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The Role of Mediation in the Transmission of Gasoline Price Effects

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Abstract: This analysis aims to investigate the direct and indirect effects of gasoline price increases on the economy. An observational study using monthly data for industrial production, employment, the consumer price index, personal consumption expenditures for services, the consumer price index for gasoline, and the effective federal funds rate for the U.S. from December 1966 through November of 2022 of indirect, direct, and causal effects. Structured equation modeling was used to examine direct and indirect effects. In contrast, impulse response functions with local projections were used to assess the causal nature of responses to a gasoline price impulse. The data is from two sources: the U. S. Bureau of Labor Statistics and FRED, the Federal Reserve Bank of St. Louis. The direct effects (standardized coefficients) of gasoline prices are 0.111 (z = 7.2) and -0046 (z = -0.2) for industrial production and employment models, respectively; the indirect effects are larger at 0.385 (z = 38.7) and 0.292 (z = 27.96). The causal effects show inflation, decreased employment, and industrial production following a gas price impulse. Following an effective federal funds rate impulse, there is no significant effect on employment or industrial production through 48 months, while the effect on the all-items consumer price index is a decrease in prices. The principal effects of an unexpected increase in gasoline prices are indirect, mediated through endogenous economic variables, while the direct effects are small. Gasoline price increases can create conditions associated with economic downturns, such as reduced employment and industrial production. The broad economic effects triggered by gasoline price increases complicate the policy considerations for those guiding the economy. They are complicated by the role of gasoline prices as an environmental policy variable.

Keywords: Policy Variable, Structural Equation Modeling, Mediation Model, Mediation Pathway, Indirect Effects, Direct Effects, Impulse Response Function

1. Introduction

In 1967, the Arab-Israeli war led to an Arab oil embargo, which affected gasoline prices [1]. When the Bretton Woods system fell apart in 1971, the Nixon administration implemented wage and price controls to manage inflation and prevent a gold run [2]. However, this resulted in long lines at gas stations and reduced production. The 1973 oil crisis started with the action of the Organization of Arab Petroleum Exporting Countries after the Yom-Kippur War [3]. The Iranian revolution of 1978 caused oil production to drop by 5 million barrels per day, and the change to an Islamic government in January 1979 doubled oil prices. The 1980 Iran-Iraq war caused oil production to drop by four million barrels daily. Deregulation in 1981 increased domestic and foreign oil production, while the U.S. Congress enacted a moratorium on new offshore drilling due to environmental concerns. Desert Storm, in January 1991, marked the entry of the U.S. into the Iraq-Kuwait war and the release of oil from the strategic petroleum reserve. The September 11th attacks in 2001 led to a decade-long surge in oil prices due to political instability associated with the wars in Afghanistan and Iraq. In the first three years of the Obama administration, gasoline prices rose from $1.74 per gallon in January 2009 to $3.35 in December 2011. In January 2017, gasoline prices began at $2.485, ending at $2.33 in January 2021. However, prices rose to $3.216 per gallon in July 2021 and reached $3.71 on May 1, 2023. There were three instances where gasoline prices increased before the federal funds rate: 2001 through 2009, 2009 through 2016, and 2021-2023 [4]. Additionally, emerging economies, political tensions, and increased consumption of petroleum products in countries like India [5, 6] and China [7] influenced the rising prices from 2000-2010. The theoretical background is well understood to be that gasoline affects the prices for goods and services whenever it has a role in the production cycle [8]. The Bureau of Labor Statistics produces the consumer price index for economic sectors and commodities, excluding prices for food and energy, which allows a comparison of the energy-excluded price index with the energy-included price index. However, these indices do not consider transmitted/mediated effects, where the higher cost of providing other goods and services when gasoline prices rise are excluded. That is, the price index of a good that uses gasoline in its production cycle reflects higher prices when gasoline prices rise, even if the index is reported less prices for energy [9].

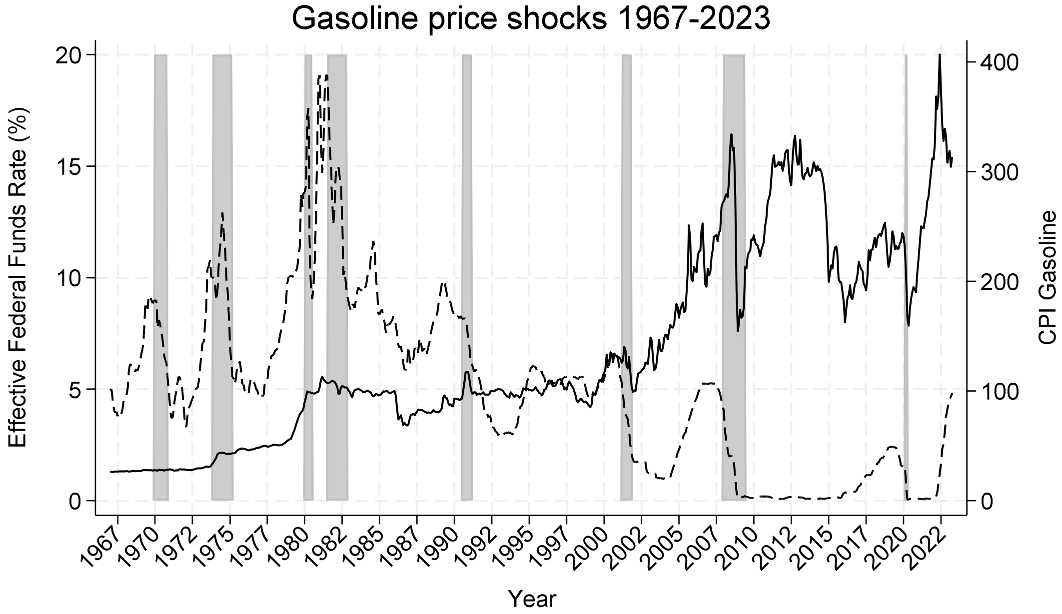

Figure 1. *This graph depicts the history of gasoline prices in the United States from January 1967 to April 2023. The solid black line represents the gasoline price index, while the dashed black line shows the effective federal funds rate. The gray shaded bars indicate the timing and duration of economic recessions.*

2. Research Question

Monetary and environmental policies can affect macroeconomic output and prices [10]. Although not traditionally considered a monetary policy variable, the collateral effects of limiting domestic oil production and refinement to gasoline to achieve environmental policy objectives may, directly and indirectly, affect macroeconomic performance. For this reason, this paper assesses the effects of gasoline prices in the context of the traditional monetary policy variables of the federal funds rate, industrial production, price levels, and employment. The "a priori" hypothesis is that the role of gasoline prices in the economy is large and that a large portion of that effect is indirect, mediated through other economic variables.

3. Methods

3.1. Data Sources

The data include monthly observations from December 1966 through November 2022 (n = 672) and the natural logs of the gasoline consumer price index (Bureau of Labor Statistics series CUUR0000SETB01, referred to below as CPIGAS), the employment level (Federal Reserve Bank of St. Louis (FRED) series CE16OV), the Federal Funds effective rate (FRED series FEDFUNDS), industrial production (FRED series INDPRO), CPI-all items (FRED series CPIAUCSL), and Personal Consumption Expenditures: Services (FRED series PCES). The units for CPIGAS, CPIAUCSL, and INDPRO are in index form; CE16OV is expressed in thousands of persons, PCES is reported in billions of dollars, and FEDFUNDS is reported as an effective rate. Statistical analysis was performed using Stata version 18 [11].

3.2. Structural Equation Models

Structural equation models (SEM) are a framework that allows simultaneous estimation of a system of equations that show how a set of observable endogenous variables are related to a set of explanatory variables. Structural equation mediation models via the asymptotic distribution free (ADF) method are used in this study to clarify the mediation pathways of various economic effects; the ADF approach does not assume joint normality or symmetry. ADF is a form of weighted least squares where the weights are based on an estimate of the asymptotic covariance matrix. The mediation version of SEM is chosen because the model specification is a directed acyclic graph (DAG) whose direction assumptions about how much of the effect of x on y is either direct or transmitted through an intermediate variable can be tested. Direct and indirect effects post-estimation analysis confirm hypothesized pathways. An impulse response function using local projections was used to estimate the effect of a gasoline price shock on the consumer price index, industrial production, employment, and personal consumption expenditures for services.

Direct effects are estimated based on the path coefficients of the structural equation models; indirect effects are estimated by the product of a direct effect coefficient and a mediated effect coefficient; total effects are their sum. The stability of the SEM equation systems is evaluated with the eigenvalue stability condition index. SEM via the ADF method goodness of fit is tested with the discrepancy test, population error, information criteria, baseline criteria, and the size of the residuals.

3.3. Impulse Response Functions with Local Projections

Impulse response functions (IRF) can capture the empirical pattern representing theoretical economic models using a simple sequential regression of the endogenous variables [12]. IRFs also are computationally simpler than vector autoregression (VAR). Impulse–response functions allow one to discover how a shock to one variable affects other variables over time using a direct multi-step method of local projections conditional on both initial and trailing values. Simultaneous estimates of the impulse–response and dynamic multiplier coefficients allow for joint inference across all combinations of impulse variables, response variables, and time horizons. The simple impulse response functions are either the simple moving average coefficients themselves, as in the 1st horizon/step, or some combination of the moving average coefficients in subsequent steps/horizons, depending on the number of models and lags. The definition of orthogonal is when the intersection of two vectors is perpendicular, resulting in the inner product at the intersection of zero. The independence of multiplicand and multiplier and their zero product from orthogonalization creates causal IRFs (OIRFs) that meet the strict exogeneity requirement. Using the Cholesky decomposition of the residuals vector multiplied by its transpose, the IRFs can be orthogonalized (see Lutkepohl).

The orthogonalized impulse-response functions (oirfs) and forecast error variance decomposition (fevds, estimated by vector autoregression) for each combination of impulse and response variables are graphically examined for effect, effect duration, and response magnitude. Oirfs and fevds are also graphically compared across models. Gasoline price effects on INDPRO and CE16OV were evaluated to confirm the magnitude and duration of effects, while PCES, FEDFUNDS, and CPIAUCSL were control variables. The SEM mediation models employed are linear, and all the variables were transformed to their natural log.

4. Results

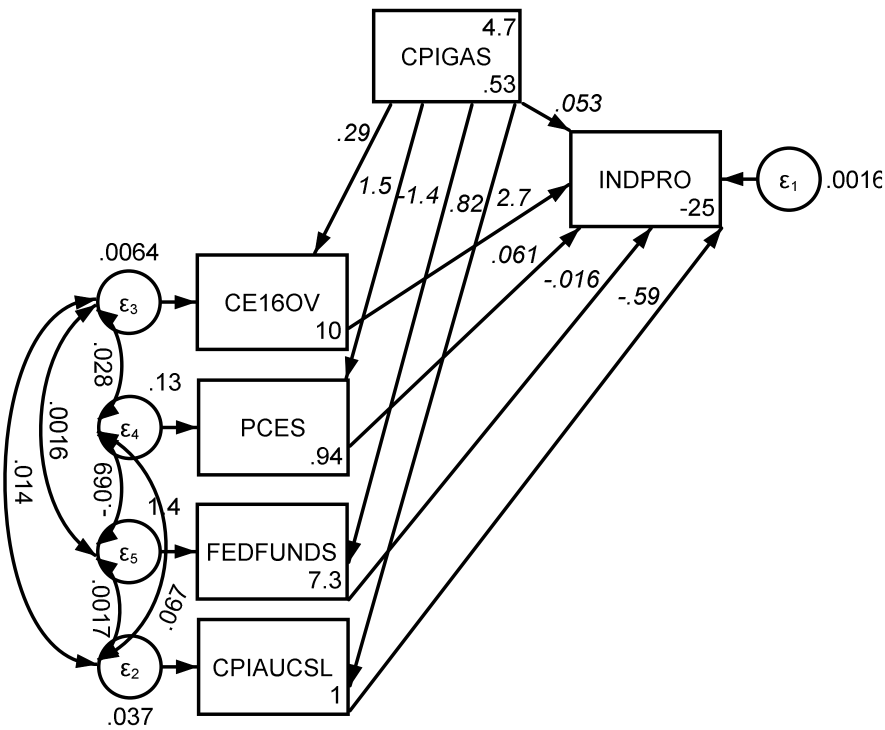

Figure 2. The structural equation specification for the INDPRO mediation model. The direct effects on INDPRO are (standardized coefficients): CPIGAS is 0.053 (0.111) (P>|z|<0.00005); CPIAUCSL is -0.591 (-1.606) (P>|z|=0.00005); CE16OV is 2.657 (1.696) (P>|z|<0.00005); PCES is 0.061 (0.1969) (P>|z|<0.00005); and FEDFUNDS is -0.16 (-0.0699) (P>|z|<0.00005). The indirect effect of the CPIGAS on INDPRO, mediated through the other exogenous variables, is 0.385 (0.8057) (P>|z|<0.00005). The total effect of CPIGAS on INDPRO is the sum of the direct and indirect effects = 0.438 (0.9165) (P>|z|<0.00005), 87.9 percent of the total effect of CPIGAS on INDPRO is mediated through the other economic variables. Since the signs among indirect, direct, and total effects for CPIGAS are the same, the portion of the signal mediated can be estimated. Whenever the signs are the opposite for the direct and indirect effects, they confound the estimation of the proportion mediated.

Table 1. *There are four mediation pathways, as expressed in the regression coefficients from the INDPRO model.*

Equation	Coefficient Label/Value	Operator	Coefficient Label/Value	Operator	Result
1	β[CE16OV: CPIGAS]	*	β[INDPRO: CE16OV]	=	
	0.2851194	*	2.65661	=	0.75745123
2	β[PCES: CPIGAS]	*	β[INDPRO: PCES]	=	
	1.468017	*	0.0608066	=	0.08926512
3	β[FEDFUNDS: CPIGAS]	*	β[INDPRO: FEDFUNDS]	=	
	-1.373422	*	-0.0157556	=	0.02163909
4	β[CPIAUCSL: CPIGAS]	*	β[INDPRO: CPIAUCSL]	=	
	0.8177582	*	-0.5905259	=	-0.48290734

The total indirect effects of CPIGAS on INDPRO is the sum of all the mediation pathways = 0.385.

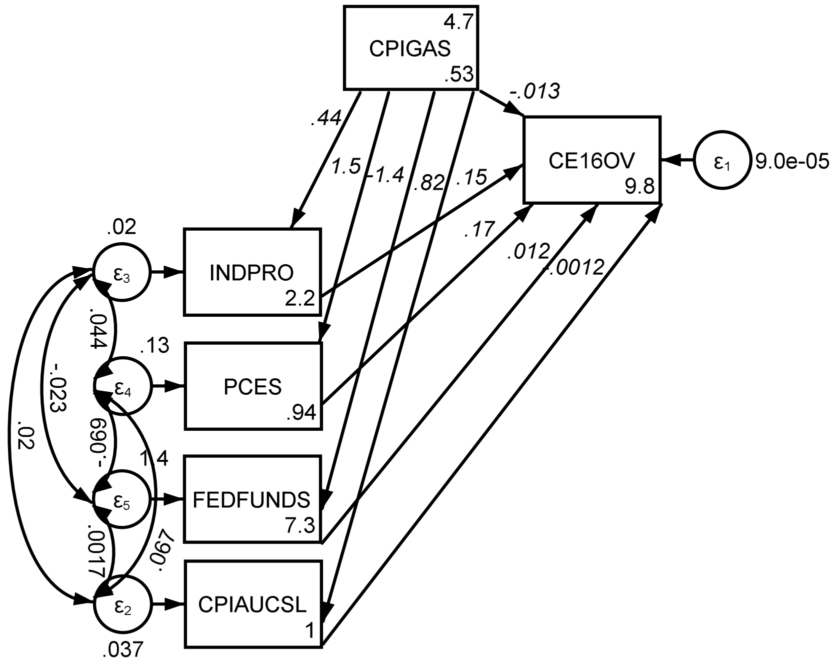

Figure 3. *This structural equation specification shows the effects on CE16OV. The direct effect of CPIGAS on CE16OV is -0.013 (-0.0432) (P>|z|<0.00005), the indirect effect is 0.298 (0.977) (P>|z|<0.00005), and the total effect is 0.285 (0.934) (P>|z|<0.00005. The negative direct and positive indirect effects confound the proportion-mediated estimate. Although they have opposite signs, indirect effects are much larger than direct effects. As in the INDPRO mediation model, there are four mediation pathways expressed in the regression coefficients from the model shown in Figure 3.*

Table 2. *There are four mediation pathways, as expressed in the regression coefficients from the CE16OV model.*

Equation	Coefficient Label/Value	Operator	Coefficient Label/Value	Operator	Result
1	β[INDPRO: CPIGAS]	*	β[CE16OV: INDPRO]	=	
	0.4384058	*	0.1494868	=	0.06553586
2	β[PCES: CPIGAS]	*	β[CE16OV: PCES]	=	
	1.468017	*	0.1703983	=	0.25014758
3	β[FEDFUNDS: CPIGAS]	*	β[CE16OV: FEDFUNDS]	=	
	-1.373422	*	.0119691	=	-0.01643859
4	β[CPIAUCSL: CPIGAS]	*	β[CE16OV: CPIAUCSL]	=	
	0.8177582	*	-0.0011547	=	-0.0009443

The total indirect effects of CPIGAS on CE16OV are the sum of the mediation pathways = 0.298

The estimation is complete once the direct effects (path coefficients) are added to the indirect effects to obtain the total effects (Table 3). The INDPRO model shown in Figure 2 and the CE16OV model shown in Figure 3 are identical except for transposing INDPRO and CE16OV; their performance on post-estimation tests is identical (Table 4). Both models show the discrepancy test of model fit at near zero; both models are saturated, indicating that the fit is quite good. The root mean squared error of approximation, comparative fit index, Tucker-Lewis index, standardized root mean squared residual, and the coefficient of determination for both models reflect a good fit. Using standardized (STD) coefficients, CPIAUCSL increases with CPIGAS at a rate such that, if the rate were constant, CPIAUCSL would increase by 0.95 standard deviations (SD) if CPIGAS increased by one SD; INDPRO would increase with CPIAUCSL at the rate of -1.06 SD for a one SD increase in CPIAUCSL. Because CPIAUCSL is an aggregate measure of prices for all goods and services, the transmission of price effects for gasoline is expected. CE16OV, PCES, and FEDFUNDS also mediate CPIGAS price changes with INDPRO at the rates of 0.03, 0.95, and -0.64 SD, respectively, for a one SD price change in CPIGAS.

The counterfactual to the hypothesis that there are significant indirect effects of CPIGAS is that there are no indirect effects, and all effects are transmitted directly in a single coefficient through only one variable; that is, gasoline prices do not affect other economic variables. The STD direct effects CPIGAS coefficients are -0.043 and 0.111 for the CE16OV and INDPRO models, respectively, compared to 0.934 and 0.916 for total effects (Table 3).

Table 3. *STD coefficients and Z-scores of total effects on INDPRO and CE16OV mediation models.*

Variable	INDPRO Coefficient	INDPRO Z score	CE16OV coefficient	CE16OV Z score
CPIAUCSL	-1.06*	-15.52*	-0.0032	-0.11
CE16OV	1.69*	21.04*		
PCES	0.197	1.46	0.865*	23.07*
FEDFUNDS	-0.07*	-6.14*	0.083*	28.34*
CPIGAS	0.916*	59.37*	0.934*	67.63*
INDPRO			0.234*	21.04*

* P>|z|<0.00005

Because asymptotic estimates and large sample sizes can be necessary, a power analysis using Monte Carlo simulations [13] is used (Figure 4). The power analysis reaches a power rating of 0.99 at n = 50 for the INDPRO model and 0.99 at n = 60 for the CE16OV model. A saturated model fits the covariances, variances, and means perfectly. The two models above contain one exogenous variable, five endogenous variables, six covariances, and five variances, with 25 degrees of freedom. The test of the target models against the saturated model reveals small discrepancy test values for both models.

Table 4. *Structural equation model fit.*

Variable	criteria	CE16OV	INDPRO
Discrepancy test model v. saturated [14]	*	3.520e-25	4.698e-22
Root mean squared error of approximation [15]	≤0.06	0.000	0.000
Pclose (P RMSEA <= 0.05) [16]	1.0	1.0	1.0
Comparative fit index [17]	>0.95	1.0	1.0
Tucker-Lewis index [18]	>0.95	1.0	1.0
Standardized root mean squared residual [19]	≤0.08	0.000	0.000
Coefficient of determination		0.923	0.923

* The larger the value of m, the greater the failure to satisfy model restrictions the values reported here are essentially zero.

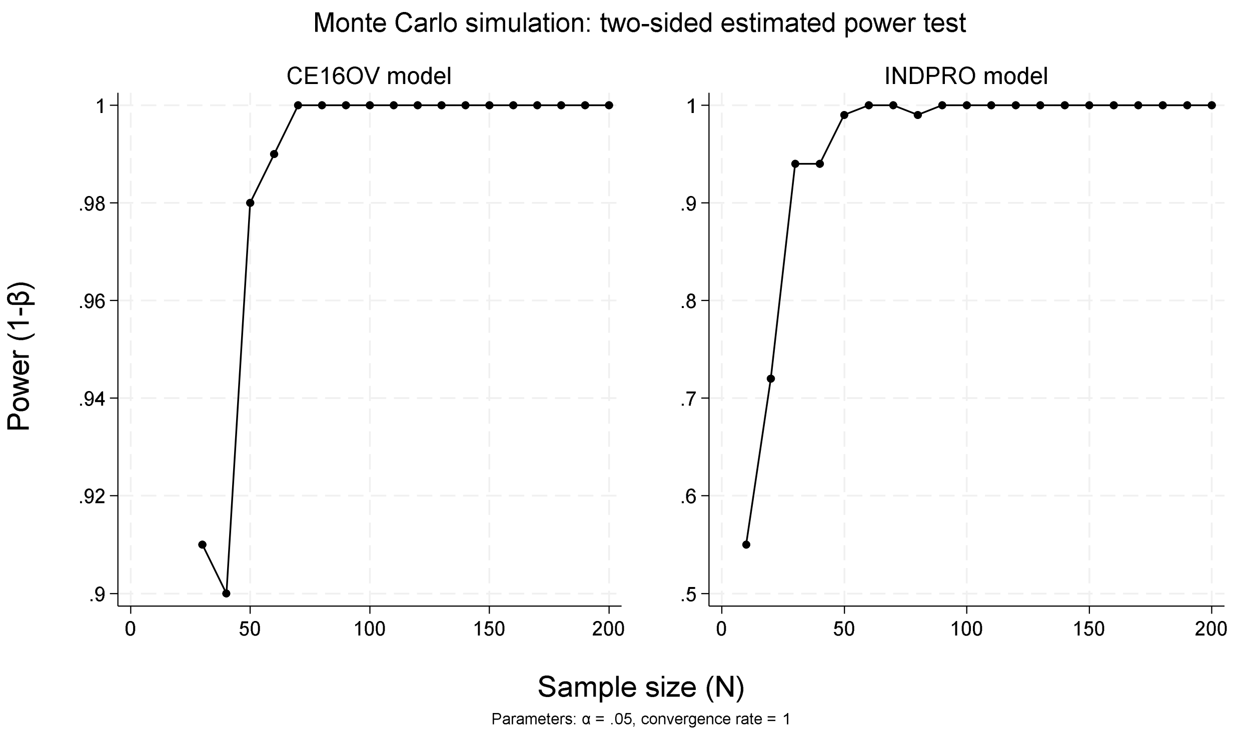

Figure 4. *The results of using Monte-Carlo simulation to calculate power for the convergence probability of both structural equation models with the number of simulations for each plotted point on the horizontal axis versus the probability of correctly rejecting a false null hypothesis on the y-axis. Different y-axis scales reflect the power ratings for each model. The simulation results are based on the means and covariance results for each model obtained after executing the structured equation models. Since n = 672, the models are sufficiently powered for this analysis, with power at 100% when n = 100.*

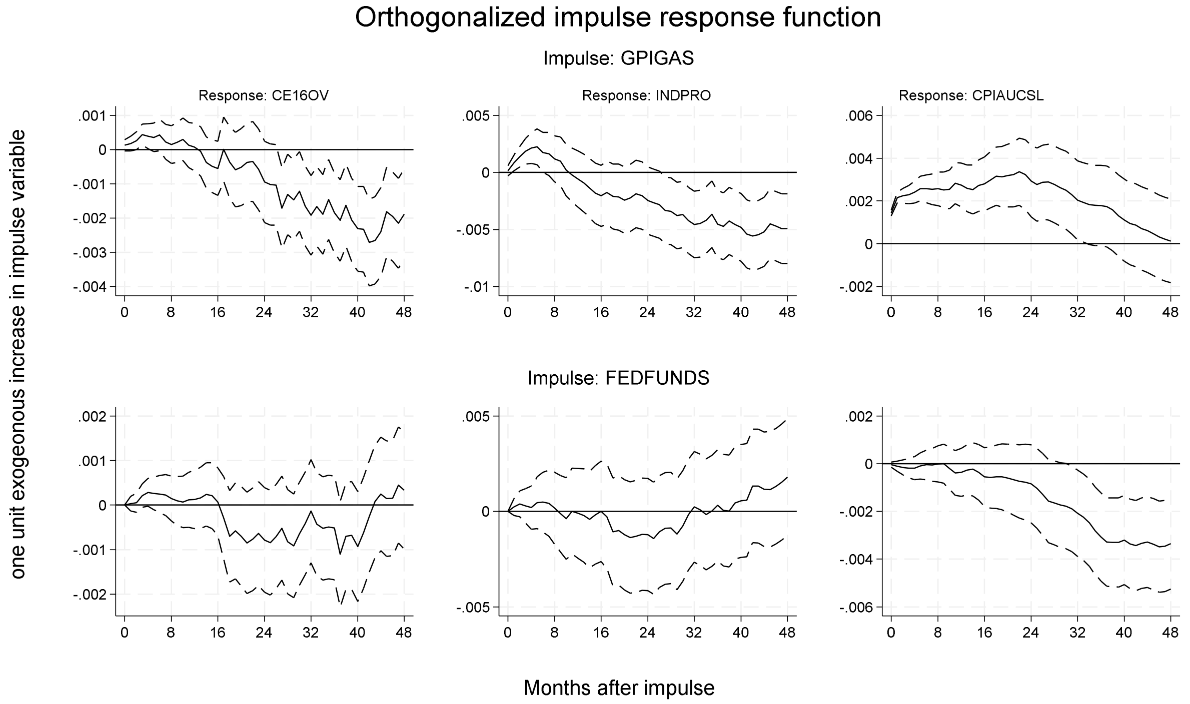

Figure 5. *IRF with local projection results are shown in this figure. The graphs are organized in rows by the impulse variable; the top row is CPIGAS, the bottom row is FEDFUNDS, and the columns by the response variable are from left to right: CE16OV, INDPRO, and CPIAUCSL. The solid black line represents the orthogonalized impulse response functions (oirfs), while the upper and lower 95% confidence intervals are black dashed lines. Vertical scales are different for each graph because the units are different by response and impulse variables.*

Σ is a symmetric positive definite matrix of the residuals vector multiplied by its transpose. The result of the Cholesky decomposition of Σ is a lower triangular matrix P such that: $P^{-1}\Sigma P'^{-1} = I_k$, an identity matrix.

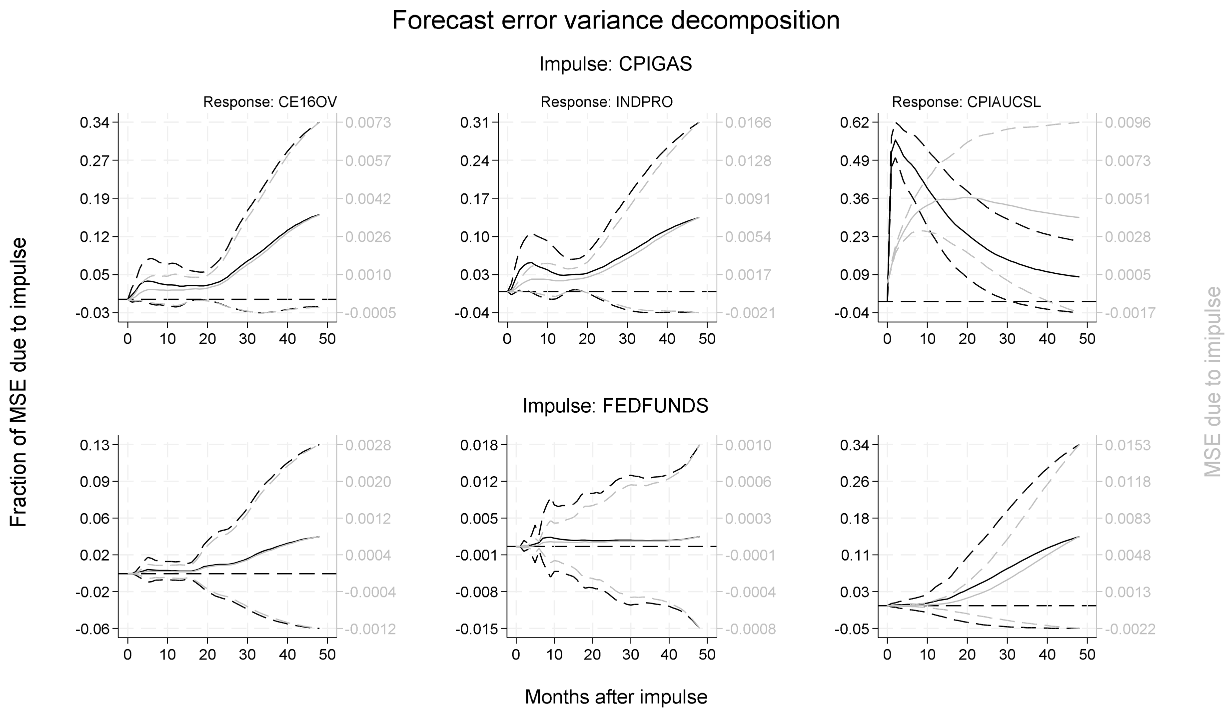

Figure 6. *Each graph's vertical scale differs because the units for each measure are different but show the forecast error variance decomposition(fevd) compared to zero y-axis reference. The forecast error variance decomposition is the fraction of the forecast error variance of the response variable attributable to the orthogonalized innovation at each step or month after the impulse. The solid black lines show the fraction of the MSE due to the impulse (left scale); the solid gray lines show the MSE due to the impulse on the right vertical axis; the dashed lines are the 95% upper and lower confidence intervals. The graphs are organized in columns by the response variable and in rows by the impulse variable. The top row shows the impulse variable, CPIGAS, and the second row, the impulse variable FEDFUNDS. CE16OV, INDPRO, and CPIAUCSL response variables identify the columns.*

Multiplying the matrix of simple IRFs by P creates the orthogonalized IRFs, which are causal, meeting the strict exogeneity requirement [20]. In Figure 5, an unexpected increase in the gasoline price leads to a rise in CE16OV (employment), peaking significantly in the third month following the impulse, becoming negative in the thirteenth month, and reaching a trough in month forty-two. The negative response of CE16OV became significant in the 27th month following the impulse and did not recover by the 48th month. A similar increase in the gasoline price leads to a similar response for INDPRO, peaking in the fifth month, becoming negative in the 11th month, and reaching a trough in the 42nd month following the impulse; the decrease in INDPRO becomes significant in the 27th month. An increase in the FEDFUNDS rate has no significant impact on CE16OV or INDPRO. The response of the CPIAUCSL to the rise in gasoline price and FEDFUNDS rate is opposing; immediately, the CPIAUCSL increases and remains significantly elevated until the 37th month after the CPIGAS impulse, peaking in the 22nd month, following an increase in the effective FEDFUNDS rate, CPIAUCSL is negative, becoming significantly so in the 31st month, reaching a trough in the 46th month.

In Figure 6, the top graph in the first column shows the forecast error variance decomposition (FEVD) for the impulse variable CPIGAS and the response variable CE16OV. At step 48, the fraction of the MSE due to the impulse is 0.1639; on the right axis, the MSE due to the impulse is 0.0213, but only 0.0035 (0.1639 * 0.0213) of the MSE at the 48th step is due to the equation that pairs the impulse variable CPIGAS with the response variable CE16OV, the remainder of the error is due to the other factors. The error shown in the response variable CPIAUCSL is different by impulse variable, as for INDPRO. The MSE of the forecast variable is a diagonal element of the MSE matrix, as described in Lutkepohl.

This analysis provides some insights into the role of gasoline prices in the economy. The greatest effect of gasoline prices is indirect, mediated through the endogenous variables in each model. In the CE16OV model, the pathway suggested by the structural equation model is that the effect is not due to increased prices of other goods and services because the total effect of CPIAUCSL is not different than zero but rather through reduced production and purchase of goods and services other than gasoline. In the INDPRO model, the pathway suggested by the SEM is increased prices of other goods, services, and gasoline. The impulse response functions confirm that there are effects resulting in inflation, unemployment, and reduced production caused by increased gasoline prices.

5. Conclusions

The observation of substantial relationships between gasoline prices and other key economic variables, including employment, industrial production, personal consumption expenditures for services, and consumer prices, provide empirical evidence of the indirect effects on the economy. Employing structural equation models, a comprehensive framework was established within which the path of gasoline price effects could be charted. The models use mediating and control variables, giving a more complete view of the effects contributed to different sectors of the economy. Investigation of the dynamic effects of gasoline prices using impulse response functions with local projections reveals the short-term and long-term effects of price fluctuations in addition to transmission methods. Two effects are identified: 1) a demand contraction for goods and services other than gasoline and 2) general price increases in response to the increase in gasoline prices, followed by reduced employment and industrial production. Realizing the direct and indirect paths of gasoline price effects gives important context to environmental, energy, and economic policy implications. This analysis is limited by the period considered and the assumptions of structural equation models and impulse response functions.

References

[1] 1850-2022: Oil Dependence and U.S. Foreign Policy. The Council on Foreign Relations. Available at: Timeline: Oil Dependence and U.S. Foreign Policy Oil Dependence and U.S. Foreign Policy | Council on Foreign Relations (cfr.org). Accessed on May 28, 2023.

[2] Nixon Ends Convertibility of U.S. Dollars to Gold and Announces Wage/Price Controls. August 1971. Federal Reserve History. Available at: Nixon Ends Convertibility of U.S. Dollars to Gold and Announces Wage/Price Controls | Federal Reserve History. Accessed on May 27, 2023.

[3] Connolly, Kevin. Legacy of 1973 Arab-Israeli war reverberates 40 years on. BBC, October 5, 2013. Available at: Legacy of 1973 Arab-Israeli war reverberates 40 years on - BBC News. It was accessed on May 28, 2023.

[4] Weekly U.S. All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon). Available at: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMM_EPM0_PTE_NUS_DPG&f=W. It was accessed on May 28, 2023.

[5] India Budget. Chapter 77. Available at: chap77 (indiabudget.gov.in). Accessed: May 29, 2023.

[6] India Petroleum & Natural Gas Statistics, 2010. Government of India Ministry of Petroleum & Natural Gas, Economic Division, New Delhi. Available at: https://mopng.gov.in/files/TableManagements/IPNG2010.pdf. Accessed May 29, 2023.

[7] Oil consumption in China from 1998 to 2021. Statista. Available at: https://www.statista.com/statistics/265235/oil-consumption-in-china-in-thousand-barrels-per-day/. Accessed on May 29, 2023.

[8] Kangni R Kpodar and Boya Liu. The Distributional Implications of the Impact of Fuel Price Increases on Inflation. Volume 2021: Issue 271. International Monetary Fund. Accessed May 23, 2023, at: https://doi.org/10.5089/9781616356156.001.

[9] Handbook of Methods, Consumer Price Index: Calculation: Estimate of price change in the Consumer Price Index: Calculation. U.S. Bureau of Labor Statistics. Available at: Calculation: Handbook of Methods: U.S. Bureau of Labor Statistics (bls.gov); accessed: October 15th, 2023.

[10] Federal Reserve Bank of San Francisco. What are the possible causes and consequences of higher oil prices on the economy? November 2007. Available at: What are the possible causes and consequences of higher oil prices on the overall economy? – Education (frbsf.org), accessed: May 22, 2023.

[11] Stata 18. StataCorp LLC. College Station, Texas, 77845.

[12] Jorda, Oscar. Estimation and Inference of Impulse Responses by Local Projections. The American Economic Review, March 2005, 95(1): 161-182. March 2005.

[13] Cain, M. Calculating power using Monte Carlo simulations, part 5: Structural equation models. The Stata Blog: Not Elsewhere Classified. 19 August 2021. StataCorp LLC.

[14] Greene, W. H. (2018). Econometric Analysis (8th ed.). Pearson.

[15] Hu, L, and P. M. Bentler (1995). Evaluating model fit. In "Structural equation modeling: Concepts, issues, and applications. Sage.

[16] Browne, M. W., and R. Cudeck. 1993. Alternative ways of assessing model fit. Reprinted in Testing Structural.

[17] Equation Models, ed. K. A. Bollen and J. S. Long, pp. 136–162. Newbury Park, CA: SAGE.

[18] Tucker L, Lewis C. A reliability coefficient for maximum likelihood factor analysis. Psychometrika. 1973; 38: 1–10.

[19] Hu, L, and P. M. Bentler (1995). Cutoff criteria for indexes in covariance structure analysis: Conventional criteria versus new alternatives. In: Structural Modeling: A Multidisciplinary Journal 6.1; 1-55. January 1999.

[20] Lutkepohl, H. New Introduction to Multiple Time Series Analysis. Springer, 2006.