# Essays on the macroeconomic effects of climate and energy price shocks

by

Naafey Sardar

B.Sc., Lahore University of Management Sciences, 2015

M.A., Kansas State University, 2017

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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2020

# Abstract

This dissertation consists of three essays. The first essay estimates the difference in the response of non-gasoline consumption spending to gasoline expenditure shocks across recessions and expansions. Using a nonlinear structural VAR (SVAR) model estimated on quarterly U.S. data for the period 1973-2018, we find that shocks to gasoline expenditures are followed by a much larger reduction in consumption if the shock occurs during a recession than if it occurs in an expansion. We also find a big difference in the response of personal savings to a gasoline expenditure shock depending on whether the economy is in a recession or expansion. This points to precautionary saving behavior as a source of the asymmetry in the response of consumption. We conclude that consumption forecasts should account for this asymmetry.

The second essay asks whether El Nino-Southern Oscillation (ENSO) has asymmetric impacts on U.S. food and agricultural stock prices. Using weekly data from 1990 through 2019, we find support for the hypothesis that food and agricultural stock prices respond asymmetrically to ENSO shocks. In particular, we provide evidence that El Nino shocks typically decrease or have no effect on U.S. food and agricultural stock prices, whereas La Nina shocks generally increase prices. Our results are robust to a variety of robustness checks.

The third essay estimates the effect of the 1999-2007 oil price spike on U.S. manufacturing employment. Using local labor market data, we estimate the change in U.S. manufacturing employment that can be explained by oil price movements that can plausibly be considered exogenous with respect to the U.S. economy. Our estimates suggest that the oil price spike may have been responsible for the movement of more than two million workers out of the manufacturing sector. When controlling for the effect of the oil price spike on manufacturing employment, the effect of import competition from China found by Autor, Dorn, and Hansen

(2013) falls by more than 20%, with the estimated effect on less-educated workers declining by 26%.

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# Acknowledgments

*"So which of the favors of your Lord would you deny?"*

– Surah Ar-Rahman: 13

This dissertation is a product of the help, support, and guidance of people I look up to. First and foremost, I consider myself extremely lucky to have had Dr. Lance Bachmeier as my major advisor. It is an often cliché, but in this case, it is no overstatement to say that this dissertation only exists because of his consistent guidance, tutelage, support, unparalleled knowledge, and encouragement. He has always been an email away, and his willingness to help me has significantly contributed to instilling a love of macroeconomics. The extensive discussions held with him on research have benefitted me a lot, and I look forward to working with him in the future.

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# Dedication

*To my grandfather, Zahid Bashir Virk, for this is all because of you.*

*To my father, Imran Ali Chaudhry, for encouraging me to follow my dreams.*

*To my mother, Khadija Imran, for all your sacrifices.*

# Chapter 1

# Do Gasoline Expenditure Shocks Have Different Effects in Recessions and Expansions?

## 1.1 Introduction

An important question in macroeconomics is how aggregate consumption responds to a shock to gasoline expenditures. In one sense, the mechanism by which consumption is affected is straightforward. If gasoline consumption is inelastic in the short run, a positive shock to the price of gasoline will lead to higher gasoline expenditures, crowding out spending on other goods and services.[1] Consumers will have to decide whether to continue buying the same amount of gasoline at the higher price, in which case there will be less discretionary income available for other expenditures (Hamilton, 2009). Higher gasoline expenditures have an indirect effect on consumption, as the demand for goods that complement gasoline in consumption, most notably automobiles, will fall (Hamilton, 1988). A recent study by

[1] For empirical evidence on the response of consumption to gasoline and oil price shocks, see Bernanke (1983), Hamilton (1988), Pindyck (1991), Bernanke (2006) , Hamilton (2009), Edelstein and Kilian (2009), Hamilton (2016), Kilian and Baumeister (2016), Kilian et. al. (2018), Herrera et al. (2019), Gorodnichenko et al. (2019).

Farrell and Greig (2015) concluded that the marginal propensity to consume non-energy goods out of a dollar saved on gasoline is roughly 0.8.[2] Gicheva et. al. (2008) use scanner data to infer that as gasoline expenditures rise, consumers shift towards groceries as opposed to eating out in order to offset this increase. This is also followed by switching to lower cost grocery items.[3]

The mechanisms described previously can explain a shift in consumption from non-energy to energy goods, but not necessarily a change in the *level of aggregate consumption*. Figure 1.1 shows that in every month from January 1973 through May 2019, the U.S. was a net importer of crude oil.[4] Increases in gasoline expenditures have historically caused a transfer of U.S. income to foreign oil producers. Thus, higher gasoline expenditures have the same effect as a tax on the U.S. economy, and should therefore be expected to reduce aggregate consumption.[5]

Using quarterly data on the U.S. economy from 1973 through 2018, this paper tests for an asymmetric response of consumption to gasoline expenditure shocks across recessions and expansions. The motivation for our analysis is the recent literature showing that the impact of fiscal policy depends on the state of the economy. Tagkalakis (2008) finds that tax cuts increase consumption by more in recessions as opposed to expansions. Auerbach and Gorodnichenko (2012) estimate that fiscal multipliers range from 1-1.5 in recessions and 0-0.5 in expansions. Jorda and Taylor (2016) find that fiscal austerity depresses the economy

[2] Another channel by which energy shocks can affect consumption is increasing uncertainty about future energy prices. In the presence of uncertainty, consumers have an incentive to delay purchases of durable goods, such as cars and houses (Bernanke, 1983; Pindyck, 1991).

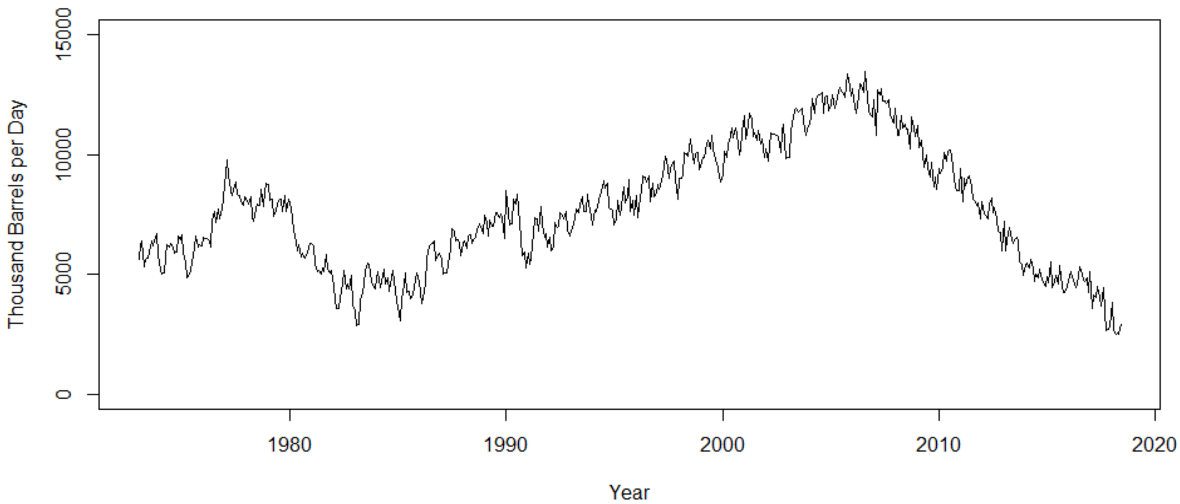
[3] "As many drivers struggle to cope with soaring fuel prices, working-class people like Ms. Lopez who commute long distances to their jobs are suffering the most..... Ms. Lopez looks for weekly specials at the supermarket. Salmon, her favorite fish is $7 a pound these days. So she buys the tilapia for $2.99 instead."
-- Full Tanks Put Squeeze on Working Class, NY Times, May 13, 2006

[4] Source: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=mttntus2&f=m

[5] In the words of Janet Yellen, "Higher oil prices lower American income overall because the United States is a major oil importer and hence much of the proceeds are transferred abroad. . . . Thus, an increase in the price of crude oil acts like a tax on U.S. households, and . . .tends to have a dampening effect on consumer spending. ...Staff analysis at the Federal Reserve Board indicates that a[n]...increase in retail gasoline prices. . .reduces household disposable income ... and hence tends to exert a significant drag on consumer spending."

In a report on 29 June, 2018, S&P Global economists Beth Bovino and Satyam Panday stated the following about higher oil prices, "This would be tantamount to a tax increase for American households. This is especially true for middle- to low-income Americans."

**Figure 1.1**: *U.S. Net Imports of Crude Oil and Petroleum Products*




***Source***: U.S. Energy Information Administration.

more when implemented in a slump as opposed to a boom. Auerbach and Gorodnichenko (2013) and Fazzari, Morley, and Panovska (2015) also find evidence that fiscal policy has asymmetric effects across states of the business cycle. [6]

If shocks to gasoline expenditures can be treated as if they are a change in taxes, and fiscal policy has different effects in recessions and expansions, it follows that the effect of a gasoline expenditure shock should also depend on the state of the business cycle. A finding of economically meaningful nonlinearity of this type would require a change to empirical and theoretical macroeconomic models that include energy prices. The analysis would also emphasize the need for the Federal Reserve to consider asymmetries in the impact of gasoline expenditure shocks across recessions and expansions when it is forecasting consumption, as failure to do so might result in misleading conclusions about the effect of gasoline expenditures shock on the U.S. economy. On the other hand, a failure to find evidence of this type of nonlinearity would cast doubt on the treatment of a gasoline expenditure shock as a change in taxes, claims that the effect of fiscal policy depends on the state of the economy, or both.

Using quarterly data on the U.S. economy from 1973 through 2018, we begin by doc-

[6] Ramey and Zubairy (2018) did not find evidence of asymmetry for their data and specifications.

umenting the impact of a gasoline expenditure shock on non-gasoline goods and services. Consistent with expectations and the existing literature, we find that a positive shock to gasoline expenditures is followed by reduced spending on other goods. A shock that increases gasoline expenditures by 10% over the course of a year is accompanied by a 0.7% decrease in spending on non-gasoline goods and services over the same time period. Most of the consumption response comes from services (47%) and durables (33%) sector.

We then estimate a threshold model that allows the response to gasoline expenditure shocks to be different in expansions and recessions. We find asymmetry in the response of consumption to an increase in gasoline expenditures between the two states of the economy. Following a 10% increase in gasoline expenditures, total non-gasoline spending goes down by 2.7% in recessions and 0.7% in expansions over the same time period. The motor vehicles sector is responsible for driving a big proportion of the response. Spending on motor vehicles goes down by 11.9% in recessions as opposed to 2.9% in expansions over the same time period.

According to Kilian and Edelstein (2009), one of the mechanisms through which higher gasoline prices reduce discretionary income is the precautionary savings effect. As gasoline prices increase, consumers become uncertain about the future path of the economy, and reduce their consumption in order to increase precautionary savings. These savings act as an insurance against a greater likelihood of future unemployment and income losses. We present evidence that the difference in the responses of consumption is driven by an asymmetric response of private savings to gasoline expenditure shocks across recessions and expansions. Following a 10% increase in gasoline expenditures, private savings increase by 3.6% in recessions as opposed to 0.9% in expansions.[7]

The paper proceeds as follows. Section 1.2 describes the linear VAR model and the impulse response functions following gasoline expenditure increases. Section 1.3 discusses how we model the difference in response across recessions and expansions. Discussion of results and the motivation for asymmetry is also included. Section 1.4 looks at the forecasting

[7] The 10% increase in gasoline expenditures is the total increase in gasoline expenditures that occurs in the year following the initial shock to gasoline expenditures. Shocks to gasoline expenditures in a particular quarter will be followed, on average, by additional increases in gasoline expenditures. Upon experiencing an unanticipated increase in gasoline expenditures, households will adjust their consumption to account for additional future increases in gasoline expenditures.

implications of our results, with a discussion on why the Federal Reserve's consumption forecasting models need to consider asymmetries. In section 1.5, we present robustness checks in which we use alternative recession dates and a different measure of shock. Section 1.6 concludes.

## 1.2 Linear Model

### 1.2.1 Specification

We begin the analysis by estimating a (linear) bivariate VAR model,

$$f_t = \alpha + \sum_{i=1}^{p} \beta_i f_{t-i} + e_t, \tag{1.1}$$

where $f_t = (gas_t, c_t)'$, $c_t$ is a measure of consumption growth in quarter $t$, $gas_t$ is the percentage change in gasoline expenditures in quarter $t$, $e_t = (e_{gas,t}, e_{c,t})'$ is a vector of reduced form residuals, $p$ represents the lag-length,[8] $\alpha$ and $\beta_i$ are vectors of coefficients. Gasoline expenditures are defined as real personal consumption expenditures on gasoline and other energy goods. The four measures of consumption growth we use are real personal consumption expenditures (PCE), PCE: Services, PCE: Nondurables, and PCE: Durables. Estimation of the linear VAR model does not represent an original contribution, but it provides a benchmark for comparison with the results of the nonlinear model.

Data on different categories of nominal consumption during our sample period from 1973 Q1 to 2018 Q2 was downloaded from the National Income and Product Accounts Table released by the Bureau of Economic Analysis.[9] To calculate our measure of total consumption, we subtract nominal consumption expenditures on gasoline and other energy goods (NIPA Table 2.3.5, Line 11) from total nominal consumption expenditures (NIPA

[8] We impose a lag order of 2 throughout our analysis. The chosen lag order is larger than the estimates suggested by Schwarz Information Criterion conditional on an upper bound of 8 lags, which in most cases produces a lag order of only 1. The lag selection is in line with Edelstein and Kilian (2009), Iacoviello et al. (2020) who use lags from the previous two quarters.

[9] NIPA Tables: https://apps.bea.gov/iTable/index_nipa.cfm

**Table 1.1**: *Unit Root and Stationarity Tests*

**A. Tests for Variables in Levels**

| Variables | *ADF* | *ERS* | *PP* |
|---|---|---|---|
| PCE | -2.25 | -1.14 | -2.09 |
| Durables | -1.75 | -2.25 | -1.93 |
| Motor Vehicles | -1.92 | -2.14 | -2.17 |
| Furnishing | -1.81 | -2.51 | -1.68 |
| Other Durables | -2.29 | -2.02 | -2.25 |
| Nondurables | -1.88 | -1.28 | -1.74 |
| Food | -0.71 | -0.88 | -0.75 |
| Clothing | -1.48 | -2.03 | -1.66 |
| Gasoline | -2.78 | -2.18 | -2.41 |
| Other Nondurables | -2.40 | -0.91 | -2.26 |
| Services | -2.11 | -0.66 | -2.15 |

**B. Tests for Variables in Percentage Difference**

| Variables | *ADF* | *ERS* | *PP* |
|---|---|---|---|
| PCE | -6.24 | -3.96 | -10.38 |
| Durables | -8.20 | -3.49 | -13.85 |
| Motor Vehicles | -9.56 | -4.26 | -16.10 |
| Furnishing | -5.89 | -2.30 | -9.42 |
| Other Durables | -8.99 | -2.91 | -12.86 |
| Nondurables | -8.53 | -3.98 | -11.36 |
| Food | -7.99 | -3.90 | -13.23 |
| Clothing | -8.10 | -3.24 | -13.00 |
| Gasoline | -10.25 | -6.18 | -10.94 |
| Other Nondurables | -7.19 | -4.47 | -10.97 |
| Services | -6.57 | -4.65 | -9.55 |

***Notes***: All tests include an intercept and a linear trend. 5% critical values for the respective tests are: -3.42, -2.89, -3.42.

Table 2.3.5, Line 1). This is followed by deflating it using the *Price Index for Personal Consumption Expenditures* (NIPA Table 2.3.4, Line 1), and expressing it in real terms. The other categories of consumption, namely durables (NIPA Table 2.3.5, Line 3), nondurables (NIPA Table 2.3.5, Line 8) and services (NIPA Table 2.3.5, Line 13) undergo a similar transformation.

Table 1.1 presents the results of various stationary and unit root tests performed on real consumption series variables in levels and percentage changes. Panel A of Table 1.1

**Table 1.2**: *Correlations of Reduced Form Residuals*

| Variables | Correlation |
|---|---|
| PCE | -0.35 |
| Durables | -0.07 |
| Nondurables | -0.26 |
| Services | -0.45 |

presents the results for the augmented Dicky-Fuller (ADF) test.[10] We also report the Elliot, Rothenberg and Stock (1996) modified Dicky Fuller (ERS) test along with the Phillips-Perron (1988) test. Panel A suggests that the real consumption variables are non-stationery in levels since we fail to reject the null ($|DF_\tau| < |critical|$). In panel B, we see that the percentage differences for our real consumption series are stationery as we reject the null at the 5% level using all tests. As a result, our measures of consumption are expressed in percentage change throughout the course of the paper.

The impulse response functions are identified by assuming the consumption shock does not have a contemporaneous effect on gasoline expenditures, which implies a recursive system with gasoline expenditures ordered first.[11] Some information about the plausibility of our identifying assumption can be found by looking at the contemporaneous correlations of the VAR residuals. If a shock to gasoline expenditures translates directly into a decrease in aggregate consumption (of goods other than gasoline), the residuals will be negatively correlated. If there are economic shocks that cause all consumption expenditures to rise, including gasoline expenditures, the correlation will be positive. If there is no effect in either direction, the correlation will be close to zero. If we limit ourselves to the class of recursive models, the sign of the correlation determines the identification. The correlations are reported in Table 1.2. In all cases, the correlation coefficient is negative, ranging from -0.07 to -0.45. While this does not confirm that our identification is correct, it is consistent with our ordering of the variables, and we can rule out a recursive bivariate VAR model with consumption ordered first.

What is the structural shock to gasoline expenditures capturing? The obvious, and almost

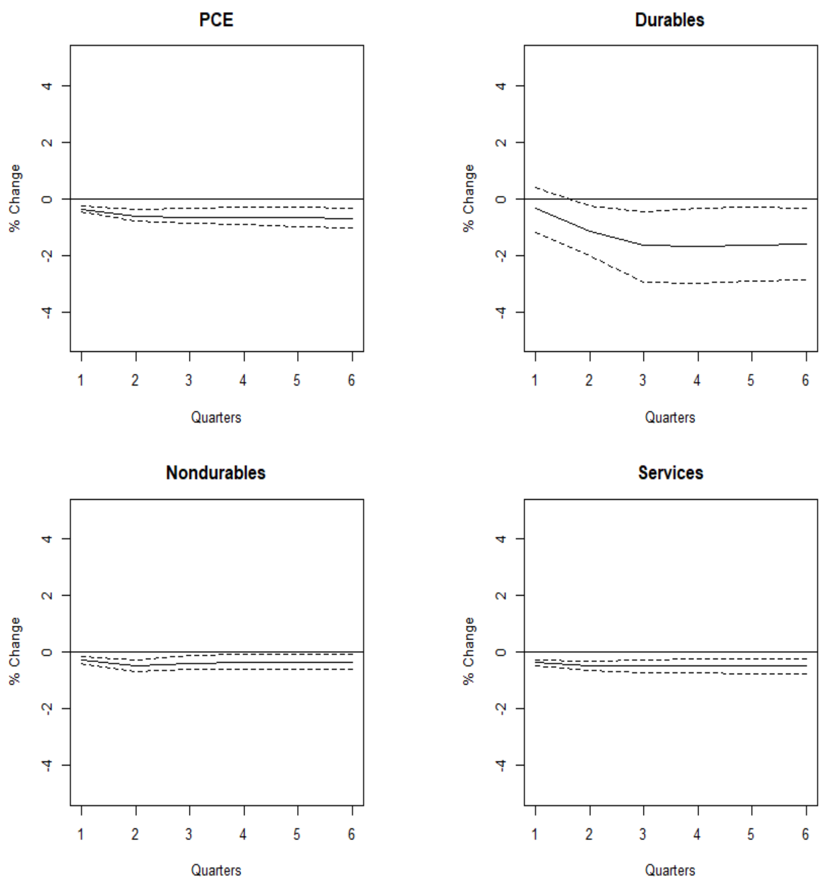
[10] See Dicky and Fuller (1981).

[11] This is similar to the identification in Edelstein and Kilian (2009).

certainly most important, source of gasoline expenditure shocks is an unanticipated change in the price of gasoline. Other sources of gasoline expenditure shocks include changes in preferences for larger or smaller vehicles, changes in travel patterns such as those witnessed in the aftermath of the 9/11 terrorist attacks, and changes in commuting behavior due to fluctuations in house prices.

### 1.2.2 Results

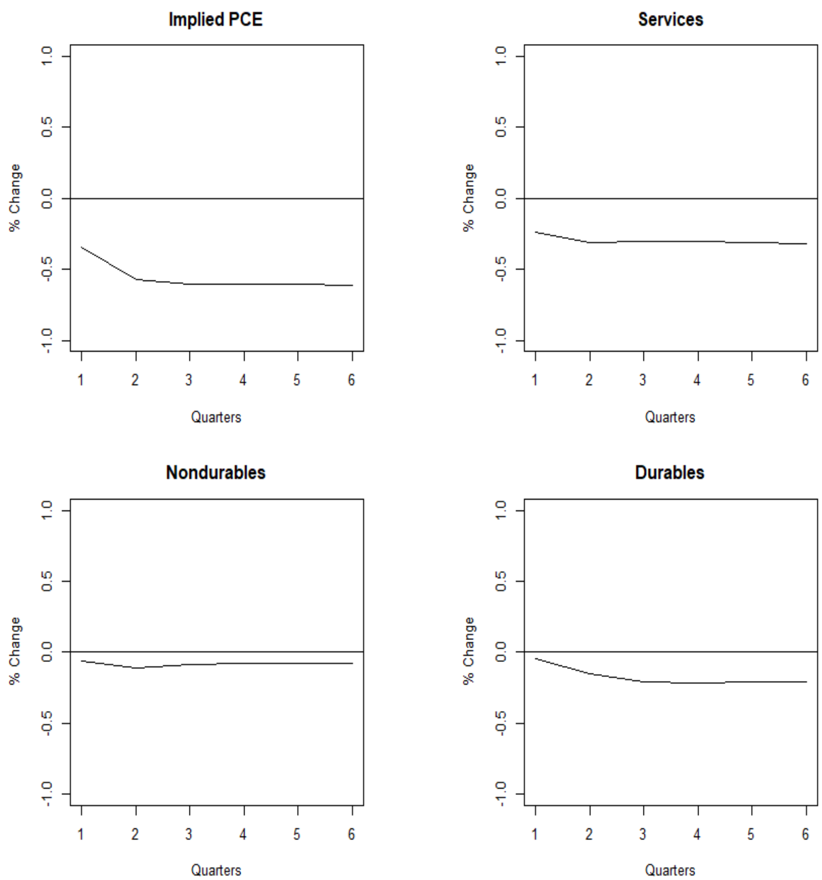
**Figure 1.2**: *Response of Aggregate Consumption Series*




***Notes***: Solid line represents the cumulative response to a 10% increase in gasoline expenditures, while the corresponding dashed lines are the 95% confidence intervals.

The responses of the four consumption series to a gasoline expenditures shock are found in Figure 1.2. Our total PCE measure consists of consumption expenditures on all goods and services except gasoline. When gasoline expenditures increase by 10% over the course of a year, non-gasoline consumption decreases by around 0.7% during the same time period, with the effect statistically significant at the 95% confidence interval. As gasoline expenditures increase, durables PCE decreases by around 1.6%. The effect on nondurables (less gasoline) and services PCE is not as amplified as durables since the demand for such categories is relatively inelastic as opposed to durable goods. Following a 10% increase in gasoline expenditures over the course of a year, nondurables PCE decreases by 0.4%, whereas services PCE reduces by 0.5%.

**Figure 1.3**: *Contribution by Each Category*




***Notes***: Solid lines represents the contribution of each category in driving the response of total consumption.

In terms of explaining aggregate consumption expenditures, however, it should be noted that services are a much larger proportion of consumption than nondurables and durables consumption combined.[12] Figure 1.3 decomposes the response of total consumption into con-

[12]For our sample, services was on average 64% of consumption, nondurables 23%, and durables only 13%.

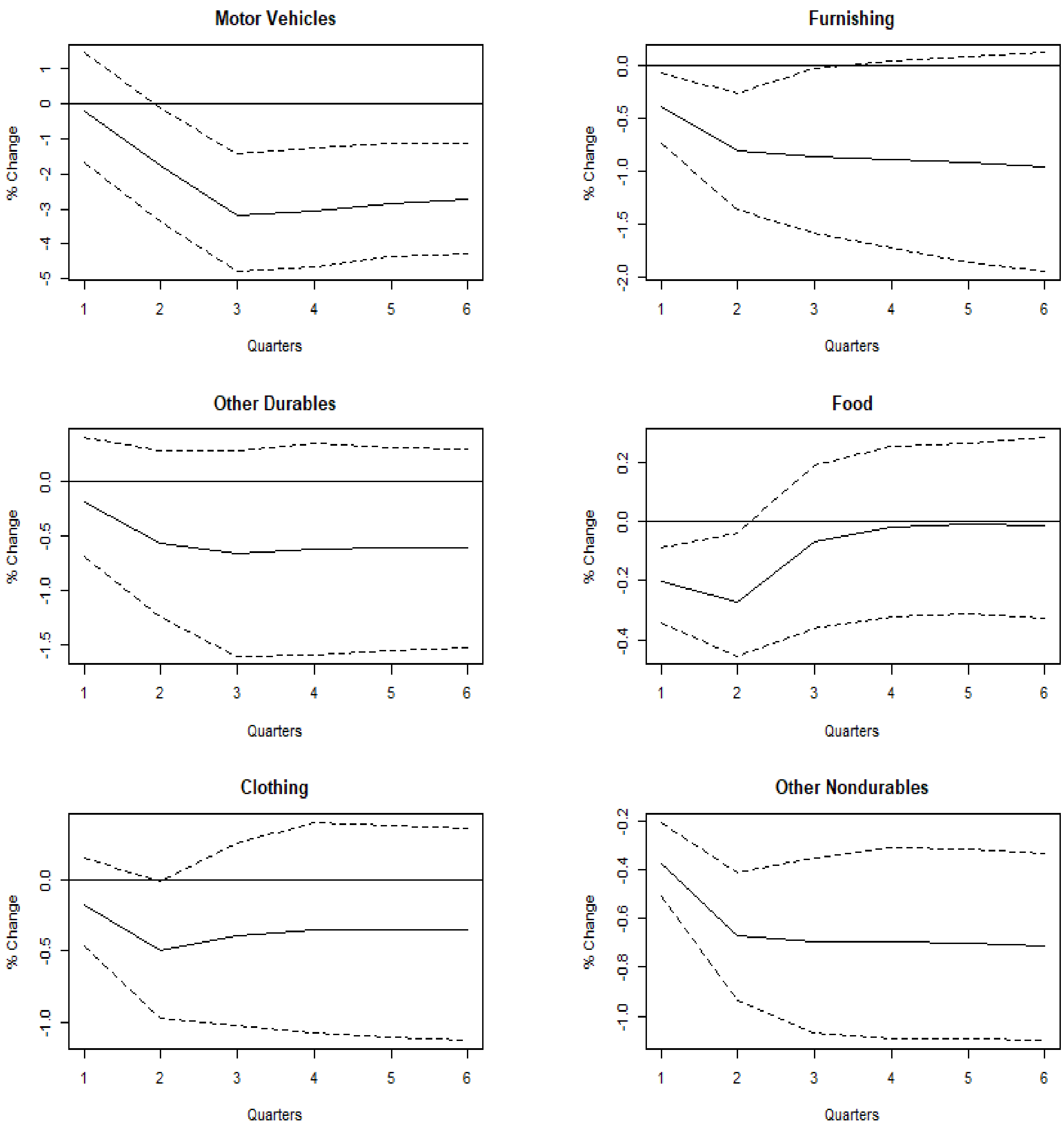
tributions made by each category. The contribution is calculated by multiplying the share of each consumption category with the impulse response estimates at each time horizon. Almost half of the drop in consumption is explained by the services sector. Durables contribute almost one-third of the drop in PCE, while nondurables only play a minor role. Thus, in order to explain the reaction of aggregate consumption, we need to focus on services and durables consumption.[13]

We also consider the following disaggregated consumption measures for our analysis. *Motor vehicles and parts* (NIPA Table 2.3.5, Line 4) consists of spending on new and used autos, and motor vehicle parts and accessories. *Furnishing and durable household equipment* (NIPA Table 2.3.5, Line 5) includes spending on furniture and furnishings, household appliances, glassware and household utensils, and tools and equipment for house and garden. *Other durable goods* (NIPA Table 2.3.5, Line 7) comprises of jewelry and watches, educational books, luggage and personal items, and telephone and related communication equipment. *Food and beverages* (NIPA Table 2.3.5, Line 9) is spending on food and nonalcoholic beverages purchased for off-premises consumption, and alcoholic beverages purchased for off-premises consumption. *Clothing and footwear* (NIPA Table 2.3.5, Line 10) is spending on garments. *Other nondurable goods* (NIPA Table 2.3.5, Line 12) comprises pharmaceutical and other medical products, recreational items, household supplies, personal care product and tobacco. *Housing and utilities* (NIPA Table 2.3.5, Line 15) consists of consumer expenditures on rent and household utilities. *Transportation services* (NIPA Table 2.3.5, Line 17) is spending on public transportation (air, rail and ground), and motor vehicle maintenance and repair. *Other Services* (NIPA Table 2.3.5, Line 21) comprises of communication, education services, professional services and household maintenance.

Figures 1.4 and 1.5 present the response of various consumption series to an increase in gasoline expenditures. We find that the decline in spending on motor vehicles is 2.8% in response to a 10% increase in gasoline expenditures after a year. Spending on furnishing and durable household equipment decreases by almost 1%. The effect is statistically significance

[13] Kilian and Edelstein (2009) also suggest that durables play a significant role in the transmission of energy price shocks to aggregate consumption.

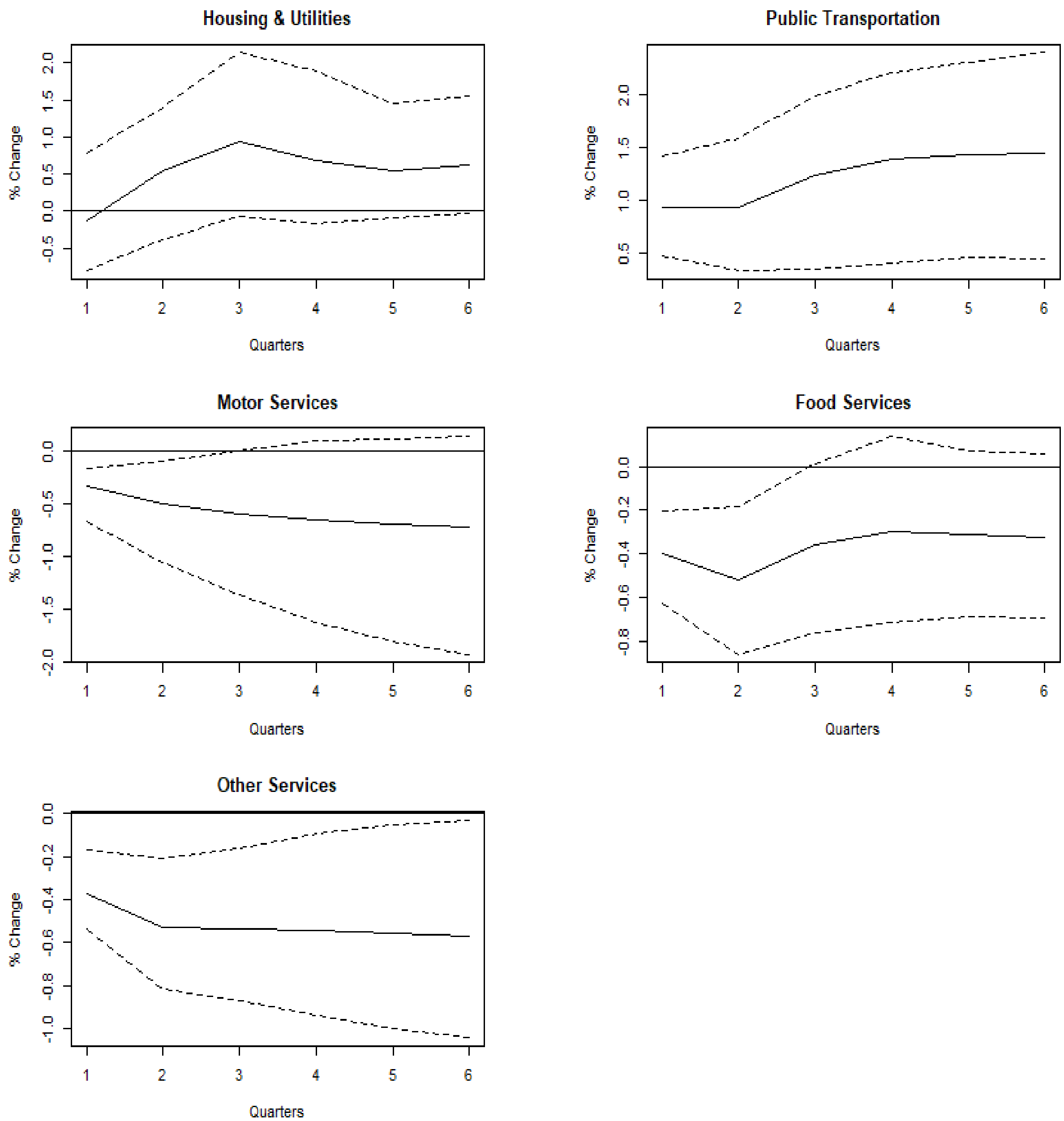
**Figure 1.4**: *Response of Disaggregated Consumption Series*




***Notes***: Solid lines represent the cumulative responses to a 10% increase in gasoline expenditures, while the corresponding dashed lines are the 95% confidence intervals.

at the 95% confidence bands. Consumption expenditure on other durables marginally decreases but the effect is not statistically significant. Food consumption expenditures initially decrease in response to consumers spending more on gasoline and other energy goods. In the long run, however, spending on food returns to its original level. Consumption expen-

**Figure 1.5**: *Response of Disaggregated Consumption Series*




***Notes***: Solid lines represent the cumulative responses to a 10% increase in gasoline expenditures, while the corresponding dashed lines are the 95% confidence intervals.

diture on clothing and other nondurables decreases marginally, and the effect is statistically significant as well.

Spending on motor vehicle services decreases in response to gasoline expenditure shocks. Consumer spending on public transportation, however, increases by 1.4% over the course of a year. There are two reasons for this increase. First, rising gasoline expenditures will most likely increase public transportation fares. Second, higher gasoline expenditures might force some consumers to abandon the usage of their personal vehicles, and shift to public transportation. Money spent by consumers on food services and accommodation goes down by 0.3% over the entire year. This category includes money spent on vacations and food away from home. As gasoline expenditures increase, the average household faces budgetary constraints and has to cut down on holidays and other leisure. A 10% increase in gasoline expenditures over the course of a year increases utility bills by 0.6%.

These results are in line with Edelstein and Kilian (2009) suggesting that spending on non-gasoline goods and services reduces in response to rising gasoline expenditures. As gasoline expenditures increase, consumers' discretionary income goes down since they have less to spend on other goods and services, resulting in a drop across most of the consumption categories. Results from the linear model also imply that the response of demand-elastic (durable) goods to gasoline expenditure shocks is stronger than that of goods for which demand is relatively inelastic (nondurables and services).[14]

## 1.3 Asymmetric Effects Over the Business Cycle

### 1.3.1 Specification

The impulse responses of different measures of consumption to gasoline expenditure shocks in recessions and expansions are calculated using local projections. Local projections have the ability to accommodate non-linear specifications (Jorda, 2005).

Assuming that consumption expenditures respond contemporaneously to an increase in gasoline expenditures, the immediate response of consumption, $c_t$, to a gasoline expenditure shock can be estimated with the following regression:

[14]Edelstein and Kilian (2009) calculate the elasticities of non-energy real consumption expenditures. They find that expenditures on durables decline more than four times as much as expenditures on both services and nondurables following a loss in purchasing power after a rise in energy prices.

$$c_t = \alpha + \sum_{i=0}^{k} \phi_i I_{t-i} + \sum_{i=0}^{k} \theta_i \triangle y_{t-i} + \sum_{i=1}^{k} \beta_i c_{t-i} + \sum_{i=0}^{k} \gamma_i gas_{t-i} + \sum_{i=0}^{k} \delta_i inter_{t-i} + \varepsilon_t. \quad (1.2)$$

Where

$$inter_{t-i} = I_{t-i} \times gas_{t-i}, \quad (1.3)$$

$c_t$ is the percentage change in consumption in quarter $t$, and $gas_{t-i}$ is the change in gasoline expenditures in quarter $t-i$. The growth rate of GDP, $\triangle y_{t-i}$ , and the recession dummy, $I_t$ have been added to control for the state of the economy. $inter_{t-i}$ represents the asymmetric response of $c_t$ when the economy is in a recession. We follow Auerbach and Gorodnichenko (2012) to estimate the probability of a recession in each quarter, and define the variable $I_t$ to be

$$I_t = \begin{cases} 1 & F(z_t) \geq 0.8 \\ 0 & F(z_t) < 0.8 \end{cases}, \quad (1.4)$$

where $F(z_t)$ is the transition function that indicates the state of the economy and takes the following functional form:

$$F(z_t) = \frac{exp(-\gamma(z_t - \bar{d}))}{1 + exp(-\gamma(z_t - \bar{d}))}, \gamma > 0. \quad (1.5)$$

$z_t$ is equal to the seven quarter moving average growth rate of output, and the value of $\gamma$ is calibrated to be equal to 3, so the economy spends 20% of time in recession i.e. $Pr(F(z_t) \geq 0.8) = 0.2$ (Auerbach and Gorodnichenko, 2012). The value for the threshold, $\bar{d}$, is defined to be 0.8. The transition function is estimated using the data set of Auerbach and Gorodnichenko (2012), which spans from 1948:Q1 to 2008:Q4. This data set is available in the 'lpirfs' package which was provided by Phillip Adammer.[15] In order to identify periods of economic downturn for the sample period 2009:Q1-2018:Q2, we rely on the NBER's recession dates.

[15] Adammer P (2019). lpirfs: Local Projections Impulse Response Functions. R package version: 0.1.5, https://CRAN.R-project.org/package=lpirfs.

Defining $gas_0$ and $inter_0$ as the change in $gas$ and $inter$ during the quarter of a gasoline expenditures shock, the contemporaneous response of $c$, $c_0$, is

$$c_0 = \hat{\gamma}_0 gas_0 + \hat{\delta}_0 inter_0 \tag{1.6}$$

Since the shock under study is a 10% increase in gasoline expenditures, $gas_0 = 10\%$, and either $inter_0 = 10\%$ (recession) or $inter_0 = 0$ (expansion). After calculating the contemporaneous response, we define the initial response vector for the two states of the economy:

$$d_i^{rec} = \begin{bmatrix} c_0^{rec} & gas_0 & inter_0 \end{bmatrix} \tag{1.7}$$

and,

$$d_i^{exp} = \begin{bmatrix} c_0^{exp} & gas_0 & 0 \end{bmatrix}. \tag{1.8}$$

The s-period impulse responses are then calculated by estimating a reduced form regression,

$$\Delta c_t = \alpha + \sum_{i=1}^{k} \phi_i I_{t-i} + \sum_{i=1}^{k} \theta_i \triangle y_{t-i} + \sum_{i=1}^{k} \beta_i c_{t-i} + \sum_{i=1}^{k} \gamma_i gas_{t-i} + \sum_{i=1}^{k} \delta_i inter_{t-i} + \varepsilon_t \tag{1.9}$$

for $s = 1, \ldots .5$. The impulse responses for both regimes are calculated using the following equation,

$$\hat{IR}_s^{rec} = \Phi_s d_i^{rec} = \hat{\beta}_s c_0^{rec} + \hat{\gamma}_s gas_0 + \hat{\delta}_s inter_0, \tag{1.10}$$

and

$$\hat{IR}_s^{exp} = \Phi_s d_i^{exp} = \hat{\beta}_s c_0^{exp} + \hat{\gamma}_s gas_0. \tag{1.11}$$

where

$$\Phi_s = \begin{bmatrix} \hat{\beta}_s & \hat{\gamma}_s & \hat{\delta}_s \end{bmatrix}. \tag{1.12}$$

Once we construct the impulse responses for both regimes, we can calculate the cumulative impulse response functions.

$$CIR_s^{rec} = \sum_{j=0}^{s} \widehat{IR}_j^{rec} \tag{1.13}$$

$$CIR_s^{exp} = \sum_{j=0}^{s} \widehat{IR}_j^{exp} \tag{1.14}$$

for $s = 1 \dots 5$. In order to calculate the asymmetric response of $c_t$ to gasoline expenditure shocks, we take the difference between the impulse responses across recessions and expansions:

$$CIR_s^{rec} - CIR_s^{exp} = \sum_{j=0}^{s} \widehat{IR}_j^{rec} - \sum_{j=0}^{s} \widehat{IR}_j^{exp} \tag{1.15}$$

$$\triangle CIR_s = \sum_{j=0}^{s} \widehat{IR}_j^{rec} - \sum_{j=0}^{s} \widehat{IR}_j^{exp} \tag{1.16}$$

If $\triangle CIR_s < 0$, this means the response of consumption is stronger in a recession than in an expansion, while $\triangle CIR_s > 0$ means the converse. We present impulse responses with 95% confidence intervals, where the standard errors are calculated using the Newey-West correction. The covariance matrices are calculated by estimating the full system of equations as a seemingly unrelated regressions (SUR) model.

### 1.3.2 Results

Table 1.3 presents the contemporaneous responses of consumption and its components to a 10% increase in gasoline expenditures across recessions and expansions. The results suggest a difference in the initial response of consumption across nearly all sectors, with the response of consumption stronger in recessions as opposed to expansions. Of greater interest are the cumulative responses of each consumption series in the year following a 10% shock to gasoline expenditures, shown in Figure 1.6. Dashed lines are the response to shocks that occur in an expansion and solid lines are the response to shocks that occur in a recession. The same shock that causes total consumption expenditures to fall by 2.7% when it hits in a recession will cause total consumption expenditures to fall by only 0.7% if it hits in an

**Table 1.3**: *Contemporaneous Responses*

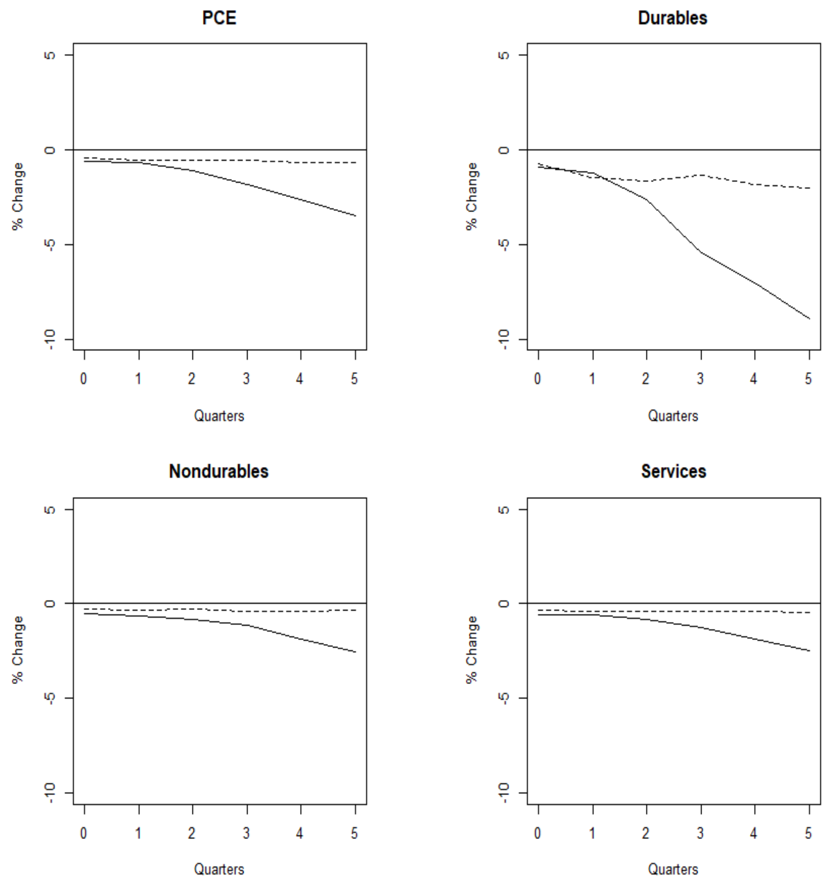
| Variable | Recession | Expansion |
|---|---|---|
| PCE | -0.61% | -0.40% |
| Durables | -0.92% | -0.77% |
| Nondurables | -0.50% | -0.26% |
| Services | -0.57% | -0.33% |
| Motor Vehicles | -1.59% | -0.97% |
| Furnishing | -0.53% | -0.58% |
| Other Durables | -0.18% | -0.43% |
| Food | -0.46% | -0.09% |
| Clothing | -0.34% | -0.38% |
| Other Nondurables | -0.62% | -0.42% |
| Housing & Utilities | -0.59% | -0.35% |
| Transportation | -0.11% | 0.00% |
| Other Services | -0.78% | -0.32% |

expansion. A similar pattern is true for the individual components of consumption. The respective responses for durables PCE are 7% and 1.8%, for nondurables 1.9% and 0.4%, and for services 1.9% and 0.4%.

Following a gasoline expenditure shock, total non-gasoline PCE shows a difference in response of -2% in the long run. This suggests that consumption drops by 2 percentage points (hereafter, refered to as pp.) more in recessions as opposed to expansions over the course of a year. The difference in response is statistically significant since zero lies outside the confidence bands constructed at the 95% level. Durables show a statistically significant asymmetry with the difference in response of -6.9 pp. across both regimes. Nondurables PCE also shows statistically significant asymmetry in the long run, with the difference in response of -2.2 pp. Services PCE drops by 2 pp. more in recessions as opposed to expansions.

Figure 1.8-1.10 represent the response of different consumption categories to a gasoline expenditure shock. As gasoline expenditures increase by 10%, spending on motor vehicles drops by around 11.9% in recessions, and by 2.9% in expansions across the same time period. The decline in furnishing goods expenditure is around 5.1% in recessions and 1.1% in expansions. The furnishing category includes spending on furniture and major household appliances. Expenditure on other durable goods category decreases by 3.7% after a year

**Figure 1.6**: *Response of Aggregate Measures of Consumption Series in Recessions and Expansions*

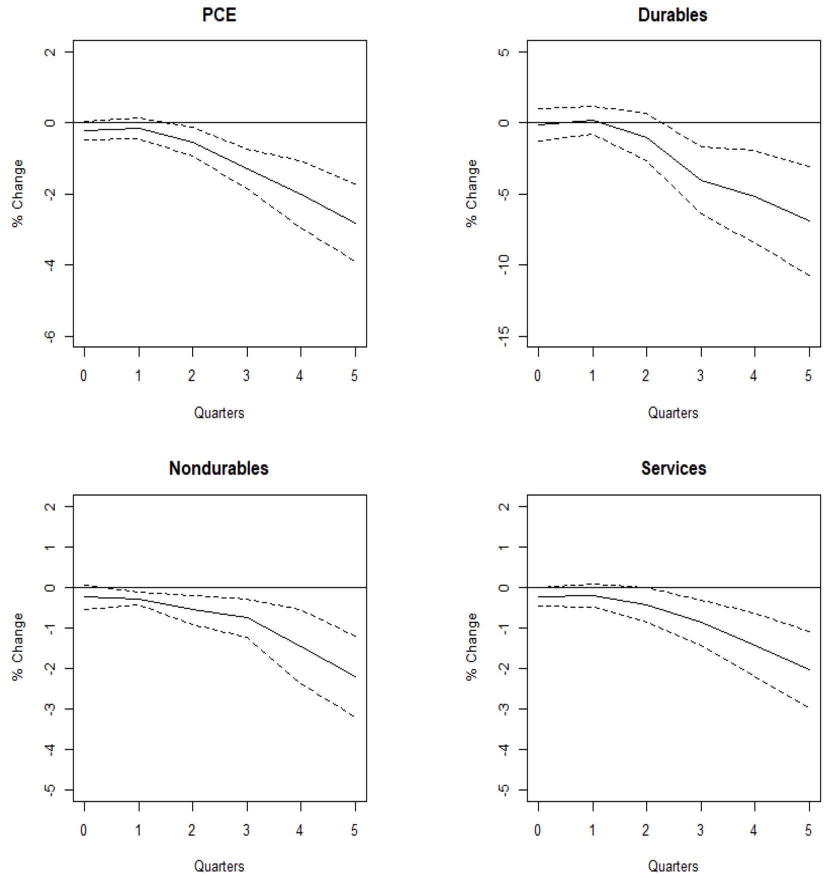



***Notes***: Solid line indicates the cumulative response of consumption series to a 10% increase in gasoline expenditures in recessions, while the corresponding dashed line is the cumulative response in expansions.

in a recessionary regime. In an expansion, the cumulative impact is -0.7%. Other durable goods category consists of spending on items like jewelery, watches and telephones. In the nondurable goods category, spending on clothing decreases by 3.1% in recessions and by 0.6% in expansions. Food spending sees a marginal increase of 0.02% in expansions and a drop of -0.7% in recessions. Other nondurables expenditures also take a hit in response to gasoline expenditures increasing. This category includes spending on household supplies, medical products and tobacco which decreases by 3.0% in recessions and by 0.8% in expansions. Different components within the services sector also show a negative response across recessions and expansions, with the effect being amplified in recessions.

The motor vehicles sector is responsible for driving a big proportion of the asymmetric

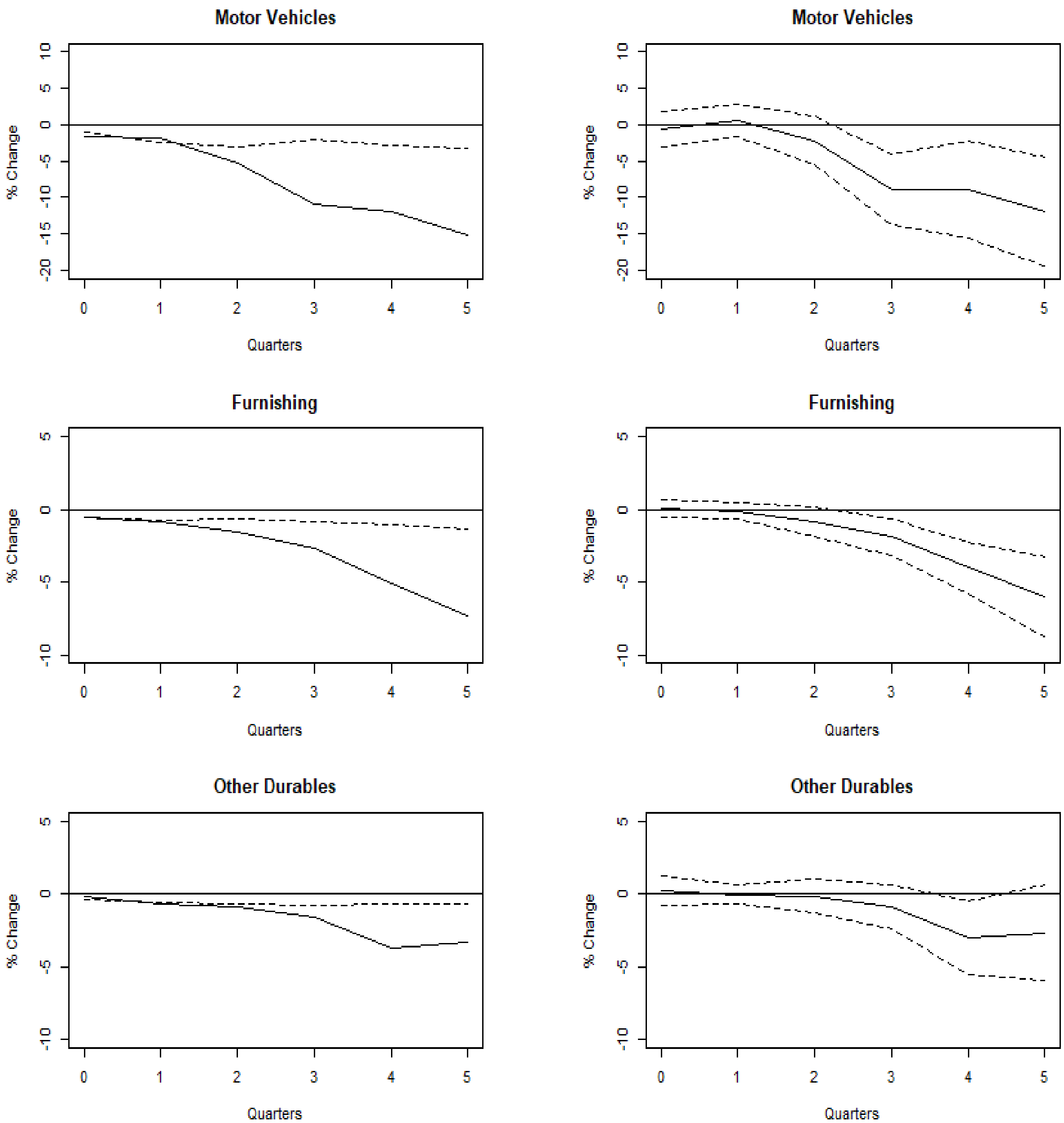
**Figure 1.7**: *Difference in Response Across Recessions and Expansions*




***Notes***: Solid line indicates the difference in response across recessions and expansions, while the corresponding dashed lines are the 95% confidence intervals. Negative value implies that the response in recessions is stronger than the response in expansions.

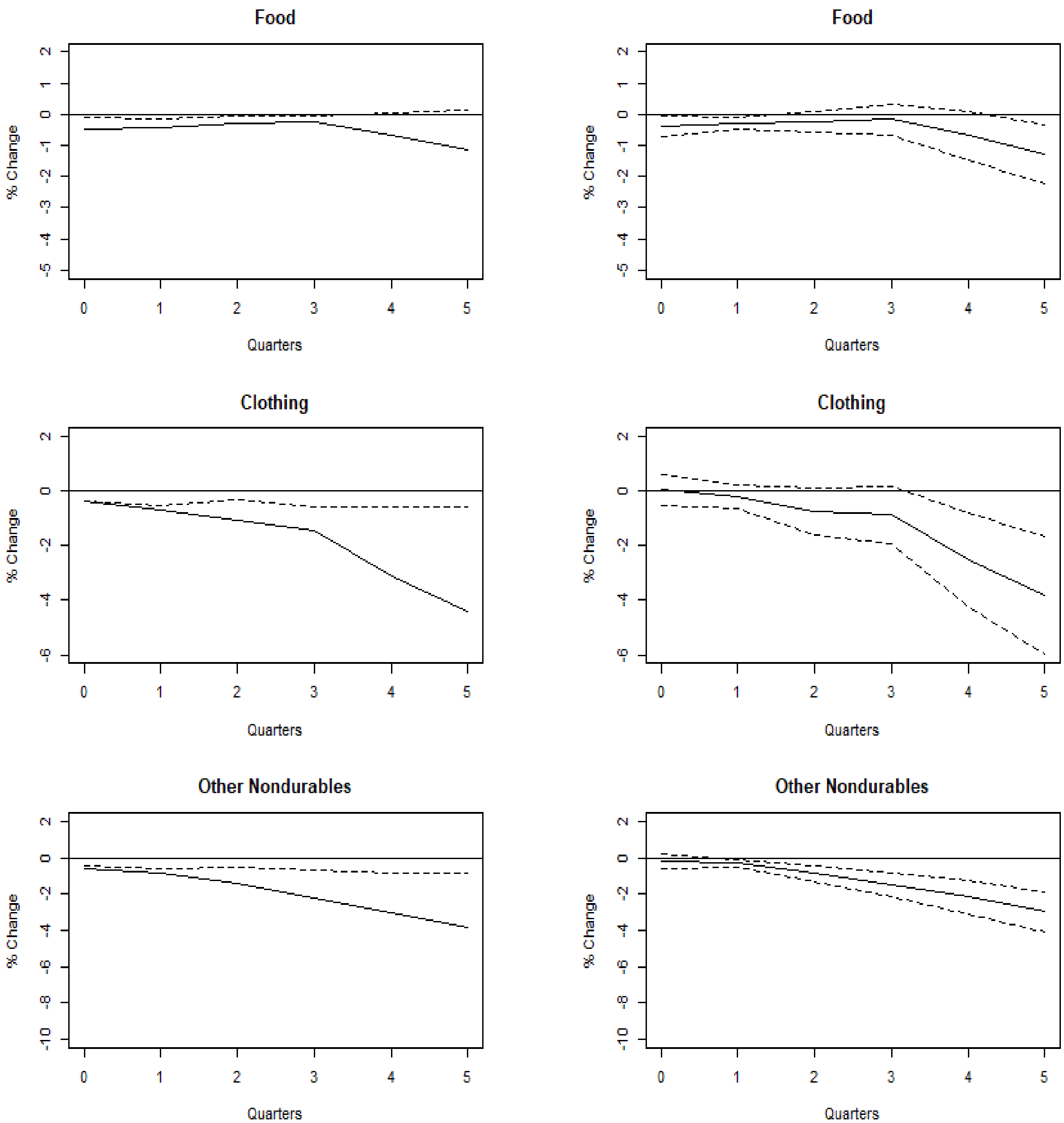
response. Spending on motor vehicles goes down by almost 9 pp. more in recessions as opposed to expansions over the course of a year. There are various reasons for this large drop in consumer spending on motor vehicles in a recession. First, is what Kilian and Edelstein (2009) call the *uncertainty effect.* Consumers postpone their purchases because motor vehicles represent big-ticket items, and will only be bought when they are confident that they can afford them. Second, credit constraints and uncertainty during recessions forces consumers to reduce spending on consumer durables more aggressively. Other categories of consumption, namely furnishing, clothing, other nondurables, housing and utilities, also show statistically significant asymmetry.

**Figure 1.8**: *Response of Disaggregate Measures of Consumption to Gasoline Expenditures Shock*



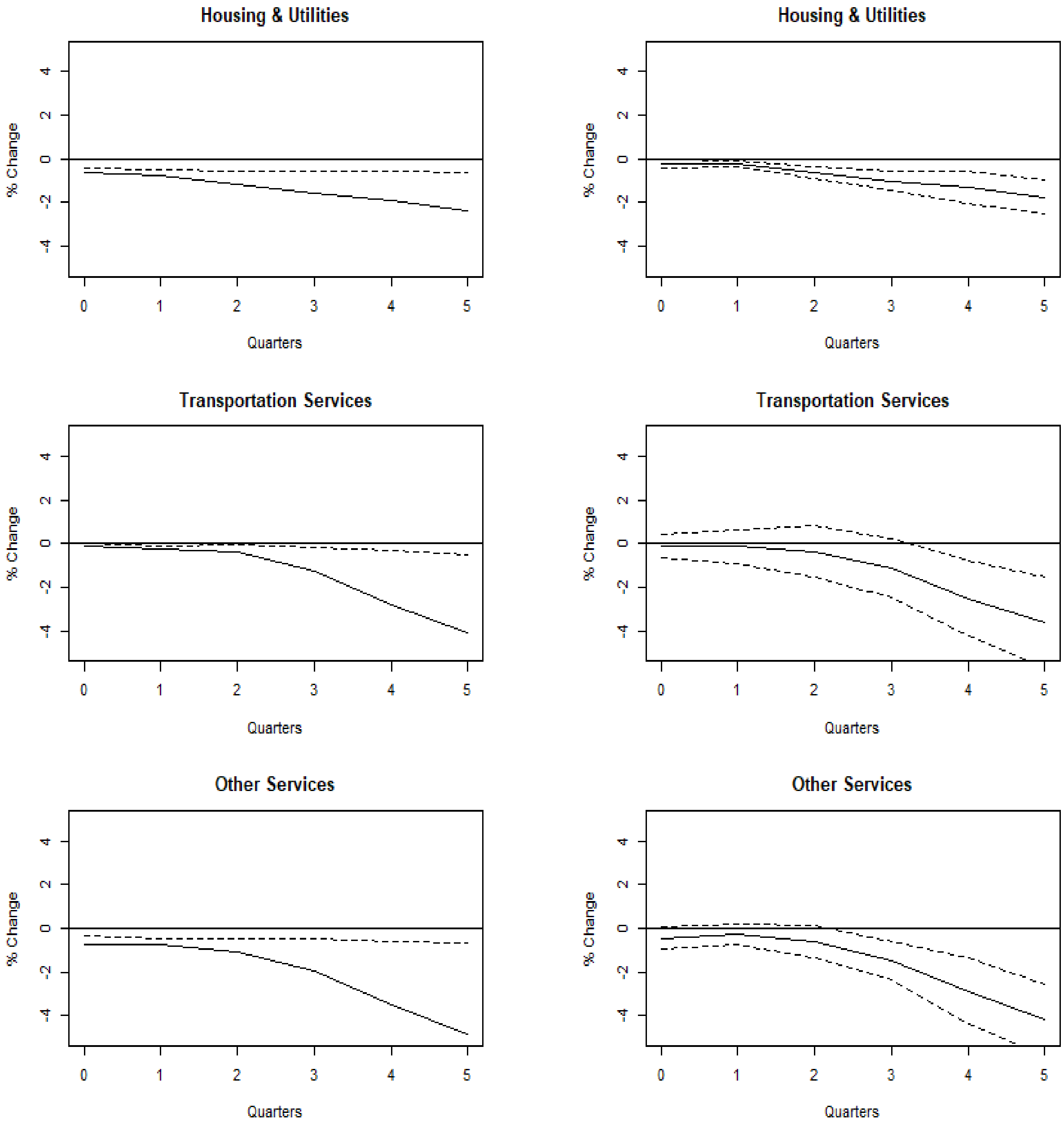

***Notes***: Solid line in the left column indicates the cumulative response to a 10% increase in gasoline expenditures during recessions while the corresponding dashed line is the cumulative response in expansions. Solid line in the right column indicates the difference in response across recessions and expansions, while the corresponding dashed lines are the 95% confidence intervals. Negative value implies that the response in recessions is stronger than the response in expansions.

**Figure 1.9**: *Response of Disaggregate Measures of Consumption to Gasoline Expenditures Shock*




***Notes***: Solid line in the left column indicates the cumulative response to a 10% increase in gasoline expenditures during recessions while the corresponding dashed line is the cumulative response in expansions. Solid line in the right column indicates the difference in response across recessions and expansions, while the corresponding dashed lines are the 95% confidence intervals. Negative value implies that the response in recessions is stronger than the response in expansions.

**Figure 1.10**: *Response of Disaggregate Measures of Consumption to Gasoline Expenditures Shock*




***Notes***: Solid line in the left column indicates the cumulative response to a 10% increase in gasoline expenditures during recessions while the corresponding dashed line is the cumulative response in expansions. Solid line in the right column indicates the difference in response across recessions and expansions, while the corresponding dashed lines are the 95% confidence intervals. Negative value implies that the response in recessions is stronger than the response in expansions.

Whereby our motivation for the asymmetric response of consumption across states of the economy is derived from the fiscal policy literature, it is also important to explore the economic factor responsible for driving it. Kilian & Edelstein (2009) argue that an increase in energy prices forces consumers to increase their precautionary savings.[16] We estimate the nonlinear model (Equation 1.2) with the growth rate of net private savings[17] as the dependent variable to investigate whether consumers save more during recessions as opposed to expansions following a shock to gasoline expenditures. Net private savings are defined as *disposable income* (NIPA Table 2.1, Line 27) less *personal outlays* (NIPA Table 2.1, Line 28). The estimates from our model suggest that a 10% increase in gasoline expenditures over the course of a year increases net private savings by 3.6% in recessions as opposed to 0.9% in expansions. This suggests that as gasoline expenditures increase, consumers increase their savings, because they perceive a higher chance of future income losses. However, recessions are generally associated with a higher degree of uncertainty about the future path of the economy, and individuals might respond to such an unanticipated shock by increasing their savings more than four times as they would during expansions. This would probably explain the stronger response of consumption to gasoline expenditure shocks during recessions.

### 1.3.3 Response of Gasoline Expenditures to Own Shock

**Table 1.4**: *Point Estimates*

| t | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| Gasoline Prices | 12% | 3.8% | -4.6% | -2.0% | -2.5% |
| Gasoline Expenditures | 10% | 3.0% | -4.0% | -2.5% | -1.7% |
| Private Savings | -2.1% | -4.2% | 0.6% | 3.5% | 3.9% |

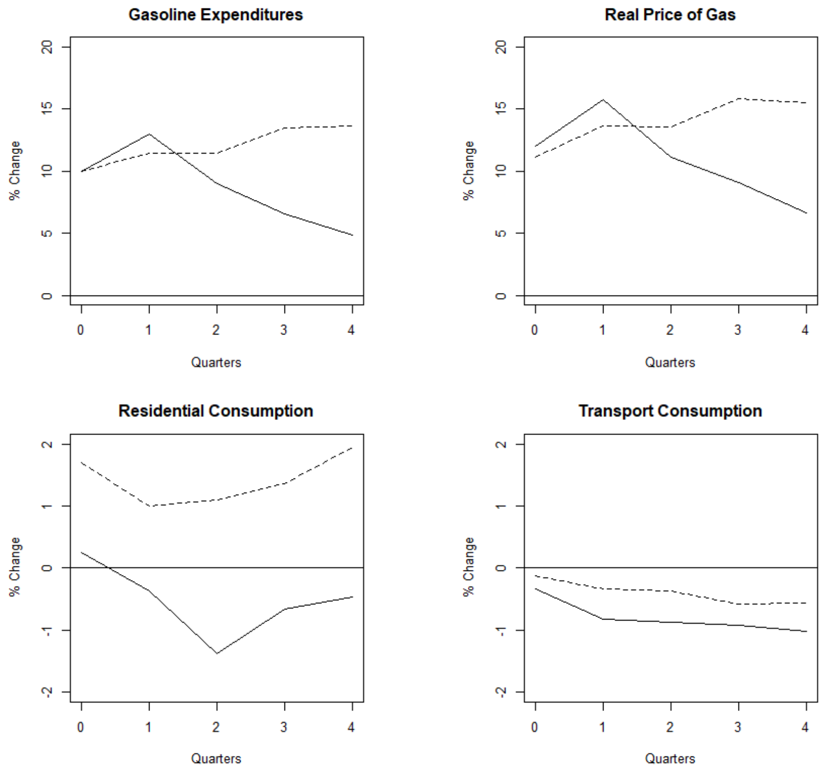
***Notes***: This table represents the response of the real gasoline price, gasoline expenditures and net private savings to a 10% increase in gasoline expenditures in recessions.

Figure 1.11 shows the response of gasoline expenditures to its own shock in recessions

[16] Edelstein and Kilian (2009): "When purchase decisions are reversible, consumption may fall in response to energy price shocks, as consumers increase their precautionary savings. This response will arise if consumers smooth their consumption because they perceive a greater likelihood of future unemployment and hence future income losses."

[17] Net private savings are the portion of household income that is used to provide funds to capital markets or to invest in real assets.

**Figure 1.11**: *Response of Gasoline Expenditures and Gasoline Consumption*



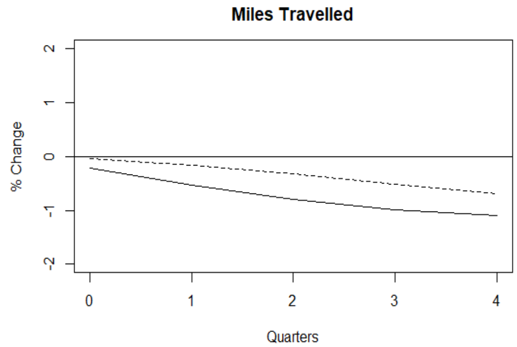

***Notes***: Solid line represents the cumulative response to a 10% increase in gasoline expenditures during recessions while the corresponding dashed line is the cumulative response in expansions.

and expansions. Following the initial increase of 10%, gasoline expenditures decrease in recessions and increase in expansions. This suggests that there is evidence of asymmetry in the response of gasoline expenditures to its own shock, which then feeds through to create asymmetry in the responses of consumption as well.

Table 1.4 compares the response of gasoline expenditures and net private savings to a one-time 10% increase in gasoline expenditures. In recessions, gasoline expenditures increase by 3% one quarter after the shock. This increase might be explained by the inelastic nature of gasoline expenditures in the short run, as emphasized by Edelstein and Kilian (2009). However, two quarters after the shock consumers reduce spending on gasoline goods and services in recessions, which frees up a portion of their income and consequently increases savings as evident from Table 1.4.

To further understand why the response of gasoline expenditures to its own shock varies

**Figure 1.12**: *Response of Miles Traveled*




***Notes***: Solid line indicates the cumulative response to a 10% increase in gasoline expenditures during recessions. The corresponding dashed line is the cumulative response in expansions.

across the state of the economy, we look at the responses of gasoline consumption by sectors, and the real price of gasoline. Data on gasoline consumption series by sector was downloaded from the Energy Information Administration website. The real price of gasoline was calculated by obtaining the average gasoline price/gallon across all cities in the U.S. (APU000074714),[18] and deflating it with U.S. CPI. We then estimate the nonlinear model (Equation 1.2) with gasoline consumption series, and the real price of gasoline as dependent variables. Impulse responses in Figure 1.11 suggest that the real price of gasoline and gasoline expenditures respond similarly to a 10% increase in gasoline expenditures across recessions and expansions.

As gasoline expenditures increase by 10%, gasoline consumed by the transportation sector is approximately 1% less than its original level in recessions, as opposed to 0.6% in expansions a year after the shock. We also estimate the response of total miles traveled to gasoline expenditure increases between recessions and expansions. Data on miles traveled was downloaded from the Travel Volume Trends released by the U.S. Federal Highway Administration. Estimation of the nonlinear model with total miles traveled as our dependent variable suggests a decrease of 1.1% in recessions as opposed to 0.7% in expansions. As the cost of operating vehicles increases, traffic volume goes down with the impact amplified during recessions.

[18] This series was downloaded from the Bureau of Labor Statistics database.

As gasoline expenditures increase by 10%, residential consumption of gasoline increases by 1.9% in expansions while it decreases by 0.5% in recessions during the same time period. The asymmetric response of gasoline expenditure to its own shock is explained by how gasoline consumption responds between recessions and expansions. The increased demand for gasoline by the residential sector drives up the price of gasoline which then feeds into higher gasoline expenditures in expansions. On the other hand, the drop in gasoline consumption by the residential and transportation sectors in recessions puts a downward pressure on gasoline prices and reduces gasoline expenditures.

## 1.4 Forecasting Implications

Since the U.S. was an oil-importer throughout the course of our sample period, higher gasoline expenditures caused a transfer of U.S. income to foreign oil producers. This reduction in disposable income leads to a decrease in spending on non-gasoline goods and services, which is evident from the results of our linear VAR model. Furthermore, we find evidence that the effect of a gasoline expenditure shock on U.S. consumption depends on the state of the economy, with the effect stronger in recessions.

The analysis thus emphasizes the need for the Federal Reserve to consider asymmetries in the impact of gasoline expenditure shocks across recessions and expansions when it is forecasting consumption or other macro variables, as failure to do so might result in misleading conclusions about the effect of gasoline expenditures shock on the U.S. economy. To make this point, we present contemporaneous forecasts of aggregate measures of consumption following a 10% increase in gasoline expenditures using a model that accounts for asymmetries (nonlinear) and a linear model. The nonlinear model is defined as,

$$\hat{c}_T^{NL} = \alpha + \sum_{i=0}^{k} \phi_i I_{T-i} + \sum_{i=0}^{k} \theta_i \triangle y_{T-i} + \sum_{i=1}^{k} \beta_i c_{T-i} + \sum_{i=0}^{k} \gamma_i gas_{T-i} + \sum_{i=0}^{k} \delta_i inter_{T-i}. \quad (1.17)$$

Whereas the linear model is,

$$\hat{c}_T^L = \alpha + \sum_{i=0}^{k} \theta_i \triangle y_{T-i} + \sum_{i=1}^{k} \beta_i c_{T-i} + \sum_{i=0}^{k} \gamma_i gas_{T-i}. \tag{1.18}$$

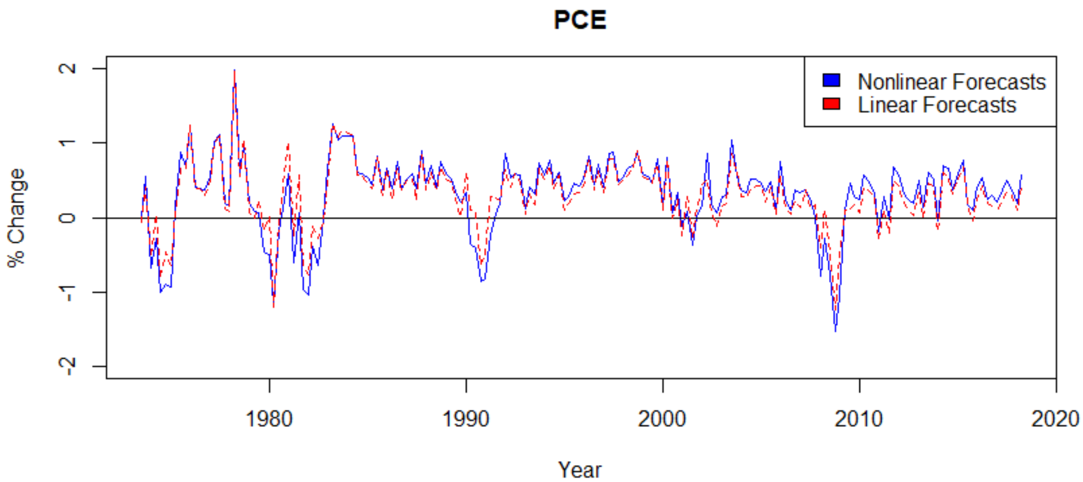
$\hat{c}_T^{NL}$represents the forecasts of consumption from the nonlinear model, and $\hat{c}_T^L$ represents the forecasts from the linear model. The shock under consideration is a 10% increase in gasoline expenditures so $gas_T = 10\%$, while values for other variables are taken from the data. We compute the difference in forecasts from both models and define $\hat{d}_t^F$ in the following manner:

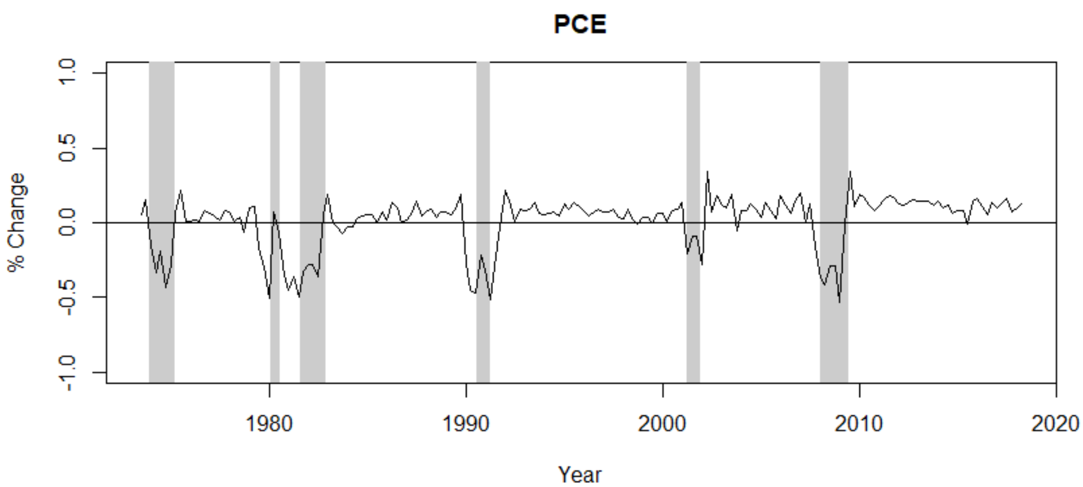
$$\hat{d}_t^F = \hat{c}_T^{NL} - \hat{c}_T^L \tag{1.19}$$

If $\hat{d}_t^F < 0$, this suggests that the linear forecasting model is on *average* understating the effect of a gasoline expenditure shock on our measures of consumption. $\hat{d}_t^F > 0$ suggests overstating on *average*, whereas $\hat{d}_t^F = 0$ indicates that forecasts from both models are the same on *average*. The upper columns in Figures 1.13-1.16 represent the contemporaneous forecasts of our consumption variables to a 10% increase in gasoline expenditures using both the linear and nonlinear models. The difference between nonlinear and linear forecasts is represented in the lower columns, with a negative value indicating that the effect of gasoline expenditure shocks on consumption is on *average* understated using the linear model.

Figure 1.13 represents the forecasts of total non-gasoline consumption following a 10% increase in gasoline expenditures using both models. Lets consider the example of 1990 Q3, for which the linear model forecast suggests that non-gasoline consumption is expected to increase by 0.1% following a 10% increase in gasoline expenditures. On the other hand, the nonlinear forecast suggests that non-gasoline consumption is expected to decrease by 0.4% in the same quarter. This implies that the linear model is understating the effect of a gasoline expenditure shock on non-gasoline consumption by around 0.5% during the third quarter of 1990. This pattern can be seen throughout our entire sample period with the difference in forecasts being negative, especially during recessions which is represented by the shaded ar-

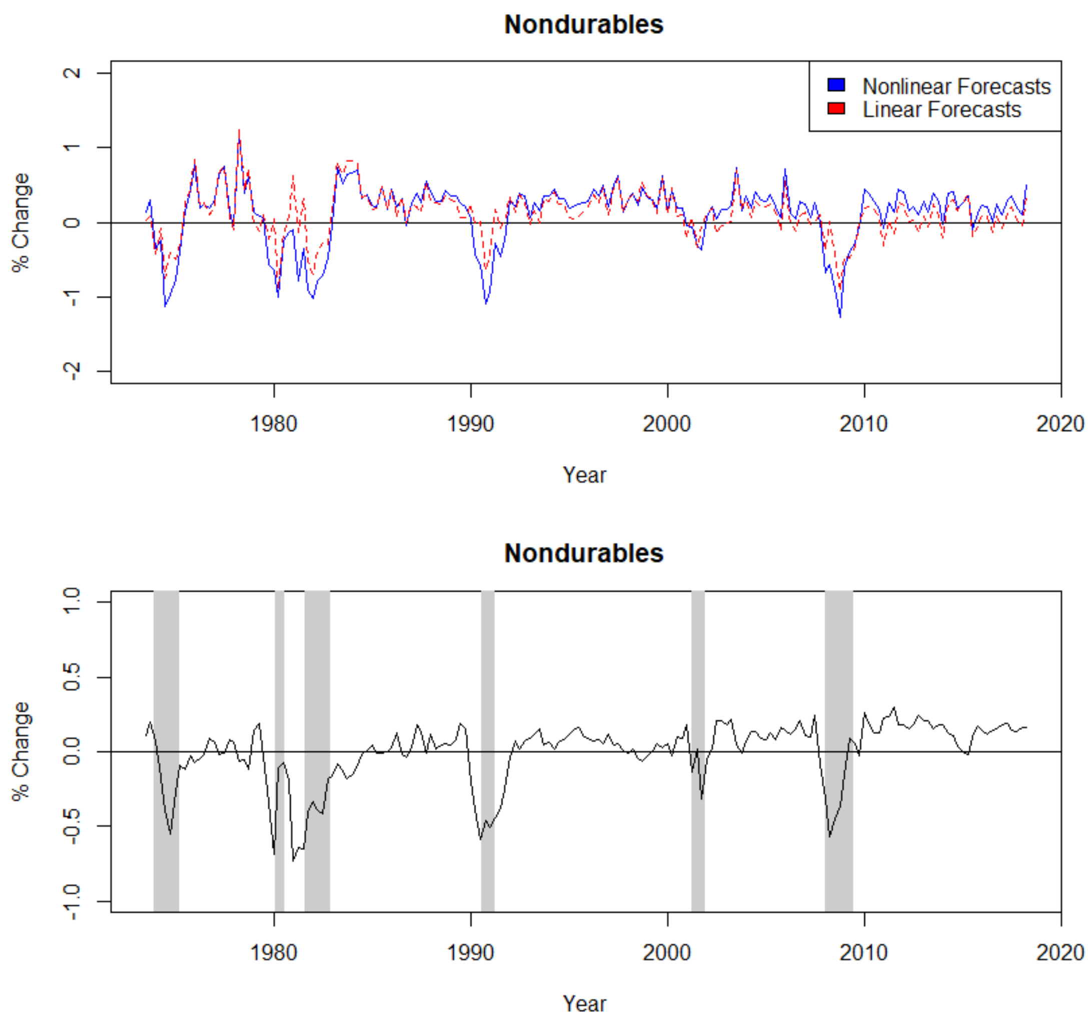
**Figure 1.13**: *Comparison of Consumption Forecasts: PCE*



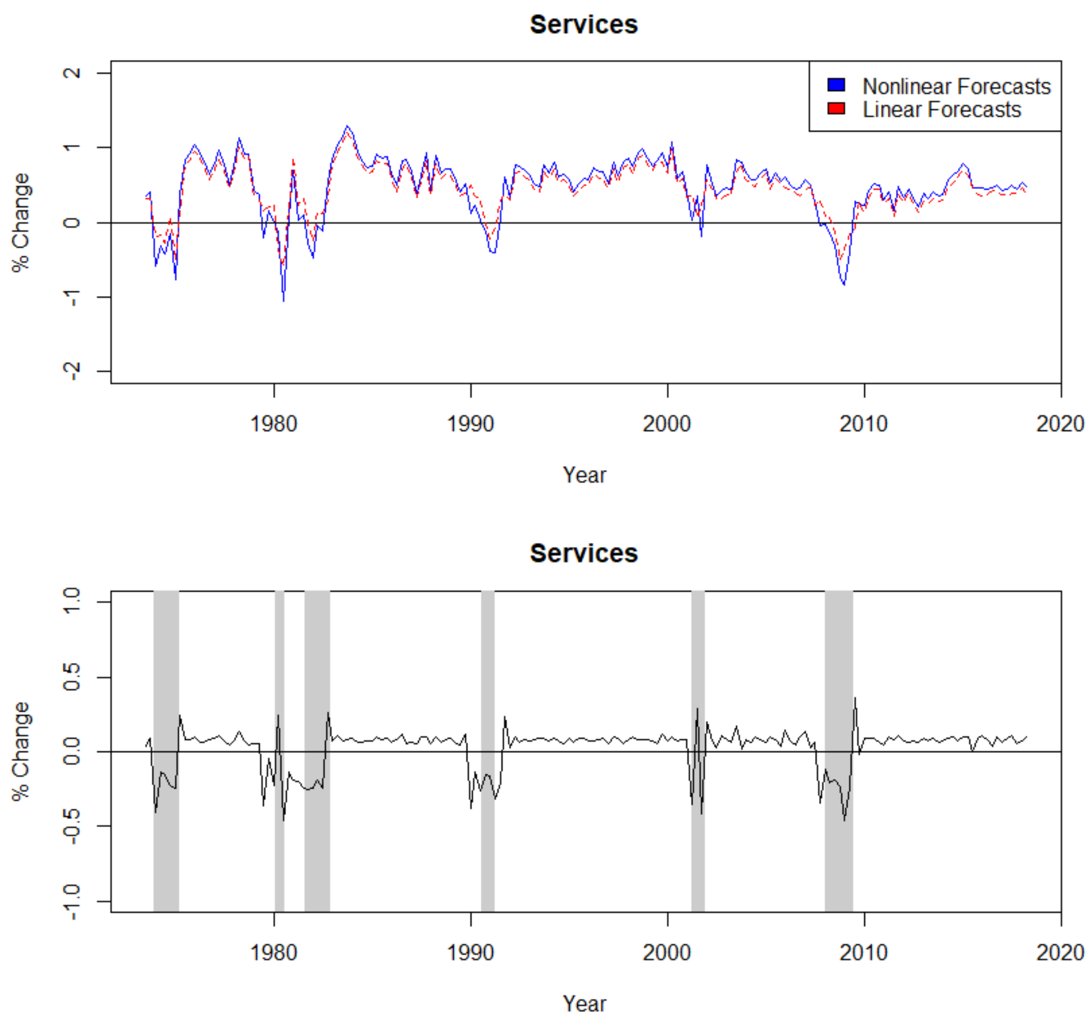

***Notes***: The upper-column indicates the linear and nonlinear consumption forecasts, and the lower-column indicates the difference in forecasts with the shaded area representing U.S. recessions. The red dashed line represents the forecast of consumption following a 10% increase in gasoline expenditures in the same time period using the linear model, whereas the solid blue line represents the forecasts of consumption using the nonlinear model. The solid line in the lower-column represents the difference in consumption forecasts, with a negative value suggesting that the forecasts with the linear model are understating the effect of a gasoline expenditure shock.

**Figure 1.14**: *Comparison of Consumption Forecasts: Nondurables PCE*



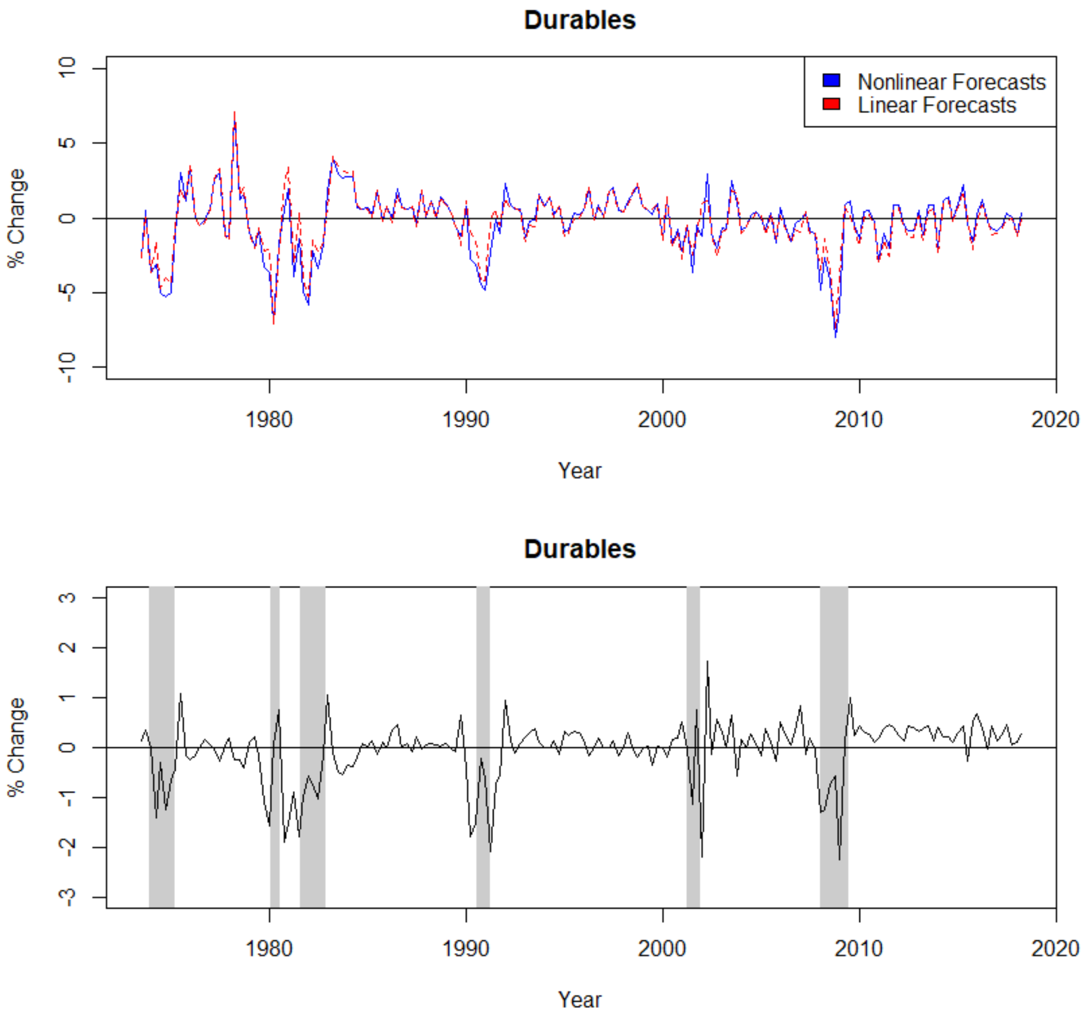

***Notes***: The upper-column indicates the linear and nonlinear consumption forecasts, and the lower-column indicates the difference in forecasts with the shaded area representing U.S. recessions. The red dashed line represents the forecast of consumption following a 10% increase in gasoline expenditures in the same time period using the linear model, whereas the solid blue line represents the forecasts of consumption using the nonlinear model. The solid line in the lower-column represents the difference in consumption forecasts, with a negative value suggesting that the forecasts with the linear model are understating the effect of a gasoline expenditure shock.

**Figure 1.15**: *Comparison of Consumption Forecasts: Services PCE*




***Notes***: The upper-column indicates the linear and nonlinear consumption forecasts, and the lower-column indicates the difference in forecasts with the shaded area representing U.S. recessions. The red dashed line represents the forecast of consumption following a 10% increase in gasoline expenditures in the same time period using the linear model, whereas the solid blue line represents the forecasts of consumption using the nonlinear model. The solid line in the lower-column represents the difference in consumption forecasts, with a negative value suggesting that the forecasts with the linear model are understating the effect of a gasoline expenditure shock.

**Figure 1.16**: *Comparison of Consumption Forecasts: Durables PCE*




***Notes***: The upper-column indicates the linear and nonlinear consumption forecasts, and the lower-column indicates the difference in forecasts with the shaded area representing U.S. recessions. The red dashed line represents the forecast of consumption following a 10% increase in gasoline expenditures in the same time period using the linear model, whereas the solid blue line represents the forecasts of consumption using the nonlinear model. The solid line in the lower-column represents the difference in consumption forecasts, with a negative value suggesting that the forecasts with the linear model are understating the effect of a gasoline expenditure shock.

**Table 1.5**: *Comparison of Consumption Forecasts*

| Date | $\hat{c}_T^{NL}$ | $\hat{c}_T^{L}$ | $\Delta\hat{d}_T^{F}$ |
|---|---|---|---|
| 1974 Q4 | -0.9% | -0.5% | -0.4% |
| 1980 Q1 | -0.5% | 0.0% | -0.5% |
| 1990 Q3 | -0.4% | 0.1% | -0.5% |
| 1991 Q2 | -0.2% | 0.3% | -0.5% |
| 2009 Q1 | -1.1% | -0.5% | -0.6% |

***Notes***: This table represents the contemporaneous forecasts of non-gasoline consumption growth following a 10% increase in gasoline expenditures.

eas. For the purpose of illustration, Table 1.5 represents the contemporaneous forecasts of total non-gasoline consumption growth following a 10% increase in gasoline expenditures for certain time periods.

Referring to Figure 1.14, the linear model is forecasting spending on nondurables to increase by around 0.6% following the shock, and decrease by 0.1% based on the nonlinear model forecasts during 1981 Q1. This suggests that the linear model is understating the effect of a gasoline expenditure shock on nondurables consumption by a magnitude of -0.7%.

Furthermore, there are also cases when the linear model might overstate the effect of a gasoline expenditure shock on consumption. Figure 1.15 represents the forecasts of services consumption to gasoline expenditures shock using both models. During 2009 Q3, a 10% increase in gasoline expenditures reduces spending on services by around 0.1% in the same time period based on the forecasts of the linear model, while the nonlinear model suggests an increase in services spending by 0.3%. These numbers imply that the linear model is overstating the impact of a gasoline expenditure shock, because it is not taking into account the asymmetric response of consumption across states of the economy. Specifically, the economy had just entered a period of expansion in 2009 Q3,[19] and consumer spending might not have been as responsive to gasoline expenditure shocks as it would have been in a recession.

Figures 1.13-1.16 suggest that not accounting for the asymmetric behavior of consumption leads to either understating or overstating the effect of a gasoline expenditure shock when

[19] The U.S. economy entered a period of recession during 2007 Q4, which lasted till 2009 Q2.

forecasting consumption.

## 1.5 Robustness Analysis

This section explores the robustness of our results to alternative specification choices.

### 1.5.1 Alternative Measure of Recession

Different measures of recessions have been proposed in the literature. Ramey and Zubairy (2018), Owyang et. al (2013) use unemployment rate to define the state of the economy and use 6.5 as the threshold. Other measures include NBER recession dates, capacity utilization and output gap. Hamilton argues that instead of relying on the NBER's subjective judgment of the committee members for recessions, it would be a better idea to estimate recession probabilities using the data.[20] Since this proposed definition of recessions by Hamilton is entirely mechanical, we rely on it as an alternative measure to the Auerbach and Gorodnichenko (2012) recession dates. Hamilton's measure corresponds to the probability that the underlying true economic regime is one of recession based on the available data. It is calculated in the following manner,

$$P(Recession|GDP) = \frac{P(Recession \bigcap GDP)}{P(GDP)} \tag{1.20}$$

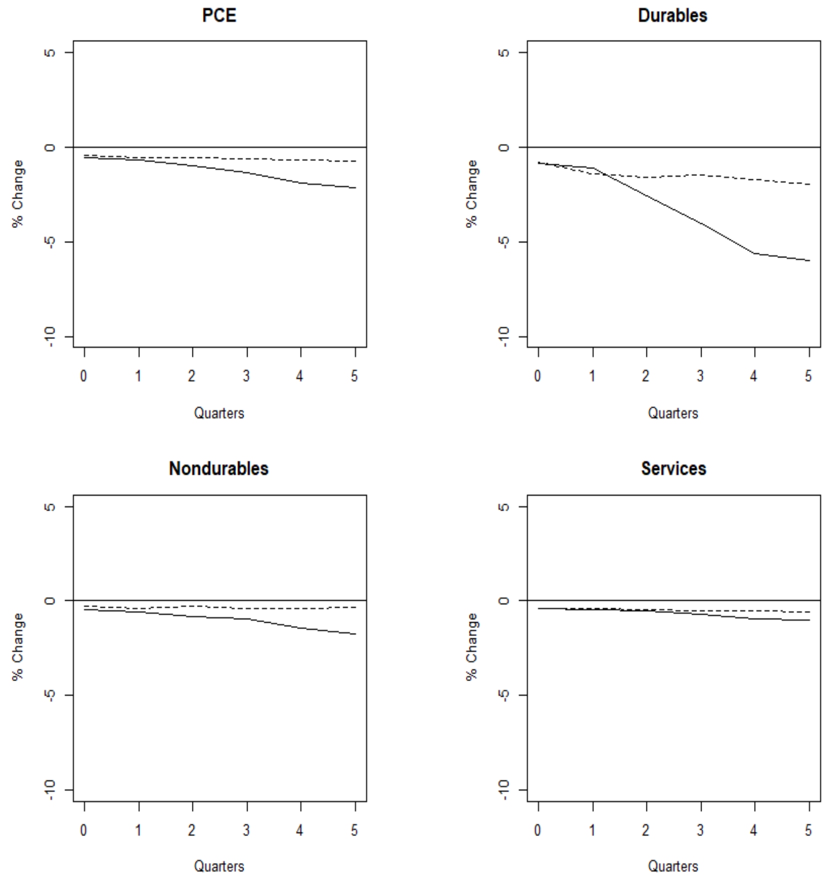
This equation gives us the conditional probability of the economy being in a recession given the value for GDP growth is observed. The numerator gives the joint probability of observing GDP growth and the occurrence of a recession, whereas the denominator measures the probability of observing the value of GDP growth.[21]

Our results in Figure 1.17 suggest that changing the definition of recession does not alter

[20] See Chauvet and Hamilton (2005) for further information on the advantages of using formal quantitative algorithms to identify business cycle turning points. They introduce a measure for dating business cycle turning points namely "quarterly real-time GDP-based recession probability index". This index denotes the probability of recession if all we observe is one quarter's GDP growth as a function of the observed rate of GDP. Their findings are consistent in simulation with real-time databases.

[21] For more details, see https://econbrowser.com/recession-index

**Figure 1.17**: *Response of Consumption Series in Recessions and Expansions: Alternative Measure of Recession*



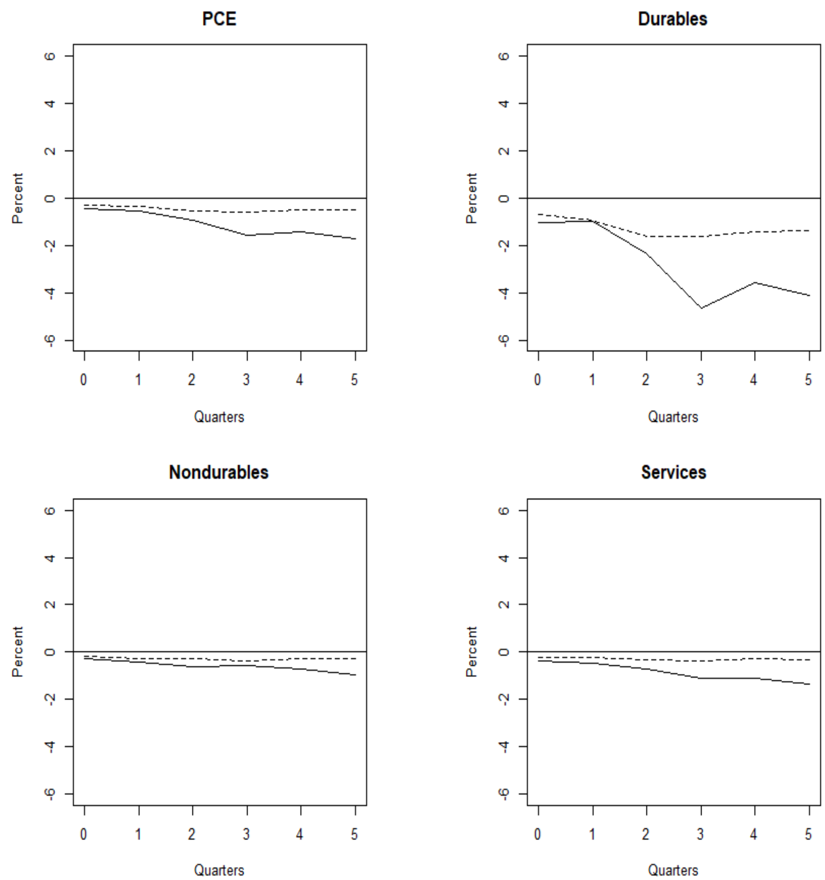

***Notes***: Solid line indicates the cumulative response of consumption series to a 10% increase in gasoline expenditures in recessions, while the corresponding dashed line is the cumulative response in expansions.

the results. The response of consumption is stronger in recessions as opposed to expansions, with this effect seen throughout the durables, nondurables and services sector.

### 1.5.2 Real Price of Gasoline

We use gasoline prices as an alternative measure of shock to make sure that our interpretation of the structural shock to gasoline expenditures is accurate. Variation in gasoline expenditures could be caused by fluctuations in the price of gasoline, changes in vehicle fuel efficiency, changes in the stock of vehicles resulting from changes in preferences for larger or smaller vehicles, changes in travel patterns as witnessed in the aftermath of the 9/11 terrorist attacks, and changes in commuting behavior as a response to fluctuations in house prices.

**Figure 1.18**: *Response of Consumption Series in Recessions and Expansions: Real Price of Gasoline*




***Notes***: Solid line indicates the cumulative response of consumption series to a 10% increase in the real price of gasoline in recessions, while the corresponding dashed line is the cumulative response in expansions.

A 10% increase in the real price of gasoline over the course of a year, will lead to a decline in total consumption spending by 1.4%. Spending on durables, nondurables and services declines by 3.6%, 0.7%, amd 1.1% in recessions respectively. On the other hand, a 10% increase in the price of gasoline over the course of a year will reduce total consumption by 0.5%. The drop in expansions for durables is 1.4%, nondurables is 0.3%, and services is 0.3%. Figure 1.18 shows that the results are robust to an alternative measure of shock, with the response of consumption to changes in the real price of gasoline being stronger in a recession than in an expansion.

## 1.6 Conclusion

This essay investigated the following research questions:

1. What happens to consumption when gasoline expenditures increase?

2. Does the response of consumption to gasoline expenditure shocks depend on the state of the economy?

3. Why does the response of consumption to gasoline expenditures shock differ across the state of the economy?

The answers to our questions were as follows. We found evidence that a shock to gasoline expenditures reduces spending on non-gasoline goods and services. When gasoline expenditures increase by 10% over the course of a year, spending on non-gasoline goods and services decreases by 0.7% during the same time period. This response is primarily driven by the durables and services sector. Consumption exhibits an asymmetric response to gasoline expenditure shocks across recessions and expansions, with a stronger response in recessions. The asymmetry in the response of consumption over the business cycle may be driven by different savings behavior in recessions and expansions. Our conclusions were robust to alternate measures of recessions and gasoline expenditure shocks.

Viewed as a whole, our findings are consistent with the notion that shocks to gasoline expenditures can be treated as if they are a shock to taxes, and that fiscal policy has different effects in recessions and expansions. One important application of these findings is forecasting aggregate consumption behavior. For example, the Federal Reserve should allow the impact of gasoline expenditure shocks to be dependent on the state of the economy. Failure to do so can result in avoidable consumption forecasting errors.

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# Chapter 2

# Exploring Asymmetries in the Effects of El Niño-Southern Oscillation on U.S. Food and Agricultural Stock Prices

## 2.1 Introduction

The El Niño-Southern Oscillation (ENSO) is an important source of interannual variability in weather and climate patterns in many parts of the world (Shabbar and Khandekar, 1996). It involves fluctuations in trade winds, precipitation, sea level pressure, and sea surface temperatures in the central and east-central equatorial Pacific basin (L'Heureux, 2014). The warm phase of ENSO, known as El Niño, is characterized by a weakening of easterly trade winds due to higher surface pressure in the eastern Pacific and lower pressure in the west, a rise in sea surface temperatures, increased rainstorms in the central and east-central equatorial Pacific ocean, wetter conditions in the Pacific coast of South America, and dry conditions in Southeast Asia and the northern tier of Australia.[1] In the United States, El Niño typically causes higher wintertime temperatures in the northern states, cooler temperatures in the Gulf Coast, higher precipitation in the southern regions, drier wintertime

[1] https://www.americangeosciences.org/critical-issues/faq/what-are-el-Niño-and-la-Niña

conditions in Hawaii and Guam, and increased rainfall in American Samoa.[2] The cold phase of ENSO, known as La Niña, generally has opposite effects. That is, easterly winds strengthen, sea surface temperatures and rainstorms decrease in the central and east-central equatorial Pacific Ocean, the Pacific coast of South America experiences drier conditions, while Southeast Asia and the northern tier of Australia encounter much wetter than normal conditions. In La Niña episodes, northwestern U.S. states experience cooler than average temperatures, southeastern and gulf Coast areas witness warmer weather, Hawaii and Guam encounter much wetter conditions, and American Samoa experiences reduced precipitation.

A large empirical literature has documented evidence that the effect of ENSO on agricultural output and prices differ between the El Niño and La Niña phases of the ENSO cycle. Hansen et al. (1998) present evidence of lower than expected corn and tobacco yields in the years immediately following La Niña events for several Southeastern U.S. states. They also find that the areas of soybean, cotton, and peanut harvested respectively decreased by about 8.3%, 5.3%, and 8.7% in La Niña years compared to non-La Niña years. Adams et al. (1999) estimate that the consequences of ENSO vary from approximately \$1.5 to \$6.5 billion in losses, with La Niña events associated with greater losses than El Niño. Cadson et al. (1996) report lower than expected corn yields during the La Niña phase of ENSO for states in the U.S. cornbelt. Iizumi et al. (2014) find that El Niño increases global average soybean yield by 2.1% to 5.4%, but changes yields of corn, rice and wheat by between -4.3% to 0.8%. On the other hand, they find lower yields of between 0% and -4.5% for all four crops in La Niña years. Using smooth transition models, Ubilava and Holt (2013) show that El Niño events cause an increase in global vegetable oil prices, while La Niña events cause a decrease in prices. Applying a vector smooth transition autoregressive (VSTAR) methodology, Ubilava (2017) reports an increase in wheat prices following La Niña, and a decrease in prices after El Niño occurrences. Further evidence of asymmetries in the impacts of El Niño and La Niña on agricultural output and prices has been documented by Hall et al. (2001), Schlenker and Roberts (2006), Ubilava (2012a, 2012b, 2014), and Smith and Ubilava (2017).

While considerable evidence exists on the asymmetric impacts of ENSO on agricultural

[2] https://oceanservice.noaa.gov/facts/NiñoNiña.html

yields and prices, much less research has examined the asymmetric impacts of ENSO on food and agricultural stock prices. As pointed out by Atems et al. (2020), an ENSO shock that decreases agricultural yields is expected to decrease current and future cash flows to food and agricultural companies, resulting in a decline in their stock prices and/or returns. As further pointed out by Atems et al. (2020), if food and other agricultural prices rise in response to this decrease in supply, cash flows, profitability, and hence, the stock prices of food and agricultural companies may rise. Using monthly data for the period 1980:3-2018:12 and a linear VAR model, Atems et al. (2020) show that an ENSO shock has a positive impact on the stock returns of most of the food and agricultural companies they consider.

This paper contributes to the literature on the economic and financial effects of ENSO along several dimensions. First, we employ weekly data spanning the period January 1990 to April 2019, as opposed to much of the related literature that typically employs monthly or quarterly data to examine the economic effects of ENSO. While the use of monthly or quarterly data in studies that examine the impact of ENSO on agricultural output and prices is perhaps appropriate, as the full impact of ENSO on agricultural yields and prices may take a long time to become apparent, our use of higher frequency (weekly) data provides a much richer and more appropriate data set for estimating the impacts of ENSO on stock prices. As pointed out by Geweke (1978), using lower frequency data for such a study may lead to considerable bias. Hence, in our case, the use of weekly rather than monthly data as in Atems et al. (2020) results in more reliable estimates, especially if, as expected, U.S. food and agricultural stock prices respond much faster to ENSO anomalies. As further pointed out by Geweke (1978), the use of low frequency data can result in a form of omitted variable bias because of misspecification of the intertemporal lag distribution.

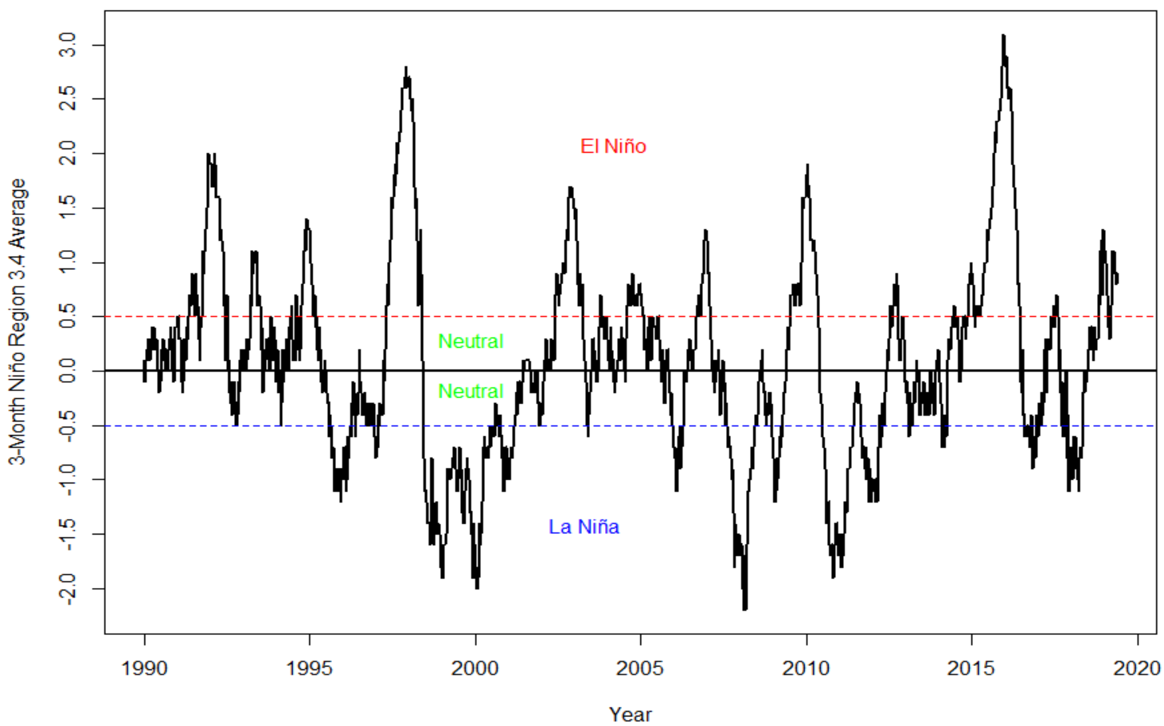
Second, we explore asymmetries in the effects of ENSO shocks by investigating the extent to which the responses of U.S. food and agricultural stock prices differ depending on whether the ENSO events are El Niño or La Niña. Given the significant evidence that the output and price responses to ENSO anomalies may be asymmetric depending on the ENSO cycle (El Niño or La Niña), there is need to estimate a model that allows for such asymmetries.

Third, we use state-of-the-art state-dependent local projection methods (Jorda, 2005), which provide a flexible, parsimonious empirical modeling framework that is ideal for capturing asymmetries, without the need to impose the type of dynamic restrictions generally required in standard VAR models, and other nonlinear and regime-dependent modeling techniques. State-dependent local projection methods such as the one used in this paper have become the state-of- the-art technique used in the macroeconomics literature to study assymmetric effects of macroceconomic shocks. Examples of recent but highly influential papers applying this methodology include Auerbach and Gorodnichenko (2012, 2013), Owyang et al. (2013), Ramey and Zubairy (2018), Alpanda and Zubairy (2018), who study the assymetric effects of fiscal policy shocks; Tenreyro and Thwaites (2016) and Jorda et al. (2019), who document asymmetric transmission of monetary policy shocks; and Basher et al. (2012), and Choi et al. (2018) when modeling asymmetries in the effects of oil shocks.

The empirical results of the paper provide evidence of asymmetries in the responses of U.S. food and agricultural stock prices to ENSO shocks. In particular, impulse response functions reveal that La Niña shocks, in general, are associated with an increase stock prices, while the responses to El Niño shocks are typically negative or insignificant. We further quantify the magnitude and significance of this asymmetry, and show that the difference in the stock price responses to El Niño shocks and La Niña shocks are significantly different from zero for eight of the twelve returns considered. These findings are robust to the use of lower frequency (monthly) data, as well as to controlling for the effect of macroeconomic conditions. The analysis, thus, emphasizes the need to disentangle ENSO shocks into corresponding El Niño, and La Niña shocks, as failure to do so might result in misleading conclusions about the effect of ENSO on U.S. food and agricultural stock prices.

The remainder of the paper is as follows. The next section discusses the data and presents the empirical methodology. Section 2.3 discusses the empirical results. Section 2.4 sheds light on the robustness of our results. Section 2.5 concludes.

**Figure 2.1**: *Weekly El Niño Southern Oscillation (ENSO): 1990:1-2019:04*




## 2.2 Data and Methodology

### 2.2.1 Data

This paper uses weekly observations on the measure of ENSO intensity and the closing values of the stock prices of twelve U.S. food and agricultural companies covering the period January 1990 to April 2019. We use sea surface temperature anomalies (SSTA) for the "Niño 3.4" region - the region between $5^0$N-$5^0$S and $120^0$W-$170^0$W - as our measure of ENSO intensity. While other measures of ENSO intensity, such as the Southern Oscillation Index (SOI) anomalies, have sometimes been used in the literature, the use of SSTA is more prevalent (see e.g. Hansen et al., 1998; Brunner, 2002; Ubilava, 2017).[3] The data on weekly SSTA come from the Climate Prediction Center (National Oceanic and Atmospheric

[3] See Atems et al. (2020) for further discussion on the advantages of using SST anomalies over the SOI anomalies to measure ENSO intensity

**Table 2.1**: *Variable Names and Descriptions*

| Variable | Description | Source | Sample Period |
|---|---|---|---|
| SSTA | Sea surface temperature anomalies: Niño 3.4 region | NOAA | 1990:01-2019:04 |
| CPI | Consumer price index for all urban consumers | FRED | 1990:01-2019:04 |
| Output | Industrial Production Index | FRED | 1990:01-2019:04 |
| Archer Daniels | The Archer Daniels Company stock prices | CRSP | 1990:01-2019:04 |
| Campbell's | The Campbell Soup Company stock prices | CRSP | 1990:01-2019:04 |
| Conagra | Conagra Brands, Inc. stock prices | CRSP | 1990:01-2019:04 |
| FMC | The FMC Corporation stock prices | CRSP | 1990:01-2019:04 |
| General Mills | General Mills, Inc. stock prices | CRSP | 1990:01-2019:04 |
| Hershey's | The Hershey Company stock prices | CRSP | 1990:01-2019:04 |
| Hormel | Hormel Foods Corporation stock prices | CRSP | 1990:01-2019:04 |
| McCormick | McCormick and Company stock prices | CRSP | 1990:01-2019:04 |
| Mosaic | The Mosaic Company stock prices | CRSP | 1990:01-2019:04 |
| Smucker | The J.M. Smucker Company stock prices | CRSP | 1994:11-2019:04 |
| Sysco | Sysco Corporation stock prices | CRSP | 1990:01-2019:04 |
| Tyson Foods | Tyson Foods, Inc. stock prices | CRSP | 1990:01-2019:04 |

***Notes***: Full meanings of the 'Source' acronyms are found in the text.

Administration (NOAA)). An El Niño event is defined as three consecutive months of SSTA of $0.5^0$C ($0.9^0$F) or higher, while a La Niña episode is defined as three consecutive months of SSTA of $-0.5^0$C ($-0.9^0$F) or less. SSTA between $0.5^0$C ($0.9^0$F) and $-0.5^0$C ($-0.9^0$F) are referred to as neutral ENSO events. Figure 2.1 shows the weekly SSTA values over our entire sample period. It is apparent that whereas neutral ENSO events are more prevalent, a nontrivial number of ENSO events have been El Niño and La Niña episodes.

We collect data on the stock prices of twelve publicly traded U.S. food and agricultural companies from the Center for Research in Security Prices (CRSP). The companies considered are listed in Table 2.1. We chose these companies because they represent some of the largest food and agricultural companies trading in U.S. stock markets. All the twelve firms, in fact, are included in the S&P index. We narrowed the number of companies to twelve by first using the Global Industry Classification Standard (GICS) to identify companies in the Consumer Staples, and Materials sectors. As it is not possible to consider the stock prices of all firms in these sectors, and it is unlikely that the output, prices, and therefore stock performance of all these firms respond to ENSO shocks, we consider only those firms in the

Packaged Foods and Meats, and the Fertilizers and Agricultural Chemicals GICS Subsectors. This leaves us with sixteen of the largest publicly traded U.S. food and agribusiness firms. Given the importance of long enough time series for our empirical methodology, we only consider twelve of these sixteen companies with long enough data.

The main results of the paper are based on weekly data. In a robustness section, however, we also utilize monthly data on SSTA and stock prices. In addition, monthly data on the U.S. consumer price index (CPI) for all urban consumers and the U.S. industrial production index (output), both collected from the Federal Reserve Economic Database (FRED) are used in some specifications. Variable descriptions are provided in Table 2.1.

The models in this paper are estimated with SSTA in levels and the stock prices in log first differences, as determined by a battery of unit root and stationarity tests.[4] Results of these tests, performed on all the variables in log levels and log first differences, show that SSTA is stationary in levels, while the stock prices are stationary only after first differences.

Tables 2.2 and 2.3 report results of four commonly used tests unit root and stationarity tests, namely the augmented Dickey-Fuller (ADF) test (see Dickey and Fuller, 1981), the Phillips-Perron (Phillips and Perron, 1988) test (PP), the Elliott, Rothenberg and Stock (1996) modified Dickey Fuller (ERS) test, and the Kwiatkowski, Phillips, Schmidt, and Shin (1992) test (KPSS). The low power of the ADF test against relevant trend stationary alternatives is well documented (see e.g. DeJong et al., 1992), hence, the reason we perform the other tests. The tests are performed for the variables in levels (panel A) and first differences (panel B). In Table 2.2, all the tests include an intercept and a linear time trend, while all the tests in panel B do not contain the intercept and/or trend.

As is apparent from Table 2.2, the null hypothesis of a unit root in the SSTA series in levels (panel A), and in first differences (panel B) is rejected at the 5% level when using the first three tests. The KPSS test shows that this series is trend stationary in levels and first differences. In addition, the table provides evidence that all the food and agricultural stock

[4] Specifically, we carry out the he augmented Dickey-Fuller (ADF) test (see Dickey and Fuller, 1981), Phillips-Perron (Phillips and Perron, 1988) test (PP), the Elliott, Rothenberg and Stock (1996) modified Dickey Fuller (ERS) test, and the Kwiatkowski, Phillips, Schmidt, and Shin (1992) test (KPSS). "In Table 2.2, we carry out the tests including an intercept and linear trend. Results in Table 2.3 are based on tests without the intercept and/or trend.

**Table 2.2**: *Unit Root and Stationarity Tests: Tests Include Intercept and Linear Trend*

**A. Tests for Variables in Levels**

| ***Variables*** | *ADF* | *ERS* | *PP* | *KPSS* |
|---|---|---|---|---|
| SSTA* | -3.43 | -3.76 | -3.77 | 0.37 |
| The Archer Daniels Company | -3.26 | -2.92 | -3.27 | 1.17 |
| The Campbell Soup Company | -2.28 | -1.88 | -2.30 | 1.01 |
| Conagra Brands, Inc. | -2.94 | -2.68 | -2.89 | 1.69 |
| The FMC Corporation | -1.34 | -1.12 | -1.36 | 3.23 |
| General Mills, Inc. | -2.65 | -2.67 | -2.81 | 2.28 |
| The Hershey Company | -1.79 | -1.54 | -1.81 | 2.06 |
| Hormel Foods Corporation | -1.08 | -0.65 | -1.05 | 3.77 |
| McCormick and Company | 1.20 | 0.84 | 1.12 | 3.42 |
| The Mosaic Company | -2.59 | -2.71 | -2.66 | 1.02 |
| The J.M. Smucker Company | -2.96 | -1.93 | -2.96 | 2.15 |
| Sysco Corporation | -1.66 | -1.40 | -1.58 | 1.27 |
| Tyson Foods, Inc. | -0.70 | -0.99 | -0.78 | 3.26 |

**B. Tests for Variables in Log First Differences**

| ***Variables*** | *ADF* | *ERS* | *PP* | *KPSS* |
|---|---|---|---|---|
| SSTA* | -28.64 | -12.14 | -39.95 | 0.02 |
| The Archer Daniels Company | -27.86 | -14.16 | -41.18 | 0.03 |
| The Campbell Soup Company | -28.03 | -8.21 | -42.16 | 0.06 |
| Conagra Brands, Inc. | -26.52 | -17.38 | -38.42 | 0.05 |
| The FMC Corporation | -26.18 | -17.34 | -39.31 | 0.04 |
| General Mills, Inc. | -28.90 | -7.55 | -42.76 | 0.03 |
| The Hershey Company | -28.32 | -8.11 | -44.04 | 0.04 |
| Hormel Foods Corporation | -27.83 | -7.09 | -40.43 | 0.02 |
| McCormick and Company | -30.45 | -3.45 | -43.77 | 0.03 |
| The Mosaic Company | -27.25 | -12.00 | -38.50 | 0.06 |
| The J.M. Smucker Company | -27.24 | -16.68 | -37.09 | 0.04 |
| Sysco Corporation | -29.76 | -7.96 | -42.48 | 0.07 |
| Tyson Foods, Inc. | -28.83 | -8.83 | -38.11 | 0.05 |

***Notes***: * These variables can be negative or positive, so we only take the first difference, not the log first difference. All tests include an intercept and a linear trend. 5% critical values for the respective tests are: -3.42, -2.89, -3.42, 0.15.

prices are nonstationary in levels but stationary after first differencing.

One concern with the results in Table 2.2 is that if the time trend is statistically important, it could mean that sea surface temperatures have been warming with the overall warming in the Earth's atmosphere. If, on the other hand, the time trend is not statistically important, its presence would affect the power of the unit root tests. Similarly, the presence

**Table 2.3**: *Unit Root and Stationarity Tests: No Trend*

**A. Tests for Variables in Levels**

| ***Variables*** | *ADF* | *ERS* | *PP* | *KPSS* |
|---|---|---|---|---|
| SSTA* | -3.41 | -3.74 | -3.77 | 0.38 |
| The Archer Daniels Company | 0.08 | -0.18 | -1.40 | 16.01 |
| The Campbell Soup Company | -0.13 | -0.54 | -2.22 | 7.30 |
| Conagra Brands, Inc. | 0.12 | -0.21 | -1.91 | 11.03 |
| The FMC Corporation | 1.55 | 1.30 | 0.44 | 13.59 |
| General Mills, Inc. | 0.90 | 0.55 | -0.93 | 17.19 |
| The Hershey Company | 2.08 | 1.87 | 0.53 | 16.51 |
| Hormel Foods Corporation | 2.33 | 2.14 | 1.13 | 14.59 |
| McCormick and Company | 4.34 | 4.74 | 3.13 | 15.69 |
| The Mosaic Company | -1.31 | -2.13 | -2.57 | 4.45 |
| The J.M. Smucker Company | 0.98 | 0.72 | -0.41 | 14.49 |
| Sysco Corporation | 1.93 | 2.18 | 0.44 | 15.49 |
| Tyson Foods, Inc. | 1.67 | 1.25 | 0.49 | 9.84 |

**B. Tests for Variables in Log First Differences**

| ***Variables*** | *ADF* | *ERS* | *PP* | *KPSS* |
|---|---|---|---|---|
| SSTA* | -28.66 | -8.79 | -39.97 | 0.023 |
| The Archer Daniels Company | -27.83 | -11.20 | -41.19 | 0.04 |
| The Campbell Soup Company | -28.00 | -4.64 | -42.13 | 0.15 |
| Conagra Brands, Inc. | -26.49 | -17.04 | -38.43 | 0.07 |
| The FMC Corporation | -26.15 | -17.30 | -39.32 | 0.09 |
| General Mills, Inc. | -28.79 | -4.15 | -42.74 | 0.08 |
| The Hershey Company | -28.18 | -4.41 | -44.04 | 0.05 |
| Hormel Foods Corporation | -27.66 | -3.81 | -40.44 | 0.05 |
| McCormick and Company | -30.22 | -1.63 | -43.78 | 0.04 |
| The Mosaic Company | -27.26 | -7.53 | -38.51 | 0.07 |
| The J.M. Smucker Company | -27.20 | -16.77 | -37.10 | 0.05 |
| Sysco Corporation | -29.58 | -4.36 | -42.47 | 0.13 |
| Tyson Foods, Inc. | -28.80 | -4.86 | -38.12 | 0.09 |

***Notes***: * These variables can be negative or positive, so we only take the first difference, not the log first difference. Tests do not include an intercept and/or a linear trend. 5% critical values for the respective tests are: -1.95, -1.94, -2.86, 0.46.

of a linear time trend and an intercept would also reduce the power of the unit root test for food and agricultural stock prices. As a consequence, we also perform the unit root and stationarity tests without the linear time trend. These results, presented in Table 2.3, continue to show that the SSTA is stationary, while the stock prices must be first differenced to achieve stationarity.

### 2.2.2 Methodology

The impulse response functions of the food and agricultural stock prices to El Niño and La Niña shocks are calculated using state-dependent local projection methods (Jorda, 2005). While this paper represents the first attempt to apply local projections to investigate asymmetries in the effects of ENSO, state-dependent local projection methods are now the state-of-the-art technique used in the macroeconomics literature to study, for instance, the asymmetric effects of fiscal policy shocks (see e.g. Auerbach and Gorodnichenko, 2012, 2013; Owyang et al., 2013; Ramey and Zubairy, 2018; Alpanda and Zubairy, 2018), monetary policy shocks (see e.g. Tenreyro and Thwaites, 2016; Jorda et al., 2019), and oil price shocks (Basher et al., 2012; Choi et al., 2018; Equiza-Goni and Perez de Gracia, 2019).

The main appeal of local projections is that they are flexible enough to accommodate nonlinear specifications without the need to impose the type of dynamic restrictions generally required in standard VAR and other nonlinear and regime-dependent modeling techniques (Jorda 2005). In addition, it is less sensitive to misspecification since it imposes no constraints on the shape of impulse response functions (Ramey and Zubairy, 2018).[5] Furthermore, unlike VAR models in particular, and other multivariate models, in general, all variables are not required to enter all equations, therefore allowing the researcher to use a more parsimonious specification that can be estimated by simple regression methods and packages. As well, local projections allow for the investigation of state-dependence using all available data, as opposed to estimating a VAR for each regime. It is possible that fewer observations in one of the regimes results in imprecise and unstable estimates (Auerbach and Gorodnichenko, 2012). For these reasons, this paper uses local projections to assess the existence of asymmetries in the response of agricultural stock prices to ENSO shocks. The method is described below.

Consider the reduced-form linear model:

$$y_t = \alpha + \sum_{i=1}^{k} \beta_i y_{t-i} + \sum_{i=1}^{k} \gamma_i z_{t-i} + \varepsilon_t \tag{2.1}$$

[5] See Jorda (2005) for further details on the robustness of local projections to misspecification.

where $y_t$ is the variable of interest at time $t$, $z_t$ is an exogenous shock, $\varepsilon_t$ refers to the error term, and $k$ denotes the maximum lag length, which is selected by minimizing the Schwartz Information Criterion (SIC) over $1 \leq k \leq 12$. In our case, $y_t$ denotes the percentage change in the agricultural stock prices, and $z_t$ denotes sea surface temperature anomalies (SSTA). We model the ENSO variable, SSTA, as exogenous because there is no reason to believe that it is caused (in Granger sense) by the agricultural stock returns. Because we use weekly data, the baseline model does not consider other control variables that potentially impact agricultural stock prices, such as macroeconomic variables, due to their unavailability at this frequency. In a robustness section, we use monthly data and a multivariate specification that controls for the impact of macroeconomic conditions. The coefficient, $\gamma_i$, is the period $t$ response of the stock returns, $y$, to an ENSO shock in period $t-i$. With this approach, impulse response functions are computed as a sequence of $\gamma_i$'s recovered from estimating sequential regressions of the form (2.1) for increasingly larger horizons.

Equation (2.1) can be modified to allow for state-dependence by estimating, for each horizon, sequential regressions of the form:

$$y_t = \alpha + \sum_{i=1}^{k} \beta_i y_{t-i} + \sum_{i=1}^{k} \gamma_i z_{t-i} + \sum_{i=1}^{k} \delta_i inter_{t-i} + \varepsilon_t \tag{2.2}$$

where the variable $inter_t$ is the interaction term:

$$inter_t = I_t \times z_t$$

and the variable, $I_t$ is an indicator variable, such that

$$I_t = \begin{cases} 1 & z_t > 0.5 \\ 0 & z_t \leq 0.5 \end{cases} \tag{2.3}$$

Hence, $I_t = 1$ in El Niño episodes and 0 in non-El Niño episodes. Note then, that non-El Niño episodes contain neutral episodes, as well as La Niña episodes. For the ease of exposition, however, we refer to non-El Niño episodes as La Niña.[6]

[6]We have divided the data into two regimes. In our robustness check, we redefine the threshold to make

The $h$-period impulse response functions are calculated by first estimating the regression:[7]

$$y_t = \alpha^h + \sum_{i=h}^{h+k-1} \theta_i y_{t-i} + \sum_{i=h}^{h+k-1} \lambda_i z_{t-i} + \sum_{i=h}^{h+k-1} \rho_i inter_{t-i} + \nu_t^h \tag{2.4}$$

where $\alpha^h$, $\theta_i$, $\lambda_i$, and $\rho_i$ are parameters to be estimated, and $h = 1, \ldots, 12$. Let $\hat{\Phi}_h$ denote the coefficient matrix calculated by sequentially estimating equation (2.4) for each forecast horizon, and let $d_i$ represent the contemporaneous impulse response vector. Then the contemporaneous stock responses in the El Niño and La Niña regimes, respectively denoted as $d_i^{Nino}$ and $d_i^{Nina}$ are:

$$d_i^{Nino} = \begin{bmatrix} y_0 & z_0 & inter_0 \end{bmatrix} \tag{2.5}$$

$$d_i^{Nina} = \begin{bmatrix} y_0 & z_0 & 0 \end{bmatrix} \tag{2.6}$$

where $y_0$ is the contemporaneous response of stock returns to an ENSO shock, and $z_0$ is the one time SSTA shock. Using equations (2.5) and (2.6), the $h$-period responses in both regimes can now be computed as:

$$\widehat{IR}_h^{Nino} = \Phi_h d_i^{Nino} = \hat{\theta}_h y_0 + \hat{\lambda}_h z_0 + \hat{\rho}_h inter_0 \tag{2.7}$$

$$\widehat{IR}_h^{Nina} = \Phi_h d_i^{Nina} = \hat{\theta}_h y_0 + \hat{\lambda}_h z_0 \tag{2.8}$$

where $\Phi_h = \begin{bmatrix} \hat{\theta}_i & \hat{\lambda}_i & \hat{\rho}_i \end{bmatrix}$.

The responses resulting from equations (2.7) and (2.8) will converge to zero over time, since the agricultural stock returns are expressed in log first differences (to achieve stationarity). To measure persistence of the responses, we construct $h$-period cumulative impulse responses:

sure that our results are not driven by neutral shocks. La Niña episodes are defined as one regime and non La Niña episodes as the other. Our results do not change, which suggests that the fluctuations in agricultural stock prices are driven only by changes in SSTA during El Niño and La Niña. We conclude that our results are not sensitive to how we define our threshold.

[7]This corresponds to equation (2) in Jorda (2005).

$$CIR_h^{Nino} = \sum_{j=0}^{h} \widehat{IR}_j^{Nino} \tag{2.9}$$

$$CIR_h^{Nina} = \sum_{j=0}^{h} \widehat{IR}_j^{Nina}. \tag{2.10}$$

Evidently, the cumulative impulse response functions, (2.9) and (2.10), show the accumulation of the effects of a shock to El Niño and La Niña through time, rather than its impact at one point in time. Hence, while we use stock returns in the VAR model, the cumulative impulse responses show the impact of the distinct ENSO shocks on agricultural stock price *levels* (not returns), thereby allowing us to trace out the deviation of the food and agricultural stock prices from their long-run level.

The primary purpose of this paper is to explore asymmetries in the stock price responses to El Niño and La Niña shocks. While the impulse responses constructed from equations (2.9) and (2.10) may suffice for this purpose, an alternative approach is to ask whether the difference between the stock price responses across the El Niño and La Niña regimes are significantly different from zero. For the purpose of exposition, we refer to this difference in responses between the regimes as "cumulative difference responses", and is calculated as:

$$\Delta CIR_h = \sum_{j=0}^{h} \left( \hat{IR}_j^{Nino} - \hat{IR}_j^{Nina} \right) \tag{2.11}$$

where $\Delta CIR_h = CIR_h^{Nino} - CIR_h^{Nina}$. A value of $\Delta CIR_h < 0$ indicates that the response to an El Niño shock is larger than that to a La Niña shock. To gauge statistical significance, we compute 90% confidence bands for the impulse responses. Due to serial correlation in the error terms induced by successive leading of the dependent variable, we apply the Newey-West correction to the standard errors (Ramey and Zubairy, 2018). If zero lies within the 90% confidence intervals, the response is not statistically different from zero.

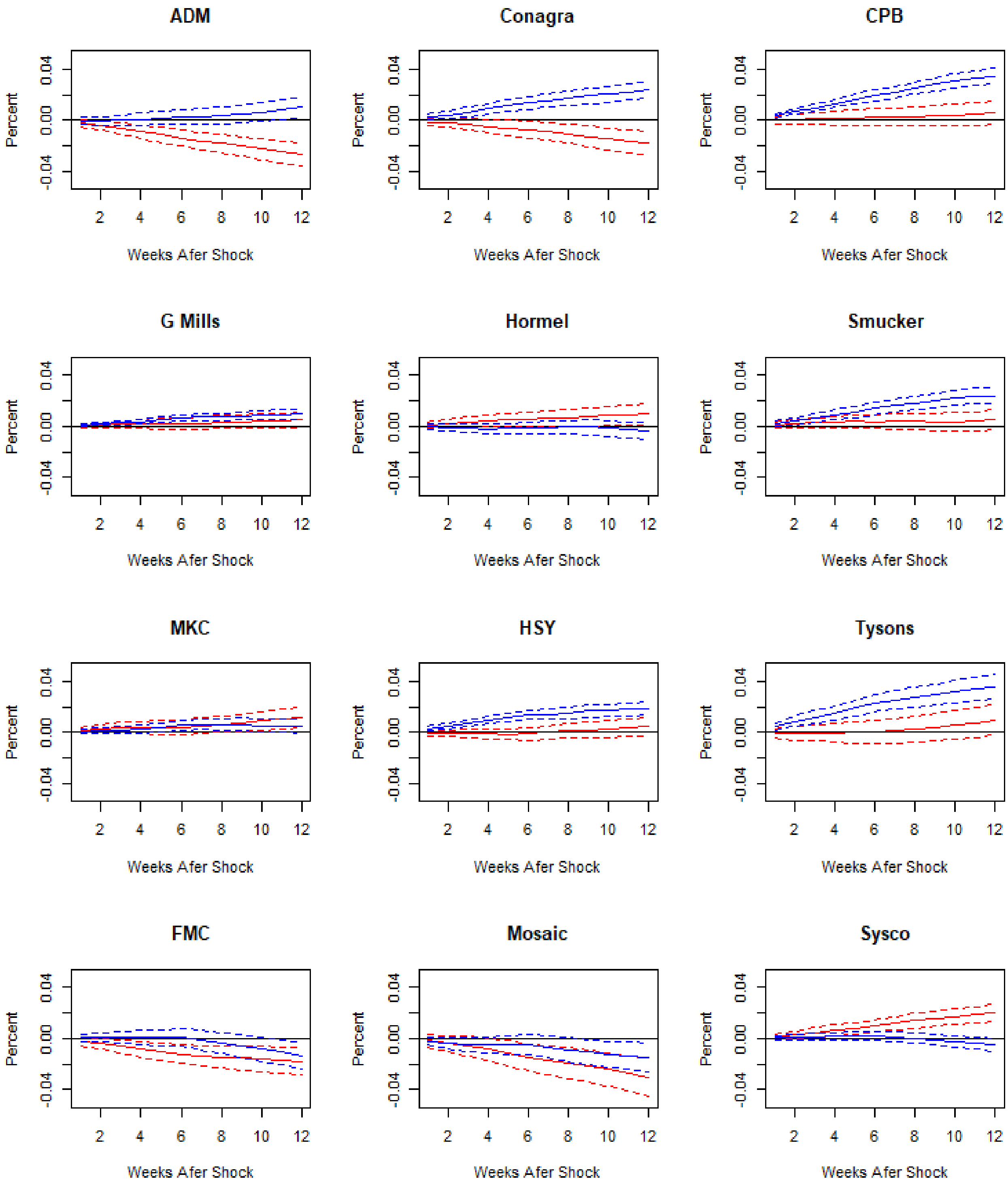
## 2.3 Results and Discussion

Figure 2.2 to shows how the twelve food and agricultural prices respond to the distinct ENSO shocks. In particular, it shows the cumulative responses of the stock prices to an El Niño shock (red solid lines) and a La Niña shock (blue solid lines). The corresponding dashed red and blue lines are the 90% confidence bands constructed as described in Section 2.2.2. For visual convenience, Table 2.4 summarizes the long run features of the impulse responses by presenting cumulative response functions at the 12-week horizon to give a sense of the magnitude of these long run effects.

The figure highlights the point that the responses of U.S. agricultural stock prices to an El Niño shock may differ from those of La Niña. For seven of the twelve companies, namely Archer Daniels, Conagra, Campbell's, General Mills, Smucker, Hershey's, and Tyson, the response to a La Niña shock is positive and significantly different from zero. For Archer Daniels, General Mills, and McCormick, the positive responses occur after a delay of several weeks, while for the four other stock prices, the contemporaneous and subsequent responses are almost always significantly different from zero. As shown in column (2) of Table 2.4, the stock prices of Campbell's and Tyson Foods each rise by as much as 3.5% after twelve weeks. The figure also shows that the responses of two stocks - Hormel, and Sysco - are not significantly different from zero at any forecast horizon. The finding that for most of the food and agricultural prices, a shock to La Niña results in a statistically significant increase in these stock prices is consistent with the related literature on the impact of La Niña on agricultural yields and prices. Several authors have found that agricultural output decreases during or immediately following La Niña events (see e.g. Hansen et al., 1998; Mauget and Upchurch, 1999; Cadson et al., 1996; and Iizumi et al., 2014). This decrease in agricultural output increases prices in the following periods, triggering a rise in firm cash flows, their profitability, and, hence, their stock prices.

Regarding the responses to an El Niño shock, Figure 2.2 shows that the prices of four firms considered, namely Archer Daniels, Conagra, FMC Corporation, and Mosaic exhibit responses that are negative and significant. For all four companies, the declines turn signif-

**Figure 2.2**: *Responses of U.S. Food and Agricultural Stock Prices to El Niño and La Niña*




***Notes***: Solid blue and red lines represent the responses to La Niña and El Niño shocks, while the corresponding dashed lines are the 90% confidence intervals.

**Table 2.4**: *Long Run Effect of ENSO Shocks on U.S. Food & Agricultural Stock Prices*

| ***Variables*** | (1)<br>El Niño | (2)<br>La Niña | (3)<br>Difference |
|---|---|---|---|
| The Archer Daniels Company | **-0.027** | **0.010** | **-0.037** |
| | [-0.036, -0.018] | [0.002, 0.018] | [-0.050, -0.024] |
| The Campbell Soup Company | 0.006 | **0.035** | **-0.029** |
| | [-0.003, 0.015] | [0.029, 0.041] | [-0.041, -0.017] |
| Conagra Brands, Inc. | **-0.018** | **0.024** | **-0.042** |
| | [-0.027, -0.008] | [0.017, 0.031] | [-0.054, -0.029] |
| The FMC Corporation | **-0.018** | **-0.011** | -0.007 |
| | [-0.028, -0.007] | [-0.024, -0.003] | [-0.020, 0.010] |
| General Mills, Inc. | 0.005 | **0.010** | -0.005 |
| | [-0.001, 0.011] | [0.006, 0.014] | [-0.013, 0.004] |
| The Hershey Company | 0.005 | **0.019** | **-0.014** |
| | [-0.002, 0.012] | [0.014, 0.024] | [-0.024, -0.005] |
| Hormel Foods Corporation | **0.010** | -0.003 | **0.012** |
| | [0.001, 0.018] | [-0.010, 0.003] | [0.001, 0.025] |
| McCormick and Company | **0.011** | 0.005 | 0.006 |
| | [0.003, 0.019] | [-0.000, 0.010] | [-0.005, 0.017] |
| The Mosaic Company | **-0.031** | **-0.015** | -0.016 |
| | [-0.045, -0.016] | [-0.026, -0.004] | [-0.036, 0.005] |
| The J.M. Smucker Company | 0.005 | **0.024** | **-0.019** |
| | [-0.002, 0.013] | [0.018, 0.031] | [-0.030, -0.008] |
| Sysco Corporation | **0.021** | **-0.002** | **0.022** |
| | [0.014, 0.027] | [-0.010, -0.001] | [0.016, 0.035] |
| Tyson Foods, Inc. | 0.010 | **0.036** | **-0.026** |
| | [-0.002, 0.022] | [0.026, 0.045] | [-0.043, -0.009] |

***Notes***: The table presents the cumulative responses to El Niño and La Niña shocks after 12 weeks. Columns 1 and 2 are the responses to El Niño and La Niña shocks. Column shows the difference in response. Numbers in brackets are the 90% confidence intervals. **Bold** indicates statistical significance at the 10% level.

icant after a delay of a few weeks, and remain significant thereafter. Table 2.4 shows that stock prices of Mosaic and Archer Daniels respectively decrease by as much as 3% and 2.7%. Our findings also demonstrate that the responses of Campbell's, General Mills, Smucker, Hershey's, and Tyson are not different from zero in a statistical sense, while for Hormel, Mc-

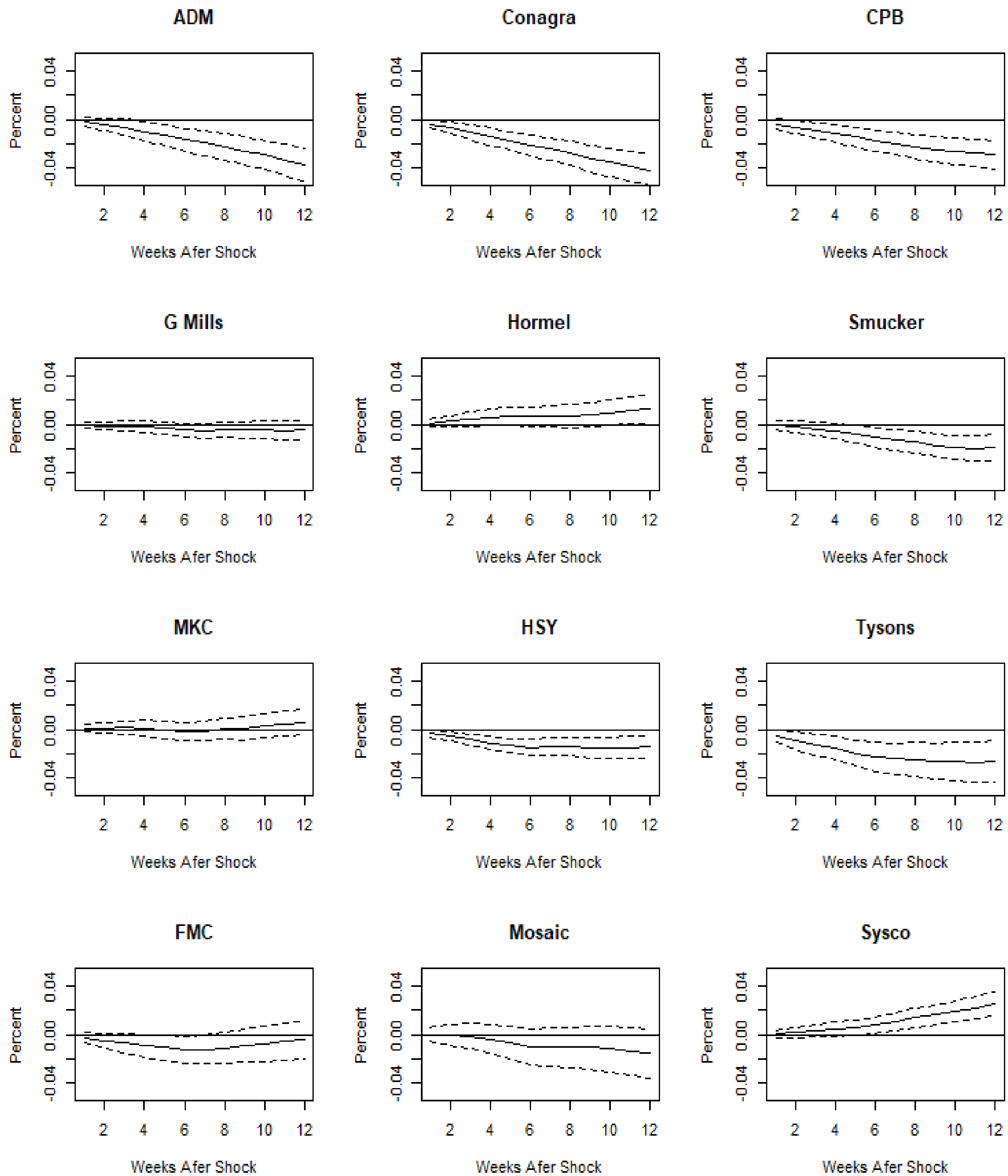
Cormick, and Sysco, an El Niño shock is shown to increase their stock prices. The finding that prices of Archer Daniels and Conagra decrease following an El Niño shock is not surprising. Archer Daniels operates within four segments, namely, Agricultural Services, Corn Processing, Oilseeds Processing, and Wild Flavors and Specialty Ingredients. Their Agricultural Services division buys, stores, and transports agricultural commodities. The Corn Processing division involves corn milling. Oilseeds Processing involves oilseeds marketing, crushing, and processing. Conagra packages and distributes various food brands to supermarkets and restaurants. Given that these companies are all involved with the food and/or grains industry, and grains constitute the largest cost share of animal feed, the warming of sea surface temperatures may decrease output (or prices). In fact, Iizumi et al. (2014) find that yields of corn, rice and wheat changed by -4.3 to 0.8% following an El Niño event. If this decrease in yields is not accompanied by a corresponding or larger increase in prices, then cash flows to these companies, their profitability, and, consequently, their stock prices are expected to decline, thereby validating the negative responses in Figure 2.2.

The significantly negative and persistent responses of Mosaic and the FMC Corporation are interesting because the products of these companies are not directly affected by ENSO. Both companies are providers of crop nutrients. Mosaic specifically concentrates in the production of phosphate, potash, and nitrogen nutrients used to maintain healthy and productive soils. The FMC Corporation manufactures herbicides, insecticides, and fungicides. The warming of sea surface temperatures should not directly impact these products. However, an El Niño shock may affect these companies indirectly for at least two reasons. First, as discussed above El Niño may cause a decrease in agricultural yields, which, in turn may decrease demand for pesticides and fertilizers. Second, El Niño is often associated with above normal temperatures in the fall and winter in the northern tier of the 48 contiguous U.S. states (Ropelewski and Halpert, 1986). Arizona, California, and western New Mexico generally experience above normal rainfall due to the more southerly, zonal, storm track (Andrade and Sellers, 1988), while greater rainfall in states in the U.S. Gulf coast and Southeast are typically attributed to the stronger than average southerly, subtropical jet stream (Beckage et al., 2003; Power et al., 2006). It is possible that the precipitation and temperature changes in these regions provide favorable conditions for crops, causing a decrease in demand for (and, therefore, price of) crop nutrients produced by the FMC Corporation and Mosaic, lowering their cash flows, and triggering a decline in their stock prices.

While Campbell's, General Mills, Smucker, and Tysons are all considered food and/or agricultural companies, they all produce a wide variety of products. Therefore, the insignificance of their responses of to El Niño shocks should not be surprising. Consider General Mills, for example. The company's main products are consumer foods within the cereal breakfast foods industry, but it also operates a number of convenience stores and foodservice segment. The company has locations in Asia, Australia, Europe, and Latin America. Given the large literature that shows spatial differences in the impact of El Niño, it is possible that an El Niño shock that is detrimental to the U.S. might be beneficial for General Mills' operations in its other global locations. If this is the case, then the insignificance of the responses of Campbell's, General Mills, Smucker, and Tysons to El Niño shocks is exactly what one would expect. For Hormel, McCormick, and Sysco, we conjecture that the significantly positive responses to an El Niño shock occur due to an increase in the prices of the products of these companies, which trigger an increase in their revenues and overall profitability.

The key question in this paper is whether there exists asymmetries in the stock price responses between El Niño and La Niña. While a look at Figure 2.2 provides some evidence of asymmetries, a preferred approach is to compute the cumulative difference impulse response functions, as defined in equation (2.11), together with their 90% confidence bands to examine whether this difference is statistically different from zero. Figure 2.3 presents these cumulative difference responses. The figure provides support for the proposition that the impacts of El Niño and La Niña on U.S. agricultural stock prices are asymmetric. For eight of the twelve stock prices, namely Archer Daniels, Conagra, Campbell's, Hershey's, Hormel, Smucker, Tyson, and Sysco, we find significant evidence of asymmetry, with the magnitude of the asymmetries being particularly large for Archer Daniels, Conagra, Campbell's, and Tyson. For the remaining four stock prices, the evidence of asymmetry is weak.

**Figure 2.3**: *Asymmetric Effects of El Niño and La Niña on U.S. Agricultural Stock Prices*




***Notes***: Solid lines represent the cumulative difference in responses between El Niño and La Niña shocks, while the corresponding dashed lines are the 90% confidence intervals.

## 2.4 Sensitivity Analysis

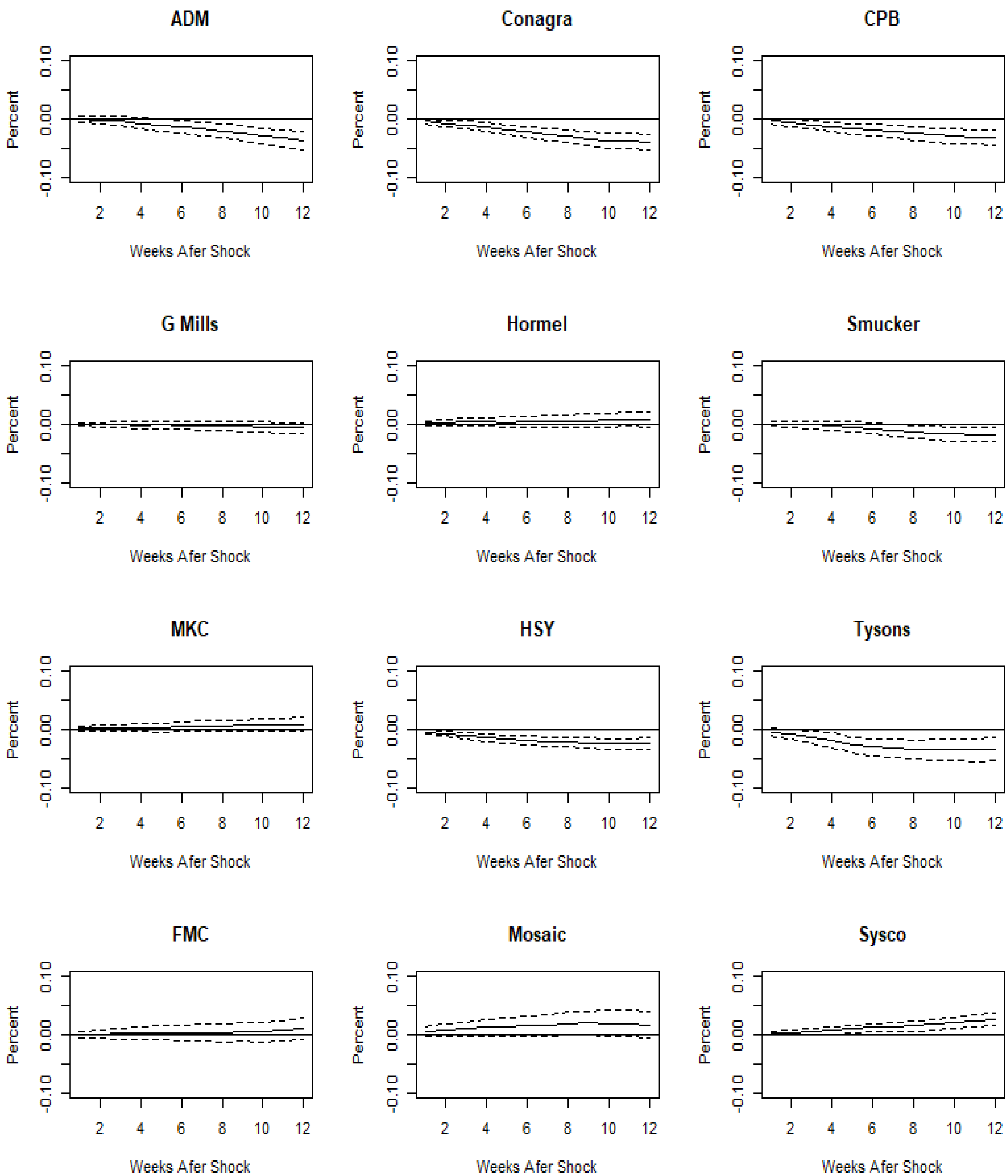
### 2.4.1 Do Neutral ENSO Shocks Matter?

Thus far, we have referred to non-El Niño events as La Niña events. Recall that an El Niño event is defined as three consecutive months of $SSTA > 0.5$, while La Niña refers to three consecutive months of $SSTA < -0.5$. When $-0.5 < SSTA < 0.5$, this is referred to as neutral ENSO events. By referring to non-El Niño events as La Niña events in our analysis thus far, we implicitly assume that neutral ENSO events have no impact of U.S. food and agricultural stock prices. If neutral shocks, however, have an impact on these prices, then the estimated responses to La Niña shocks displayed in Figure 2.2 are biased, and the evidence of asymmetry in Figure 2.3 is misleading. To ensure that neutral shocks have no significant influence on our estimated results, we now define the indicator variable as:

$$I_t = \begin{cases} 1 & SSTA < -0.5 \\ 0 & SSTA \geq -0.5 \end{cases}$$

That is, $I_t = 1$ for La Niña, and $I_t = 0$ for non-La Niña events. We then estimate impulse response functions of stock prices to La Niña and non-La Niña shocks. Since the paper is primarily concerned with the question of asymmetries, we show results of the cumulative difference responses in Figure 2.4. The evidence of asymmetry shown in Figure 2.4 is similar to that shown in Figure 2.3. This suggests that neutral ENSO shocks have no significant impact of on U.S. agricultural stock prices. Importantly, these results reveal that referring to non-El Niño shocks as La Niña shocks is not fundamentally incorrect, as treating non-El Niño shocks as La Niña shocks has no qualitative or quantitative effects on inference about the impact of La Niña on U.S. agricultural stock prices.

**Figure 2.4**: *Asymmetric Effects of El Niño and La Niña on U.S. Agricultural Stock Prices*




***Notes***: Solid lines represent the cumulative difference in responses between El Niño and La Niña shocks, while the corresponding dashed lines are the 90% confidence intervals.

### 2.4.2 Results When Using Monthly Data and Controlling for Macroeconomic Conditions

The main results discussed in Section 2.3 are based on weekly data and bivariate models. While our use of weekly data provides a much richer and more appropriate dataset for estimating the asymmetric impacts of ENSO on U.S. food and agricultural stock prices, it prevents us from controlling for other macroeconomic variables that potentially impact stock prices. Data on many of the relevant macroeconomic indicators, such as aggregate output, wages, and prices, are available only at monthly and quarterly frequencies. While this is unlikely to be a serious issue, as the macroeconomic variables may, in fact, serve as mediators, rather than confounders in the ENSO-stock price relationship, it is worthwhile investigating the potential sensitivity of our results to inclusion of macroeconomic variables shown in the literature to impact stock prices. To this end, we now redo the analysis using monthly data, and control for the impact of aggregate output and inflation.[8] As with the analysis using weekly data, the sample spans the period 1990:01-2019:04.

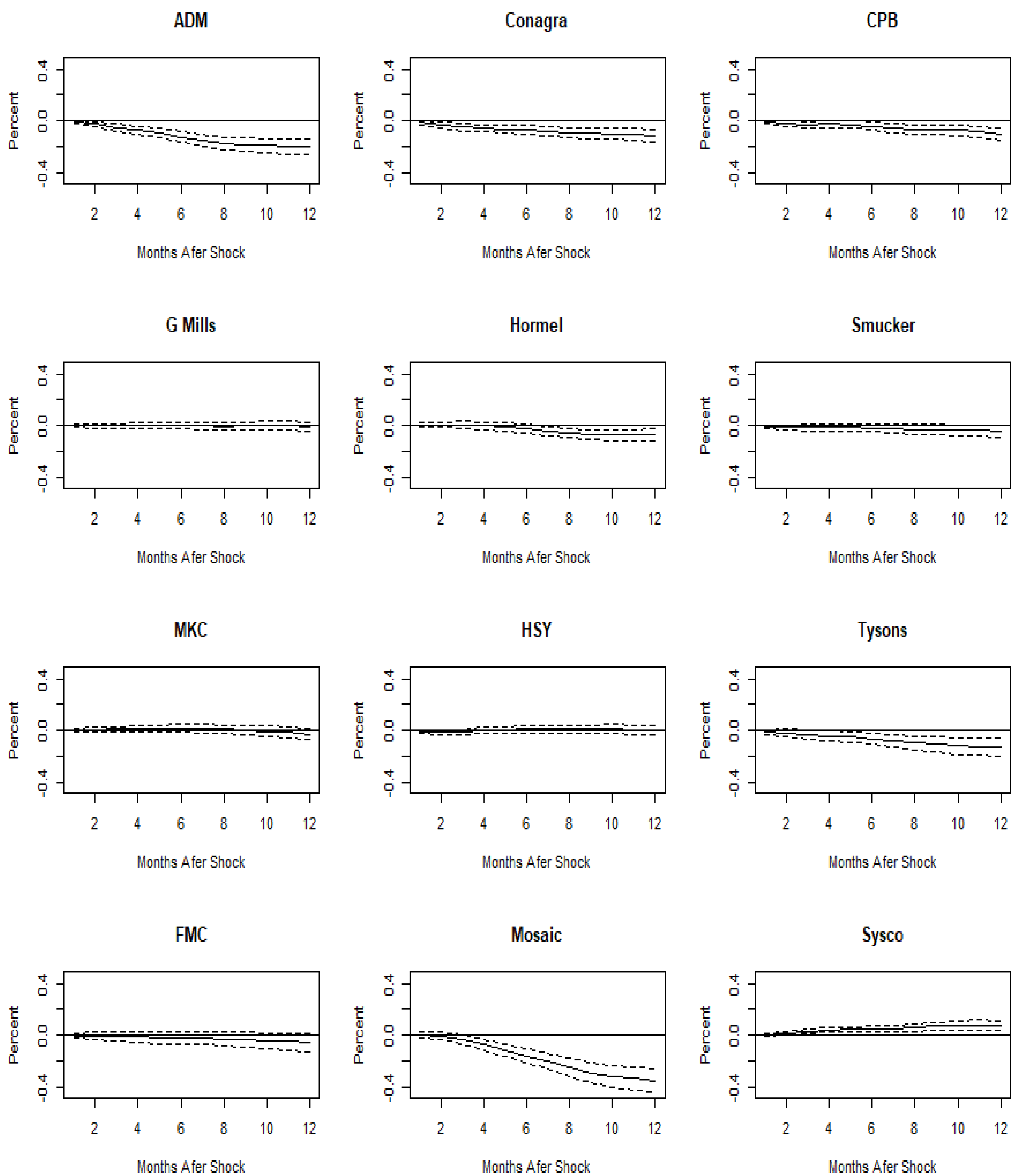
Figure 2.5 presents the cumulative difference functions. As in Figure 2.3, we continue to find that eight of the twelve stock prices display considerable evidence of asymmetry. This finding suggests that the impulse response functions resulting from the use of weekly data are not significantly contaminated by shocks other than El Niño and La Niña shocks, giving some degree of confidence in the main results of the paper.

## 2.5 Conclusion

The goal of this paper is to explore whether El Niño-Southern Oscillation has asymmetric impacts on U.S. food and agricultural stock prices. In particular, using weekly data over the period 1990:01-2019:04 and state-dependent local projection methods introduced by Jorda (2005), we study whether the magnitude, sign, significance, and persistence of the responses

[8] In another robustness check, we find that the results remain virtually unchanged when controlling for a number of other variables, including inflation uncertainty, the broad currency real trade weighted U.S. Dollar index to control for the link between stock prices and the foreign exchange rate, the monthly premium of the book-to-market factor, the monthly premium of the size factor, and momentum of the stock market.

**Figure 2.5**: *Asymmetric Effects of El Niño and La Niña on U.S. Agricultural Stock Prices: Monthly Data*




***Notes***: Solid lines represent the cumulative difference in responses between El Niño and La Niña shocks, while the corresponding dashed lines are the 90% confidence intervals.

of U.S. food and agricultural stock prices to El Niño and La Niña are significantly different from each other. The impulse response functions reveal that La Niña shocks are associated with an increase in stock prices, while the responses to El Niño shocks are typically negative or insignificant. The difference in the stock price responses to El Niño shocks and La Niña shocks are significantly different from zero for eight of the twelve stock prices considered, with our findings robust to the use of monthly data, and controlling for the effect of macroeconomic conditions on stock prices.

The analysis contributes to the rather scant but growing literature on the relationship between ENSO and agricultural stock prices, as it shows that it is not just an ENSO shock that matters for agricultural stock prices, but whether the shock is a La Niña shock or an El Niño shock. Thus, the paper emphasizes the need to disentangle ENSO shocks into corresponding El Niño, and La Niña shocks, as failure to do so might result in misleading conclusions about the effect of ENSO on U.S. food and agricultural stock prices. This presence of asymmetric behavior is of importance to farmers, stock market participants, and academicians. For example, when making predictions (and forecasting models) about movements in agricultural stock prices that arise from an ENSO cycle, this asymmetry needs to be taken into account. This need is growing in importance as climate change is likely to lead to more frequent ENSO anomalies. Furthermore, knowledge that La Niña shocks are generally beneficial to the stock prices of agricultural companies, while El Niño shocks may be detrimental or have no significant effects may guide investors keen on avoiding losses or making profits on the timing of purchases and/or sales of the shares in U.S. food and agricultural companies.

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# Chapter 3

# U.S. Manufacturing Employment and the Oil Price Shock of 1999-2007

## 3.1 Introduction

The price of crude oil rose in spectacular fashion from 1999 to 2007. West Texas Intermediate (WTI) traded at $11.28 per barrel in December 1998 and $91.73 per barrel in December 2007. This oil price spike was notable not only because the price of oil increased more than eightfold, but because it consisted of steady oil price increases for nearly a decade.[1] The only comparable episode occurred in the 1970s, but even then, the upward trend lasted less than seven years. A natural question is how such a large, sustained oil price spike affects the U.S. economy.

An extended increase in the price of oil of the magnitude witnessed from 1999 to 2007 should have meaningful effects on production costs, transportation costs, and disposable consumer income. Industrial sector consumption of oil in 2018, the most recent year for which complete data is available, was 5.13 million barrels per day, or 25% of total U.S. oil consumption. An increase of $80.45 per barrel (the difference in price of WTI in December 2007 and December 1998) translates into $150 billion in increased annual production costs.

[1] WTI rose from December 1998 through June 2008, covering a total of 115 months.

Consumption for transportation purposes was 14.16 million barrels per day, or 69% of total U.S. oil consumption, in 2018. An $80.45 per barrel increase in the price of oil translates into more than $400 billion in increased annual transportation costs. The combined cost to these two sectors alone would have been 2.7% of 2018 GDP.[2]

This paper presents estimates of the effect of the 1999-2007 oil price spike on U.S. manufacturing employment. Using local labor market data, we estimate the change in U.S. manufacturing employment that can be explained by oil price changes driven by oil demand shocks and economic growth in emerging economies.[3] We find that these two oil shocks may have been responsible for the disappearance of more than two million U.S. manufacturing jobs between Decemeber 1998 and December 2007. It is important to emphasize that the "disappearance" of manufacturing jobs may involve a reallocation of labor to other sectors rather than the elimination of U.S. jobs. The U.S. unemployment rate was 4.5% at the end of 1998 and 4.6% at the end of 2007.

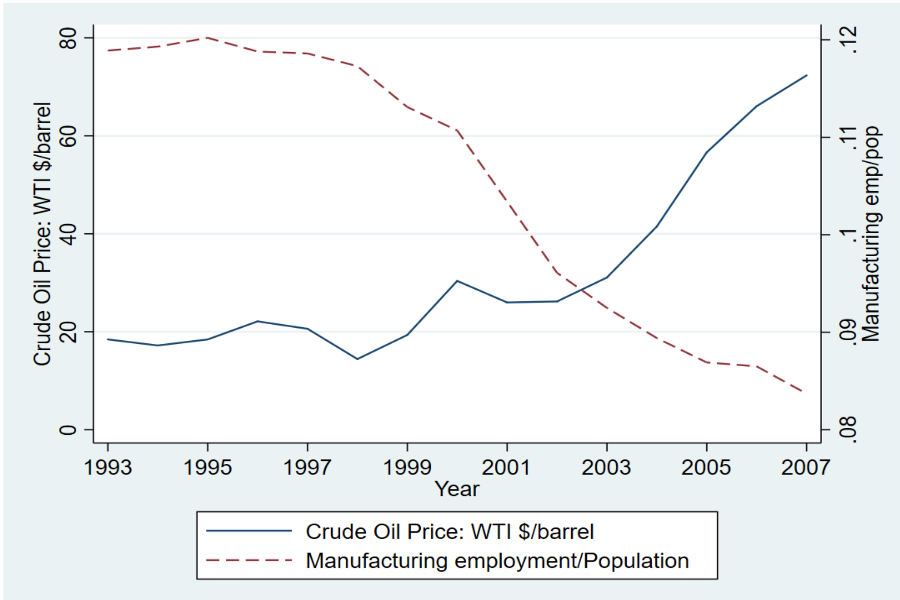
Figure 3.1 shows the share of the U.S. working-age population employed in manufacturing (dashed line/right axis) and West Texas Intermediate crude oil prices (solid line/left axis) between 1993 and 2007. Over the entire time period, the fraction of the working-age population employed in the manufacturing sector across the U.S. fell 30%, while real oil prices rose 174%. Especially notable in the figure is the stability of U.S. manufacturing employment through 1998. Manufacturing employment did not begin its dramatic fall until after the price of oil started rising in 1999.

Another well-documented shock to U.S. manufacturing at this time was the expansion of trade with China. This reallocation of workers away from manufacturing has been called the "China shock" (Autor, Dorn, and Hansen (2013)). We reestimate the model of Autor et al. (2013) controlling for the loss in manufacturing employment that occurred due to oil price shocks. We find that the effect of import exposure on manufacturing employment falls by

[2]These calculations are only intended to demonstrate that a large oil price increase has the potential to decrease manufacturing activity and reallocate manufacturing workers to other sectors of the economy. It is not possible to assign them any further interpretation.

[3]Increases in the price of oil due to developing economy growth are endogenous, but by definition are not a response to U.S. growth. To the extent that these shocks caused developing economies to import more goods from the U.S., we are underestimating the effect of higher oil prices on U.S. manufacturing employment.

**Figure 3.1**: *Share of U.S. Working-Age Population in Manufacturing and Crude Oil Prices*




***Source***: Federal Reserve Economic Data, St. Louis Fed.

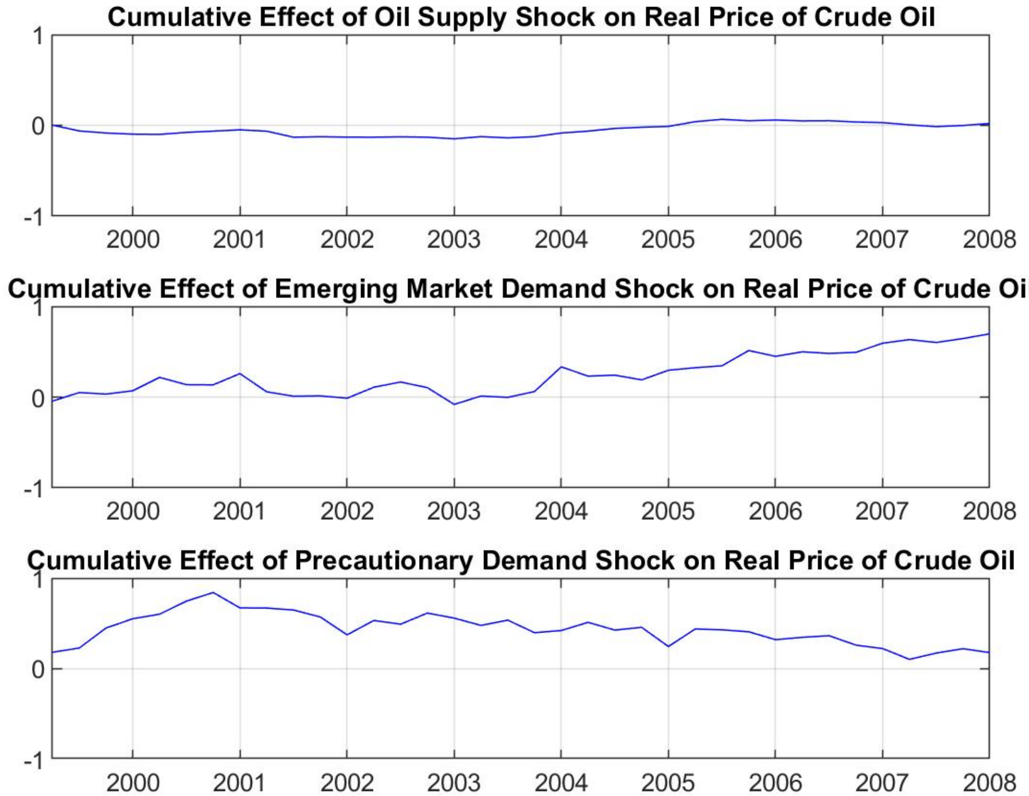
about 21% relative to Autor et al. (2013), primarily due to non-college educated workers, for whom the effect of the China shock on employment is 26% lower when accounting for the oil price spike. This is consistent with a model in which less educated manufacturing workers are hurt more by oil shocks.

The essay proceeds as follows. Section 3.2 investigates the causes of the 1999-2007 oil spike. Section 3.3 describes the econometric methodology used to capture the change in manufacturing employment due to oil price shocks and discusses the estimates. In section 3.4, we reconsider the impact of rising Chinese import exposure on the U.S. local labor market. Section 3.5 concludes.

## 3.2 Understanding the 1999-2007 Oil Price Spike

We begin by decomposing shocks to the real price of oil into global aggregate demand, oil supply, and precautionary demand shocks following Kilian (2009). We then further decompose the global aggregate demand shock into the parts due to developed economy and emerging economy aggregate demand shocks using the methodology proposed by Aastveit,

**Figure 3.2**: *Contribution of oil price shocks during 1999-2007*




***Notes***: Estimates of the cumulative effect are derived from 3.1.

Bjornland, and Thorsrud (2014). This gives us four possible explanations for the oil price spike of 1999-2007. We emphasize that the methods used in this section are not new, with similar results have been reported elsewhere in the literature, including Kilian (2009) and Aastveit et al. (2014). The goal is to provide a foundation for studying the effects of the oil price spike on manufacturing employment.

The first stage of our analysis involves reestimating Kilian's VAR model, which includes 24 lags of global oil production, the real price of oil,[4] and the index of world economic activity based on global shipping rates.[5]

[4] The real price of oil is calculated by deflating the refiner's acquisition cost of crude oil using U.S. CPI.

[5] The real economic activity index was downloaded from Lutz Kilian's personal website (https://sites.google.com/site/lkilian2019/research/data-sets).

$$z_t = A_o^{-1}\alpha + \Sigma_{i=1}^{24} A_o^{-1} A_i z_{t-i} + A_o^{-1}\varepsilon_t \tag{3.1}$$

$$e_t = A_o^{-1}\varepsilon_t = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{s} \\ \varepsilon_t^{ad} \\ \varepsilon_t^{pd} \end{bmatrix} \tag{3.2}$$

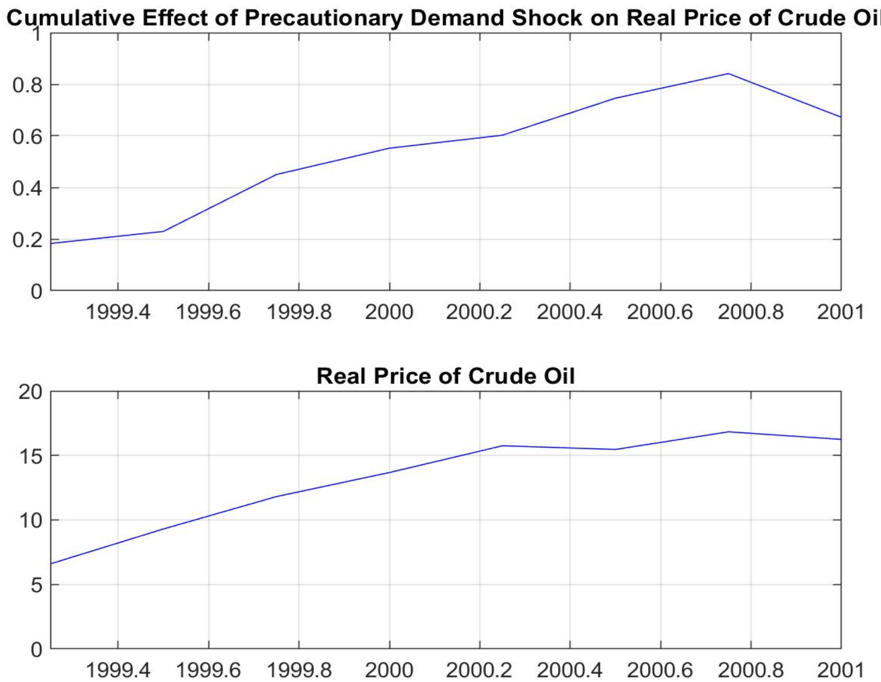
where $z_t = (\Delta prod_t, rea_t, rpo_t)$, $\Delta prod_t$ is the change in global oil production, $rea_t$ is the real economic activity index, and $rpo_t$ is the real price of oil. The VAR residuals are then converted into global aggregate demand ($\varepsilon_t^{ad}$), oil supply ($\varepsilon_t^{s}$), and precautionary oil demand shocks ($\varepsilon_t^{pd}$). The aggregate demand shock can be interpreted as a composite of all shocks to world economic activity as captured by cargo shipping rates. The oil supply shock captures traditional disruptions to the oil supply such as the overthrow of the Shah of Iran in 1979. The precautionary demand shock captures news about events that will affect the supply of oil in the future, but do not immediately affect the supply of oil.

The dataset is nearly identical to that of Kilian (2009). It spans the time period 1973-2007. The real price of oil is computed by deflating the refiner's acquisition cost of crude oil by the U.S. CPI.[6] The real economic activity index based on global shipping rates was downloaded from Lutz Kilian's website. Global crude oil production data was downloaded from the EIA.

The global aggregate demand shock captures shocks to world oil demand, including those originating in the United States. In order to compute a meaningful measure of the effect of oil shocks on U.S. manufacturing, it is necessary to focus on changes in the demand for oil originating outside the U.S. Aastveit et al. (2014) decomposed the global aggregate demand shock into the parts due to emerging economy growth (including countries such as China and India) and developed economy growth (including the U.S.). We apply the methodology of Aastveit et al. (2014) to our dataset to isolate the shocks to oil demand originating in emerging economies. The Aastveit et al. (2014) dataset contains the gross domestic product

[6] The cost of crude of oil is downloaded from the Energy Information Administration (EIA).

**Figure 3.3**: *Precautionary Demand Shock & Price of Crude Oil: 1999-2000*




***Notes***: Estimates of the cumulative effect are derived from 3.1, and the real price of crude oil is plotted using data from the U.S. Energy Information Administration.

and industrial production series for 14 major emerging economies.[7]

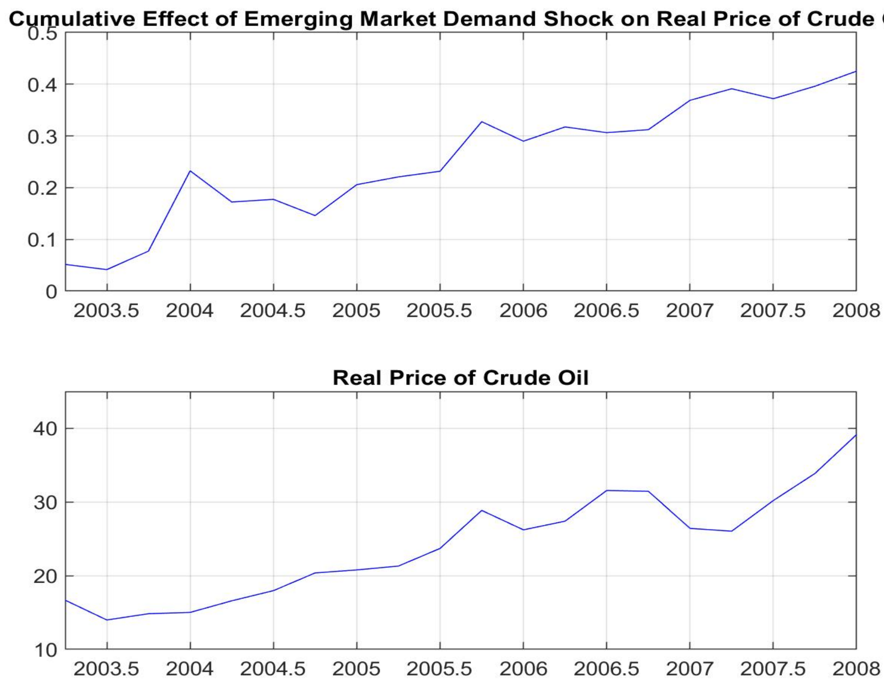
The second stage of our analysis consists of estimating the unobserved activity factors for emerging economies, $EF_t$, using the method of principal components. We then regress the global aggregate demand shock on lags zero through four of the emerging markets factor. The fitted value of that regression is the component of the world aggregate demand shock attributable to emerging economy growth, and the residual is the component due to growth in other countries.

$$\varepsilon_t^{ad} = \beta_0 + \Sigma_{k=0}^4 \beta_k EF_{t-k} + \upsilon_t \tag{3.3}$$

Figure 3.2 shows the contributions of each of the shocks to the 1999-2007 oil price spike cumulatively starting in 1999. The first thing that is apparent in that figure is that the oil

[7]These emerging economies include Argentina, India, South Korea, Malaysia, Taiwan, Singapore, Hong Kong, China, Thailand, Brazil, South Africa, Peru, Chile, and Indonesia.

**Figure 3.4**: *Emerging Market Demand Shock & Price of Crude Oil: 2003-2007*




***Notes***: Estimates of the cumulative effect are derived from 3.1, and the real price of crude oil is plotted using data from the U.S. Energy Information Administration.

supply shock was not responsible for any of the oil price spike. Second, as shown in Figure 3.3, the first two years of the spike were due to concerns about the future oil supply, in the form of precautionary oil demand shocks. Third, the time period after the invasion of Iraq is explained by emerging market demand as represented in Figure 3.4.

Figures 3.3 and 3.4 strongly suggest that oil price shocks originating because of developing economies growth and conflict in the Middle East are mostly responsible for the upward trajectory in oil prices. In light of these results, we focus on the effects of the emerging market demand and precautionary demand shocks on the U.S. manufacturing sector. Those shocks can explain the 1999-2007 oil price spike, and they capture factors external to the U.S. economy.

The detail about the steps of our analysis are as follows. First, we measure the employment effects of emerging market demand and precautionary demand shocks in Section 3. Second, we use the fitted value of industry-level employment changes to calculate the exposure of U.S. manufacturing employment to oil price shocks in Section 4. This is followed by reevaluating the effects of U.S. exposure to Chinese imports at the local labor market level after controlling for the loss in employment due to oil demand shocks in the same section.

## 3.3 Predicting Changes in Employment Due to Oil Price Shocks

This section focuses on the stage of our analysis in which we capture movements in oil prices due to emerging market demand and precautionary demand shocks. This is followed by iteratively computing the predicted manufacturing share of the workforce for each industry. A discussion of the data also follows.

### 3.3.1 Manufacturing Data

**Table 3.1**: *Manufacturing Industries (3-digit NAICS)*

| Industry | NAICS | Industry | NAICS |
|---|---|---|---|
| Food & Beverages | 311 | Nonmetallic Minerals | 327 |
| Textile Mills | 313 | Misc. Nondurables | 329 |
| Textile Products | 314 | Primary Metals | 331 |
| Apparel Manufacturing | 315 | Fabricated Metals | 332 |
| Wood Product | 321 | Machinery Manufacturing | 333 |
| Paper Manufacturing | 322 | Computers & Electronic Products | 334 |
| Printing & Support | 323 | Electrical Equipment | 335 |
| Petroleum & Coal Products | 324 | Transportation Equipment | 336 |
| Chemical Manufacturing | 325 | Furniture & Related Product | 337 |
| Plastics & Rubber Products | 326 | Misc. Durables | 339 |

The investigation about the predicted change in U.S. manufacturing as a result of the two oil demand shocks originating in developing countries, and because of political instability in the Middle East uses quarterly data on employment for twenty industries aggregated at the 3-digit of the NAICS. These twenty industries listed in Table 3.1 as a whole comprise the U.S. manufacturing sector.

### 3.3.2 Employment Changes Due to Oil Shocks

**Table 3.2**: *p-values for* $\Sigma_{k=0}^{8}\beta_k = \Sigma_{k=0}^{8}\gamma_k = 0$

| Industry | p-value | Industry | p-value |
|---|---|---|---|
| Apparel | 0.00 | Nonmetallic | 0.00 |
| Chemicals | 0.00 | Paper | 0.00 |
| Computer | 0.00 | Petroleum | 0.00 |
| Electrical | 0.00 | Plastics | 0.00 |
| Fabricated | 0.00 | Primary | 0.00 |
| Food | 0.00 | Printing | 0.00 |
| Furniture | 0.00 | Textile Mills | 0.00 |
| Machinery | 0.00 | Textile Product | 0.00 |
| Misc. Durables | 0.00 | Transportation | 0.00 |
| Misc. Nondurables | 0.00 | Wood | 0.00 |

This section computes the change in manufacturing employment that would have been expected to occur on the basis of the emerging market demand and precautionary demand shocks observed over the 1999-2007 time period.[8] We estimate the following equation for each industry using quarterly data:

$$\triangle man_{j,t} = \beta_0 + \Sigma_{k=0}^{8}\beta_k\varepsilon_{t-k}^{pd} + \Sigma_{k=0}^{8}\gamma_k\varepsilon_{t-k}^{ed} + v_t \tag{3.4}$$

where $\Delta man_{j,t}$ is the quarterly change in industry $j$ manufacturing employment as a share of the working age population, $\varepsilon_t^{pd}$ is the precautionary demand shock, $\varepsilon_t^{ed}$ is the emerging market demand shock, and a lag length of eight was selected using the AIC. Moreover, we also rely on an F-test for the purpose of lag selection. We reject the F-test for the null hypothesis $\Sigma_{k=0}^{8}\beta_k = \Sigma_{k=0}^{8}\gamma_k = 0$ of zero coefficients at a 5% level in every case. The p-values from the test are reported in Table 3.2. The fitted values of this equation, $\triangle\widehat{man}_{j,t}$ can be interpreted as the predicted change in the percentage of the working age population employed in manufacturing conditional on the two oil shocks. A negative fitted value implies manufacturing employment fell in that sector in response to the oil shocks that hit the economy that quarter.[9]

[8] We start the data in 1999 because the price of oil bottomed out at the end of 1998.

[9] "Response" is used in the sense of an impulse response function.

Letting $man_{j,t}$ be the manufacturing share of the working age population in industry $j$ in quarter $t$, the predicted level of manufacturing employment in industry $j$ in quarter $t+1$ is

$$\widehat{man}_{j,t+1} = (1 + \Delta\widehat{man}_{j,t+1})\, man_{j,t}. \tag{3.5}$$

Given the initial manufacturing shares for each industry and the oil shock series, we are able to iterate on the above formula to compute the predicted end of sample manufacturing share of the workforce for each industry. With that information, and the working age population at the start and end of the sample, we are able to calculate the change in manufacturing employment across all industries for the years 1993 through 2007. The representation of the growth rate of manufacturing employment as a share of the workforce for each industry for the years 1993 through 1998 and 1999 through 2007 is as follows:

$$\triangle\widehat{L}_{j1}^{man} = \frac{\widehat{man}_{j,1998:4} - man_{j,1993:4}}{man_{j,1993:4}} \tag{3.6}$$

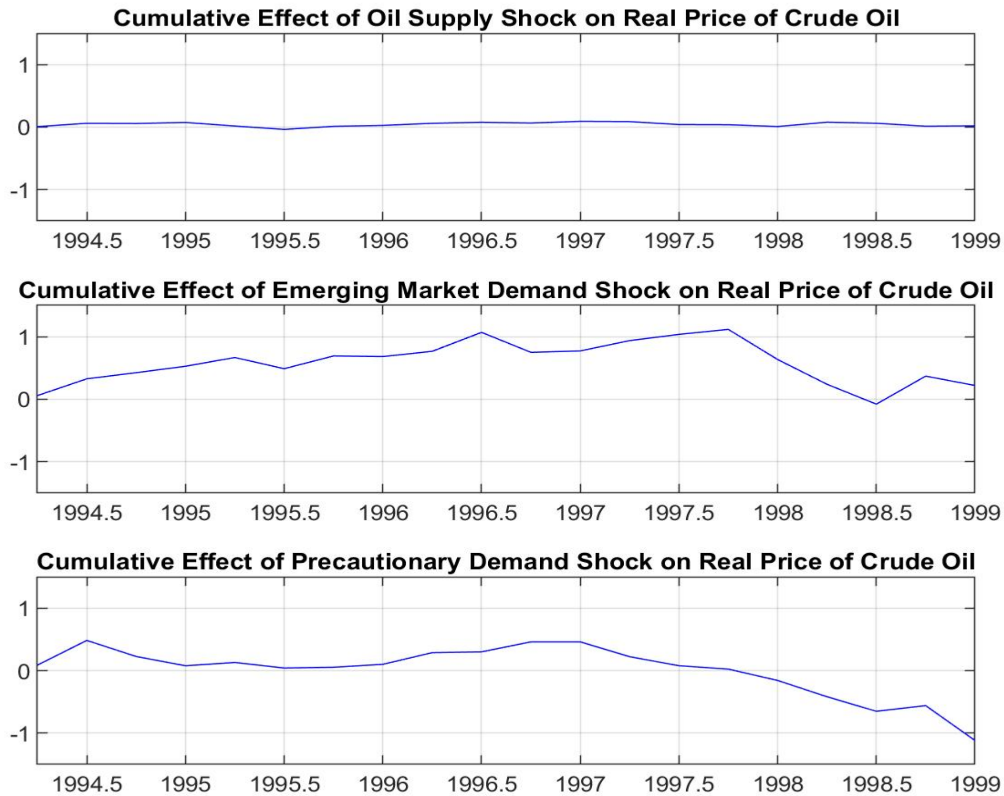
$$\triangle\widehat{L}_{j2}^{man} = \frac{\widehat{man}_{j,2007:4} - \widehat{man}_{j,1998:4}}{\widehat{man}_{j,1998:4}} \tag{3.7}$$

### 3.3.3 Results

Table 3.3 shows the predicted change in manufacturing employment as a result of oil shocks in the pre-spike (1993-1998) and spike (1999-2007) time periods. The change in employment and the percentage change in employment as a share of the working age population are shown for each period. Our estimates suggest that oil price shocks were responsible for the disappearance of about 430,000 manufacturing jobs between 1993 and 1998, and 2.4 million jobs between 1999 and 2007.[10] The job loss in the early subsample was mostly due to a $10 increase in the price of oil over the 1994-1996 time period. The increase was driven by the emerging market demand shock prior to the Asian financial crisis, as shown in Figure 3.5.

[10] These numbers are also in line with the change in employment described by Acemoglu et al. (2016)

**Figure 3.5**: *Contribution of oil price shocks during 1994-1998*




***Notes***: Estimates of the cumulative effect are derived from 3.1.

In percentage terms, the industries hit hardest by the oil demand shocks were those in which i) the U.S. did not have comparative advantage, and ii) were intensive in unskilled labor. This included industries like apparel, textile mills, and textile products. Using only the oil shocks observed in the 1999-2007 time period, we predict more than 560,000 workers moved out of those three industries. Our estimated model predicts that every industry would have lost at least 12% of employment as a share of the workforce based on the oil shocks in that time period. There are two mechanisms that explain this response. First, production and distribution costs increased. This led to firms cutting production and raising prices. Second, an increase in the price of oil leaves consumers with less disposable income. It is possible that the availability of cheap imports resulted in a shift to lower-priced imported goods in these sectors as the U.S. economy shifted to production of other goods, such as

**Table 3.3**: *Manufacturing Employment Response to Oil Shocks*

| | 1993-1998 | | 1999-2007 | |
|---|---|---|---|---|
| | Change | Share of WA Population | Change | Share of WA Population |
| Apparel | -296,058 | -38.5% | -334,773 | -65.9% |
| Chemicals | -54,735 | -10.2% | -107,828 | -21.4% |
| Computers | -64,899 | -8.9% | -315,809 | -29.2% |
| Electrical | -23,156 | -8.9% | -125,560 | -31.5% |
| Fabricated | 101,803 | 1.2% | -63,520 | -14.9% |
| Food | -590 | -5.1% | -52,969 | -14.5% |
| Furniture | -8470 | -6.5% | -55,527 | -20.0% |
| Machinery | -53,297 | -1.3% | -213,613 | -25.0% |
| Misc. Durables | -10,818 | -6.6% | -54,095 | -18.4% |
| Misc. Nondurables | -33,054 | -14.8% | -58,843 | -29.3% |
| Nonmetallic | 2772 | -4.6% | -4558 | -12.3% |
| Paper | -51,778 | -12.8% | -132,045 | -31.4% |
| Petroleum | -6637 | -9.5% | -23,813 | -26.8% |
| Plastics | -8207 | -6.0% | -98,824 | -21.8% |
| Primary | -9915 | -3.6% | -92,424 | -24.5% |
| Printing | -19,655 | -7.5% | -153,164 | -29.1% |
| Textile Mills | -131,590 | -31.3% | -180,988 | -57.9% |
| Textile Products | -30,243 | -17.3% | -50,982 | -33.5% |
| Transport | -49,197 | -2.7% | -257,192 | -23.1% |
| Wood | -5496 | -4.1% | -41,942 | -18.3% |
| Total | -429,666 | | -2,418,469 | |

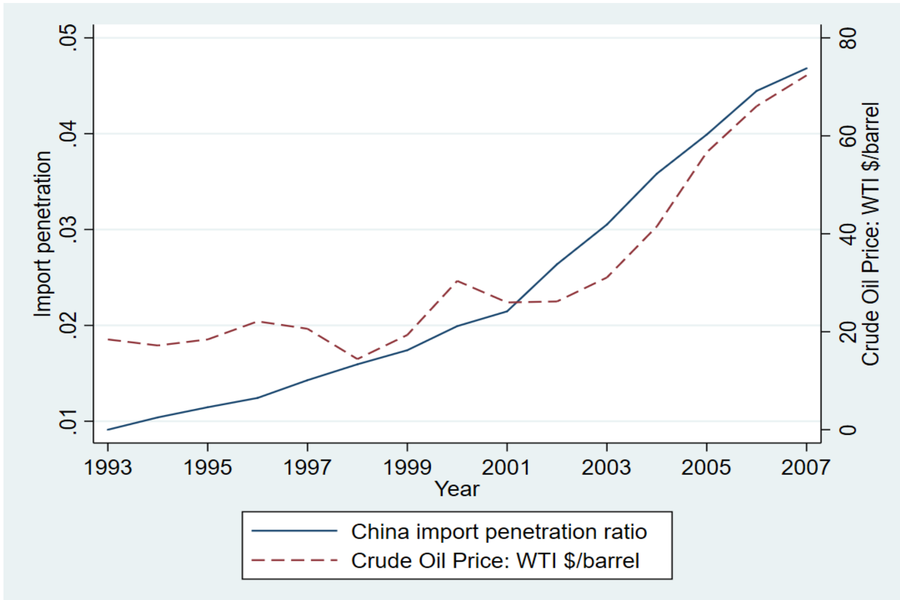
housing.[11] A standard macroeconomic model (e.g. Blanchard and Gali (2009)) implies that firms will offset oil shocks by cutting the wage. In the presence of demand for workers from other sectors, manufacturing firms would not been able to cut wages, and instead would have had to cut production, continuing to employ workers that were not able to move from manufacturing to other sectors.

## 3.4 International Trade and Manufacturing Employment

The previous section established that a structural VAR model predicts more than two million workers left the U.S. manufacturing sector as a response to the 1999-2007 oil price spike. Autor et al. (hereafter referred to as ADH) estimated a model in which the change in

[11] Construction employment rose by more than 20% over this time period (1.4 million workers) compared to an increase in the labor force of less than 9%.

**Figure 3.6**: *Import Penetration Ratio For U.S. Imports from China and Crude Oil Prices*




***Source***: Autor et al. (2013), and Federal Reserve Economic Data, St. Louis Fed.

manufacturing employment as a share of the working age population depends on the "import exposure" of the local labor market. A potential complication arises from the fact that there is likely to be overlap between a sector's sensitivity to oil price shocks and the sensitivity to import competition. One reason to expect a correlation in responses is that an increase in the price of oil can cause a shift to purchases of imported goods. As shown in Figure 3.1, the large exodus out of manufacturing employment didn't occur until the price of oil started its sustained upward movement.

Figure 3.6 plots the import penetration ratio (defined and calculated by ADH) and West Texas Intermediate (WTI) crude oil prices across our entire sample period. There are two points to consider in that figure. First, import penetration and the price of oil both had strong upward trends in this time period. Second, import penetration increased rapidly over the entire 1993-2007 time period. Import penetration nearly doubled in the 1993-1998 time period (prior to the oil price spike) yet manufacturing employment didn't change much over that time period. The question we ask in this section is how the results of ADH are affected if we control for the oil price exposure of local labor markets.

### 3.4.1 Local Labor Market Data

We utilize the dataset on employment by industry at the commuting zone level for the years 1990 and 2000 analyzed by Silva and Shen (2018) to calculate the oil exposure variable. This dataset is organized at the 4-digit of the 1987 Standard Industrial Classification (SIC) System. We proceed by using a concordance that relates the 4-digit of the SIC to a particular industry at the 6-digit of the NAICS, which is folllowed by aggregating an industry organized at 6 digit of the NAICS to an industry at the 3 digit level. This allows us to match the local labor market data with the fitted value of industry-level employment changes due to oil demand shocks calculated in Section 3.

### 3.4.2 Measuring Oil Price Exposure

ADH constructed a measure of import exposure for each of 722 commuting zones covering the U.S. We use the results above to construct a corresponding measure of exposure of manufacturing employment in each commuting zone to oil price shocks through two time periods, i.e. 1993-2000 and 2000-2007. This variable measures the vulnerability of each labor market zone to oil price shocks between 1993 and 2007. Defining the start of period employment share of industry $j$ in commuting zone $z$ as

$$s_{jz} = \frac{L_{jz}}{L_z} \tag{3.8}$$

where $L_{jz}$ is industry $j$ employment in commuting zone $z$ and $L_z$ is total employment in commuting zone $z$.[12] Using $\triangle\widehat{L}_{j1}^{man}$ and $\triangle\widehat{L}_{j2}^{man}$ that we calculated earlier, we have

$$\Delta OPE_{z1} = \sum_{j=1}^{20} s_{jz}\triangle\widehat{L}_{j1}^{man} \tag{3.9}$$

[12] Since local labor market data is available for every 10 years, we define the start of period as 1990 and 2000 similar to ADH.

**Table 3.4**: *Descriptive Statistics of Oil Exposure Variable, Manufacturing*

| Time Period | Obs. | Mean | Min | Max |
|---|---|---|---|---|
| 1993-2000 | 722 | -2.77% | -17.46% | 0 |
| 2000-2007 | 722 | -3.26% | -13.11% | -0.003% |

as a measure of oil price exposure in the first (pre-spike) subsample and

$$\Delta OPE_{z2} = \sum_{j=1}^{20} s_{jz} \triangle \widehat{L}_{j2}^{man} \tag{3.10}$$

for the second (spike) subsample.[13] Commuting zones with higher values of $OPE$ have a greater exposure to oil price shocks based on the distribution of employment across sectors. Note that it is necessary to compute different $OPE$ measures for each time period because the distribution of the two oil shocks was not the same across the first and second subsamples. The distributions of the oil exposure variable across the 722 commuting zones are plotted in Figures 3.7 and 3.8. The variation in the oil exposure variable stems from two sources: differential response of each industry's employment to oil price shocks $\Delta\hat{L}_{jt}^{man}$, and start of period employment share of industry j in commuting zone z $s_{jz}$.

The model of ADH modified to include the oil exposure variable is

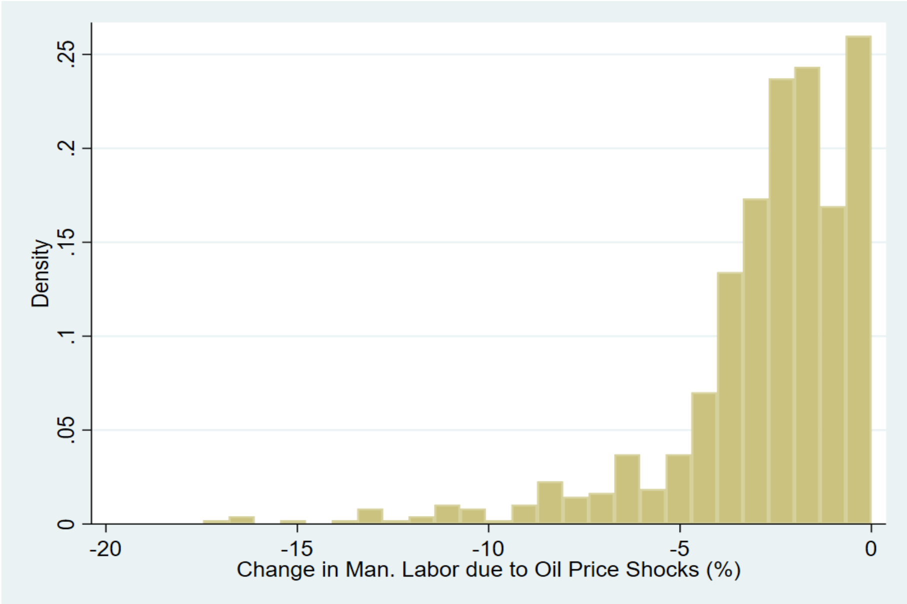
$$\Delta L_{zt}^{m} = \gamma_z + \beta_1 \Delta IPW_{uzt} + \beta_2 \Delta OPE_{zt} + X_{zt}^{'}\beta_2 + e_{zt} \tag{3.11}$$

where $\Delta L_{zt}^{m}$ is the commuting zone $z$ change in manufacturing employment as a share of working-age population in period $t$ for $t = 1, 2$; $\Delta IPW_{uzt}$ is the exposure of commuting zone $z$ to import competition from China; and $X_{zt}^{'}$ are controls specific to commuting zone $z$.[14] Similar to ADH, we also instrument for $\Delta IPW_{uzt}$ using the Chinese imports growth in eight other developed economies which include, Australia, Denmark, Finland, Germany, Japan, New Zealand, Switzerland, and Spain. Our estimation equation is identical to that of ADH

[13] $\Delta\hat{L}_{jt}^{man}$ is the predicted change in manufacturing employment in industry j between the start and end of both periods. Period 1 starts in 1993 Q4 and ends in 2000 Q1, whereas period 2 starts in 2000Q1 and ends in 2007Q4. These time periods were chosen to allow the matching of our data with that of ADH.

[14] We use the same controls as ADH.

**Figure 3.7**: *Distribution of the Change in Manufacturing Labor due to Oil Price Shocks, 1993-2000*



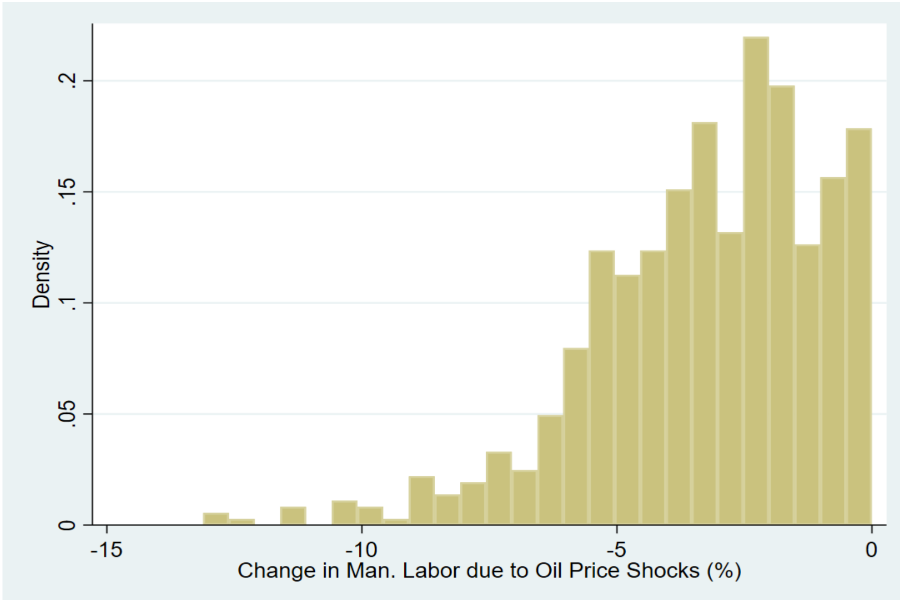

***Notes***: Calculations based on Equation 3.9.

other than the addition of the $OPE$ term.

### 3.4.3 Results

We estimate equation 3.11 using the full sample, as well as for the subsample of workers with and without a college degree. The estimated coefficients for all workers, workers with a college degree, and workers without a college degree are reported in Table 3.5. For comparison, we use the coefficients reported in column 6 from Table 3 in ADH for all workers, row 3 from Table 5 in ADH for workers with a college degree, and row 4 from Table 5 in ADH for workers without a college degree. Coefficients on the control variables are not interpreted and therefore are not reported. For all workers, ADH reported a coefficient on exposure to Chinese imports of -0.596. When controlling for oil price exposure, the coefficient is -0.47, roughly 20% smaller in magnitude than in ADH. The oil price exposure variable is constructed so that as oil price exposure rises, manufacturing employment in that commuting zone falls by a greater amount. The coefficient on oil price exposure is more than four standard errors from zero (p-value = 0.00) .

**Figure 3.8**: *Distribution of the Change in Manufacturing Labor due to Oil Price Shocks, 2000-2007*




***Notes***: Calculations based on Equation 3.10.

ADH found that increased Chinese import exposure had similar effects on workers with a college degree as it did on workers without a college degree. The coefficients in the last four columns of Table 3.5 show that an increase in oil price exposure results in twice as many workers without a college degree leaving the manufacturing sector (-0.628 vs -0.310). As a result, controlling for oil price exposure is less important for the coefficient on Chinese import exposure (-0.592 vs -0.516) for workers with a college degree than it is for workers without a college degree (-0.581 vs -0.429). The effect of Chinese import exposure is 26% smaller for workers without a college degree when controlling for oil price exposure. A potential explanation for this finding is that it is easier to substitute Chinese imports for goods that rely more heavily on less-educated workers in the aftermath of an oil price shock. A proper investigation of the different effects across worker education levels is beyond the scope of this paper.[15]

[15] A recent paper by Xu, Ma, and Feenstra (2019) argues that the effects of Chinese import exposure found in ADH were inflated by failing to control for the behavior of the U.S. housing market.

**Table 3.5**: *Effect of Import Exposure on Manufacturing Controlling for Oil Price Exposure*

| | All Workers | | College Degree | | No College Degree | |
|---|---|---|---|---|---|---|
| Import Exposure | -0.596 | -0.470 | -0.592 | -0.516 | -0.581 | -0.429 |
| (s.e.) | (0.099) | (0.097) | (0.125) | (0.129) | (0.095) | (0.083) |
| Oil Price Exposure | | -0.521 | | -0.310 | | -0.628 |
| (s.e.) | | (0.123) | | (0.127) | | (0.138) |

### 3.4.4 Calculating employment changes due to oil price shocks and China shock

We now use the estimated coefficients in Table 3.5 to recalculate employment changes associated with the China shock. Based on our data, the working age population for all persons aged 15-64 in the United States was 164.9, 178.3, and 196.2 million in 1993 Q4, 2000 Q1, and 2007 Q4 respectively. The coefficient for ADH (2013) is 0.596 pp, which translates to 0.00596. However, ADH (2013) consider the ten-year change in import growth between 1990-2000, and the seven-year change in import growth between 2000-2007. Since our data availability allows us to conduct the analysis from 1993 onwards, we multiply the 1990-2000 change in import growth by 7/10 to compare it in seven-year equivalent terms (1993-2000).

Based on this calculation, U.S. imports from China increased by \$798/worker through 1993-2000, and by \$1,839/worker through 2000-2007. The ADH (2013) estimate of the change in the share of manufacturing employment due to rising Chinese import exposure through 1993-2000 is as follows,

$$\hat{\beta}_{IV} \times \Delta IPW_{2000} \times 0.48 = 0.596 \times 0.798 \times 0.48 = 0.23.$$

Whereas, the calculation through 2000-2007 is,

$$\hat{\beta}_{IV} \times \Delta IPW_{2007} \times 0.48 = 0.596 \times 1.839 \times 0.48 = 0.53.$$

These numbers suggest that the supply-shock driven net reduction in U.S. manufacturing employment was approximately 1.37 million workers through 1993-2007,

$$[0.5 \times (164.8 + 178.3) \times 0.798 + 0.5 \times (178.3 + 196.2) \times 1.84] \times (-0.00596 \times 0.48) = -1,377,294.$$

Since our re-estimated coefficient in column (2) of Table 3.5 is 0.0047, the supply-shock driven net reduction in U.S. manufacturing employment implies a net loss of approximately 1.08 million jobs.

$$[0.5 \times (164.8 + 178.3) \times 0.798 + 0.5 \times (178.3 + 196.2) \times 1.84] \times (-0.00470 \times 0.48) = -1,086,121.$$

As mentioned earlier, there is likely to be overlap between a sector's sensitivity to oil price shocks and the sensitivity to import competition. One reason to expect a correlation in responses is that an increase in the price of oil can cause a shift to purchases of imported goods. We argue that the China shock operated partially through the oil market, and the loss of approximately 291,173 U.S. manufacturing jobs was in response to rising oil exposure.

$$-1,377,294 + 1,086,121 = -291,173$$

We also calculate employment losses across workers with varying levels of education. Despite not having information on college and non-college educated workers, we are able to calculate these using the data sets of ADH (2013) and Acemoglu et al. (2016). ADH (2013) provide data on college and non-college educated workers as a share of working-age population from 1990 to 2007. The Acemoglu et al. (2016) data set contains information on the working-age population by commuting zones for 1993, 2000, and 2007. We extract the variables of interest from both these data sets and calculate the number of workers for each education level in the following manner.

$$College\ Educated\ Workers = Share\ of\ College\ Educated \times Working\ Age\ Pop.$$

This calculation is done at the commuting zone level, so we aggregate data at the national level and find that the share of college-educated workers for 1993, 2000, and 2007 is 48.2%, 53.6%, and 58.7% respectively. Our estimates further suggest that college-educated workers are 79.4, 95.6, and 115.2 million for 1993, 2000, and 2007 respectively. On the other hand, non-college educated workers amount to 85.5, 82.7, and 81 million in 1993, 2000, and 2007 respectively. ADH (2013) estimates of job losses due to the China shock between 1993 and 2007 are as follows,

College, Manufacturing:

$$[0.5 \times (79.4 + 95.6) \times 0.798 + 0.5 \times (95.6 + 115.2) \times 1.84] \times (-0.00592 \times 0.48) = -749,503$$

Noncollege, Manufacturing:

$$[0.5 \times (85.5 + 82.7) \times 0.798 + 0.5 \times (82.7 + 81) \times 1.84] \times (-0.00581 \times 0.48) = -607,165.$$

On the other hand, our estimates of job losses due to China shock between 1993 and 2007 are as follows,

College, Manufacturing:

$$[0.5 \times (79.4 + 95.6) \times 0.798 + 0.5 \times (95.6 + 115.2) \times 1.84] \times (-0.00516 \times 0.48) = -653,283$$

Noncollege, Manufacturing:

$$[0.5 \times (85.5 + 82.7) \times 0.798 + 0.5 \times (82.7 + 81) \times 1.84] \times (-0.00429 \times 0.48) = -448,320.$$

We find that in both cases the impact of import exposure decreases following controlling for the loss in employment due to oil price shocks. However, it is more important to control for oil exposure in the case of non-college educated workers as opposed to college educated ones. The job losses associated with the China shock reduce by 160,000 for non-college workers in comparison to 96,000 for college workers after controlling for oil exposure.

## 3.5 Conclusion

The 1999-2007 oil price spike was the longest sustained upward movement of oil prices in history. The timing of the oil price spike coincided with a rapid decline in U.S. manufacturing employment. We conclude that there was a reallocation of more than two million manufacturing workers in response to the oil price shocks observed over that time period. In addition, we found that the estimated effect of trade exposure declines substantially when controlling for a local labor market's exposure to oil price shocks, particularly for workers that do not have a college degree.

The methodology of this paper is able to provide an estimate of the number of workers that left U.S. manufacturing in response to the oil spike, but it is not able to provide identify the mechanisms by which the changes take place. Of particular interest is the interaction between oil shocks and international trade. A ready supply of cheap imports may induce a reallocation of labor among sectors. Properly isolating the different mechanisms by which oil shocks affect manufacturing employment would require a fully-specified open economy macroeconomic model.

It is also worth noting that we have modeled the effects of oil price shocks using linear models. While a linear model might provide a reasonable approximation in many situations, we have focused on a time period with extreme behavior of oil prices, with WTI increasing eightfold from the start to the end of the spike. It is times like these, with extreme behavior of oil prices, that accounting for nonlinearities is most important.

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