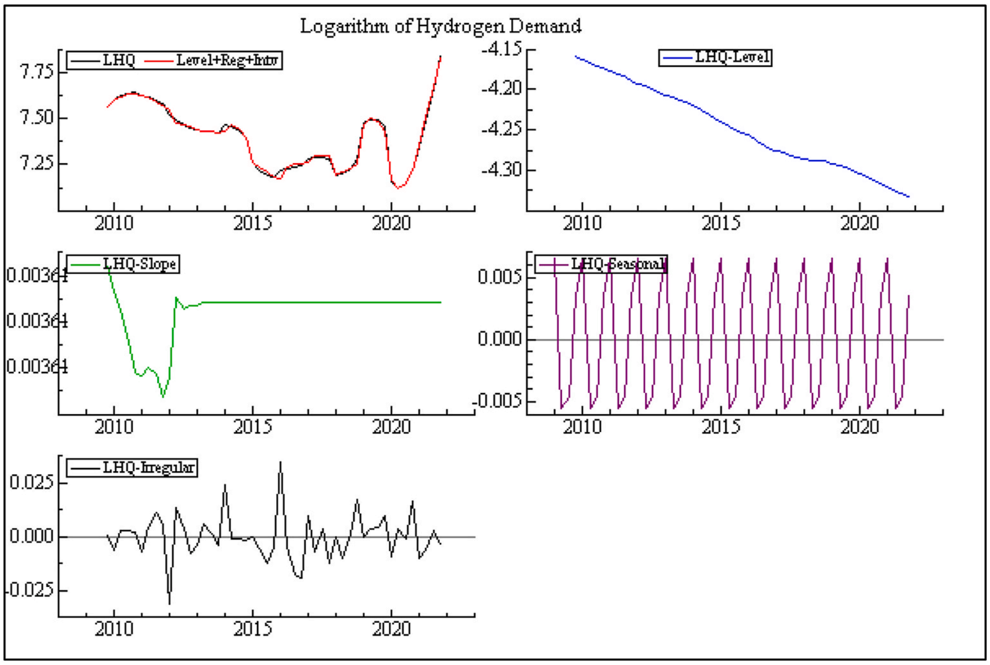

Fig. 8. Case 2 – Stochastic Level with Fixed Slope for Underlying Trend (Logarithm of Hydrogen demand, 1000$).

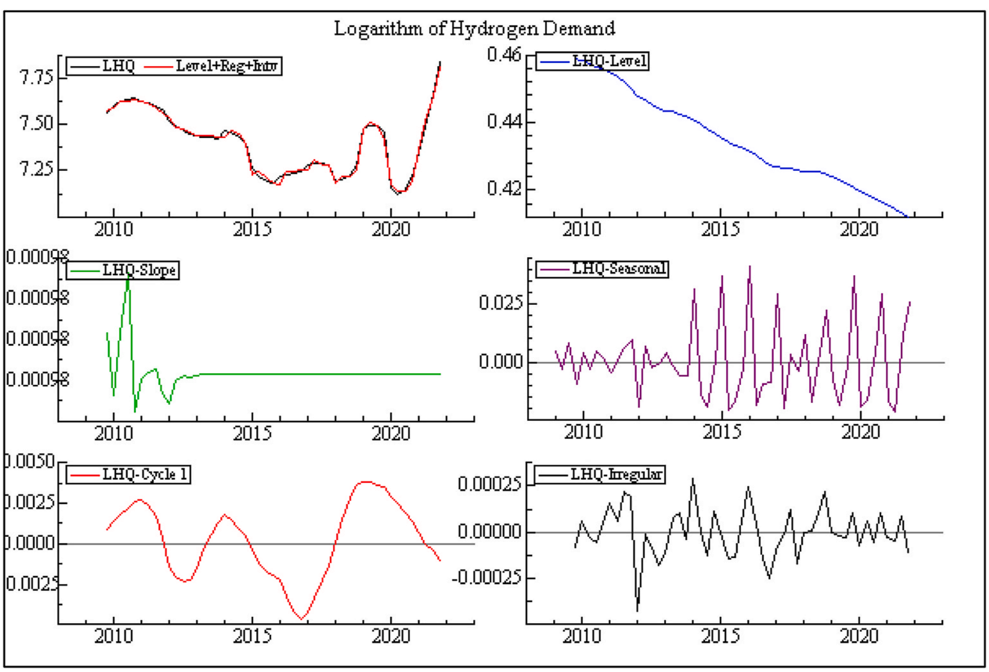

Fig. 9. Case 3 - Stochastic Level with a Fixed Slope for the Underlying Trend and an Incorporated Cycle Component (Logarithm of Hydrogen demand, 1000$).

In the third case, the cycle component is also added to the unobserved factors. The movement pattern of the unobserved components is shown in Fig. 9. The results of the underlying trend are similar to the previous cases. The movement pattern of seasonal effects is the same as in the first case. The cyclical effects of the global hydrogen demand show the fact that the depth of the cycle was low at the beginning of the period, but the depth of cyclical fluctuations has increased in recent years. It took two years to reach from one maximum point to another maximum point at the beginning of the period, but at the end of the period, it takes 5 years to reach from one peak point to the next peak point. The recent turbulence in the energy market, driven by geopolitical conflicts such as the war in Ukraine and economic disruptions resulting from the COVID-19 pandemic, has presented diverse challenges and opportunities for the hydrogen sector. Geopolitical uncertainties can sway the supply and pricing dynamics of conventional energy sources, potentially paving the way for cleaner alternatives like hydrogen. Economic downturns linked to energy market fluctuations may influence the rate of investment in hydrogen projects, as exemplified by the drastic drop in oil prices from 60 USD to 20 in 2020.

Therefore, it is expected that the depth of the cycle will decrease with the subsidence of the war in Ukraine and the end of the COVID-19 pandemic.

Instead of the cyclical component, the unobserved autoregressive component can be considered. The results of this situation are in the

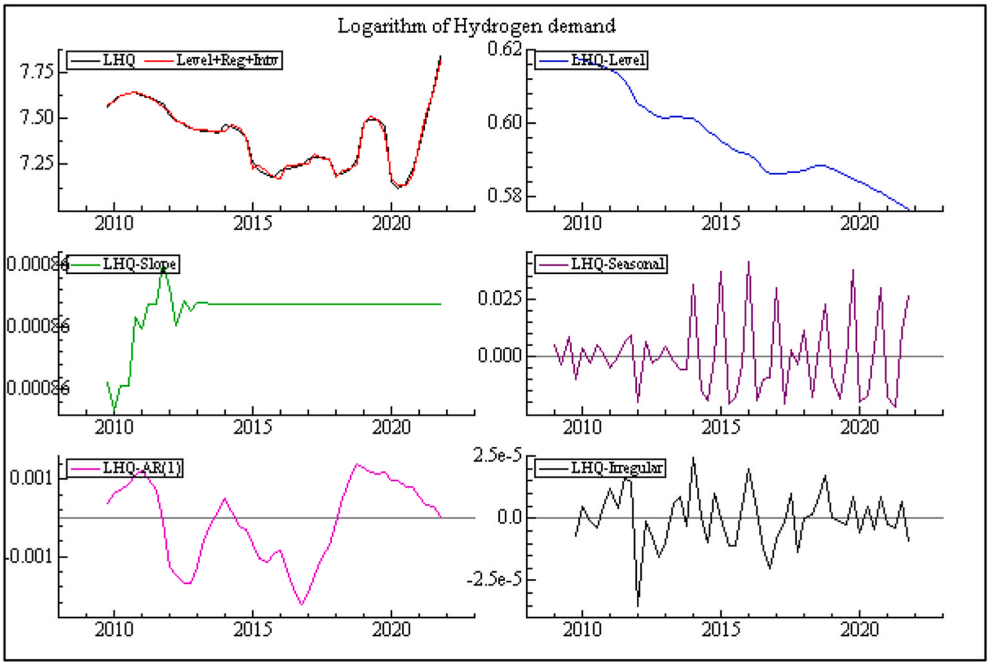

Fig. 10. Case 4 - Stochastic Level with a Fixed Slope for the Underlying Trend and an Incorporated Unobserved Autoregressive Component (Logarithm of Hydrogen demand, 1000$).

form of case 4 as described in Fig. 10. The unobserved autoregressive component can capture many of the movements in the time series data that indicate the inertia of business cycles. This refers to a part of the time series data that is not directly observed or measured. Autoregressive means that the current value of this component is dependent on its past values. In the context of business cycles, this component captures patterns and trends that are not explicitly observed but are inferred from the historical behavior of the time series. Movements in this context refer to patterns or fluctuations observed in the time series data. For business cycles, these movements could represent economic expansions and contractions over time. The unobserved autoregressive component is designed to capture and model these inherent movements in the data that are indicative of the inertia or persistence of business cycles. Inertia in this context implies that there is a tendency for the business cycle to persist or continue its current trajectory. The unobserved autoregressive component is a mathematical representation of this inertia, helping to account for the historical behavior that influences the current state of the business cycle. The movement pattern of this component is not much different from the cycle component that was interpreted in the previous case. The observed outcome could be attributed to the prevalent cyclical patterns in hydrogen demand data, which recur consistently. In such cases, the autoregressive terms might inadvertently encapsulate these

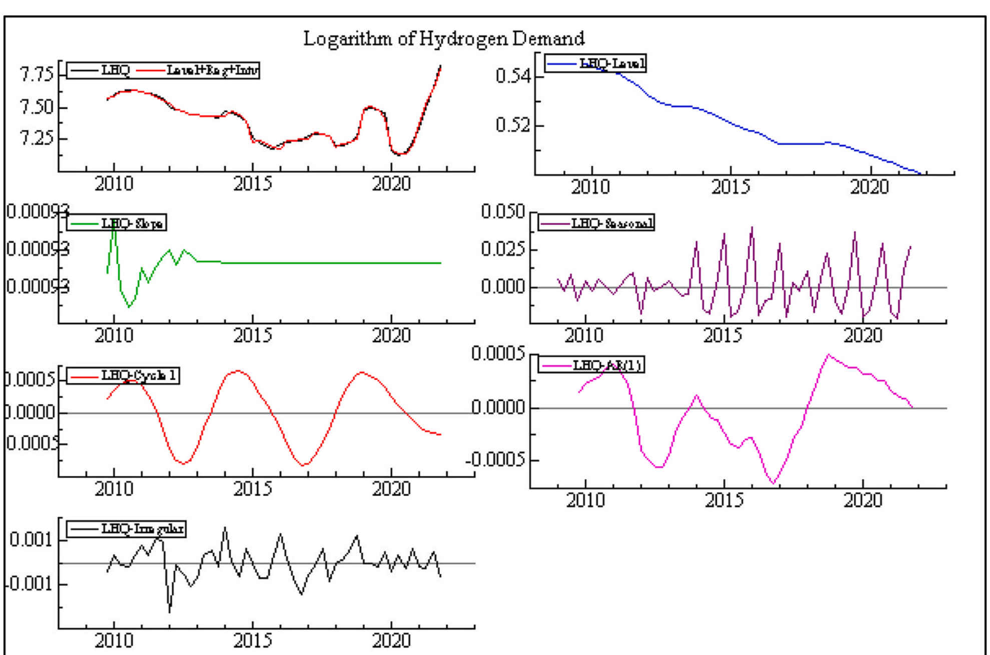

Fig. 11. Case 5 - All Unobserved Components are Controlled (Logarithm of Hydrogen demand, 1000$).

cyclical fluctuations.

In the fifth case, all the unobserved components are controlled together. The results of the underlying trend are still the same as before. The result of the seasonal effect is the same as the first, third, and fourth cases (Fig. 11). Because the cyclical effect is combined with the unobserved autoregressive effect, the cyclical effect is regular, but the unobserved autoregressive effect is the same as in the previous case. As a result, the cyclical effect is due to the business cycle.

Finally, from the comparison of 5 cases, it can be concluded that the effect of technology in production, organizational technology (institutions), and consumer behavior, which are important factors affecting the demand function, in the case of global hydrogen demand, the demand function has moved to the left over time. It should be noted that the decreasing effect of the underlying trend in the hydrogen demand function is not large, for example, in case 5, the intercept of the demand function has decreased from 0.54 in 2009 to 0.5 in 2021, that is, in 12 years, only 0.04 of the logarithm of hydrogen demand has decreased due to the mentioned cases.

The delayed impact of technology on increasing the demand for hydrogen is intricately tied to challenges in both consumption and production domains. On the consumption side, a lack of awareness among consumers about the benefits of hydrogen technologies, coupled with established preferences for conventional energy sources, impedes the rapid adoption of hydrogen. Consumer education initiatives and targeted marketing strategies are crucial to shifting preferences. On the production side, despite technological advancements, high production costs and efficiency challenges persist, affecting the competitiveness of hydrogen against other energy sources. Continued research and development efforts focused on cost reduction and efficiency improvement are essential to make hydrogen production more economically viable (Dawood et al., 2020). Bridging the gap between consumer preferences and technological capabilities is vital for unlocking the full potential of hydrogen as a clean energy solution. Promoting entrepreneurship in hydrogen production and consumption is crucial for advancing hydrogen technology. This is supported by research indicating that fostering entrepreneurship contributes to sustainable development and climate change mitigation (Abid et al., 2023a, 2023b; Karimi et al., 2023).

5. Conclusion

This paper applies a Structural Time Series Model (STM) to estimate both long-run and short-run global hydrogen demand. In order to obtain the real value of the demand for hydrogen, the nominal value of the import is divided by the price index of the producer of hydrogen and argon gas manufacturing to the base price of 2009, and this variable is a proxy for the global demand of hydrogen.

We have found evidence indicating that in the short term, the global demand for hydrogen exhibits a high degree of price inelasticity. In the long term, the price elasticity of demand becomes statistically significant at approximately 0.15, although its value remains below 1 unit. Consequently, the demand for hydrogen worldwide displays a relatively low sensitivity to changes in price. In the short term, an increase in the price of natural gas leads to a decrease in the demand for hydrogen. In other words, natural gas and hydrogen serve as complementary fuels in the short term. However, this complementarity diminishes significantly over time. In the short term, this elasticity is approximately -0.1, whereas in the long term, it decreases to -0.02.

Additionally, our findings indicate that oil can act as a substitute for hydrogen, and this substitution effect intensifies in the long term. A one percent increase in the price of oil immediately raises the demand for hydrogen by 0.02 units, but this effect nearly triples in the long term. This outcome suggests that a decline in oil prices may pose a threat to the global demand for hydrogen, which is regarded as a clean fuel, as an increase in oil prices can stimulate the hydrogen market.

Our conclusion is that, in the short run, hydrogen can be classified as a luxury commodity. The income elasticity of demand for hydrogen is substantial, meaning that in the short term, a one percent rise in income can lead to an 8.8 percent increase in hydrogen demand. However, this elasticity is adjusted after two years. Consequently, the luxury aspect of hydrogen is instantaneous for consumers, and in the long run, hydrogen is no longer regarded as a luxury commodity. The income elasticity for hydrogen demand in the long term is approximately 0.3, indicating that hydrogen becomes a normal commodity.

Finally, based on the underlying component in the demand function for hydrogen and its decomposition into the trend, seasonal, cyclical, and irregular components, it was discovered that technological advancements in production, organizational technology (such as institutions), and changes in consumer behavior, which are significant factors influencing the demand function, have collectively shifted the demand function to the left over time in the case of global hydrogen, but this is not large. The movement pattern of the seasonal component shows that until 2013, the seasonal effects were negligible. From 2014 to 2017, the peak of demand was in the spring season, and the bottom was in the summer. From 2017 onwards, the calendar effect has changed so that the autumn season has the peak demand and the spring season has the lowest demand. The cyclical effects of the global hydrogen demand show the fact that the depth of the cycle was low at the beginning of the period, but the depth of cyclical fluctuations has increased in recent years.

The results of this study can be used to provide useful tools for the policymakers to identify the obstacles and formulate their policies accordingly, due to the fact that technology is not only technical, but also role of institutions and laws and regulations act like technical technology. The study revealed that technology has not significantly impacted the demand for hydrogen. However, it remains unclear why technological advancements have not been effective in stimulating demand. Therefore, future research should aim to uncover the reasons behind this phenomenon. Subsequent studies must investigate whether production technology or organizational technology—such as laws and regulations at national and international levels concerning clean energy—has contributed less to the advancement of hydrogen demand. Finally, we strongly recommend that future research endeavors focus on studying the prediction of hydrogen demand. Understanding and forecasting hydrogen demand trends is crucial for informed decision-making in various sectors, including energy, transportation, and industry.

CRediT authorship contribution statement

Mohammad Sharif Karimi: Writing – review & editing, Writing – original draft, Software, Project administration, Data curation. **Saleh Ghavidel Doostkouei:** Writing – review & editing, Writing – original draft, Software, Methodology, Data curation. **Babak Naysary:** Writing – review & editing, Data curation. **Mir Hossein Mousavi:** Visualization, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2024.142331.

References

Abada, I., Briat, V., Massol, O., 2013. Construction of a fuel demand function portraying interfuel substitution, a system dynamics approach. Energy 49, 240–251.

Abid, N., Ahmad, F., Aftab, J., Razzaq, A., 2023a. A blessing or a burden? Assessing the impact of climate change mitigation efforts in Europe using quantile regression models. Energy Pol. 178, 113589.

Abid, N., Ceci, F., Aftab, J., 2023b. Attaining sustainable business performance under resource constraints: insights from an emerging economy. Sustain. Dev.

Ackah, I., Kizys, R., 2015. Green growth in oil producing African countries: a panel data analysis of renewable energy demand. Renew. Sustain. Energy Rev. 50, 1157–1166.

Alarenan, S., Gasim, A.A., Hunt, L.C., 2020. Modelling industrial energy demand in Saudi Arabia. Energy Econ. 85, 104554.

Amarawickrama, H.A., Hunt, L.C., 2008. Electricity demand for Sri Lanka: a time series analysis. Energy 33 (5), 724–739.

Ball, M., Wietschel, M., 2009. The future of hydrogen–opportunities and challenges. Int. J. Hydrogen Energy 34 (2), 615–627.

Box, G., Jenkins, G., Reinsel, G., 2008. Time Series Analysis: Forecasting and Control. John Wiley & Sons.

Brändle, G., Schönfisch, M., Schulte, S., 2021. Estimating long-term global supply costs for low-carbon hydrogen. Appl. Energy 302, 117481.

Chen, H., Wu, H., Kan, T., Zhang, J., Li, H., 2023. Low-carbon economic dispatch of integrated energy system containing electric hydrogen production based on VMD-GRU short-term wind power prediction. Int. J. Electr. Power Energy Syst. 154, 109420.

Commandeur, J.J.F., Koopman, S.J., 2007. An Introduction to State Space Time Series Analysis. Oxford University Press.

Dawood, F., Anda, M., Shafiullah, G.M., 2020. Hydrogen production for energy: an overview. Int. J. Hydrogen Energy 45 (7), 3847–3869.

Dilaver, Z., Hunt, L.C., 2011. Industrial electricity demand for Turkey: a structural time series analysis. Energy Econ. 33 (3), 426–436.

Dutta, S., 2014. A review on production, storage of hydrogen and its utilization as an energy resource. J. Ind. Eng. Chem. 20 (4), 1148–1156.

Espey, M., 1998. Gasoline demand revisited: an international meta-analysis of elasticities. Energy Econ. 20, 273–295.

Filippini, M., Hunt, L.C., 2012. US residential energy demand and energy efficiency: a stochastic demand frontier approach. Energy Econ. 34 (5), 1484–1491.

Harvey, A.C., 1990. Structural Time Series Models: A Guide to the Kalman Filter for Time Series Analysis. Cambridge University Press.

Hassan, Q., Algburi, S., Sameen, A.Z., Jaszczur, M., Salman, H.M., Mahmoud, H.A., Awwad, E.M., 2023. Saudi Arabia energy transition: assessing the future of green hydrogen in climate change mitigation. Int. J. Hydrogen Energy.

Houghton, R.A., 2019. Applied Time Series Analysis for Energy Data. Springer.

Huang, J., Li, W., Wu, X., 2022. Forecasting the hydrogen demand in China: a system dynamics approach. Mathematics 10 (2), 205.

Hunt, L.C., Lynk, E.L., 1995. Privatisation and efficiency in the UK water industry: an empirical analysis. Oxford Bull. Econ. Statist. 57 (3), 371–388.

Hunt, L.C., Ryan, D.L., 2015. Economic modelling of energy services: rectifying misspecified energy demand functions. Energy Econ. 50, 273–285.

IEA, 2017. International Energy Agency Technical Report. Key world energy statis- tics' [Online]. Available: https://www.iea.org/publications/freepublications/publication/KeyWorld2017.pdf. (Accessed 29 December 2022).

International Energy Agency, 2021. Global hydrogen review 2021. Available: https://www.iea.org/reports/the-future-of-hydrogen.

International Energy Agency, 2023. Global Hydrogen Review 2023.

Jiang, W., Zhang, W., Li, J., Zhang, X., Wang, S., 2021. Demand response potential of flexible electric water heaters under high renewable energy penetration. Appl. Energy 306, 117871.

Kani, A.H., Abbasspour, M., Abedi, Z., 2014. Estimation of demand function for natural gas in Iran: evidences based on smooth transition regression models. Econ. Modell. 36, 341–347.

Karimi, M.S., Doostkouei, S.G., Shaiban, M., Easvaralingam, Y., Khan, Y.A., 2023. Investigating the role of entrepreneurship in advancing renewable energy for sustainable development: evidence from a System-GMM panel data approach. Sustain. Dev.

Lee, Y., Lee, M.C., Kim, Y.J., 2022. Barriers and strategies of hydrogen fuel cell power generation based on expert survey in South Korea. Int. J. Hydrogen Energy 47 (9), 5709–5719.

Ma, R., Abid, N., Yang, S., Ahmad, F., 2023. From crisis to resilience: strengthening climate action in OECD countries through environmental policy and energy transition. Environ. Sci. Pollut. Control Ser. 1–16.

McGookin, C., Gallachóir, B.Ó., Byrne, E., 2021. An innovative approach for estimating energy demand and supply to inform local energy transitions. Energy 229, 120731.

Moghaddam, M.J.H., Kalam, A., Nowdeh, S.A., Ahmadi, A., Babanezhad, M., Saha, S., 2019. Optimal sizing and energy management of stand-alone hybrid photovoltaic/wind system based on hydrogen storage considering LOEE and LOLE reliability indices using flower pollination algorithm. Renew. Energy 135, 1412–1434.

Mousavi, M.H., Ghavidel, S., 2019. Structural time series model for energy demand in Iran's transportation sector. Case Studies on Transport Policy 7 (2), 423–432.

Nagasawa, K., Davidson, F.T., Lloyd, A.C., Webber, M.E., 2019. Impacts of renewable hydrogen production from wind energy in electricity markets on potential hydrogen demand for light-duty vehicles. Appl. Energy 235, 1001–1016.

Ni, J., Johnson, N., Ogden, J.M., Yang, C., Johnson, J., 2005. Estimating Hydrogen Demand Distribution Using Geographic Information Systems (GIS).

Nikolaidis, P., Poullikkas, A., 2017. A comparative overview of hydrogen production processes. Renew. Sustain. Energy Rev. 67, 597–611.

Park, C., Lim, S., Shin, J., Lee, C.Y., 2022. How much hydrogen should be supplied in the transportation market? Focusing on hydrogen fuel cell vehicle demand in South Korea: hydrogen demand and fuel cell vehicles in South Korea. Technol. Forecast. Soc. Change 181, 121750.

Rahmouni, S., Settou, N., Negrou, B., Gouareh, A., 2016. GIS-based method for future prospect of hydrogen demand in the Algerian road transport sector. Int. J. Hydrogen Energy 41 (4), 2128–2143.

Rao, B.B., Rao, G., 2009. Co-integration and the demand for gasoline. Energy Pol. 37 (10), 3978–3983.

Sadorsky, P., 2009a. Renewable energy consumption, CO2 emissions and oil prices in the G7 countries. Energy Econ. 31 (3), 456–462.

Sadorsky, P., 2009b. Renewable energy consumption and income in emerging economies. Energy Pol. 37 (10), 4021–4028.

Salisu, A.A., Ayinde, T.O., 2016. Modeling energy demand: some emerging issues. Renew. Sustain. Energy Rev. 54, 1470–1480.

Shang, Y., Han, D., Gozgor, G., Mahalik, M.K., Sahoo, B.K., 2022. The impact of climate policy uncertainty on renewable and non-renewable energy demand in the United States. Renewable *Energy*, 197, 654–667.

Weger, L.B., Leitao, J., Lawrence, M.G., 2021. Expected impacts on greenhouse gas and air pollutant emissions due to a possible transition towards a hydrogen economy in German road transport. Int. J. Hydrogen Energy 46 (7), 5875–5890.

Wei, D., Ahmad, F., Abid, N., Khan, I., 2023. The impact of digital inclusive finance on the growth of the renewable energy industry: theoretical and logical Chinese experience. J. Clean. Prod. 428, 139357.

Weng, C., Huang, J., Chua, C.L., 2023. Asymmetric adjustment of clean energy demand in the OECD countries. Appl. Econ. Lett. 1–14.

World Bank Group, 2022. World Integrated Trade Solution (WITS).

Xuesong, B., 2003. An analysis on the production and consumption of hydrogen in the world and China. Chem. Techno-Econ. 21 (12), 18e25.

Yusaf, T., Laimon, M., Alrefae, W., Kadirgama, K., Dhahad, H.A., Ramasamy, D., et al., 2022. Hydrogen energy demand growth prediction and assessment (2021–2050) using a system thinking and system dynamics approach. Appl. Sci. 12 (2), 781.