Spring 5-5-2017

Consumer Gasoline Prices in 2014: What Caused the Decline?

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Consumer Gasoline Prices in 2014: What Caused the Decline?

AN ALL COLLEGE THESIS

College of St. Benedict/St. John's University

In Partial Fulfillment

of the Requirements for Distinction

in the Department of Economics

by

Travis A. Spillum

May, 2017

Project title: Consumer Gasoline Prices in 2014: What Caused the Decline?

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Abstract:

Though a large body of literature analyzes commodity markets in general as well as the crude oil market, little work looks at the determinants of gasoline price shocks and which variables contributed to specific historical shocks. Using a structural vector autoregression (SVAR) model, one can determine how gasoline prices typically respond to shocks in price determinants, how much each variable, on average, contributes to the variation in gasoline, and which variables influenced gasoline prices during particular shocks. This paper proposes a simple SVAR model of the gasoline market and uses the model to determine what caused gasoline prices to decline between June 2014 and February 2015.

1. Introduction

What causes domestic gasoline prices to change? Answering this question is difficult, but looking for an answer is very important. The effect of a gasoline price change on firm behavior and policy decisions differs depending on which variable caused the shock. For example, falling gasoline prices due to improvements in refining technology will cause less concern to policymakers than a decrease in prices due to retracting aggregate demand. Determining exactly what causes gasoline prices to change in general may not be possible, but looking at a specific gasoline price change simplifies this question.

United States gasoline prices have experienced several significant changes throughout the 2000s, the most recent occurring from June 2014 to February 2015. During this period, gasoline prices fell from an average of $3.62 to $1.98, a 45.3 percent decrease[1]. Unlike other price decreases in this century, the price has not rebounded quickly, rising to only $2.35 as of January 2017. One might expect low gasoline prices would lead to an expansion in production, but U.S. gross domestic product (GDP) has not increased much since 2014. Understanding what caused gasoline prices to decline will give insight into the reaction by the U.S. economy, and recent innovations in econometric analysis will help find an answer.

One recently developed econometric tool is the vector autoregression (VAR) model. This model treats every variable as endogenous, or affected by every other variable in the model. A specific type of VAR model, a structural vector autoregression (SVAR) model, allows variables to react contemporaneously, or instantaneously, to shocks in other variables[2]. Since gasoline prices are highly volatile and react quickly to changes in price determinants, an SVAR model represents the gasoline market well.

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1 Reported by the U.S. Energy Information Association. Dollar values reported in nominal terms.
2 See Appendix A for a detailed description of VAR and SVAR methodology.

Although countless variables affect gasoline prices, SVAR models work best with few variables. If each variable included in the model represents changes in numerous variables, together representing most gasoline price determinants, the SVAR model remains effective while accurately describing the gasoline market. Both Kilian (2010) and Weinhagen (2003) create insightful, accurate depictions of the gasoline market using SVAR models, but a model with fewer variables and easily understood relationships gives meaningful insights as well. The variables in this paper's model represent gasoline supply, gasoline-specific demand, aggregate demand, and gasoline price. The model estimates that, in the short-run, gasoline supply causes 72% of the variation in gasoline prices while the two demand variables make no contribution. In the long run gasoline supply contributes to 66% of the variation in gasoline prices while the two demand variables each contribute to roughly 6% of the variation[3].

With these estimates, one would expect a positive gasoline supply shock as the cause of the 2014 drop in gasoline prices. The U.S. did not experience any adverse shocks to its GDP or unemployment rate during this time, but crude oil prices, a significant factor of gasoline production, experienced substantial changes. Throughout the second half of 2014, world crude oil prices experienced a 54% decrease. This decrease contributed to a positive supply shock in the gasoline market, which, according to a simple SVAR model, accounted for 88% of the decline in gasoline prices from June 2014 to February 2015.

The remainder of the paper will proceed as follows. Section 2 discusses developments in commodity, oil, and gasoline market research. Section 3 outlines the two primary theoretical approaches to modelling gasoline prices, which approach this paper's model will use, and how this paper's model is simpler than current gasoline market SVAR models. Section 4 reviews

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3 The remaining 28% of short run variation and 22% of long run variation attribute to variables not captured by this model, such as inventory costs and uncertainty.

current SVAR models of the gasoline market. Section 5 explains which variables are included in the model and why. Section 6 describes the pre-estimation results for this paper's model. Section 7 illustrates how the model defines contemporaneous relationships. Section 8 discusses the impulse response function, forecast error variance decomposition, and historical decomposition results as well as the interpretations of these results. Section 9 provides concluding remarks.

2. Commodities, Oil Prices, and the Gasoline Market

In order to understand the factors that influence gasoline prices, one must understand literature pertaining to commodity markets, the global crude oil market, and the U.S. gasoline market. Gasoline is a storable commodity, so literature pertaining to commodities will help one determine the formation of gasoline prices. Also, since crude oil is the primary input to gasoline production, crude oil literature helps explain a large aspect of gasoline supply. A substantial body of research exists which examines commodity markets and the global crude oil market, but most relevant literature analyzes price formation in the commodity and crude oil market, historical oil price shocks, and macroeconomic consequence of oil price shocks.

Research on commodity price formation identifies the marginal convenience yield price volatility and as factors attributing specifically to commodity price changes. The marginal convenience yield is a measure which corresponds to the convenience of being able to sell inventories in the present or waiting to sell them in the future. Pindyck (2001) explains that spot prices and the marginal convenience yield are positively correlated. He determines that gasoline inventory owners pay, on average, 8.1% of their revenues each month for the benefit of having physical inventories. Pinyck also finds a positive correlation between volatility and commodity prices. Cashin and McDermott (2002) determine exchange rate fluctuations following the end of the Breton Woods exchange agreement caused a period of high commodity price volatility during the 1970s. Iacoviello, Schiantarelli, and Schuh (2011) conclude that commodity prices were less volatile from 1984-2007 as compared to 1960-83, though a decrease in inventory shocks during the former period did not attribute to the change in price volatility. These findings suggest commodity prices are positively correlated with the convenience yield as well as volatility, though these variables have not influenced commodity prices as much between 1984 and 2007 as opposed to 1960-83.

In the crude oil market, macroeconomic variables influence prices more than commodity-specific factors. Kilian (2009) identifies demand variables as the major cause of crude oil price shocks. These demand variables include global aggregate demand and precautionary demand (shifts in future price expectations caused by political conflicts, perceived future availability of crude oil, etc.). Hamilton (2009) also determines price speculation and global economic activity as determinants of crude oil prices, but he also concludes supply factors, such as production constraints or expanses by the Organization of Petroleum Exporting Countries (OPEC), may cause variation in crude oil prices during particular periods. When crude oil price shocks occur, one should analyze movements in these macroeconomic variables to determine the underlying cause of the price shock.

The most recent oil price shock occurred in 2014, and researchers examined which variables led to the price shock. Baffes et al. (2015) and Baumeister and Kilian (2016) both extensively analyzed this oil price decline. Baffes et al. observed both short-term and long-term variables contributed to declining oil prices. The short-term variables included an appreciation of the U.S. dollar, unexpected increases in U.S. oil production, unexpectedly low global aggregate demand, and a response by OPEC to maintain current oil production levels. The long-term variables included steady increases in non-OPEC oil production and improvements in oil exploration technologies. Baumeister and Kilian found that half of the decline was predictable by June 2014. Adverse global demand shocks and positive oil supply shocks in the first half of 2014 attributed to this predicted decline. The unanticipated declines resulted from a shock to oil price expectations, which lowered inventory demand beginning in June 2014, and low global economic productivity in December 2014. Thus, a combination of supply and demand factors attributed to this negative price shock.

Many have researched how macroeconomic variables respond to crude oil shocks, but their conclusions are conflicting. Morey (1993) as well as Jiménez-Rodríguez and Marcelo (2004) estimate the crude oil elasticity of U.S. GDP as -0.0551 and -0.04648, respectively. In other words, a one percent increase in the price of crude oil was estimated to cause roughly a 0.05 percent decrease in U.S. GDP. Morey as well as Lee, Ni, and Ratti (1995) identify asymmetric responses to crude oil price shocks. Morey finds U.S. GDP responds significantly to an increase but not an equal decrease in crude oil prices. Lee, Ni, and Ratti conclude U.S. GDP responds more significantly to a crude oil price shock during a time of relative price stability than to a shock occurring during a period of price volatility. Barsky and Kilian (2004), however, find no evidence to support a significant response in U.S. GDP to crude oil shocks, and Kilian and Vigfusson (2011) rule out asymmetric responses to oil price shocks. With these conflicting findings, future research will be important in answering how macroeconomic variables respond to crude oil price shocks.

Likewise, research on the response of gasoline prices to crude oil price shocks has reached differing conclusions. Borenstein, Cameron, and Gilbert (1997) observe gasoline prices responding in greater magnitude to oil price increases than decreases, hypothesizing the asymmetry is a result of temporary market power in the short run as well as different costs for adjusting inventories. Brown, Stephen, and Yücel (2000) observe asymmetry in gasoline price responses as well, though they do not find evidence of market power as the cause. Instead, they hypothesize the asymmetry results from differing consumer responses and refinery adjustment costs. Davis and Hamilton (2004) find the asymmetry results from the combination of menu costs and expected responses to price changes by consumers and competitors. On the other hand, Bachmeier and Griffin (2003) find little evidence of any asymmetry in wholesale gasoline prices. Further research will be important in answering how gasoline prices respond to oil price shocks.

Studies have also estimated both short-run and long-run gasoline price elasticity of demand, though these elasticities have not stayed constant over time. Brons et al. (2008) estimate the average price elasticity of demand from 1949 and 2004 to be -0.34 in the short run and -0.84 in the long run. When Hughes, Knittel and Sperling (2008) estimate elasticities from two different periods, they find the short-run elasticities differ between the periods. They estimate the short-run price elasticity of demand from 1975 to 1980 to be in the range of -0.21 to -0.34 versus a range of -0.034 to -0.077 from 2001 to 2006. Thus, there is evidence to suggest the average short-run price elasticity of demand decreased over time, and both short- and long-run elasticities reveal a negative, inelastic relationship between gasoline prices and gasoline demand.

Less work, however, has looked at the determinants of gasoline price movements as well as which variables contributed to historical gasoline price shocks. Weinhagen (2003) determines gasoline price shocks contributed most to variation in gasoline prices, but he does not include historical analyses of specific gasoline shocks. Kilian (2010) includes a historical analysis of gasoline price determinants, but his model is a joint model of the crude oil market and gasoline market. A model focusing specifically on the gasoline market should give clearer insights into the interactions of the variables that influence gasoline price. This paper serves to develop an understanding of which variables, on average, contributed to gasoline price movements as well as which variables influenced gasoline prices during specific historical price shocks, such as the 2014 gasoline price shock.

3. Modeling Gasoline Prices

There are two primary theoretical approaches to modeling gasoline prices. The first approach is a commodity pricing approach. Pindyck (2001) explains the dynamics of commodity pricing models, which demonstrate the relationship between inventory levels, volatility, and commodity prices. When prices are volatile, consumption and production of the commodity tends to be volatile as well, so the demand for inventories increases as inventory owners increase their inventories to buffer against these fluctuations. This increased demand for storage then leads to an increase in price. Commodities differ from typical consumer goods in two ways. Firstly, since inventory owners wish to keep a certain level of inventories, they impose demand in addition to consumer demand when market changes occur. Secondly, commodities can be used in two different ways, either as a consumption good or a store of value. Thus, the market for commodities can be split into two submarkets, the cash market and the storage market.

The cash market determines the spot price, or immediate price, of the commodity while the storage market determines the futures price, or the price of delivering a commodity at an agreed future date. When commodity prices are high, in general, the cost of storage will be higher. Likewise, increases in oil price volatility increases the demand for inventories, for those who own inventories can decide whether to use the stored gasoline as an asset or sell to consumers. This results in the marginal convenience yield. The marginal convenience yield, price expectations, and inventory levels all affect commodity prices in addition to supply and demand factors.

Since finished gasoline is a storable commodity, gasoline prices are affected by commodity market factors. Price transition dynamics for commodities differ from standard consumable goods because inventory owners, like consumers, demand gasoline. For example, if there is a temporary increase in gasoline consumption, inventories suppress some of the price increase by selling some of their gasoline inventory and allowing their inventories to decrease. When gasoline consumption returns to its previous level, inventory owners will demand gasoline to refill their inventories. This will cause the price to decrease more slowly back into equilibrium. Conversely, if inventory owners expect the demand to be permanent, inventory owners will increase their own demand for gasoline in the short run. Thus, the price of gasoline will increase due to increased consumer demand as well as increased inventory demand. When the quantity demanded by consumers decreases in response to the additional price increase, inventory owners will replenish their reserves, and the price will slowly decrease to the new, higher consumer demand equilibrium. Once the market is in equilibrium, however, the commodity-pricing model yields the same price and quantity as the supply and demand model. The advantage of the commodity-pricing model is that it describes the gasoline market more accurately than a supply and demand model. The transition dynamics and relationships among variables, however, are less straightforward.

The second approach is a standard supply and demand model. Since gasoline is a consumer good, one can model the gasoline market like any other consumer good using a supply and demand model. This model includes variables that affect the supply of gasoline (such as crude oil price and availability, refining costs and capacities, and transportation costs) along with variables that affect the demand for gasoline (such as the number of domestic vehicles in use and aggregate demand, for gasoline is an input of many other goods). This modeling approach focuses on the cash market of commodities. One advantage of supply and demand models is that researchers can determine if a change in one variable will have a positive or negative effect on price. For example, since crude oil is a factor of gasoline production, an increase in the price of crude oil should cause gasoline prices to increase. A second advantage is straightforward interpretation. The laws of supply and demand, as well as transition dynamics, which govern this model are easy to understand. This allows clear understanding of the relationships and interactions among variables in the model.

SVAR models can utilize either approach, but a model using the supply and demand approach reduces the complexity involved in interpreting transition dynamics. This paper aims to use variables with simpler relationships than previous literature, and using a supply and demand approach helps achieve this aim due to the simpler transition dynamics. Also, SVAR models treat relationships among the variables as a relationship of shocks rather than levels or quantities. Since shocks do not typically originate in the market for storage, as Iacoviello, Schiantarelli, and Schuh (2011) suggest for the period from 1984 to 2007, including a variable to capture storage shocks in an SVAR model that accounts for inventory determinants makes little sense. One could include a variable to capture changes in price volatility, though it would be difficult to argue the contemporaneous relationships among the variables. Thus, this paper's empirical model is based on the theoretical supply and demand model.

4. Current SVAR Gasoline Models

Economists, over the last two decades, have utilized different forms of vector auto regression (VAR) models to determine how certain factors affect the price of gasoline in the United States (see, e.g., Kilian 2010; Weinhagen 2003). Christopher Sims (1980) was the first to promote the use of VAR models in macroeconomic analysis, and Stock and Watson (2001) have shown VAR models to be an accurate data analysis and forecasting tool. VAR models can be of three forms: reduced form, recursive, and structural. Reduced form and recursive VAR models do not require economic theory in determining the model (see Sims 1980), but these forms do not account for contemporaneous relationships among the variables (see Stock and Watson 2001). SVAR models, however, can account for these types of relationships, though one must identify these relationships using economic theory. An SVAR model is most appropriate to model U.S. gasoline prices because gasoline prices react quickly to changes in oil prices (see Emmons and Neely).

Both Kilian (2010) and Weinhagen (2003) modeled U.S. gasoline prices using supply and demand variables in SVAR models. Kilian constructed a joint model combining the crude oil market and U.S. gasoline market. His model traced changes in global oil production, global real economic activity, real price of crude oil, real U.S. price of gasoline, and U.S. gasoline consumption, where shocks in the variables represented shocks in oil supply, aggregate demand, oil-market specific demand, U.S. supply of gasoline (represented as refinery shocks), and gasoline demand, respectively. In the short run, Kilian recognized refining shocks (shocks to the U.S. supply of gasoline) as the leading factors attributing to U.S. gasoline price shifts. In the long run, he observed oil-specific demand shocks and shocks to the global business cycle contributed most.

Weinhagen (2003) constructed a model which focused specifically on the U.S. gasoline market. His model tracked changes in the producer price index (PPI) for crude oil, PPI of gasoline, consumer price index (CPI) for gasoline, U.S. gasoline consumption, and U.S. industrial production. Shocks incurred by each variable do not have additional interpretations[4]. Weinhagen did not analyze variable shocks in the short-run or long-run but over a one-year period. He estimated that, during an average year, shocks in the PPI for crude oil and gasoline contributed most to variations in gasoline price.

Though Kilian (2010) and Weinhagen (2003) constructed their models differently, neither found gasoline demand variables, such as gasoline consumption and U.S. industrial production, as a major determinant of gasoline prices. These estimates, however, represent an average contribution based on observations over the entire dataset. For specific gasoline price shocks, the variables contribute in varying degrees.

5. A Simplified Gasoline Model

The variables in this paper's empirical model represent innovations in gasoline supply, gasoline-specific demand, aggregate demand, and the price of gasoline. Kilian (2009) inspires this approach with his oil market model. His model includes three variables: global oil production, global economic activity, and the price of crude oil. Shocks in these variables correspond with shocks in oil supply, aggregate demand, and oil-specific demand, respectively. Kilian associates shocks in the price of crude oil apart from changes in oil supply and demand as shocks to oil-specific demand. The price of gasoline could represent shocks in gasoline-specific demand, but gasoline consumption more accurately embodies changes in gasoline-specific

[4] For example, a shock to the CPI for gasoline corresponded with a shock to the consumer price of gasoline.

demand. Shocks incurred by the price of gasoline in this paper's model apart from shocks in other variables will correspond with unobserved variable shocks, such as shocks in price volatility and future price uncertainty. Compared to current SVAR models of the gasoline market, this paper's model includes one fewer variable, and one can understand relationships among the variables with the help of a basic supply and demand model. To establish the empirical model, one must identify variables to capture shocks in gasoline supply, gasoline-specific demand, aggregate demand, and the price of gasoline.

Understanding gasoline's supply chain is essential to determine which variables capture gasoline supply shocks. The Depro et al. (2007) outlines the process from gasoline production to gasoline consumption. Gasoline starts out beneath the earth's surface in the form of crude oil. Once extracted, firms transport the oil to a refinery. The refinery processes the crude oil into the finished gasoline product. Commercial inventory owners purchase the gasoline, transport the gasoline by pipeline or rail car, and store it in a single inventory or a series of inventories (terminals). These firms transport gasoline to gas stations by truck and sell the finished product to consumers. A supply variable is one that contributes to the production of a good or service. The price refineries sell their finished gasoline, the producer price of gasoline (PPI), should capture shocks in any supply variable, because the production of gasoline is complete once it leaves the refinery. Thus, the PPI for gasoline should capture gasoline supply shocks.

While a singular shock represents all supply, two different variables represent demand shocks. Since gasoline is a consumer good as well as an input in the production for many goods and services, separating demand shocks into two different categories is appropriate. Researchers typically use U.S. gross domestic product (GDP) as a measure of aggregate demand; however, since this paper's model uses monthly data and GDP reports come out quarterly, the model must find a different variable. The Federal Reserve Bank of St. Louis reports the Industrial Production Index monthly, which is a suitable measure of U.S. aggregate demand. Likewise, this variable captures shocks in aggregate demand in this paper's model.

The final variable, which will capture is gasoline-specific demand, is gasoline consumption. Gasoline-specific demand accounts for all demand for gasoline which is not a result of aggregate demand. One way to measure this demand is by calculating the number of gallons of gasoline consumed within the United States. Since monthly gasoline consumption data is not readily available, one can estimate gasoline consumption by finding the monthly amount of gasoline produced within the United States, adding in monthly gasoline imports, and subtracting out monthly gasoline exports. The model assumes consumers consume all gasoline imported or produced in the United States, since this model does not include gasoline inventories. This variable should capture an unexpected shock in the amount of gasoline consumed within the United States when an aggregate demand shock does not occur.

6. Pre-estimation Tests

The variables included in the model are the PPI of gasoline, U.S. gasoline consumption, U.S. industrial production index, and the U.S. consumer price index (CPI) for gasoline. Each variable is seasonally adjusted and measured by month from January 1979 to December 2015. In addition, each variable was converted into percentage growth form by taking a first difference of logs and multiplying the result by 100. This transformation is imposed on the data to interpret changes in the model as percent changes as well as to make the estimation process stationary. According to Woolridge (2008), a process is stationary if the joint distribution for a collection of adjacent time indices is equal to an equal size collection of adjacent future time series. In other words, the mean, variance, autocorrelation, and other measures of the distribution remain equal over time. This ensures that the estimates obtained from the OLS estimation of the SVAR model are valid.

To ensure a process is stationary, one can apply the Augmented Dickey-Fuller Test on the dataset. The Augmented Dickey-Fuller test performs a t-test on the coefficients of the lagged variables. If any of the estimated coefficients are equal to one, which means the current value of a variable is perfectly correlated with a certain lag, then there is evidence to suggest the process is nonstationary. In the t-test, the null hypothesis is that the process is nonstationary, or the estimated coefficients are equal to one. Thus, rejecting the null hypothesis will give evidence that the dataset is in fact stationary. A test statistic is statistically significant at the 1% level if the test statistic is less than -3.983. Table 1 displays the results of the Dickey-Fuller test.

Table 1. Dickey-Fuller Test Statistic

Variable	PPI Gasoline	Consumption	Industrial Production	CPI Gasoline
Test Statistic	-7.05	-6.56	-5.714	-6.943

NOTES: The 1% critical value is -3.983.

Since each test statistic is less than the 1% critical value, there is little evidence to suggest the process is nonstationary. Thus, there is evidence to suggest the parameter estimates are accurate.

A second test, the Score Test (or Lagrange Multiplier Test), will ensure serial correlation (autocorrelation) does not exist among the residuals. When a correlation exists among variables a given interval apart, there is serial correlation. Serial correlation does not affect the unbiasedness or consistency of the model, but it does influence the model’s efficiency. In other words, the p-values of the estimated coefficients in a model with serial correlation are smaller than the true p-values. Thus, one may reject the null hypothesis when it should not be rejected. In monthly, non-seasonally adjusted data, serial correlation will most likely occur among variables that are 12 steps apart. Woolridge (2008) states that serial correlation is especially present in models with lagged variables and can result in inconsistent OLS estimations. The SVAR model used in this paper will have a lag order of 12, so it is important to test for serial correlation among the error terms. The null hypothesis of the Score Test is that autocorrelation does not exist in the model, and this paper's model failed to reject the null hypothesis for lag order up to 12 (see Appendix B). Thus, there is little evidence to suggest this model exhibits serial correlation.

7. Model Identification

To reduce the number of unknown parameters in the model, contemporaneous relationships among variables are restricted. The following is a matrix representation of the model's contemporaneous relationships:

$$\begin{pmatrix} e_t^{Producer\ Price\ Index} \\ e_t^{Gasoline\ Consumption} \\ e_t^{Industrial\ Production} \\ e_t^{Consumer\ Price\ Gasoline} \end{pmatrix} = \begin{bmatrix} \beta_{11} & 0 & 0 & 0 \\ \beta_{21} & \beta_{22} & 0 & 0 \\ \beta_{31} & \beta_{32} & \beta_{33} & 0 \\ \beta_{41} & \beta_{42} & \beta_{34} & \beta_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{Gasoline\ Supply\ Shock} \\ \varepsilon_t^{Gasoline-Specific\ Demand\ Shock} \\ \varepsilon_t^{Aggregate\ Demand\ Shock} \\ \varepsilon_t^{Unobserved\ Variable\ Shock} \end{pmatrix}$$

Displaying these relationships in expanded form helps reveal the meaning of the contemporaneous relationships:

$$e_t^{PPI} = \beta_{11}\varepsilon_t^{GS}$$

$$e_t^{CONS} = \beta_{21}\varepsilon_t^{GS} + \beta_{22}\varepsilon_t^{GD}$$

$$e_t^{IND} = \beta_{31}\varepsilon_t^{GS} + \beta_{32}\varepsilon_t^{GD} + \beta_{33}\varepsilon_t^{AD}$$

$$e_t^{CPI} = \beta_{41}\varepsilon_t^{GS} + \beta_{42}\varepsilon_t^{GD} + \beta_{43}\varepsilon_t^{AD} + \beta_{44}\varepsilon_t^{UV}$$

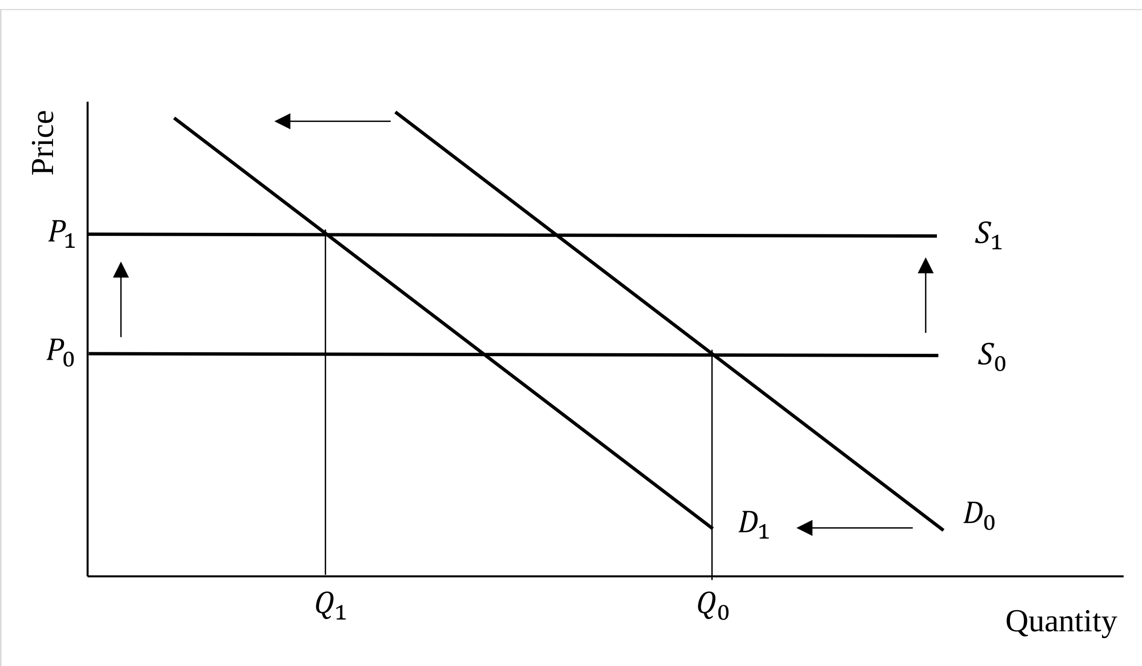
where e_t^{CPI}, e_t^{IND}, e_t^{CONS}, and e_t^{PPI} correspond to the estimated residual (the difference between the predicted value of the dependent variable and the actual value of the dependent variable) in the U.S. consumer price index for gasoline, the level of U.S. industrial production, the level of gasoline consumption in the U.S., and the producer price of gasoline, and ε_t^{GS}, ε_t^{GD}, ε_t^{AD}, ε_t^{UV} correspond to unexpected shifts in gasoline supply, gasoline demand, aggregate demand, and unobserved variables, respectively.

This form has important meaning in an SVAR model. In SVAR models, the relationships among variables are modeled as a relationship of shocks. Thus, an SVAR model models fluctuations in estimated residuals for a specific period as a function of unexpected variable shocks occurring during the same period, a theoretical assumption in SVAR methodology. After estimating the model by OLS and obtaining the predicted residuals, one can decompose the residuals into the contribution of each unexpected variable shock by inverting the beta matrix and multiplying the inverted beta matrix by the residual vector. Thus, one can use this mechanism to identify which variable shocks caused unpredicted changes in the model's variables during specific periods.

The identification relationships were made under the following economic assumptions: (1) the consumer price of gasoline reacts quickly to shocks in gasoline supply, aggregate demand, and gasoline-specific demand; (2) industrial production will react to disturbances in gasoline supply, for gasoline is an input to a large number of goods and services, as well as gasoline-specific demand, since gasoline-specific demand is a subset of aggregate demand; (3) the quantity of domestic gasoline consumption will only react quickly to changes in gasoline supply because shocks in this variable will represent demand for gasoline apart from aggregate demand. Researchers, such as Hughes et al. (2008), have shown gasoline demand to be inelastic in the short-run and therefore will not react quickly to changes in gasoline prices, and Aczel and Fullam (1986) have shown gasoline consumption can change dramatically to gasoline supply shocks; (4) the PPI of gasoline react contemporaneously with its own shocks because supply variables in the gasoline supply market tend to react slowly to changes in demand variables. For example, it takes time to increase oil production or reopen refineries.

An example of a gasoline supply shock will help give context to the relationships among the variables in the model. Figure 1 shows the impact of an adverse gasoline supply shock on the other variables. Before the supply shocks, price and quantity are at P_0 and Q_0. The supply curve is horizontal since supply is fixed in the immediate short-run. An adverse supply shock will cause supply to shift upwards. At the same time, due to the identification of simultaneous relationships, changes in both aggregate demand and gasoline-specific demand will cause demand to shift left. This results in an increase in price from P_0 to P_1 and a decrease in quantity from Q_0 to Q_1.

Figure 1: Impact of a Gasoline Supply Shock on the Gasoline Market



8. Model Estimation

Once identified, the model parameters were estimated by OLS (see Appendix C for results). Using the estimated parameters of the model, impulse response functions (IRF) and forecast error variance decomposition (FEVD) verify the performance of the model. If valid, the results of these analyses should mirror Weinhagen's (2003) results. Impulse response functions trace the impact of a one-standard deviation shock in one variable and the effect of this shock on other variables over a specified number of time steps[5]. In other words, IRF analysis begins by assuming all variables are at their mean values. Then, a one-standard deviation shock occurs in a variable, the impulse variable, represented by a one-standard deviation change in ε_1^i, or the first period error term of the impulse variable *i.* Any variable which reacts contemporaneously with this variable will experience some shock, calculated in using the β estimates in the identification equations. This will result in the zero period responses. These responses are then used to estimate the next period responses by all the other variables, since all variables respond to shocks in other variables after one period (one month). This process repeats, and responses by all variables are recorded for all subsequent periods up to a specified number. Since it is helpful to look at the total change in a variable caused by a shock to the other variable, one can calculate the cumulative impulse response function by adding the current period response to the sum of the responses from all previous periods.

Appendix D contains cumulative impulse response functions for this model. These results suggest unexpected shocks in the consumption of gasoline have a statistically significant impact on gasoline prices only in the initial period, and this impact is not very large. This suggests that

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5 The time-step used in this analysis was a 12-month period.

shocks in gasoline-specific demand do not contribute much at all to fluctuations in the price of gasoline. Furthermore, industrial production does have a statistically significant impact on the price of gasoline after two periods, and this impact remains statistically significant over the next nine periods. The size of the impact is not extremely large, but these results suggest an interesting dynamic between aggregate demand and the price of gasoline. When the U.S. experiences an increase in industrial production, this change has a lagged influence on the price of gasoline, i.e. it takes time for gasoline prices to respond to changes in aggregate demand. Supply shocks have a statistically significant impact on gasoline prices throughout the entire observation period, and the impact is rather large. This suggests that prices do not return to equilibrium quickly after a supply shock occurs. Instead, it seems supply variables do not return to previous levels quickly, so equilibrium price itself moves. Unobserved shocks, on the other hand, impact gasoline prices only temporarily, with prices returning to equilibrium after a period of four to five months. These results are consistent with Weinhagen's (2003) impulse response analysis, giving evidence to the validity of this paper's simpler model.

These findings are embedded in the forecast-error variance decomposition (FEVD) results. FEVD decomposes the variance of a variable into contributions from shocks in other variables. This is done by calculating the forecast error during each period, equal to the model's predicted values $\hat{y}_i$ minus the actual value y_i, squaring the differences to obtain the forecast error variances (since mean forecast error is equal to zero) and using the β estimates to determine how much shocks in each variable contributed to the forecast error variance over a specified period. These contributions are then averaged to obtain how much shocks in one variable attributed to the variation in another variable. In principle, this analysis reveals how much shocks in each of the variables contribute to the variability of one variable over a given period. Table 2 contains the FEVD for all variables over a 12-month horizon, and Appendix E contains the FEVD results for gasoline price for a number of different time horizons.

Table 2. Forecast Error Variance Decomposition (FEVD)

FEVD Variable	Percent of forecast error variance due to shocks in:			
	Supply	Gasoline-Specific Demand	Aggregate Demand	Unobserved Shocks
Supply	88.65	3.96	2.80	4.59
Gasoline-Specific Demand	1.23	93.29	4.18	1.30
Aggregate Demand	2.94	5.82	89.87	1.36
Unobserved Shocks	67.15	4.73	5.17	22.94

NOTES: Values represented as a percent of total variation. Time horizon for each result is 12.

This analysis attributes 67.15% of the variance in gasoline prices, during a 12-month period, to shocks in supply. Therefore, during an average year, shocks in gasoline supply attribute to over half of the variation in gasoline prices. On the other hand, shocks in gasoline-specific demand and aggregate demand together account for only 10% of the variation in gasoline prices during an average year. These results are consistent with Weinhagen (2003), who found supply variables to contribute a total of 74% and demand variables to contribute a total of 2.5% to the variation in gasoline prices over an average year[6].

The 12-month FEVD results lead to a couple important observations. Firstly, consistent with the IRF results, gasoline-specific demand and aggregate demand seem to influence gasoline prices very little in an average year. If demand shocks are only temporary, inventory owners allow their reserves to decrease to accommodate the demand shock rather than purchasing more

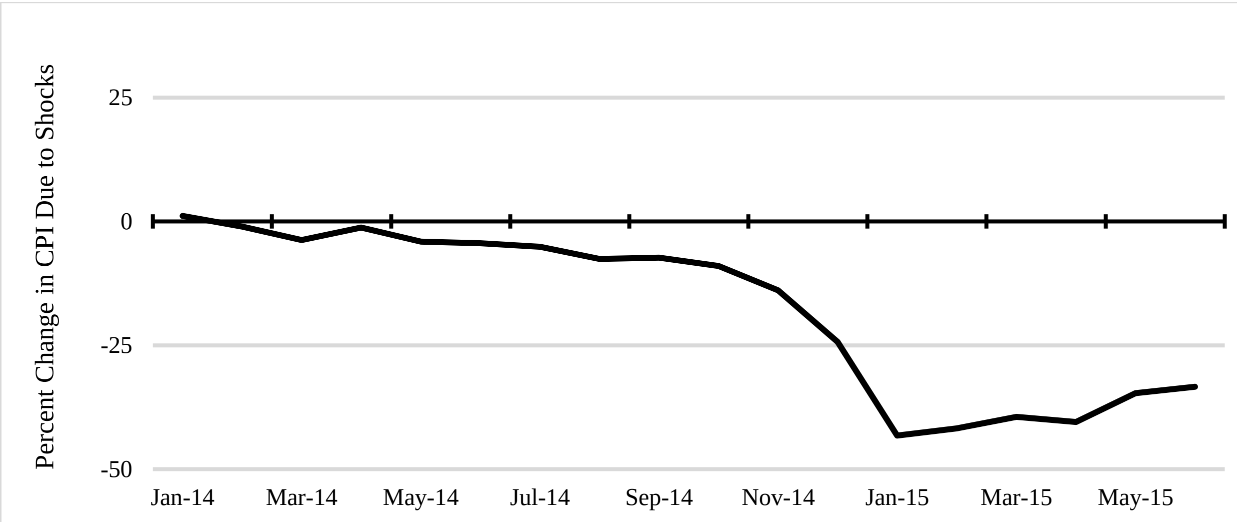
6 Weinhagen's (2003) model identified contemporaneous relationships differently than the model in this paper, so one would expect FEVD results for the two models to differ.

inventories. This reduces the size of the demand shock on the market. Prices, then, do not respond as much to temporary demand shocks. After demand returns to equilibrium, the price of gasoline will slowly return to equilibrium as inventories return to their pre-shock levels. Thus, it makes sense that demand variables do not contribute much to variation in gasoline prices. Secondly, the results from multiple horizons suggest supply shocks and unobserved shocks have a large impact on prices in the early horizons with their impact decreasing over longer horizons. Demand shocks, on the other hand, have little to no impact on gasoline prices over short periods while their impact increase over longer periods. Thus, demand shocks have a lagged influence on gasoline prices. Lastly, since the results are consistent with previous literature, this paper's simpler model should be a valid tool for analyzing specific price shocks, like the 2014 gasoline price shock.

To determine which variables contributed to the decline in gasoline prices in 2014, the model undergoes historical decomposition. Historical decomposition decomposes shocks, i.e. the error terms e_t^i, in one variable into the contribution of each variable to that shock. This is done for each month during the observation period, and summing the next period decomposition with the sum of the previous period decompositions reveals the portion of the shock caused by shocks in each variable over a certain horizon. Appendix F contains the cumulative historical decomposition of gasoline prices over the entire observation period. One will notice that gasoline supply shocks contribute to gasoline price shocks much more than any of the other three shocks. To determine the historical decomposition during a specific period, one must simply pick a relevant starting date and perform the same type of summation over a specified horizon.

Looking at the historical decomposition of gasoline prices in 2014 and 2015 reveals which factors contributed to the gasoline price decline. Figure 2 outlines shocks incurred by the price of gasoline between June 2014 and June 2015.

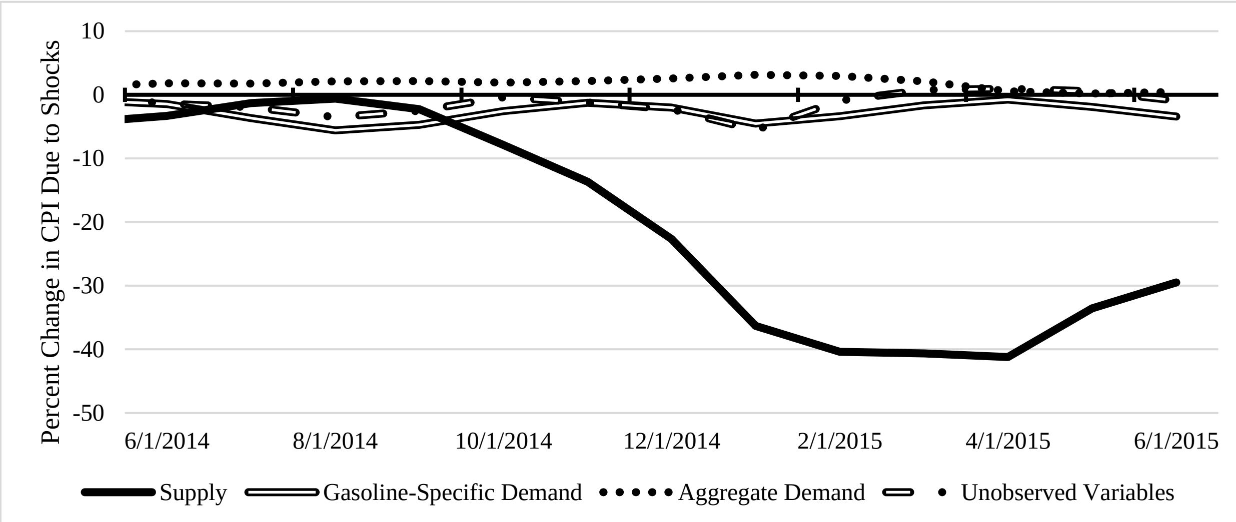
Figure 2. Cumulative Shock to CPI, 2014-2015



This represents the summation of error terms for the CPI of gasoline over the period. Since the sum of the error terms deviates from zero, one can conclude a price shock indeed occurred during this period. This is important to note, for although a gasoline prices began to decrease in June 2014, a significant shock in gasoline prices did not begin to occur until October of 2014. Thus, visible factors prior to June 2014 and price expectations by gasoline sellers contributed to a certain amount of expected price decreases. Economists typically define a shock as an event which causes significant, unexpected changes in a variable, and the gasoline price error terms suggest a significant price shock occurred, though only after October 2014.

This paper determined the contribution of each variable to this gasoline price shock using historical decomposition. Figure 3 outlines the cumulative contribution of each variable to the 2014 shock in gasoline prices. Shocks to the PPI of gasoline contributed most to unexpected changes in the price of gasoline during this period, making up 88% of the cumulative shock.

Figure 3. Decomposition of CPI Shock, 2014-2015

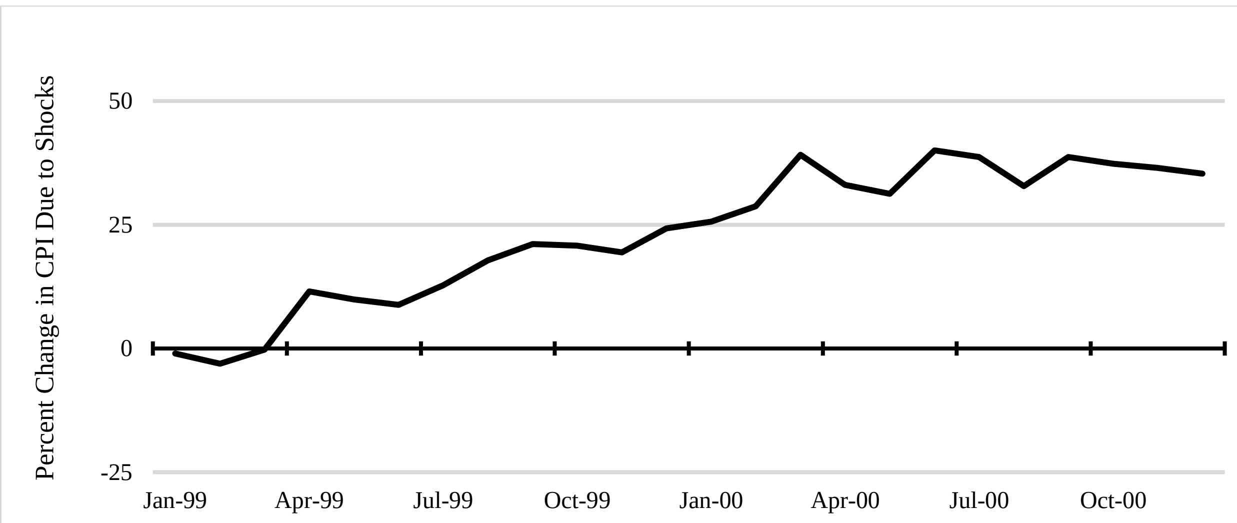


Shocks to gasoline consumption and industrial production account for only 6% and 4% of this shock, respectively, and unobserved variable shocks contributed to the remaining 2%. It appears gasoline supply shocks were the primary, if not the only contributor to the 2014 gasoline price shock. These results are consistent with the historical evidence of the period; U.S. economic growth did not experience any significant changes in the second half of 2014, and world crude oil prices experienced a significant negative shock, causing a positive supply shock in gasoline supply.

The gasoline price shock in 2014 was a negative shock, so analyzing a positive price shock will give greater context to the model. Between February 1999 and June 2000, U.S. gasoline prices rose from an average of $0.96 per gallon to $1.62, a 69.3 percent increase. This period occurs in the later part of the dot-com bubble, in which technology and web company stocks experienced extraordinary increases in price. The U.S. economy, in general, was at the tail end of an extended expansionary period, in which only a minor recession occurred between 1983 and 2000[7]. On the supply side, Hamilton (2011) explained the movement of gasoline prices between 1999 and 2001. While Asian economies grew rapidly during the early and mid-1990s, a number of Asian markets experienced a financial crisis from 1997 to 1998. This caused crude oil prices to drop as low as $12 per barrel near the end of 1998. The crisis, however, was short-lived, and crude prices rebounded rather quickly, almost tripling in price in the following two years.

With this background, historical decomposition allows one to analyze which variables contributed to the increase in gasoline prices. Firstly, Figure 4 displays the cumulative shocks incurred by the price of gasoline.

Figure 4. Cumulative Shock to CPI, 1999-2000



The results suggest gasoline prices experienced positive shocks between March 1999 and March 2000. Secondly, Figure 5 displays the decompositions of these price shocks. As with 2014, the demand variables did not contribute much to the price shocks during this time.

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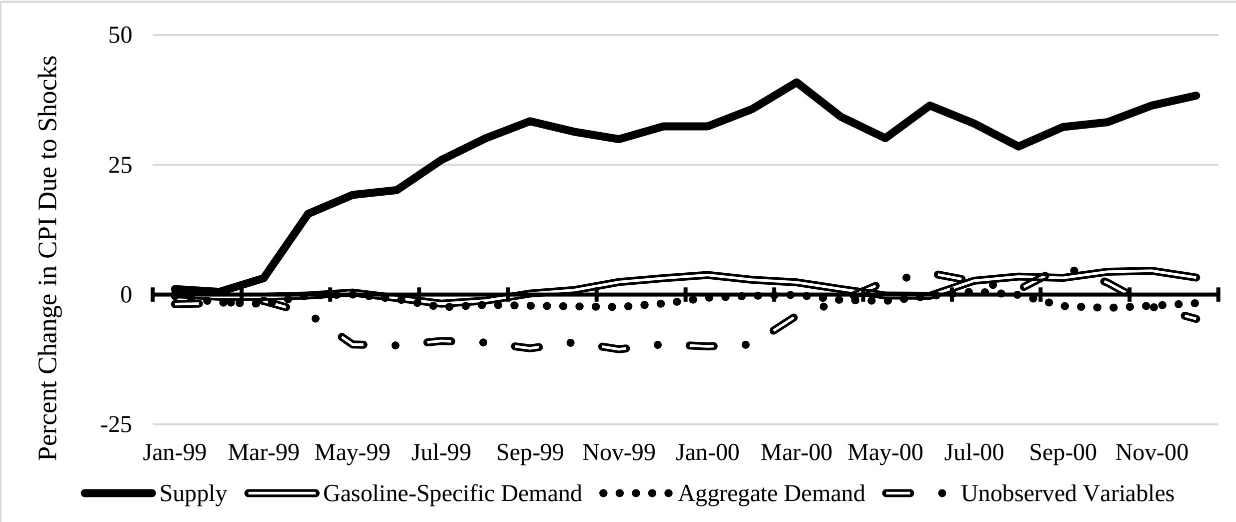
7 A short recession occurred between July 1990 and March 1991, in which unemployment reached a peak of 7.8%.

Figure 5. Cumulative Shock to CPI, 1999-2000



Supply shocks, on the other hand, contributed to large positive shocks between March and September of 1999, but unobserved shocks contributed to a negative shock in the same period. Thus, the unobserved shocks kept the price of gasoline from rising even more.

With rising crude oil prices, it is no surprise supply shocks contributed most to the price shock. The unobserved variable shocks are no surprise as well for the following reason: When crude oil prices fell to $12 per barrel in November of 1998, the demand for gasoline inventories increased, since inventory owners knew the price of oil would rise in the near future. Thus, inventory owners bought up inventory to sell to consumers at a later date. When the price of crude oil began to rebound, causing gasoline prices to increase in March 1999, inventory owners had sufficient reserves and could afford to allow their inventory levels to decrease. This, as explained earlier, would repress a gasoline price increase. Therefore, the observed negative impact of unobserved shocks to the price of gasoline in this period is not surprising.

9. Concluding Remarks

Based on evidence from historical events and the model's estimations, a shock in the supply of gasoline, specifically a shock in the price of crude oil, was the primary cause of the 2014 gasoline price shock. Also, shocks to gasoline supply are the primary contributor of gasoline price variation. These results suggest a few implications. Firstly, with the expectation that crude oil prices will increase in the future, gasoline prices will most likely increase as well. This may be problematic if consumers are not able to change their consumption behaviors quickly and switch to products which do not rely on gasoline. Secondly, if the price of crude oil remains low, firms and consumers will have little incentive to invest in alternative fuel sources, such as electric vehicles. With the rising concern of global climate change, this may hinder objectives which aim to reduce air pollution. Thirdly, it is possible that factors of gasoline supply may contribute in opposing ways to gasoline price shocks, as they did in the 1999 gasoline price shock. Historical decomposition, then, reveals important information regarding the underlying causes of gasoline price changes.

The model presented in this paper serves as a simple model of the gasoline market. Future research can certainly add factors to the model to obtain more accurate results. Since the model only included one variable to represent all of gasoline supply, one may look to create a model which focuses more intently on gasoline supply variables. Kilian's (2010) model is a good start, and others may look analyze variables which connect more closely with the U.S. gasoline market. Shocks to the price of gasoline caused by unobserved shocks were most likely influenced by commodity factors such as uncertainty and other commodity-pricing factors. One may wish to construct a model using the commodity-pricing approach to determine how inventory demand and futures prices affect the price of gasoline. Future research into accurately modeling the gasoline market will aid in policy analysis as well as allow firms to make better-informed decisions when faced with uncertainty in future gasoline prices.

References

Aczel, A., & Fullam, T. (1986). Time Series Analysis of U.S. Consumption of Motor Gasoline. *The American Economist*, 30(1), 21-27. Retrieved from http://www.jstor.org/stable/25603676

Bachmeier, L.J. and J.M. Griffin (2003). “New Evidence on Asymmetric Gasoline Price Responses,” *Review of Economics and Statistics*, 85, 772-776.

Baffes, J., Kose, M.A., Ohnsorge, F., Stocker, M. (2015). “The Great Plunge in Oil Prices—Causes, Consequences, and Policy Responses”. Policy Research Note No. 1, World Bank, Washington D.C.

Balke, N.S., S.P.A. Brown, and M.K. Yücel (1998). "Crude Oil and Gasoline Prices: An Asymmetric Relationship?” *Federal Reserve Bank of Dallas Economic Review*, First Quarter: 2-11.

Barsky, R.B., and L. Kilian (2004). "Oil and the Macroeconomy since the 1970s," *Journal of Economic Perspectives*, 18(4), 115-134.

Baumeister, C. and L. Kilian (2015). “Understanding the Decline in the Price of Oil since June 2014.” (CFS Working Paper No. 501).

Brons, M., P. Nijkamp, E. Pels, and P. Rietveld (2008). “A MetaAnalysis of the Price Elasticity of Gasoline Demand: A SUR Approach.” *Energy Economics*, 30(5), 2105–22.

Brown, Stephen P. A., and M. K. Yücel (2000). “Gasoline and Crude Oil Prices: Why the Asymmetry?” *Economic and Financial Review*, 23-29.

Cashin, P., and McDermott, C. (2002). "The Long-Run Behavior of Commodity Prices: Small Trends and Big Variability". *IMF Staff Papers*, 49(2), 175-199. Retrieved from http://www.jstor.org/stable/3872481

Davis, M. C., and J. D. Hamilton (2004). "Why Are Prices Sticky? The Dynamics of Wholesale Gasoline Prices," *Journal of Money, Credit and Banking*, 36(1), 17–37.

Davis, S. J., and J. Haltiwanger (2001). "Sectoral Job Creation and Destruction Response to Oil Price Changes," *Journal of Monetary Economics*, 48, 465-512.

Depro, B., K. Jones, S. Patil, and D. Wood (2007). *Economic Impact Analysis for the Gasoline Distribution Industry*. Report Prepared for the U.S. Environmental Protection Agency at the RTI International Health, Social, and Economics Research Institute, Research Triangle Park, NC.

Emmons, W., and C. J. Neely (2007). "Why Do Gasoline Prices React to Things That Have Not Happened?" *Inside the Vault*, Fall, 10-11.

Gottschalk, J. (2001). "An Introduction into the SVAR Methodology: Identification, Interpretation, and Limitations of SVAR models," (Kiel Working Paper No. 1072). Kiel, Germany: Kiel Institute of World Economics.

Hamilton, J.D. (2009). "Understanding Crude Oil Prices." *Energy Journal*, 30(2), 179–206.

Hamilton, J.D. (2011). "Historical Oil Shocks". National Bureau of Economic Research, San Diego. Working Paper Series.

Hughes, J. E., C. R. Knittel and D. Sperling (2008). "Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand." *Energy Journal*, 29(1), 93-114.

Iacoviello, M., Schiantarelli, F., & Schuh, S. (2011). "Input and Output Inventories in General Equilibrium". *International Economic Review*, 52(4), 1179-1213. Retrieved from http://www.jstor.org/stable/41349192

Jiménez-Rodríguez, R. and S. Marcelo (2004). "Oil Price Shocks and Real GDP Growth: Empirical Evidence for Some OECD Countries," (ECB Working Paper No. 362). Available at SSRN: https://ssrn.com/abstract=533107

Jones, D., Leiby, P., & Paik, I. (2004). "Oil Price Shocks and the Macroeconomy: What Has Been Learned Since 1996". *The Energy Journal, 25*(2), 1-32.

Kilian, L. (2009). "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, 99, 1053-1069.

Kilian, L. (2010). "Explaining Fluctuations in Gasoline Prices: A Joint Model of Global Crude Oil and the U.S. Retail Gasoline Market," *The Energy Journal*, 31, 87-112.

Kilian, L., and R.J. Vigfusson (2011), "Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases?", *Quantitative Economics*, 2, 419-453.

Lee, K., Ni, S., & Ratti, R. (1995). "Oil Shocks and the Macroeconomy: The Role of Price Variability". *The Energy Journal*, 16(4), 39-56. Retrieved from http://www.jstor.org/stable/41322616

Mory, J. F. (1993). "Oil Prices and Economic Activity: Is the Relationship Symmetric," *The Energy Journal*, 14(4), 151-161.

[Omnia O H]. (2016, Mar 7). *Module 5: Session 12: Introduction to Structural VAR Identification*. [Video File]. Retrieved from https://www.youtube.com/watch?v=hpCW5fQ0fhk

Pindyck, R. (2001). "The Dynamics of Commodity Spot and Futures Markets: A Primer". *The Energy Journal*, *22*(3), 1-29. Retrieved from http://www.jstor.org/stable/41322920

Sadorsky, P., "Oil Price Shocks and Stock Market Activity," *Energy Economics*, 21 (October 1999), 449-69.

Sims, C. (1980). "Macroeconomics and Reality". *Econometrica*, 48(1), 1-48.

Stock, J.H., and M.W. Watson (2001). "Vector Autoregressions," *Journal of Economic Perspectives*, 15, Fall, 101-115.

Weinhagen, J. (2003). "Consumer Gasoline Prices: An Empirical Investigation," *Monthly Labor Review*, 3-10.

Wooldridge, J. (2008). *Introductory Econometrics: A Modern Approach (with Economic Applications, Data Sets, Student Solutions Manual Printed Access Card)*. South-Western College Pub. ISBN: 0324581629

Appendix A

SVAR Methodology

A vector autoregression (VAR) model is a type of simultaneous equation model. Simultaneous equation models are a system of equations where each dependent variable is a function of every other dependent variable as well as exogenous, or external, variables. The following is a simple two-variable simultaneous equation model:

(1) $y_1 = \alpha_1 y_2 + \beta_1 z_1 + u_1$

$y_2 = \alpha_2 y_1 + \beta_2 z_2 + u_2$

where y_1, y_2 are the dependent variables, z_1, z_2 are exogenous variables, and u_1, u_2 are the structural error terms[8]. In this case y_1 and y_2 are considered endogenous variables, for their values are dependent on the value of the other (i.e. the two variables are correlated). Thus, simultaneous equation models have the advantage of allowing the inclusion of endogenous variable, where ordinary least squares (OLS) estimation is only valid in single-equation models when each independent variable is uncorrelated with the dependent variable.

Estimating simultaneous equation models results in equilibrium estimates for the coefficients (α_1, α_2 and β_1, β_2) as well as intercept terms. In order to allow for changes over time, one must include lagged variables in the model[9]. This results in a dynamic simultaneous equation model. VAR models are dynamic simultaneous equation models where each variable is a function of each of its lags and the lags of every other variable. Thus, each variable in a VAR model is endogenous.

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8 In this simplified model, and the intercept term is assumed to be zero. Also note that because z_1, z_2 are exogenous variables, they are uncorrelated with the structural error terms.

9 For example, if our variable is y_t, a lagged variable could be y_{t-1}, y_{t-2}, etc. for time period *t*.

Christopher Sims (1980) was the first to propose a model in which each variable is endogenous. He believed more accurate macroeconomic estimates could be attained by constructing simultaneous equation models this way. In a typical simultaneous equation model, the decision to treat some variables as exogenous and others as endogenous is difficult to argue, for what real-world variable is truly uncorrelated with any other variable? The VAR model avoids this problem by simply allowing correlation among all variables.

VAR models also differ from typical simultaneous equation models in their identification. Identification is the method in which relationships among variables are restricted in order to reduce the number of parameters that require estimation, for simultaneous equation models contain a greater number of unknown parameters than OLS regression can estimate. According to Gottschalk (2001), simultaneous equation models are identified by imposing restrictions on the relationship between the dependent variables and the variables included in the model. For example, in a dynamic simultaneous equation model in which a dependent variable y_t does not react quickly to changes in an endogenous variable x_t, one may assume the coefficient of the first lagged variable x_{t-1} is equal to zero. Restrictions are imposed until the number of unknown parameters of the simultaneous equation model is sufficiently small.

Simultaneous equation models, therefore, are typically identified without making restrictions to relationships among the structural error terms. In other words, structural disturbances are not orthogonal (statistically independent). Structural error terms in simultaneous equation models are treated as errors in the model due to small changes in unobserved variables, so it does not make sense to impose restrictions on the error parameters. VAR models, on the other hand, treat structural error terms as exogenous shocks in its corresponding dependent variable. Thus, when VAR models are identified, structural disturbances are considered to be independent, which eliminates a number of necessary restrictions. In fact, any VAR model is able to be estimated by OLS when these restrictions are imposed. What would happen, though, if one wished to assume exogenous shocks in one variable simultaneously affected a number of dependent variables? A special form of VAR model, the SVAR, can accomplish this.

SVAR models have the following form:

(2) $A_0 Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t$

(3) $E\varepsilon\varepsilon' = \sum \varepsilon = \begin{bmatrix} \sigma_{\varepsilon 1}^2 & 0 & & 0 \\ 0 & \sigma_{\varepsilon 2}^2 & & 0 \\ & & \ddots & \\ 0 & 0 & & \sigma_{\varepsilon n}^2 \end{bmatrix}$

where each A_i is an (n x n) matrix of parameters[10], Y_t is an n-length vector of endogenous variables, p is the lag order, and ε_t is a matrix of uncorrelated error terms, where the expected value of the error terms is zero. The variance-covariance matrix, $E\varepsilon\varepsilon'$, has a diagonal of variances with all other elements being equal to zero[11]. In order to estimate this equation, (2) must be written in reduced-form, where each endogenous variable is written as a function of its own lags and the lags of all other variables. Thus, the reduced form of the above model is

(4) $Y_t = \sum_{i=1}^{p} A^* Y_{t-i} + e_t$

(5) $\sum e = {A_0}^{-1} \sum \varepsilon \, {A_0}^{-1\prime}$

where $A^* = {A_0}^{-1} A_i$ and $e_t = {A_0}^{-1}\varepsilon_t$, and $\sum e$ is the variance-covariance matrix of (4). In order to make this reduction, matrix A_0 must be invertible, which this model assumes[12]. Essentially, this is the condensed form of a system of equations, with n equations in total, where each

10 This includes the matrix A_0.

11 The error terms are assumed to be independent, so each covariance in the variance-covariance matrix is equal to zero.

12 i.e. there exists a matrix ${A_0}^{-1}$ such that $A_0 {A_0}^{-1} = {A_0}^{-1} A_0 = I$, where I is the identity matrix.

variable y_t will be regressed on its past values as well as past values of all other variables (Stock and Watson, 2001).

To estimate all the parameters in the model, additional restrictions must be imposed on (2) and (3). To begin, one can restrict the diagonal elements of $\sum \varepsilon$ to equal 1. This normalizes the model, for $\sum \varepsilon$ is now equal to the identity matrix One must note that normalizing the model is only a rescaling; all relationships and functions of the model remains unchanged. A result of this normalization is that now $\sum e = {A_0}^{-1}{A_0}^{-1\prime}$, which reduces the number of unknown parameters requiring estimation. Next, restrictions are imposed on the coefficients of A_0. These restrictions focus on the relationship $e_t = {A_0}^{-1}\varepsilon_t$, for SVAR models depict relationships among economic variables as relationships of shocks. Thus, one must use a priori economic theory to impose restrictions among variable shocks. For example, shocks in the PPI for Gasoline react slowly or not at all to shocks in industrial production, so one can assume the PPI for gasoline and industrial production shocks are independent. To be exact, a total of $\frac{n(n-1)}{2}$ restrictions must be made to A_0 (See Omnia O H for a detailed explanation). A simple reduction which will exactly identify A_0 is to make it lower triangle, or cause every entry above the main diagonal to equal zero. Doing so causes the relationship between e_t and ε_t to become

(6) $$e_t = \begin{bmatrix} \beta_{1,1} & & & & 0 \\ \beta_{2,1} & \beta_{2,2} & & & \\ \beta_{3,1} & \beta_{3,2} & \ddots & & \\ \vdots & \vdots & \ddots & \ddots & \\ \beta_{n,1} & \beta_{n,2} & \cdots & \beta_{n,n-1} & \beta_{n,n} \end{bmatrix} \varepsilon_t$$

After imposing these restrictions, the model can be estimated using OLS to obtain estimates for each β_i and $\sigma^2_{\varepsilon_i}$.

Appendix B

Lagrange-Multiplier Test

Lag Order	Chi-squared Statistic	Degrees of Freedom	Probability of Observed Test Statistic
1	12.064	16	0.73955
2	18.009	16	0.32339
3	22.841	16	0.11806
4	16.918	16	0.3909
5	17.287	16	0.36726
6	22.882	16	0.11694
7	23.844	16	0.09298
8	20.012	16	0.2197
9	15.239	16	0.50721
10	9.4946	16	0.89166
11	12.021	16	0.74252
12	12.224	16	0.7284

NOTES: The null hypothesis is that no autocorrelation exists at the given lag order.

Appendix C

A_0 and A_0^{-1} estimations with identification equations

$$A_0 = \begin{bmatrix} 0.150 & 0 & 0 & 0 \\ 0.005 & 0.499 & 0 & 0 \\ -0.001 & -0.073 & 1.646 & 0 \\ -0.245 & 0.069 & -0.005 & 0.509 \end{bmatrix} \qquad A_0^{-1} = \begin{bmatrix} 6.669 & 0 & 0 & 0 \\ -0.065 & 2.004 & 0 & 0 \\ 0.001 & 0.089 & 0.607 & 0 \\ 3.214 & -0.270 & 0.607 & 1.964 \end{bmatrix}$$

$$e_t^{CPI} = 3.214 e_t^{PPI} - 0.270 e_t^{CON} + 0.607 e_t^{IND} + 1.964 \varepsilon_t^{Unobserved\ Variable\ Shock}$$

$$e_t^{IND} = 0.001 e_t^{PPI} + 0.089 e_t^{CONS} + 0.607 \varepsilon_t^{Aggregate\ Demand\ Shock}$$

$$e_t^{CONS} = -0.065 e_t^{PPI} + 2.004 \varepsilon_t^{Gasoline-Specific\ Demand\ Shock}$$

$$e_t^{PPI} = 6.669 \varepsilon_t^{Gasoline\ Supply\ Shock}$$

NOTES: Statistical significance of the coefficients could not be calculated. Impulse response functions instead serve as a measure of whether or not a shock in one variable causes a significant shock in another variable.

Appendix D

Forecast Error Variance Decomposition of Gasoline Price

Percent of forecast error variance in Gasoline Price due to shocks in:				
Time Horizon	Supply	Gasoline-Specific Demand	Aggregate Demand	Unobserved Shocks
1	72.44	0.51	0.00	27.05
2	78.24	0.45	0.22	21.09
3	75.49	0.47	2.03	22.02
6	70.83	0.90	4.22	24.05
12	67.15	4.73	5.17	22.94
Infinite	66.30	6.24	5.59	21.87

NOTES: Values represented as a percent of total variation. The values for horizon infinite are approximated using a horizon of 400.

Appendix E

Impulse Response Functions

Table 1E. Mean Impulse Response Function Coefficients

Mean Impulse Response to Supply Shock				
Response Variable	PPI Gasoline	Gasoline Consumption	Industrial Production	CPI Gasoline
Period				
1	6.669*	-0.065	0.001	3.214*
2	7.953*	-0.171	0.039	5.262*
3	7.296*	-0.221*	0.048	5.121*
4	7.535*	-0.336*	0.057	4.882*
5	7.792*	-0.500*	0.082	4.968*
6	7.533*	-0.424*	0.080	4.935*
7	6.741*	-0.425*	0.035	4.572*
8	6.927*	-0.358*	-0.005	4.518*
9	6.846*	-0.501*	-0.035	4.463*
10	7.038*	-0.531*	-0.027	4.548*
11	7.296*	-0.513*	-0.111	4.531*
12	8.105*	-0.470*	-0.142	5.233*

Mean Impulse Response to Gasoline-Specific Demand Shock				
Response Variable	PPI Gasoline	Gasoline Consumption	Industrial Production	CPI Gasoline
Period				
1	0.000	2.004*	0.089*	-0.270*
2	0.075	0.473*	0.146*	-0.162
3	0.281	0.645*	0.173*	-0.085
4	0.176	0.747*	0.220*	-0.110
5	0.291	0.523*	0.266*	-0.033
6	0.370	0.621*	0.307*	0.264
7	0.796	0.543*	0.333*	0.463
8	1.699	0.196	0.327*	0.938
9	2.118*	0.468*	0.298	1.329*
10	1.751	0.577*	0.384*	1.120
11	1.078	0.246	0.419*	0.604
12	0.531	0.721*	0.401*	0.204

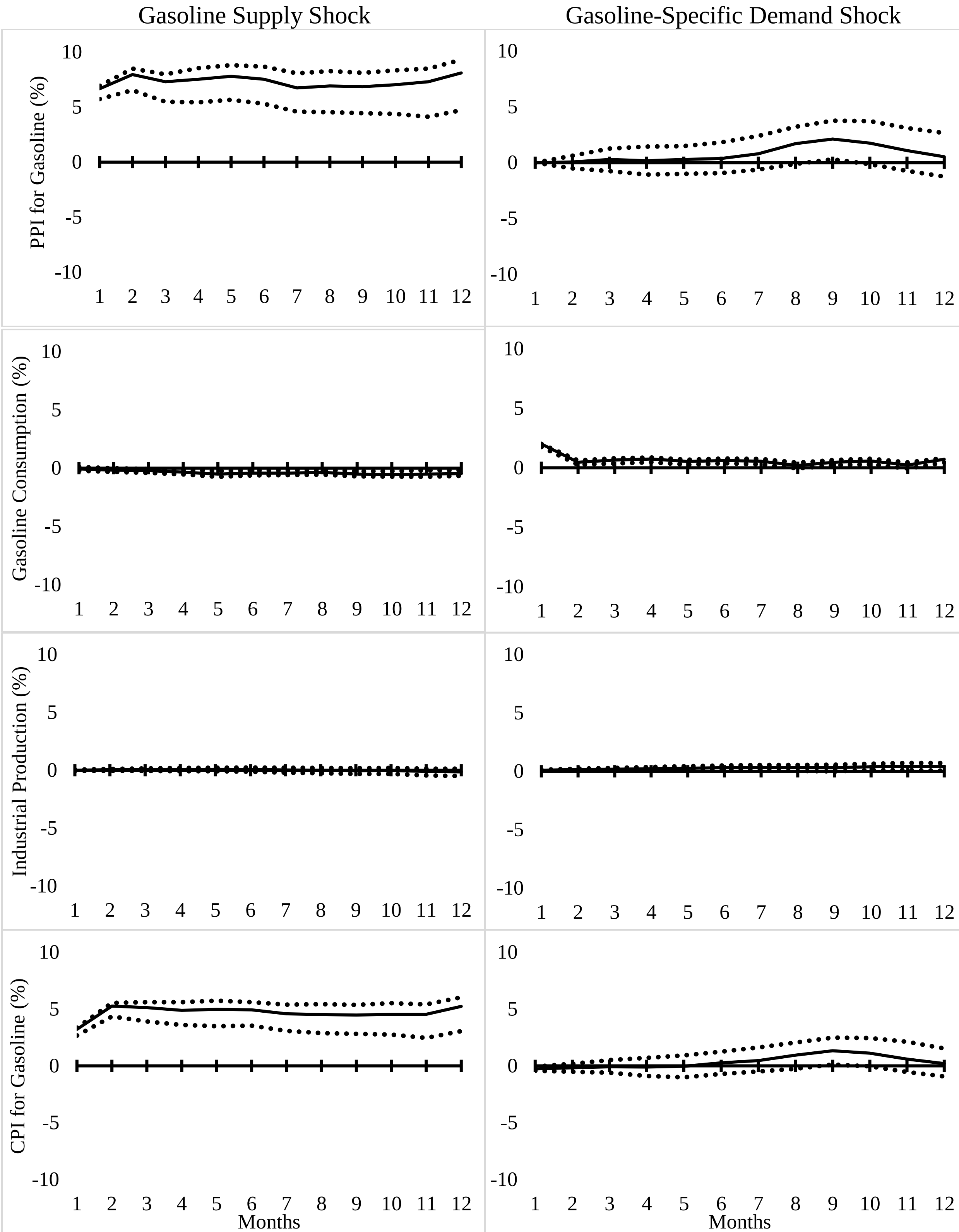
NOTES: * indicates statistical significance at the 0.05 level.

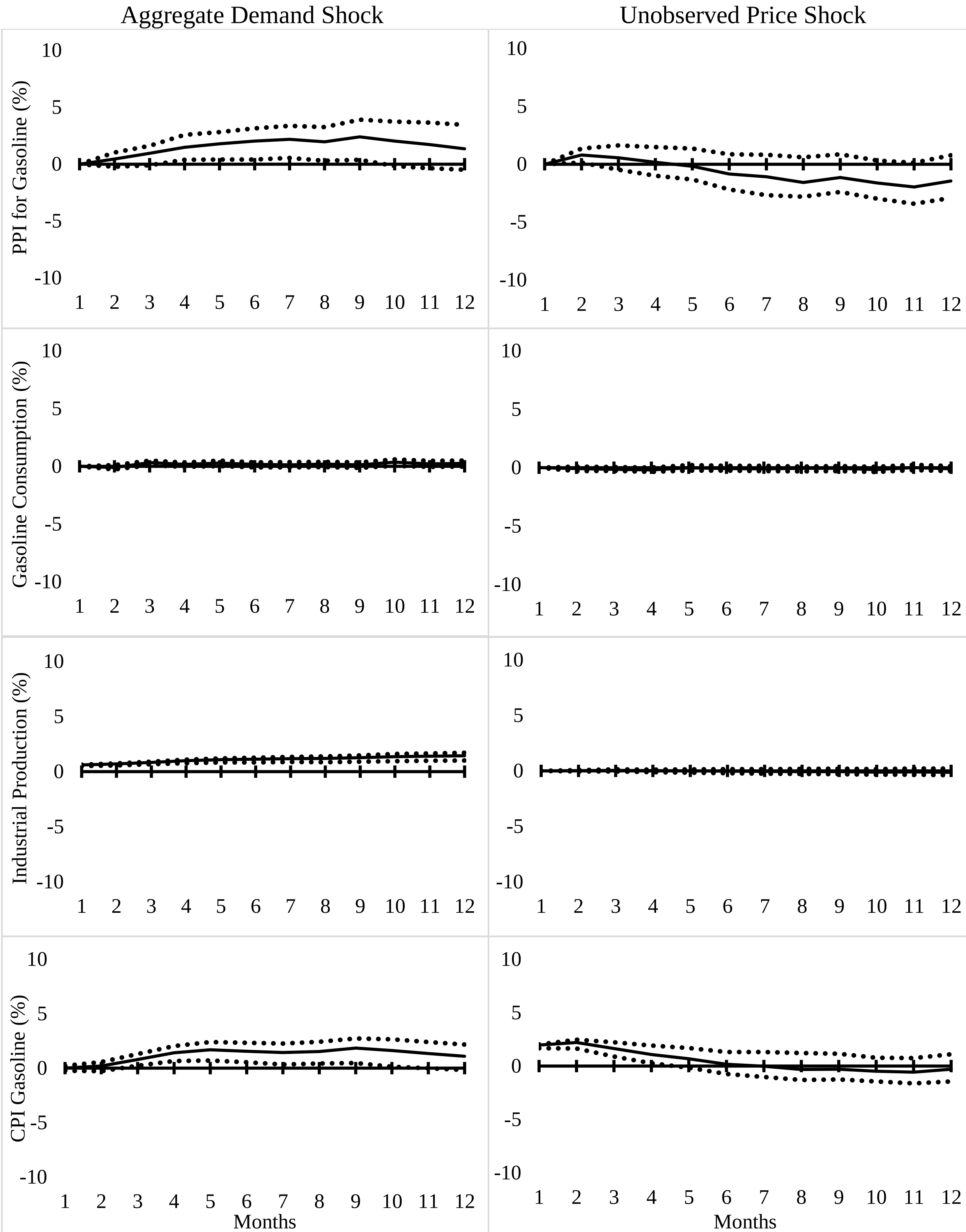
Mean Impulse Response to Aggregate Demand Shock				
Response Variable	PPI Gasoline	Gasoline Consumption	Industrial Production	CPI Gasoline
Period				
1	0.000	0.000	0.607*	0.005
2	0.457	-0.102	0.697*	0.206
3	0.949	0.320*	0.841*	0.798*
4	1.493*	0.169	0.989*	1.415*
5	1.785*	0.271*	1.094*	1.697*
6	2.029*	0.179	1.122*	1.558*
7	2.184*	0.120	1.185*	1.445*
8	1.974*	0.195	1.191*	1.528*
9	2.406*	0.134	1.262*	1.843*
10	2.043	0.360	1.350*	1.619*
11	1.719	0.219	1.401*	1.333*
12	1.354	0.252	1.439*	1.100

Mean Impulse Response to Unobserved Variable Shock				
Response Variable	PPI Gasoline	Gasoline Consumption	Industrial Production	CPI Gasoline
Period				
1	0.000	0.000	0.000	1.964*
2	0.800*	-0.066	0.015	2.206*
3	0.561	-0.139	0.043	1.634*
4	0.165	-0.188	0.013	1.087*
5	-0.179	-0.011	0.000	0.677
6	-0.834	-0.068	-0.026	0.177
7	-1.083	-0.089	-0.038	-0.026
8	-1.578	-0.063	-0.074	-0.312
9	-1.145	-0.064	-0.080	-0.290
10	-1.623	-0.163	-0.120	-0.495
11	-1.962	0.010	-0.099	-0.569
12	-1.438	-0.094	-0.132	-0.289

NOTES: * indicates statistical significance at the 0.05 level.

Figure 1E. Cumulative Impulse Response Functions





NOTES: IRFs impulse variable stated above columns, response variable stated left of each row on y-axis. Dotted lines represent a 95% confidence interval for impulse responses. Confidence intervals calculated using a bootstrap.

Appendix F

Historical Decomposition of Gasoline Price Shocks, 1980-2015