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Essays On The Effects Of Oil Price Shocks On The U.s. Stock Returns

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DEDICATION

To my lovely family

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Chapter 1: Introduction

Are energy price increases perceived to have larger effects than energy price decreases on the U.S. financial markets? Is the effect different between energy-intensive and non-intensive sectors? Does the size of the oil shock matters. This dissertation takes a fresh look at these questions using a conventional model proposed by Kilian and Vigfusson (2009). Since the 1970s, the macroeconomic literature has been testing for the oil price-macroeconomy relationship (see, e.g., Loungani (1986); Mork (1989); Lee, Ni and Ratti (1995); Hooker (1996); Hamilton (2010)), and questioning the symmetric responses of macroeconomic aggregates (see, e.g., by Kilian and Vigfusson (2009); Hamilton (2009); Herrera, Lagalo, and Wada (2010)), mainly after the major unanticipated falls in the price of oil, as appeared in 1986, 1998, and late 2008. On the other hand, the structural stability and functional form of the oil price-financial market relationship have been widely ignored in the literature. Although there are quite a few papers in the literature examining the impact of oil price changes on stock returns (see e.g. Ciner (2001); Basher and Sadorsky (2006); Cong et al. (2008); Park and Ratti (2008); Sadorsky (2008); Ramos and Veiga (2011); and Kilian and Park (2009)), none has directly tested for asymmetries in the transmission of oil price innovations to stock returns.

While stock market analysts and journalists have considered changes in oil prices as one of the main factors that explain instability in the stock market (see among others the Financial Times August 21, 2006, Wall Street Journal, August 8, 2008), there are still mixed evidence among academic researchers regarding the nature of the relationship between changes in crude oil prices and stock returns (see Chen, Roll & Ross (1986), Jones & Kaul (1996) and Sadorsky (1999). Until recently, Kilian and Park (2009) show that the effect depends on the source of the shock. They show that the response of aggregate stock returns may differ greatly depending on whether the increase in the price of crude oil is driven by demand or supply shocks in the crude oil market. Thus, one explanation for the mixed results in the literature is that the source of the shock matters as shown in Kilian and Park (2009).

An alternative explanation for these contrasting results could stem from the asymmetry and possibly nonlinear nature of the relationship. If true, then the effect of an oil price shock on stock returns will depend on the size and the sign of the shock. In other words, agents respond differently to positive and negative oil price innovations, or firms' stock returns react differently to the oil price increase that constitutes a correction for a previous decline than to an increase in a previously stable environment (Hamilton 1996, 2003).

Uncertainty and financial stress brought about by the oil price shock could explain why oil price shocks could have an asymmetric, and possibly nonlinear, effect on stock returns. Thus, using a bivariate GARCH-in-mean VAR model, this dissertation directly tests for the uncertainty effect of oil price changes on stock returns and whether the response of stock returns to an increase and a decrease in oil price volatility is symmetric. Moreover, considering seasonality in risk and returns is essential for financial managers and analysts. For instance, detecting a particular pattern in volatility might assist investors in making decisions based on both return and risk (Kiymaz and Berument, 2003). Thus, this dissertation examines the day-of-the-week effect in the crude oil market using GARCH models.

In addition, this dissertation characterizes the relationship between oil price changes and the U.S. stock returns not only at the aggregate level but also across sectors. Since results at the aggregate level might hide important effects of oil price volatility at the sectoral level, we examine the oil uncertainty effects on sectoral stock markets, and investigate whether the relationship between oil prices and sectoral stock returns is symmetric. Investigating the effect of oil price shocks at a sectoral level is important for a number of reasons. First, as we mentioned before, evidence regarding the presence (or absence) of asymmetry differs among sectors and in the aggregate (see Kilian and Vigfusson (2009) and Herrera et al (2010) for the oil price-macroeconomy relationship). Second, Fama and French (1997), among others, show that returns and volatility at the sectoral level offer important information about the return and volatility process at the aggregate level. Similarly, Hong et al. (2007) also recognize the importance of sectoral returns to give information about the movements of aggregate stock returns. Accordingly, it is important to examine the effect of oil price uncertainty on stock returns across industries especially during periods of instabilities in oil prices; so that investors can adjust their portfolios accordingly.

This dissertation is organized as follows, in chapter 2 we first inquire whether aggregate and industry-level stock returns respond to oil price shocks and then use state-of-the-art techniques to directly test for symmetry in the response to positive and negative real oil price innovations. We find no evidence of asymmetry for aggregate stock returns, and only very limited evidence at the sectoral level. We inquire whether the size of the shock matters in that doubling the size of the shock more (or less) than doubles the size of the response. Consistent with our finding that a linear model fits most of the industries, we conclude that the effect of a 2.s.d innovation is just double the magnitude of the impact of a 1.s.d innovation. Furthermore, we find no support for the conjecture that shocks that exceed a threshold have an asymmetric effect on stock returns. We then explore whether our results are robust to specifying our model in terms of the nominal oil price. Our test results indicate a considerable increase in the number of rejections for the net oil price increase over the previous 12-month maximum, even after controlling for data mining.

Chapter 3 uses a bivariate GARCH–in-mean VAR model to examine the effect of oil price uncertainty on the U.S. real stock returns at the aggregate and sectoral level. Estimation results suggest that there is no statistically significant effect of oil price volatility on the U.S. stock returns. The absence of an uncertainty effect might be explained by the view that companies across sectors, the airline industry for instance, are likely to hedge against fluctuations in oil prices. It could also stem from the ability of most companies to transfer the higher cost of oil to customers. Moreover, the impulse responses indicate that oil price increases and decreases have symmetric effects on the U.S. stock returns, in that energy price increases and decreases are estimated to have equal and opposite effects on the U.S. financial market.

Using high frequency data, chapter 4 addresses the issue of uncertainty in oil prices and its effect on U.S. stock returns, taking into account the day of the week effect. The results suggest that the-day-of-the-week effect is present in both the mean and volatility equations. While the Wednesday dummy has a statistically significant effect on the conditional mean, Thursdays and Wednesdays appear to have the highest and the lowest aggregate returns volatilities, respectively. We also find that the U.S. stock market is sensitive to oil price variations not only at the aggregate level but also across some industries, such as chemicals, entertainment, and retail, where uncertainty in oil prices proves to have positive and statistically significant effect. On the other hand, many sectors, such as transportation, automobiles, consumer goods, aircraft, and many others, came out to be unaffected by variations in oil prices.

Chapter 5 presents the contribution of this research to the literature of oil prices and stock returns. It also summarizes the major findings of this dissertation and suggests implications for future directions.

Chapter 2: Oil Price Shocks and the U.S. Stock Market: Do Sign and Size Matter?[1]

This paper investigates the effects of oil price innovations on the U.S. stock market using a model that nests symmetric and asymmetric responses to positive and negative oil price innovations. We first inquire whether aggregate and industry-level stock returns respond to oil price shocks and then use state-of-the-art techniques to directly test for symmetry in the response to positive and negative real oil price innovations. We find no evidence of asymmetry for aggregate stock returns, and only very limited evidence for the 49 industry-level portfolios studied in this paper. We inquire whether the size of the shock matters in that doubling the size of the shock more (or less) than doubles the size of the response. Consistent with our finding that a linear model fits most of the industries, we conclude that the effect of a 2.s.d innovation is just double the magnitude of the impact of a 1.s.d innovation. Furthermore, we find no support for the conjecture that shocks that exceed a threshold have an asymmetric effect on stock returns. We then explore whether our results are robust to specifying our model in terms of the nominal oil price. Our test results indicate a considerable increase in the number of rejections for the net oil price increase over the previous 12-month maximum, even after controlling for data mining. Do sign and size matter? The answer to this question appears to depend on whether the model is specified in terms of the real or the nominal price of oil.

[1] This chapter is co-authored with professor Ana María Herrera.

2.1 Introduction

Headlines such as "U.S. stocks plunge after oil climbs $6" (New York Times, June 11, 2008) or "U.S. stocks rally after crude drops to 3-month low" (Wall Street Journal, August 8, 2008) highlight the shared belief among journalists and stock market commentators that oil price shocks have a direct effect on U.S. stock markets. Moreover, these headlines put in evidence the belief that the effect might depend on the behavior of crude oil prices in the recent history.

For many years, researchers compiled conflicting evidence regarding the nature of the relationship between changes in crude oil prices and stock returns. On the one hand, Huang, Masulis and Stoll (1996) found no evidence of a negative relationship between prices of oil futures and stock returns. Similarly, Wei (2003) encountered that the oil price shock of 1973-74 had no impact on stock returns. On the other hand, work by Jones and Kaul (1996) pointed towards a negative effect of oil price shocks on stock returns. Yet, in recent years, a consensus appears to have emerged among academics: oil price shocks exert a negative impact on most stock returns, though the nature of the relationship depends on the underlying shock. In particular, Kilian and Park (2009) find that oil price shocks that are driven by innovations to the precautionary demand for crude oil have a negative impact on U.S. stock returns. They show that the response differs significantly depending on the source of the oil price shock (e.g., supply or demand driven). Thus, changes in the composition of oil price shocks over time help explain why, in the past, researchers failed to find evidence in favor of an effect of oil price innovations on U.S. stock returns.

An alternative explanation for these contrasting results could stem from the possibly nonlinear nature of the relationship. For instance, if people's perception of the importance of an oil price shock depends on the past history of oil prices (Hamilton 1996, 2003), or if firms' cash flows respond differently to positive and negative oil price innovations, then the effect of an oil price shock on stock returns will also depend on the size and the sign of the shock.

There are a number of reasons why oil price shocks could have an asymmetric, and possibly nonlinear, effect on stock returns. First, oil prices do not appear to have an asymmetric effect on aggregate real GDP (Kilian and Vigfusson 2011a) and aggregate industrial production (Herrera, Lagalo, and Wada 2011). Yet, they seem to have an asymmetric effect on some (but not all) industries that use energy intensively in their production process such as rubber and plastics, or in consumption such as transportation equipment (Herrera, Lagalo and Wada 2011). Asymmetries in the response of production could thus translate into an asymmetric response of profits and, thus, stock returns.

In addition, the optimal decision for a firm that pays dividends to its shareholders and seeks to maximize the expected present value of its dividends (without closing), could be to pay dividends only when its surplus exceeds a threshold (Wan 2007). Therefore, a negative (or a positive) oil price innovation could push the surplus below the cutoff required to pay dividends for an oil company (or an industry that uses energy intensively). If that is the case, the company could choose not to pay dividends and face a decline in stock prices. The negative impact that such a decision would have on stock returns is likely to be larger than the increase in stock returns that would stem from higher dividend payments due to a larger surplus.

Another possibility is that uncertainty and financial stress brought about by the oil price shock, could lead to asymmetries in the response of interest rates (Ferderer 1996; Balke, Brown and Yücel 2002). Such an effect would also be evident if people believed the monetary authority will respond differently to oil price increases and decreases. For instance, Ferderer (1996) and Bernanke, Gertler and Watson (1997) find that part of the decline in economic activity brought about by a positive oil price innovation can be attributed to a more restrictive monetary policy. Although the importance of this systematic monetary policy response --on average and after the Great Moderation-- is a question of debate (see, for instance, Hamilton and Herrera 2004, Herrera and Pesavento 2009, Kilian and Lewis 2010), one could conjecture that an asymmetric response of interest rates to oil price innovations could have an asymmetric effect on the expected present discounted value of the dividends and, thus, on stock returns.

These arguments merit careful investigations of the presence of possible asymmetries in the response of stock returns to unexpected variation in crude oil prices --both at the aggregate and disaggregate level. The contribution of this paper is threefold. First, we explore the question of asymmetry in the response of U.S. real stock returns. To do so we estimate a simultaneous equation model that nests symmetric and asymmetric responses to positive and negative oil price innovations using monthly data on aggregate US stock returns and 49 industry-level portfolios. We then employ state-of-the art techniques to directly test the null of symmetry in the response of real stock to real oil price innovations (see Kilian and Vigfusson 2011).

Our estimation results suggest the response of aggregate stock returns is well captured by a linear model. This is also the case for most of the 49 industry-level portfolios. Yet, there are a number of portfolios (food products, candy& soda, beer and liquor, apparel, textiles, construction materials, automobiles and trucks, aircraft, communication, retail, banking, and insurance) where we find evidence of asymmetry. These results imply that financial investors interested in these industries should consider asymmetries in the response of stock returns to oil price innovations when forming their portfolios. Similarly, for financial forecasters, innovations of the same magnitude but opposite sign should not enter their loss function in a symmetric manner.

Second, we investigate whether the response of stock returns depends nonlinearly on the size of the shock. To do that, we evaluate whether the test of symmetry leads to different results when we consider innovations of one and two standard deviations. In addition, we explore whether only shocks that exceed a threshold have an asymmetric effect on stock returns as one could conjecture that agents chose to be inattentive to small oil price changes but re-optimize when changes are large.

Does the size of the shock matter? Consistent with our findings for the symmetry test, we conclude that for aggregate stock returns and for most industry-level portfolios the size of the shock matters only to the extent that it scales up the effect on stock returns. In addition, we show that a transformation of the oil price change that filters out movements that do not exceed one (or two) standard deviation(s) (as in Kilian and Park 2009) does considerably worse in fitting the data.

Third, we explore whether our findings regarding asymmetry (or the lack thereof) in the response of stock returns is robust to specifying our model in terms of the nominal price of oil. Even though theoretical models of the transmission of oil price shocks that imply an asymmetric response of economic activity are specified in terms of the real oil price, it is conceivable that individuals and financial investors might choose to change their consumption or financial decisions when changes in the nominal oil price occur (Hamilton 2011). To explore this conjecture we specify our simultaneous equations model in terms of the nominal oil price and compute the test of symmetry in the response to positive and negative innovations in the nominal oil price.

We find ample evidence of asymmetry in the response to 1 s.d. innovation in the nominal price of oil, especially when we use the net oil price increase with respect to the previous 12-month maximum. In other words, while a linear model constitutes a good approximation to the relationship between real oil prices and real stock returns, a nonlinear model appears to provide a better description of the relationship between nominal oil prices and real stock returns. Hence, both the size and the sign matter when analyzing the effect of innovations in the nominal oil price.

Finally, we investigate whether oil price changes help forecast stock returns one year ahead. To do so, we compute the impulse response functions using local projection (Jordà 2005). We find evidence that the oil price increase, x_t^1, helps forecast aggregate U.S. stock returns as well as industry-level returns one-year ahead. For automobiles and trucks, an industry that is commonly thought to be largely affected by oil price changes, we find that the oil price increase, x_t^1, and the net oil price increase relative to the previous 36-month maximum, x_t^{36}, have predictive content. Of the four considered non-linear oil price measures, oil price increases seem to do a better job at forecasting stock returns.

This paper is organized as follows. Section 2 describes the data on stock returns and oil prices. Section 3 explores the response of aggregate and industry-level stock returns to oil price innovations. The results of the tests of symmetry in the response to a one standard deviation innovation (hereafter 1 s.d.) are reported in section 4. The following section explores whether our findings are robust to considering larger innovations (2 s.d.) or defining the nonlinear transformation in terms of oil price changes that exceed one or two standard deviations. Section 6 investigates the robustness of our results to specifying the model in terms of the nominal oil price. Section7 explores whether oil prices help forecast stock returns. Section 8 concludes.

2.2 Data Description

We use aggregate and industry-level U.S. real stock returns spanning the period between January 1973 and December 2009. Although data on stock returns and oil prices was available starting January 1947, we restrict the sample to the period between January 1973 and December 2009. This decision is motivated by the fact that oil prices behaved very differently during the years when the Texas Railroad Commission set production limits in the U.S. In fact, it was not until 1972 when U.S. production had increased significantly that nominal oil prices stopped being fixed for long periods of time[2].

All of the data on monthly nominal stock returns were obtained from Kenneth French's database available on his webpage[3]. As a measure of aggregate stock returns we use the excess return on the market, which is defined as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks from the Center for Research in Security Prices (CRSP) minus the one-month Treasury bill rate. For industry level stock returns we use the

[2] Estimation results for the full sample are available from the authors upon request.
[3] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

returns on 49 industry portfolios provided on French's webpage[4]. In this database each NYSE, AMEX, and NASDAQ stock is assigned to an industry portfolio based on its four-digit SIC code as reported by Compustat or, in absence of a Compustat code, by the four-digit SIC classification provided in CRSP. These portfolios include industries in agriculture, mining, construction, manufacturing, transportation and public utilities, wholesale and retail trade, finance, insurance and real estate, and services. (A complete list of the 4-digit SIC industries included in each portfolio is provided in the Appendix.) We then compute real stock returns by taking the log of the nominal stock returns and subtracting the CPI inflation.

Regarding the nominal oil price, we follow the bulk of the literature (see, for instance Mork 1989, Lee and Ni 2002) and use the composite refiners' acquisition cost (RAC) for crude oil from January 1974 until December 2009. Then, to compute prices for the previous months, we extrapolate using the rate of growth in the producer price index (PPI) for crude petroleum, after making adjustment to account for the price controls of the 1970s. The real price of oil is then computed by deflating the price of oil by the U.S. CPI.

To assess whether oil price innovations have an asymmetric effect on U.S. stock returns, we use three different nonlinear transformations of the real oil price, o_{t}. The first nonlinear transformation is a modified version of Mork's (1989) proposal to split percent changes in oil prices into increases and decreases to allow for an asymmetric response of aggregate production to positive and negative oil price shocks. That is, we use the oil price increase, which is defined as:

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[4] The data are available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We use the file containing 49 industry portfolios.

$$x_t^1 = \max(0, \ln o_t - \ln o_{t-1}). \qquad (1)$$

Alternatively, Hamilton (1996, 2003) suggests that agents might react in a different manner if the oil price increase constitutes a correction for a previous decline and not an increase in a previously stable environment. To account for this behavior, he proposes to use the net oil price increase as a measure of oil price shocks. Thus, as a second nonlinear transformation of oil prices we use the net oil price increase relative to the previous 12-month maximum (Hamilton 1996), which is given by:

$$x_t^{12} = \max(0, \ln o_t - \max(\ln o_{t-1}, \ldots, \ln o_{t-12})). \qquad (2)$$

The last measure is the net oil price increase over the previous 36-month maximum (Hamilton 2003), which is defined in a similar manner:

$$x_t^{36} = \max(0, \ln o_t - \max(\ln o_{t-1}, \ldots, \ln o_{t-36})). \qquad (3)$$

Although, the last two measures do not have a direct grounding on economic theory, there are behavioral explanations as to why agents might react differently in the face of a positive shock if oil prices have been stable in the near past or if they only represent a correction for a previous decline. In fact, the headlines reported in the news often suggest analysts and stock market commentators consider the behavior of oil prices in the recent past when thinking about the impact of shocks on stock returns.

2.3 The Effect of Oil Price Shocks on Stock Returns

To evaluate the effect of positive and negative oil price innovations on stock returns we use a simultaneous equation model that nests both symmetric and asymmetric responses of stock returns. In addition, the nonlinear nature of this model allows for small and large oil price innovations to have different effects on the stock market. Thus, consider the data generating process for each of the stock return series, $y_{i,t}$, to be given by the following simultaneous equation model:

$$x_t = a_{10} + \sum_{j=1}^{12} a_{11,j} x_{t-j} + \sum_{j=1}^{12} a_{12,j} y_{i,t-j} + \varepsilon_{1t} \qquad (4a)$$

$$y_{i,t} = a_{20} + \sum_{j=0}^{12} a_{21,j} x_{t-j} + \sum_{j=1}^{12} a_{22,j} y_{i,t-j} + \sum_{j=0}^{12} g_{21,j} x^{\#}_{t-j} + \varepsilon_{2t} \qquad (4b)$$

where x_t is the log growth of the crude oil price at time t, y_{t-j} is the return on the the i-th portfolio at time t, $x_t^{\#}$ is one of the nonlinear transformations of oil prices described in the previous section, and ε_{1t} and ε_{2t} are, by construction, orthogonal disturbances. That is, for identification purposes, we assume that changes in oil prices have a contemporaneous effect on stock returns but stock returns do not affect oil prices contemporaneously. As for the number of lags included in the model, we follow Hamilton and Herrera (2004) in selecting twelve monthly lags to capture the effect of oil prices on economic activity.

Note that the inclusion of $x_t^{\#}$ in equation (4b) invalidates the computation of the impulse response functions in the usual textbook manner (see Gallant, Rossi and Tauchen 1993 and Koop, Pesaran and Potter 1996). Instead, to compute the response of stock return i to an innovation of size δ in ε_{1t} we use Monte Carlo integration. That is, we first calculate the impulse response functions to a positive innovation, $I_y(h,\delta,\Omega_t)$, and to a negative innovation, $I_y(h,-\delta,\Omega_t)$ of size δ --conditional on the history Ωt-- for h=0,1,2,...,12. We perform this computation for 1,000 different histories and then calculate the unconditional impulse response functions, $I_y(h,-\delta)$, by averaging over all the histories[5].

The first panel of Figure 1 illustrates the response of aggregate stock returns to positive and negative innovations of one standard deviation in the real oil price. For ease of comparison, we report the response to a positive innovation and the negative of the response to a negative innovation of size δ=1 s.d. Note that, regardless of the oil price measure, the effect of a 1 s.d. innovation in oil prices has a statistically insignificant effect on stock returns in the short-run. Using the oil price increase (the net oil price increase relative to the previous 36 months) the response of aggregate stock returns to both positive and negative innovations becomes significant at the 5% level 8 months (12 months) after the shock. In both cases, an unexpected increase in real oil prices leads to a decline in U.S. aggregate stock returns of less than 1%, whereas an unexpected decrease causes an increase of about the same magnitude. At a first sight, the fact that the IRFs to positive and negative innovations lie almost on top of each other suggests no asymmetry is present in the response of aggregate stock returns.

The remaining panels of Figure 1 plot the response of stock returns for a group of portfolios that are thought to be affected by oil prices (see Kilian and Park 2009). Evidence of a negative relationship between positive oil price innovations and real stock returns at the industry-level, for at least two of the oil price measures, is apparent for food products, candy and soda, beer and liquor, tobacco products, entertainment, printing and

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[5] See Herrera, Lagalo and Wada (2011) for a detailed description of the computation.

publishing, consumer goods, apparel, medical equipment, pharmaceutical products, rubber and plastic products, textiles, construction materials, steel works, automobiles and trucks, aircraft, utilities, communication, personal services, computer hardware, electric equipment, measuring and control equipment, shipping containers, transportation, retail, restaurants, hotels, and motels, banking, insurance, real estate, and other. For most of these portfolios, the responses to positive and negative innovations of 1 s.d. lie on top of each other. This suggests that a negative innovation of 1 s.d. would have a positive effect on stock returns of the same magnitude but opposite sign.

These results are in line with Kling (1985) and Jones and Kaul (1996) who find a negative impact of oil price shocks on stock returns. Note that we find a statistically significant effect, even though we do not account for the source of the shock as in Kilian and Park (2009). In light of their result, one would expect the economic and statistical significance of oil price innovations to change over time depending on variations in the composition of the shock.

2.4 Does the Sign of the Shock Matter?

Recent research into the question of asymmetry in the response of economic activity to positive and negative oil price innovations suggests that the magnitude of the effect of a positive innovation is not larger (in absolute terms) than the magnitude of the effect of a negative innovation. Is this also the case for the response of U.S. stock returns? We address this question by implementing Kilian and Vigfusson's (2011) impulse response based test. That is, we use the impulse response functions computed in the previous section to construct a Wald test of the null hypothesis:

$I_y(h,\delta)=-I_y(h,-\delta)$ for h=0,1,2,...,12.

Note that this test jointly evaluates whether the response of stock returns (for a particular portfolio) to a positive shock of size δ equals the negative of the response to a negative shock of the same size, -δ, for horizons h=0,1,2,...,12. Our motivation for focusing on a one-year horizon is twofold. First, the extant literature on the effect of oil price shocks has found that the largest and most significant impact on economic activity takes place around a year after the shock (see, for instance, Hamilton and Herrera 2004). Therefore, one could conjecture a similar lag in the transmission of oil price shocks to dividends, and thus to stock returns. But, even in the case where financial investors rapidly incorporate the information regarding oil price changes in their expected dividends, since the Wald test is a joint test for horizons h=0,1,2,...,12, we take into account the response at shorter horizons.

Second, by focusing on the 12-months horizon we avoid issues of data mining related to repeating the test over a different number of horizons. That is, if we were to repeat the impulse response based test with a 5% size say for 6 different horizons H, then the probability of finding at least one rejection would exceed 5% under the null.

Having addressed the possible issue of data mining across horizons by focusing on H=12, we still have to tackle data mining concerns related to repeating the impulse response based test over 49 different portfolios. To avoid this potential problem, we compute data-mining robust critical values by simulating the distribution of the supremum of the bootstrap test statistic, under the null, across all portfolios for each of the oil price transformations[6]. To compute the data mining robust critical values we generate 100 pseudo-series using the estimated coefficient for the 49 portfolios in model (4). We then use 100 histories to get the conditional impulse response functions for each pseudo-series and compute the IRFs by Monte Carlo integration. We repeat this procedure 100 times to obtain the empirical distribution of the test statistic.

The left panel of Table 1 reports the p-values for the test of symmetry in the response to positive and negative innovations of 1 s.d in the real oil price. In addition we denote significance at the 5% and 10% level, after controlling for data mining, by ** and *, respectively. As the 'eyeball metric' would have suggested when looking at Figure 1, there is no evidence of asymmetry in the response of aggregate stock returns. Regardless of the oil price transformation ($x_t^{\#} = x_t^1, x_t^{12}, x_t^{36}$), we are unable to reject the null at a 5% level. As for the industry-level portfolios, we find some evidence of asymmetry when we use the oil price increase, x_t^1, or the net oil price increase relative to the previous 12-month maximum, x_t^{12}. In particular, using x_t^1, we reject the null at a 5% significance level for candy & soda, apparel, textiles, construction materials, automobiles and trucks, communication, retail, and insurance. Note that these rejections are roughly consistent with what we would have obtained had we not controlled for data mining. When we use x_t^{12}, we reject the null for food products, candy & soda, beer & liquor, aircraft, banking, and insurance. Interestingly, we fail to reject the null for all industry-level portfolios but insurance, when we use the net oil price increase with respect to the previous 36-month maximum, x_t^{36}.

6 See Inoue and Kilian(2004) and Kilian and Vega (2010) for the effect of data mining and solutions to the problem of data mining in the related context of tests of predictability.

Finding asymmetries in the response of automobiles and trucks, aircraft, or apparel might not be surprising to the reader, as the use of transportation equipment requires considerable amounts of refined products and apparel is somewhat energy intensive in production (see Table 2). Thus, a-priori, one could expect the demand for these goods to contract more in response to positive oil price innovations than it would expand when faced by negative innovations. After all, firms might postpone the purchases of planes and individuals their purchases of cars when hit by an unexpected oil price surge, but they might not increase their demand when faced by an unexpected price drop. As a consequence, one would expect the response of profits, and thus stock returns, to be asymmetric. On the contrary, evidence of asymmetry in the food industries as well as in banking and insurance might be more puzzling as the total (direct and indirect) cost of crude petroleum and natural gas used to produce a dollar of output in these industries is less than 4 cents (see Table 2). A possible explanation for this finding could be that consumers increase precautionary savings when faced with a positive shock (Edelstein and Kilian 2009), reduce the demand for these goods, and this shortfall in demand leads to lower expected dividends and stock returns.

It is interesting to compare our results with those obtained by Herrera, Lagalo and Wada (2011) who study the question of asymmetry in the response of industrial production, as such a comparison could shed some light on the source of the asymmetry in stock returns. Using data mining robust critical values, they fail to reject the null of symmetry for H=12 for the total industrial production index, as well as for all the industry-level indices, when using x_t^1 and x_t^{12}. Instead, they find evidence of asymmetry in transit equipment, petroleum and coal, plastics and rubber, and machinery, when using

x_t^3[6]. In brief, there is no correspondence between our results and those for industrial production, which suggests that asymmetries in the response of industry-level stock returns are not driven by asymmetries in the response of production. Instead, other transmission mechanism influencing expectations of future dividends might be at play.

Does the sign of the shock matter? For aggregate stock returns, the answer is only to the extent that the response has the opposite sign but not in the sense that positive and negative innovations have a symmetric effect. For most industry-level portfolio returns we find no evidence that positive innovations have a larger impact than negative innovations up to a year after the shock. Yet, there are a few industries where the sign of the shock matters in that the response of real stock returns is asymmetric.

2.5 Does the Size of the Shock Matter?

In a linear model, the magnitude of the response to a 2 s.d. deviation shock is simply twice of the response to a 1 s.d. shock. Nevertheless, in a nonlinear model such as that in (4) the magnitude of the response depends on the size of the shock and on the history of oil price changes and stock returns. Thus, we estimate the IRFs to 2 s.d. innovations and test for symmetry in the response to positive and negative innovations of this magnitude, as we did in the previous section. The second panel of Table 1 reports the p-values for the test of symmetry in the response to a 2 s.d. innovation.

At first glance, it would appear that a doubling in the size of the innovation leads us to find more evidence of asymmetry. Note how there are more p-values below 5%, which are marked in bold, for a 2 s.d. innovation than for a 1 s.d. innovation. Yet, when we control for data mining, we find very little evidence of asymmetry. In fact, using x_t^1 we are unable to reject the null for the aggregate and all of the industry-level portfolios. For x_t^{12} we find evidence of asymmetry for candy & soda, coal, banking and insurance. The difference between the test results before and after controlling for data mining is indicative of the higher degree of uncertainty associated with the estimation of the IRFs to a 2 s.d. innovation. Moreover, since our data mining robust critical values are computed using the supremum of the bootstrap test statistic across all industry-level portfolios, it would suffice for the IRFs to be estimated with a higher degree of uncertainty for one portfolio in order to get larger critical values.

To further evaluate whether the size of the oil price shock matters, we consider a different oil price transformation along the lines of Edelstein and Kilian (2007). Consider a situation in which firms and individuals only respond to shocks that exceed a certain threshold. Such behavior could be observed if there are adjustment costs that prevent agents from optimizing when the change in the price of an input or a consumption good is small, or if dividends are paid only if the surplus exceeds a threshold.

Let us define

$$x_t^{sd} = \begin{Bmatrix} 0 & if & |x_t| \leq \delta \\ x_t & if & |x_t| > \delta \end{Bmatrix} \qquad (5)$$

where x_t is the percentage change in the oil price, and δ equals one (4.45%) or two (9.9%) standard deviations of the oil price change.

The fourth column of the left and right panels of Table 1 report the p-values for the test of symmetry computed using this alternative transformation of the oil price change. Clearly, there is no evidence of asymmetry in the response to 1 s.d. or 2 s.d. innovations when we use x_t^{sd}. In fact, our estimates suggest that x_t^{sd} does a very bad job at capturing possible asymmetries in the response of U.S. stock returns.

All in all, the response of aggregate stock returns to innovations in the real oil price, as well as that of most industry-level portfolios, is well captured by a linear model. Hence, the impact of innovations that differ only in size should differ only in the same scale. Yet, for a number of industries such as candy&soda, coal, banking, and insurance, the magnitude of the shock matters, as the response is a nonlinear function of the innovation.

2.6 The Real Price of Oil versus the Nominal Price of Oil

Theoretical models that imply an asymmetric response of economic activity to oil price innovations are specified in terms of the real price of crude oil. However, Hamilton (2011) suggests that consumers of crude oil and refined products might respond to the nominal oil price, as it is more visible and readily available. Such a behavioral argument would seem to have more relevance for stock returns where financial investors could choose to buy or sell stocks in response to changes in the nominal crude oil price. To investigate whether our results are robust to the use of nominal oil prices, we specify model (4) in terms of the nominal oil price, estimate the impulse response functions to positive and negative innovations in the nominal oil price and compute the test of symmetry.

Table 3 reports the p-values for the test of symmetry in the response of stock returns to positive and negative nominal oil price innovations. In addition we denote significance at the 5% and 10% level, after controlling for data mining, by ** and *, respectively. As can be seen in first line of the table, the results for aggregate stock returns are unchanged. That is, whether we specify our simultaneous equation model in terms of the real oil price or the nominal oil price, a linear model appears to approximate well the effect of oil price innovations on returns for the U.S. stock market. As for the industry-level portfolios, using x_t^1 we reject the null of symmetry in the response to a 1 s.d. innovation for the same industries as we did using the real oil price. The only difference being that we now reject the null at a 5% level for real estate. Regarding the net oil price increase, evidence of asymmetry is more widespread when we use the nominal oil price, especially for the net oil price increase relative to the previous 12-month maximum. Note that for x_t^{12} (x_t^{36}) we reject the null for 36 (6) of the 49 industry-level portfolios versus 6 (1) when we specified the model in terms of the real oil price. Similarly, for shocks that exceed one standard deviation, x_t^{sd}, the p-values are lower when we use the nominal oil price. The decrease is such, that we are able to reject the null using the robust critical values for consumer goods and defense.

Comparing the right panels of Table 1 and Table 3 reveals only a slight increase in the number of rejections when we consider a 2 s.d. innovation. For instance, using x_t^1 we reject the null for automobiles and trucks at a 5% level, whereas we obtained no rejections when we used the real oil price. Similarly for x_t^{12}, we reject the null at a 5% significance level for computer software and at a 10% level for rubber and plastic products, and automobiles and trucks, in addition to the four portfolios where we found evidence of asymmetry to a 2 s.d. real oil price shock (candy&soda, coal, insurance and real estate). Here again, the fact that the number of rejections decreases considerably after controlling for data mining suggests an increase in the uncertainty involved in estimating the response to a 2 s.d. innovation.

All in all, our test suggest that the net oil price increase relative to the previous 12-month maximum, x_t^{12}, does a better job than any of the other oil measures in capturing possible asymmetries in the response of stock returns to positive and negative innovations. In particular, the fact that we reject the null of symmetry for a large number of industry-level portfolios suggests behavioral models of stock returns where financial investors respond to changes in the nominal oil price, but take into account the history of the price in the recent past are worth considering.

2.7 Do Oil Prices Help Forecast U.S. Stock Returns?

A related question is whether lagged oil price changes are helpful in forecasting U.S. stock returns. Hamilton (2011) suggests that a similar question -the predictive content of oil price changes for U.S. GDP growth-- can be addressed by computing the impulse response functions using local projections (Jordà's, 2005). Hence, we investigate whether non-linear measures of oil prices help predict U.S. stock returns h periods ahead. To do so we estimate the equation for forecasting stock returns h periods ahead directly by OLS

$$y_{i,t+h-1} = \alpha + \sum_{j=0}^{12} \phi_j x_{t-j} + \sum_{1}^{12} \beta_j y_{i,t-j} + \sum_{j=0}^{12} \gamma_j x^{\#}_{t-j} + u_t \qquad (6)$$

and test the null hypothesis that lags of the non-linear measure of oil price, $x_t^{\#}$, help forecast U.S. stock returns: $\gamma_1=\gamma_2=...=\gamma_{12}$. As in the previous sections, we focus on the one year horizon, h=12. We correct for serial correlation using Newey-West (1987) using 13 lags.

Table 4 reports the results for this test for each of the non-linear measures. Interestingly, we find evidence that the oil price increase, x_t^1, helps forecast aggregate U.S. stock returns as well as industry-level returns one-year ahead. For 30 out of the 49 industry portfolios, as well as for aggregate returns, we can reject the null that the coefficients on current and lagged values of x_t^1 are jointly equal to zero. Evidence that other non-linear measures of oil prices help forecast stock returns is less widespread. First, we cannot reject the null for aggregate stock returns when we use x_t^{12}; x_t^{36}; and x_t^{sd}. Second, the number of industry-level portfolios where we are able to reject is lower: 19, 25 and 24, respectively.

Regardless of the oil price transformation, we reject the null for twelve industry-level portfolios: agriculture, recreation, entertainment, consumer goods, healthcare, medical equipment, pharmaceutical products, construction, electrical equipment, precious metal, mines, and computer software. As for automobiles and trucks, both the oil price increase, x_t^1, and the net oil price increase relative to the previous 36-month maximum, x_t^{36}, have a predictive content for one year ahead stock returns. Briefly, while only the oil price increase, x_t^1, tends to predict aggregate U.S. stock returns one year ahead, the results are still mixed for industry-level returns.

2.8 Conclusions

We started our study by inquiring whether the size and the sign of oil price shock matter for the response of U.S. real stock returns. To answer these questions we estimated a simultaneous equation model that nests symmetric and asymmetric responses to positive and negative innovations in the price of crude oil. We found that positive oil price innovations depress aggregate stock returns, as well as the returns of about 60% of the industry-level stock returns.

We explored the question of asymmetry in the response of real stock returns by implementing Kilian and Vigfusson's (2011) impulse response based test. To avoid issues of data mining related to the repetition of the test over all the portfolios, we bootstrapped the distribution of the supremum of the Wald test across all portfolios. Estimation results suggested that a linear model fits the data well for aggregate returns, as well as for most industry-level portfolios. Notable exceptions are candy and soda, automobiles and trucks, and insurance for which we find evidence of asymmetry in the response to a 1 s.d. innovation using the oil price increase, x_t^1, and the net oil price increase relative to the 12-month maximum, x_t^{12}. No evidence of asymmetry is found when we use the net oil price increase relative to the 36-month maximum, x_t^{36}. Consistent with these findings, we concluded that, for the aggregate and for most portfolios, the sign of the shock mattered only in that it determined the sign of the response. Yet, the absolute magnitude of the responses coincided.

To investigate whether the size of the shock matters we explored the question of symmetry in the response to a 2 s.d. innovation. For this larger shock, evidence of asymmetry was absent for all portfolios but candy and soda, coal, banking, and insurance, when we used x_t^{12}. We then explored the conjecture that only oil price innovations that exceed a threshold (1 s.d. or 2 s.d. of the percentage change in the real oil price) have an asymmetric effect on real stock returns. Our estimation results lead us to strongly reject such a model. We thus concluded that the size of an innovation in real oil prices only matters in that it determines the scale of the effect. That is, consistent with our finding of symmetry, a doubling in the size of the innovation in real oil prices lead to a doubling (no more, no less) in the response of almost all analyzed stock returns.

Subsequently, we evaluated the robustness of our results to specifying the model in terms of the nominal, instead of the real oil price. Such a modeling choice could be grounded on a behavioral motivation along the lines of Hamilton (2011). That is, one could surmise that financial agents react to changes in prices that are easily visible and thus stock returns respond to innovations in the nominal price of crude oil. Our test results implied a significant increase in the number of rejections, especially after controlling for data mining. In particular, we rejected the null of symmetry in the response to a 1 s.d. innovation for 36 of the 49 portfolios, when we used x_t^{12}.

Finally, we examine whether oil price changes help forecast stock returns. Thus, we follow Hamilton (2011) and compute the impulse response functions using local projection (Jordà 2005). Results show that the oil price increase, x_t^1, helps forecast aggregate U.S. stock returns as well as industry-level returns one-year ahead. Regarding an industry that is commonly thought to be most affected by oil price increases, automobiles and trucks, we find that only the oil price increase, x_t^1, and the net oil price increase relative to the previous 36-month maximum, x_t^{36}, tend to forecast its returns one-year ahead.

In brief, our results suggest a linear model provides a good approximation to the response of real stock returns to real oil price innovations. However, this is not the case when the model is specified in terms of the nominal price of crude oil. Do sign and size matter? The answer to this question appears to depend on whether the model is specified in terms of the real or the nominal price of oil.

Table 2.1. Test of symmetry in the response to positive and negative innovations in the real oil price for h = 1, 2, …, 12

Sector	1sd				2sd			
	$x_t^{\#} = x_t^{1}$	$x_t^{\#} = x_t^{12}$	$x_t^{\#} = x_t^{36}$	$x_t^{\#} = x_t^{sd}$	$x_t^{\#} = x_t^{1}$	$x_t^{\#} = x_t^{12}$	$x_t^{\#} = x_t^{36}$	$x_t^{\#} = x_t^{sd}$
Aggregate	0.34	0.76	0.73	1.00	0.35	0.51	0.84	1.00
Agriculture	0.48	0.72	0.61	1.00	0.56	0.14	0.93	1.00
Food Products	0.37	0.24**	0.64	0.99	0.57	**0.03**	0.87	1.00
Candy & Soda	**0.04****	*0.09***	0.45	1.00	**0.01**	**0.00****	0.86	1.00
Beer & Liquor	0.48	0.20**	0.65	0.86	0.20	*0.09*	0.95	1.00
Tobacco Products	0.49	0.44	0.78	1.00	0.27	0.21	0.80	1.00
Recreation	0.29	0.57	0.66	1.00	0.28	0.36	0.90	1.00
Entertainment	0.20	0.45	0.55	0.99	*0.07*	0.17	0.74	1.00
Printing and Publishing	0.25	0.48	0.54	1.00	0.13	0.12	0.85	1.00
Consumer Goods	0.10*	0.31*	0.76	0.91	*0.07*	**0.03**	0.92	1.00
Apparel	**0.01****	0.53	0.79	1.00	**0.00**	**0.02**	0.91	1.00
Healthcare	0.64	0.51	0.48	0.93	0.66	**0.04**	0.71	1.00
Medical Equipment	0.16	0.41	0.63	1.00	**0.04**	0.18	0.94	1.00
Pharmaceutical Products	0.36	0.40	0.88	0.99	0.15	0.25	0.96	1.00
Chemicals	0.57	0.63	0.62	1.00	0.56	0.21	0.84	1.00
Rubber and Plastic Products	0.25	0.70	0.92	1.00	0.22	*0.06*	0.93	1.00
Textiles	*0.07***	0.57	0.69	1.00	**0.02**	**0.01**	0.77	1.00
Construction Materials	**0.05****	0.29*	0.52	1.00	**0.04**	0.16	0.89	1.00
Construction	0.79	0.77	0.53	1.00	0.79	0.50	0.77	1.00
Steel Works Etc.	0.29	0.79	0.50	1.00	0.16	0.37	0.48	1.00
Fabricated Products	0.63	0.59	0.53	1.00	0.73	0.12	0.73	1.00
Machinery	0.47	0.66	0.59	1.00	0.49	0.19	0.71	1.00
Electrical Equipment	0.56	0.64	0.74	1.00	0.66	0.39	0.86	1.00
Automobiles and Trucks	**0.01****	0.27*	0.79	1.00	**0.00**	**0.03**	0.71	1.00
Aircraft	0.16	0.18**	0.52	1.00	**0.03**	**0.03**	0.67	1.00
Shipbuilding, Railroad Equipment	0.10*	0.61	0.58	1.00	0.15	0.37	0.92	1.00
Defense	0.23	0.46	0.50	0.95	**0.04**	**0.01**	0.65	1.00
Precious Metals	0.93	0.50	0.41	0.93	0.97	**0.05**	0.71	1.00
Mines	0.58	0.92	0.89	1.00	0.43	0.80	0.89	1.00
Coal	0.77	0.57	0.42	1.00	0.75	**0.00****	0.47	1.00
Petroleum and Natural Gas	0.94	0.81	0.76	1.00	0.94	0.24	0.74	1.00
Utilities	0.45	0.72	0.64	1.00	0.23	*0.09*	0.57	1.00
Communication	**0.03****	0.80	0.68	1.00	**0.01**	0.36	0.79	1.00
Personal Services	0.52	0.57	0.46	1.00	0.34	0.19	0.85	1.00
Business Services	0.54	0.70	0.78	0.99	0.57	0.42	0.97	1.00
Computer Hardware	0.14	0.56	0.51	1.00	0.16	0.11	0.62	1.00
Computer Software	0.41	0.73	0.85	1.00	0.11	0.25	0.96	1.00
Electronic Equipment	0.10*	0.68	0.52	1.00	0.16	0.35	0.80	1.00
Measuring and Control Equipment	0.67	0.73	0.64	1.00	0.64	0.27	0.90	0.99
Business Supplies	0.35	0.32*	0.42	1.00	0.39	**0.01**	0.62	1.00
Shipping Containers	0.70	0.56	0.78	1.00	0.84	0.11	0.92	1.00
Transportation	0.29	0.38	0.35*	0.99	0.28	*0.07*	0.81	1.00
Wholesale	0.86	0.58	0.75	1.00	0.92	0.20	0.94	1.00
Retail	**0.04****	0.84	0.77	1.00	**0.00**	0.43	0.92	1.00
Restaraunts, Hotels, Motels	0.46	0.59	0.79	1.00	0.24	0.23	0.94	1.00
Banking	0.12	*0.08***	0.79	1.00	**0.03**	**0.00****	0.79	1.00
Insurance	**0.02****	*0.06***	0.20**	1.00	**0.00**	**0.00****	0.57	1.00
Real Estate	*0.09**	0.47	0.68	1.00	**0.01**	**0.01**	0.87	1.00
Trading	0.36	0.62	0.94	1.00	0.47	**0.04**	0.92	1.00
Other	0.10*	0.31*	0.77	0.99	**0.02**	**0.01**	0.88	1.00

Notes: based on 1000 simulations of model (4). p-values are based on the χ^2_{H+1} . Bold and italics denote significance at the 5% and 10% level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Table 2.2. Direct and total requirements of crude petroleum and natural gas

	Direct cost		Total cost	
Industry	1977	1999	1977	1999
Food and Kindred Products	0.000	0.000	0.036	0.023
Tobacco Products	0.000	0.000	0.025	0.006
Apparel	0.000	0.000	0.033	0.020
Textiles	0.000	0.000	0.057	0.033
Paper and Allied Products, except Containers (Business Supplies)	0.000	0.000	0.062	0.031
Chemicals and selected Chemical Products.	0.025	0.097	0.187	0.268
Petroleum Refining and related industries	0.607	0.484	0.720	0.785
Plastics and Synthetic Materials.	0.016	0.006	0.118	0.075
Rubber and Miscellaneous Plastics Products.	0.001	0.000	0.059	0.030
Primary Iron and Steel Manufacturing	0.000	0.000	0.047	0.031
Lumber and Wood Products	0.000	0.000	0.064	0.017
Computer and Office Equipment	0.000	0.000	0.021	0.010
Household Appliances	0.000	0.000	0.028	0.020
Motor Vehicles and Equipment	0.000	0.000	0.027	0.034
Transportation and Warehousing	0.001	0.003	0.067	0.177
Wholesale and Retail Trade	0.000	0.000	0.020	0.018
Finance and Insurance	0.000	0.000	0.010	0.009
Private Electric, Gas, Water, and Sanitary Services (Utilities)	0.125	0.466	0.237	0.876
Amusements	0.000	0.000	0.022	0.007

This table reports, as a measure of energy-intensity, total and direct costs of crude petroleum and natural gas required to produce a dollar of output of the particular industry in 1977 and 1999. These requirements are computed using the 1977 and 1999 annual Input-Output tables published by the BEA.

Table 2.3. Test of symmetry in the response to positive and negative innovations in the nominal oil price for h = 1, 2, …, 12

	1sd				2sd			
Sector	$x_t^{\#} = x_t^{1}$	$x_t^{\#} = x_t^{12}$	$x_t^{\#} = x_t^{36}$	$x_t^{\#} = x_t^{sd}$	$x_t^{\#} = x_t^{1}$	$x_t^{\#} = x_t^{12}$	$x_t^{\#} = x_t^{36}$	$x_t^{\#} = x_t^{sd}$
Aggregate	0.36	0.43	0.66	0.73	0.38	0.40	0.86	0.98
Agriculture	0.36	0.36	0.84	0.77	0.36	*0.07*	0.91	1.00
Food Products	0.40	0.08**	0.80	0.65	0.55	**0.02**	0.75	0.98
Candy & Soda	**0.05****	**0.00****	0.39	0.49	**0.01**	**0.00****	0.72	1.00
Beer & Liquor	0.50	0.12**	0.65	0.43	0.16	0.12	0.89	1.00
Tobacco Products	0.55	0.12**	0.61	0.44	0.34	*0.07*	0.58	1.00
Recreation	0.32	0.15**	0.49	0.22	0.28	0.15	0.74	0.96
Entertainment	0.23	0.12**	0.57	0.36	*0.08*	*0.09*	0.76	0.87
Printing and Publishing	0.31	0.07**	0.60	0.46	0.14	**0.02**	0.88	1.00
Consumer Goods	0.14*	0.16**	0.30*	**0.04****	*0.08*	**0.05**	0.72	0.92
Apparel	**0.01****	0.14**	0.87	0.76	**0.00**	**0.00**	0.82	0.97
Healthcare	0.63	0.21**	0.24*	0.34	0.63	**0.04**	0.55	1.00
Medical Equipment	0.17	**0.02****	0.59	0.57	**0.04**	**0.04**	0.84	0.97
Pharmaceutical Products	0.38	*0.08***	0.58	0.57	0.14	0.11	0.87	0.99
Chemicals	0.61	0.21**	0.43	0.87	0.60	*0.06*	0.71	1.00
Rubber and Plastic Products	0.28	0.27*	0.75	0.31	0.24	**0.03**	0.77	0.91
Textiles	*0.08***	0.18**	0.68	0.97	**0.02**	**0.00***	0.56	0.99
Construction Materials	*0.07***	*0.07***	0.26*	0.56	*0.06*	**0.04**	0.66	1.00
Construction	0.80	0.31	0.79	0.87	0.81	0.35	0.78	0.98
Steel Works Etc.	0.33	0.27*	0.55	0.95	0.19	*0.09*	0.61	0.99
Fabricated Products	0.64	0.13**	0.60	0.94	0.72	**0.03**	0.72	0.95
Machinery	0.51	0.11**	0.61	0.57	0.55	**0.03**	0.82	0.95
Electrical Equipment	0.60	0.20**	0.88	0.85	0.70	0.19	0.86	0.98
Automobiles and Trucks	**0.01****	*0.06***	0.47	0.62	**0.00****	**0.00***	0.60	1.00
Aircraft	0.22	*0.07***	*0.09***	0.80	**0.05**	**0.02**	0.67	0.99
Shipbuilding, Railroad Equipment	0.12**	0.18**	0.79	0.81	0.16	0.16	0.72	0.98
Defense	0.27	0.39	0.24*	0.12**	**0.05**	**0.02**	0.28	0.72
Precious Metals	0.94	0.35	0.72	0.54	0.97	0.12	0.76	0.96
Mines	0.57	0.44	0.90	0.99	0.34	0.43	0.70	0.99
Coal	0.77	**0.03****	0.30*	0.44	0.73	**0.00****	0.37	0.91
Petroleum and Natural Gas	0.94	0.48	0.08**	0.97	0.93	0.31	0.51	0.95
Utilities	0.50	0.21**	0.44	0.83	0.26	**0.01**	0.27	1.00
Communication	**0.04****	0.56	0.55	0.47	**0.01**	0.36	0.60	0.98
Personal Services	0.56	0.23*	0.38*	0.68	0.38	0.11	0.55	0.98
Business Services	0.59	0.13**	0.74	0.63	0.60	*0.09*	0.86	0.99
Computer Hardware	0.17	0.19**	0.51	0.28	0.20	**0.04**	0.70	0.94
Computer Software	0.49	0.06**	0.70	0.66	0.13	**0.00****	0.87	0.95
Electronic Equipment	0.16*	0.18**	0.54	0.18*	0.24	*0.08*	0.86	0.81
Measuring and Control Equipment	0.76	0.19**	0.67	0.45	0.72	**0.05**	0.91	0.84
Business Supplies	0.45	0.10**	0.13**	0.62	0.47	**0.01**	0.44	1.00
Shipping Containers	0.66	0.23*	0.58	0.73	0.83	**0.04**	0.71	0.98
Transportation	0.25	**0.05****	0.18**	0.65	0.26	**0.01**	0.71	0.96
Wholesale	0.88	0.13**	0.72	0.64	0.92	*0.06*	0.81	0.96
Retail	*0.06***	0.57	0.91	0.87	**0.00**	0.32	0.85	0.99
Restaraunts, Hotels, Motels	0.51	0.11**	0.47	0.63	0.24	0.11	0.88	0.99
Banking	0.12**	**0.01****	0.80	0.63	**0.02**	**0.00****	0.59	0.99
Insurance	**0.02****	**0.00****	0.22*	0.79	**0.00**	**0.00****	0.48	1.00
Real Estate	0.11**	0.26*	0.81	0.54	**0.01**	**0.01**	0.74	1.00
Trading	0.37	0.17**	0.93	0.57	0.48	**0.01**	0.90	1.00
Other	0.13*	**0.03****	0.70	0.51	**0.02**	**0.01**	0.71	0.97

Notes: based on 1000 simulations of model (4). p-values are based on the χ^2_{H+1} . Bold and italics denote significance at the 5% and 10% level, respectively.
** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Table 2.4. P-values for the test of null hypothesis of linearity of 12-month-ahead forecasts of real stock returns

Sector	$x_t^\# = x_t^1$	$x_t^\# = x_t^{12}$	$x_t^\# = x_t^{36}$	$x_t^\# = x_t^{sd}$
Aggregate	**0.00**	0.11	0.26	0.12
Agriculture	**0.00**	**0.00**	**0.00**	**0.00**
Food Products	0.37	0.46	0.30	**0.02**
Candy & Soda	0.22	0.26	0.48	0.21
Beer & Liquor	0.38	0.29	0.95	**0.03**
Tobacco Products	**0.00**	0.12	**0.00**	**0.02**
Recreation	**0.00**	**0.00**	**0.04**	**0.02**
Entertainment	**0.01**	**0.01**	**0.00**	**0.03**
Printing and Publishing	0.26	*0.07*	**0.01**	0.16
Consumer Goods	**0.00**	**0.04**	**0.05**	0.10
Apparel	**0.00**	*0.09*	0.33	**0.00**
Healthcare	**0.00**	**0.05**	**0.04**	0.51
Medical Equipment	**0.00**	**0.00**	**0.00**	0.39
Pharmaceutical Products	**0.00**	**0.01**	**0.03**	**0.02**
Chemicals	**0.02**	0.16	*0.09*	**0.02**
Rubber and Plastic Products	**0.00**	0.60	0.35	0.12
Textiles	**0.02**	0.21	0.46	**0.03**
Construction Materials	**0.04**	0.23	0.53	**0.04**
Construction	**0.00**	**0.00**	**0.00**	*0.06*
Steel Works Etc.	**0.00**	0.41	0.31	*0.08*
Fabricated Products	**0.00**	*0.07*	**0.05**	0.30
Machinery	**0.00**	**0.03**	0.11	*0.10*
Electrical Equipment	**0.03**	**0.02**	**0.00**	**0.01**
Automobiles and Trucks	**0.02**	0.27	**0.03**	*0.06*
Aircraft	0.31	0.61	0.38	**0.00**
Shipbuilding, Railroad Equipment	0.36	0.57	0.65	**0.05**
Defense	0.33	0.42	*0.06*	**0.05**
Precious Metals	**0.00**	**0.01**	**0.00**	*0.06*
Mines	**0.00**	**0.00**	**0.00**	**0.01**
Coal	**0.00**	*0.08*	0.77	0.48
Petroleum and Natural Gas	0.57	0.21	0.61	**0.03**
Utilities	**0.00**	0.49	0.93	0.88
Communication	0.32	0.26	**0.00**	**0.00**
Personal Services	0.12	**0.01**	**0.00**	**0.01**
Business Services	0.16	0.53	0.21	**0.04**
Computer Hardware	0.34	**0.01**	**0.03**	*0.10*
Computer Software	**0.00**	**0.05**	**0.00**	0.60
Electronic Equipment	0.11	**0.01**	**0.02**	*0.06*
Measuring and Control Equipment	**0.02**	*0.07*	**0.04**	0.18
Business Supplies	*0.07*	**0.02**	0.21	**0.01**
Shipping Containers	*0.10*	**0.01**	*0.07*	**0.00**
Transportation	*0.10*	0.06	**0.02**	**0.04**
Wholesale	**0.03**	*0.06*	**0.03**	0.34
Retail	**0.01**	0.13	**0.01**	*0.06*
Restaraunts, Hotels, Motels	**0.00**	0.13	0.29	**0.00**
Banking	**0.02**	0.34	**0.05**	0.22
Insurance	*0.07*	**0.02**	**0.01**	0.16
Real Estate	0.33	*0.07*	*0.08*	*0.06*
Trading	*0.09*	0.49	0.46	*0.09*
Other	**0.00**	**0.04**	0.33	0.10

Notes: Bold and italics denote significance at the 5% and 10% level, respectively.

Figure 2.1(a-c): Response to one standard deviation positive and negative innovation in the real oil price change

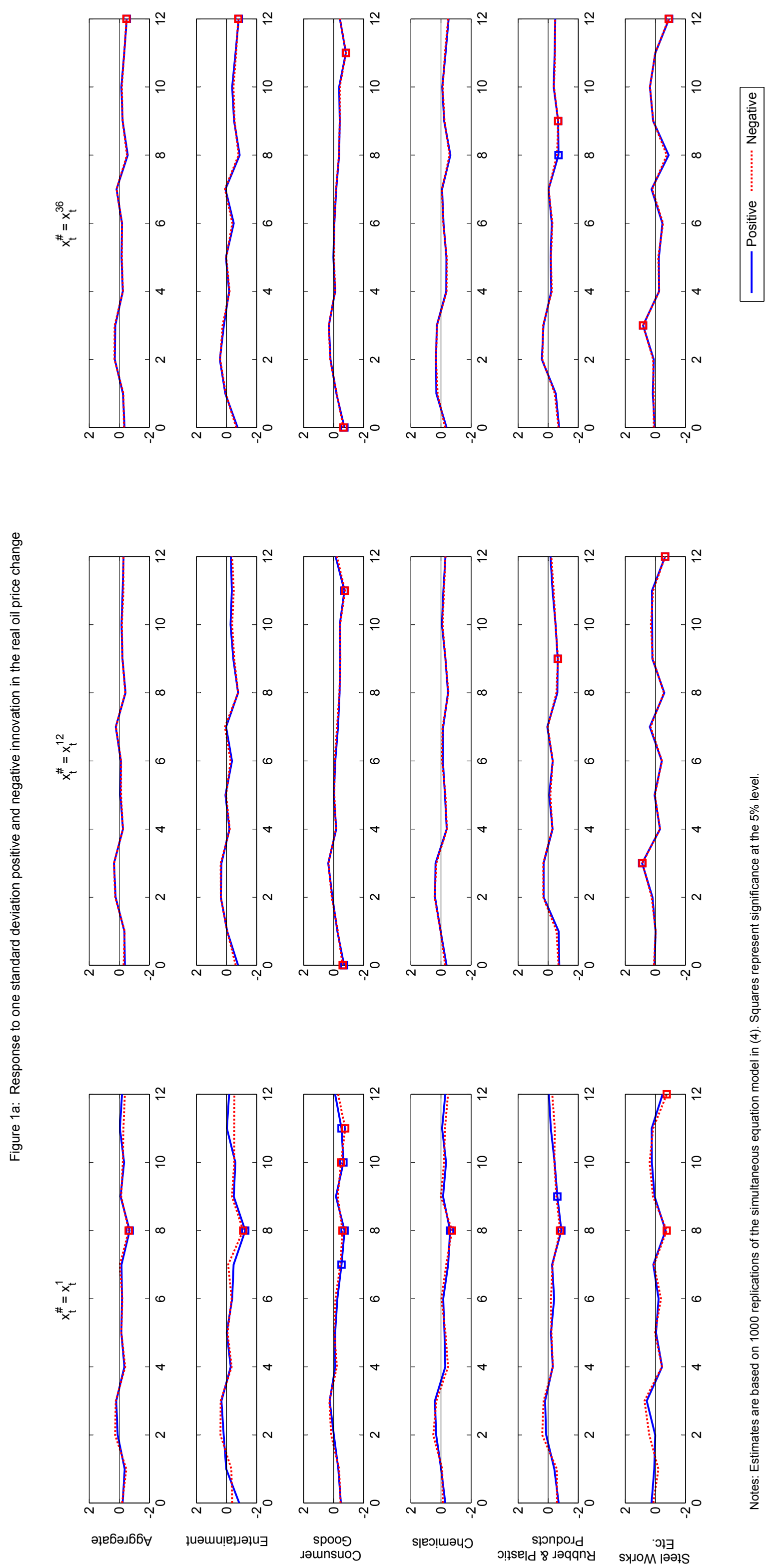


Figure 2.1(a-c): Response to one standard deviation positive and negative innovation in the real oil price change

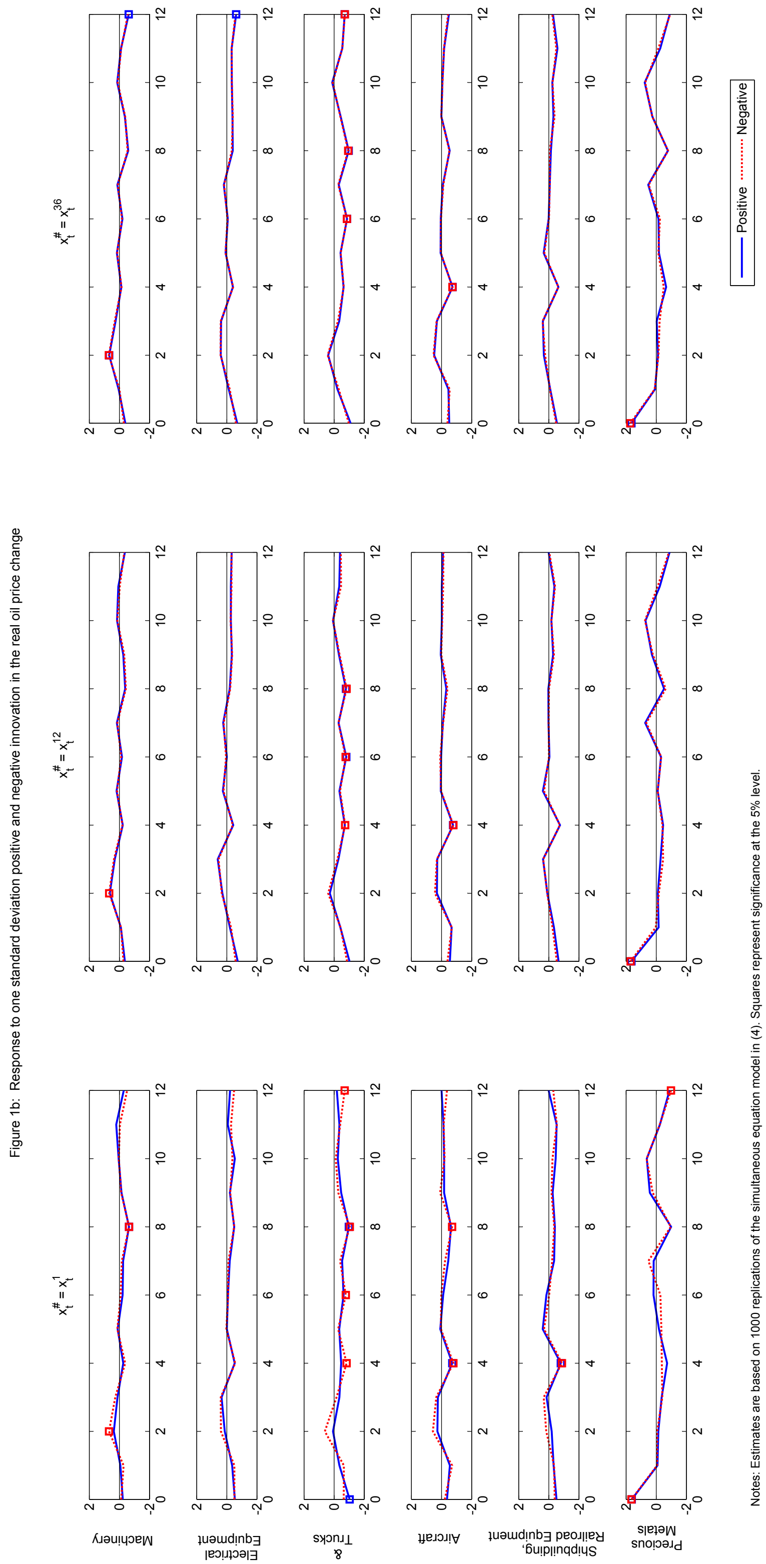


Figure 2.1(a-c): Response to one standard deviation positive and negative innovation in the real oil price change

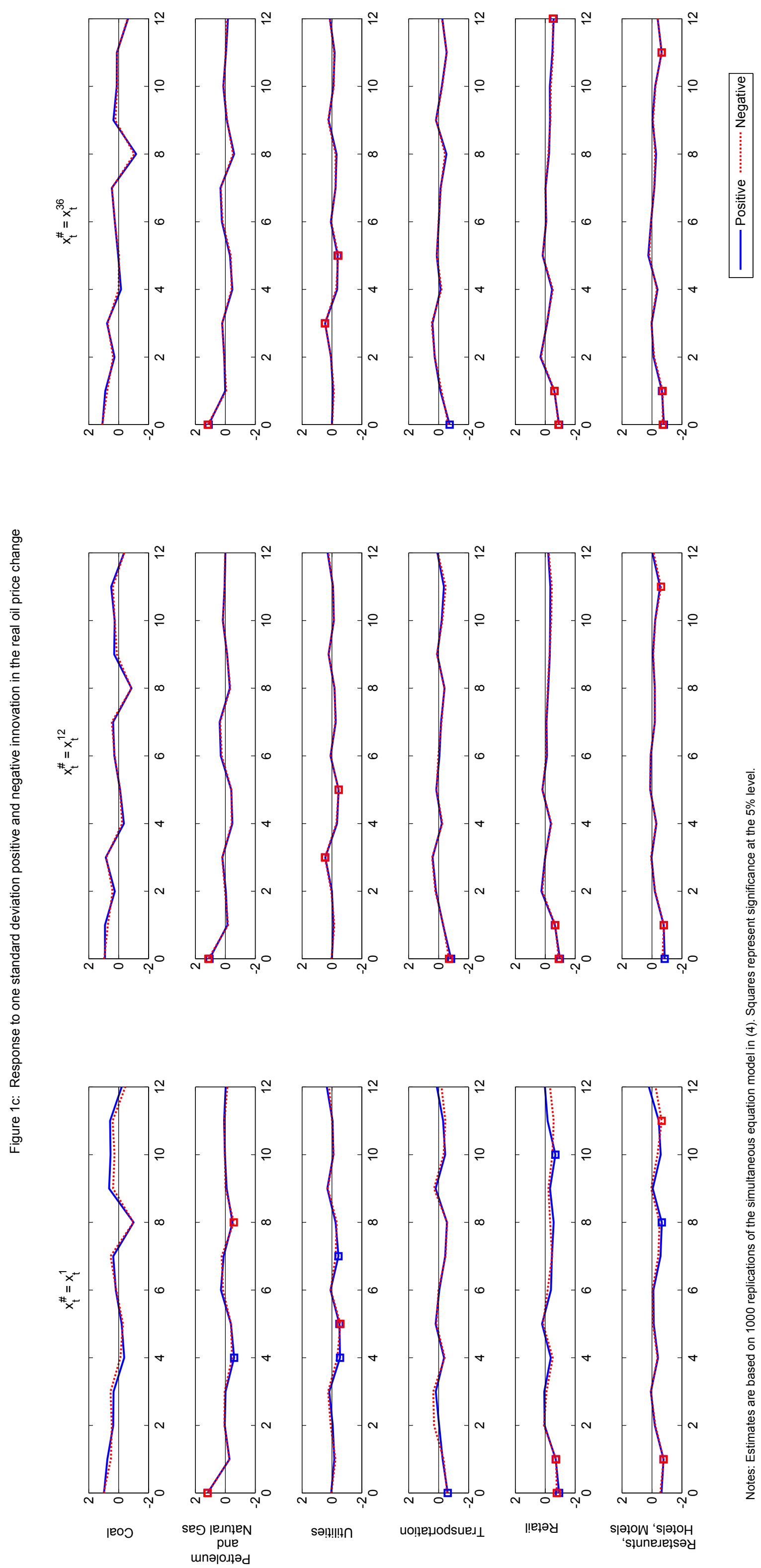


Figure 2.2(a-c): Response to two standard deviation positive and negative innovation in the real oil price change

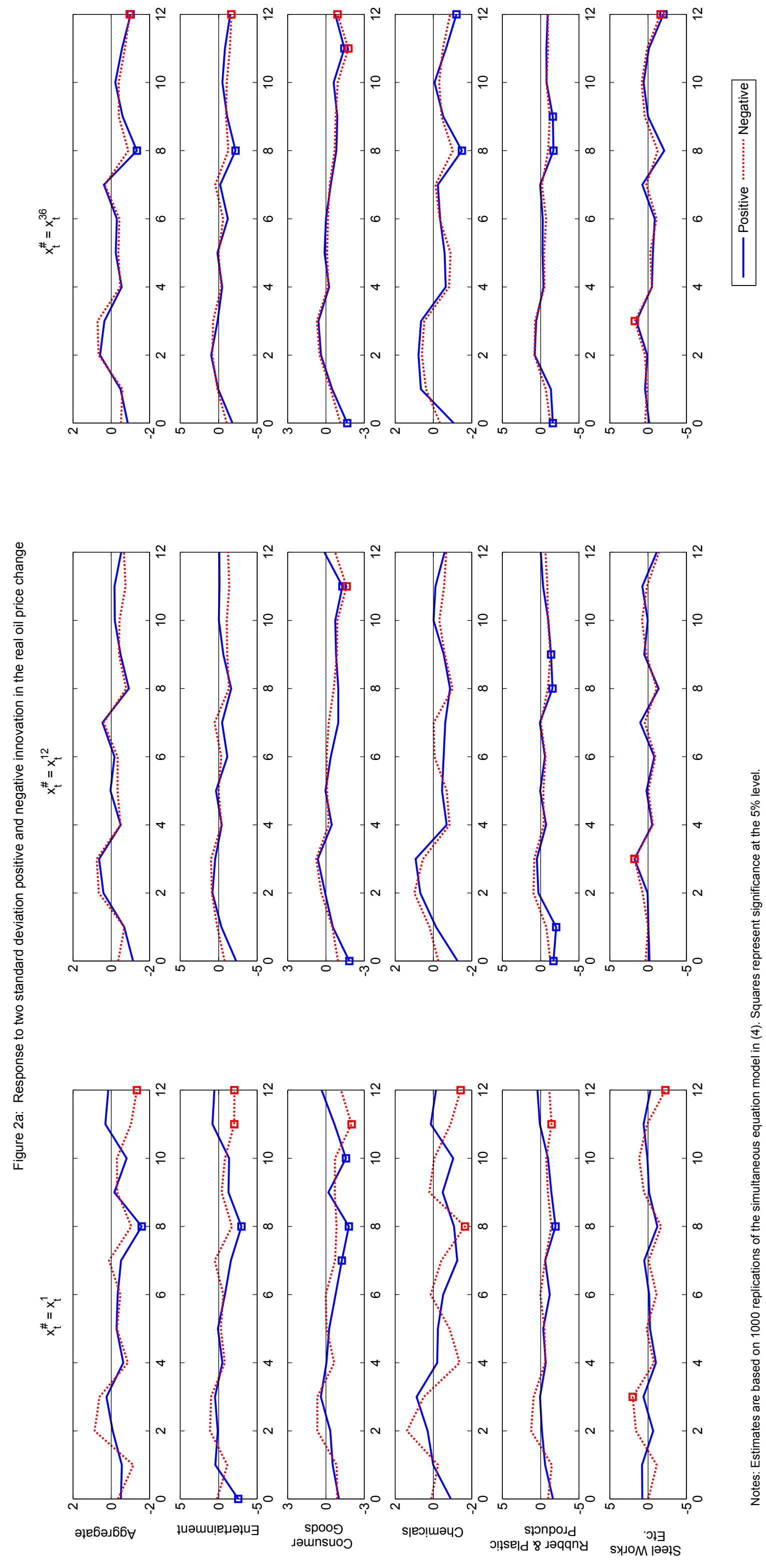


Figure 2.2(a-c): Response to two standard deviation positive and negative innovation in the real oil price change

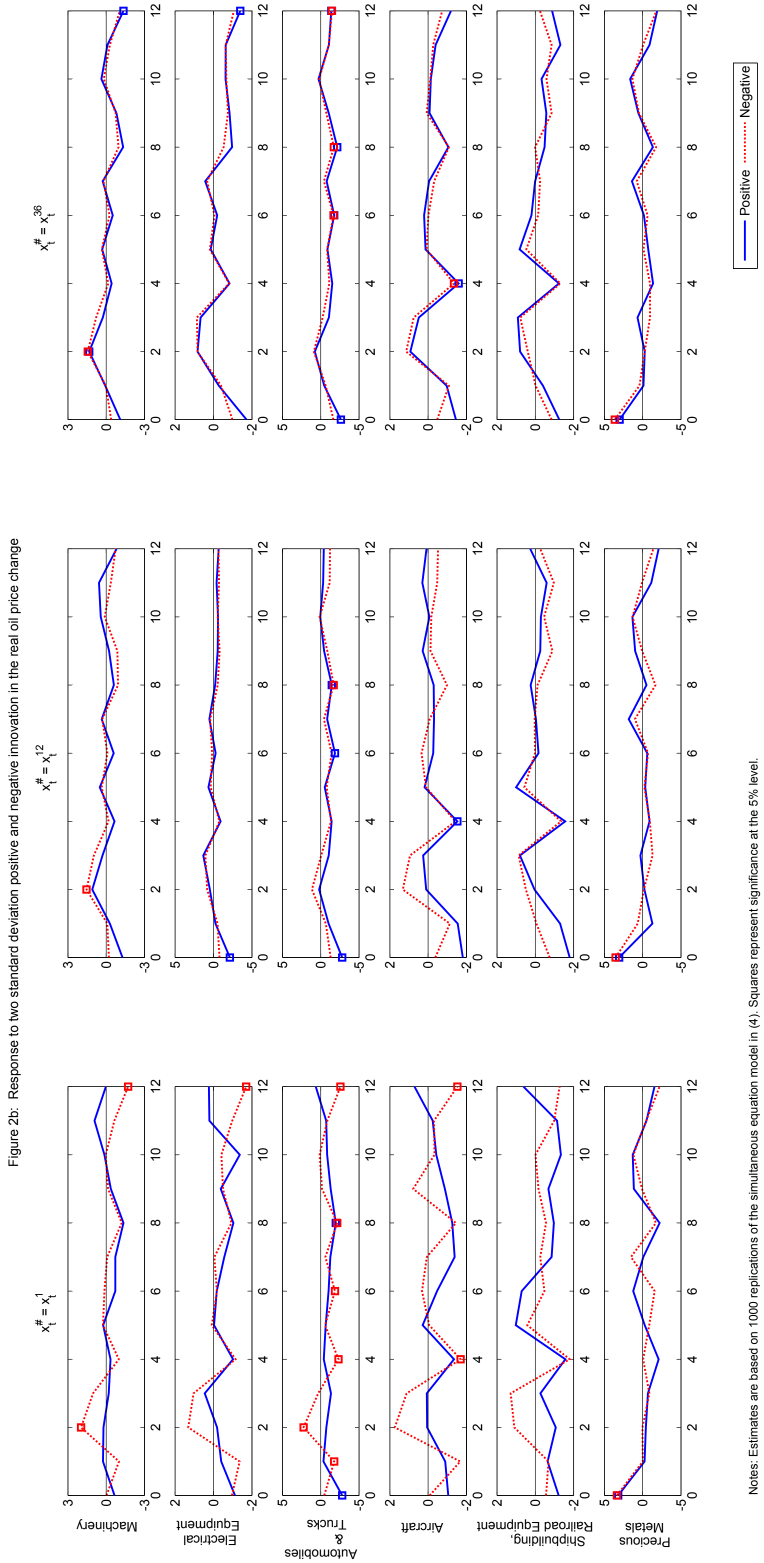
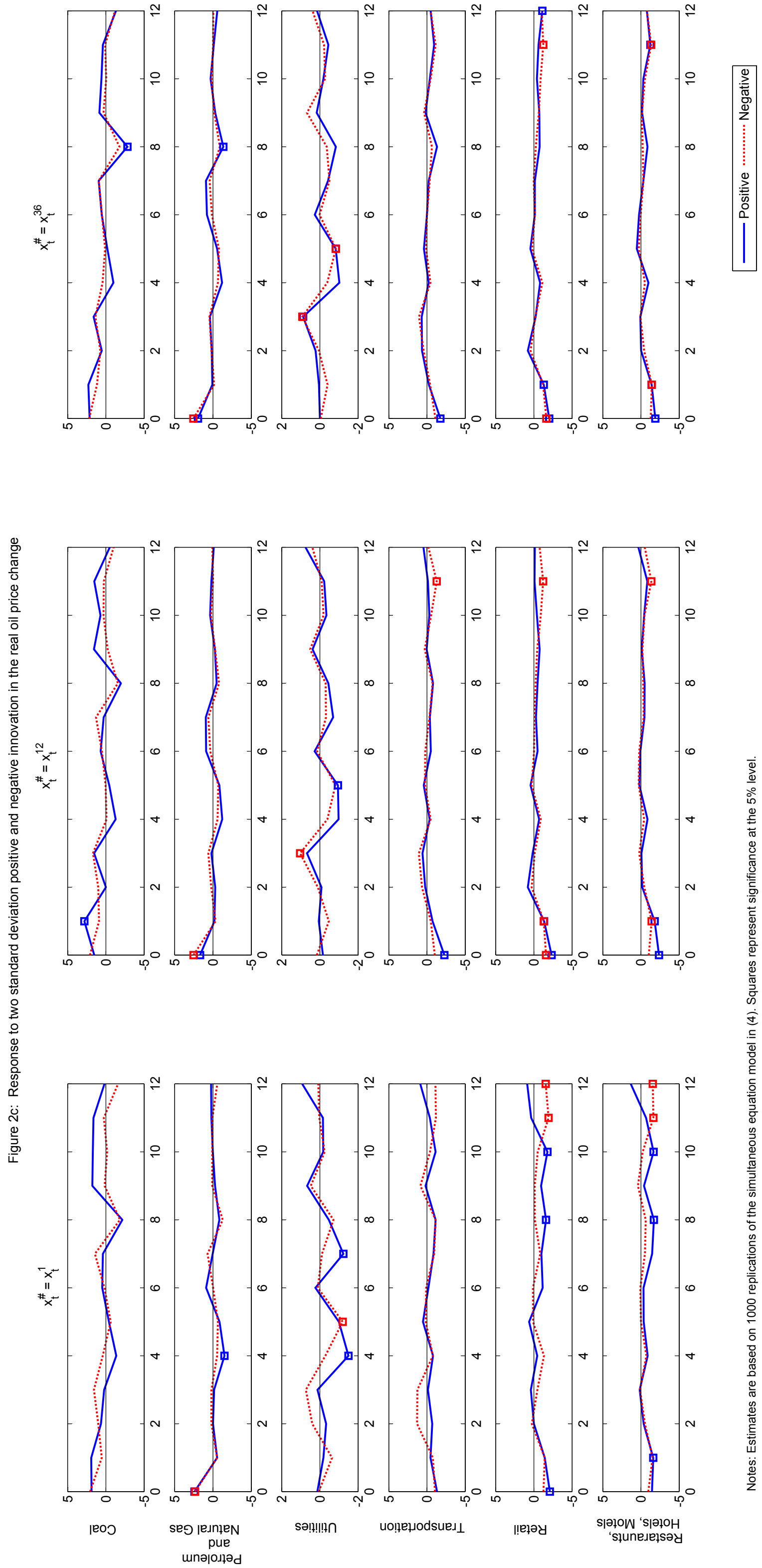


Figure 2.2(a-c): Response to two standard deviation positive and negative innovation in the real oil price change



Chapter 3: Oil Price Uncertainty and the U.S. Stock Market: Analysis Based on a GARCH-in-Mean VAR Model

Although there is empirical evidence in the financial literature that oil shocks play an important role on the U.S. stock market, no study has directly tested for the uncertainty effect of oil price changes on stock returns. This paper uses a bivariate GARCH–in-mean VAR model to examine the effect of oil price uncertainty on the U.S. real stock returns at the aggregate and sectoral level. Estimation results suggest that there is no statistically significant effect of oil price volatility on the U.S. stock returns. The absence of an uncertainty effect might be explained by the view that companies across sectors, the airline industry for instance, are likely to hedge against fluctuations in oil prices. It could also stem from the ability of most companies to transfer the higher cost of oil to customers. Moreover, the impulse responses indicate that oil price increases and decreases have symmetric effects on the U.S. stock returns, in that energy price increases and decreases are estimated to have equal and opposite effects on the U.S. financial market.

3.1. Introduction

During the 1970s energy crises, the U.S. went through a period of stagflation, a combination of raising prices and falling output. This period of stagflation was very costly in terms of lost corporate growth and profits, thus limiting stock price appreciation. Since the onset of the energy crisis and the subsequent instability in oil prices during the 1970s, the interaction between energy prices and the stock market became of considerable interest to investors, policy makers and academic researchers.

Even though some might believe that shocks in crude oil prices have a drastic effect on the financial market, the relationship between changes in oil prices and stock returns is still not clear. While there is a consensus among many researchers in the literature that boosts in oil prices play a significant role on the behavior of the stock returns (see among others, Kling 1985, Jones and Kaul 1996, Park and Ratti 2008, and Sadorsky 2011)[7], some researcherd had found that oil price shocks have no impact on stock returns (see among others, Chen, Roll and Ross (1986), Huang, Masulis, and Stoll (1996) and Wei (2003)). One explanation of these diverse results is that none of the papers above mentioned identified the source of oil shock as in Kilian and Park (2009). The latter noted that the source of the shock is vital to determine its effect on stock markets, and that different types of shocks might have different effects on stock markets. By separating oil price shocks into demand and supply shocks, Kilian and Park show, for instance, that oil price shocks that are driven by innovations to the precautionary demand for crude oil have a negative impact on U.S. stock returns.

These contrasting results in the effect of oil price innovations on stock returns raise the question of whether the nature of the relationship might make a difference. Meaning that, the impact of oil price shock on stock returns might be affected by whether an increase in the real price of oil is symmetric or asymmetric in oil price increases and decreases. The divergent results in the literature also question the effect of uncertainty and variability in oil prices on stock returns. For instance, Lee, Ni and Ratti (1995) argue that, "an oil shock is likely to have greater impact in an environment where oil prices have been stable than in an environment where oil price movement has been frequent and erratic". Furthermore,

[7] These studies find that the impact of oil price shock on stock returns is negative.

they find that during periods of high volatility in oil prices, the present oil price contains little information about the future and is often rapidly reversed.

This paper investigates whether the effect of oil price uncertainty on stock returns is symmetric. To the best of our knowledge, there are only a limited number of studies that address this question (Ciner 2001, Park and Ratti 2008, Alsalman and Herrera 2013) that test whether the relationship between oil prices and stock returns is linear. Yet, none of these papers directly tests whether the response of stock returns to increases and decreases in oil price volatility is symmetric, but instead focus on the response to innovations in the mean. There are, however, some studies that directly test the effect of oil price uncertainty on the stock market (Elyasiani, Mansur and Odusami (2011)). However, none of these papers separate increases and decreases in oil price uncertainty. This paper contributes to this literature by directly testing for the effect of oil price uncertainty on stock returns using a GARCH-in-Mean model.

Using a modified structural vector autoregression (VAR) to accommodate GARCH-in-Mean errors as in Elder (1995, 2004) and Elder and Serletis (2010), this paper studies the direct effects of oil price uncertainty on the U.S. stock returns at the aggregate and sectoral levels. Hence, the volatility of oil price change is measured by the conditional variance of the oil price change forecast error. We also simulate the response of U.S. stock returns to positive and negative oil price shocks, to examine whether the responses to positive and negative shocks are symmetric.

Empirical evidence on whether increases and decreases in the real price of oil have asymmetric effects on industry level data remains mixed. Kilian and Vigfusson (2009) show that there is no statistically significant evidence of asymmetry in the response functions for U.S. real aggregate GDP. Herrera, Lagalo and Wada (2011) show that there is no statistically significant evidence of asymmetry for total industrial production, while there is strong evidence of asymmetries in output at the disaggregate level for industries that are energy intensive in production (such as chemicals) or those that are energy-intensive in use (such as transportation equipment). While, Alsalman and Herrera (2013) find no evidence of asymmetry for aggregate stock returns, and only very limited evidence for the 49 industry-level portfolios studied in the paper. Using a GARCH-in-mean model, Elder and Serletis (2010) show that the response of real output is asymmetric in unexpected oil price increases and decreases in the variance. One of the explanations of asymmetric response functions is based on the effects of uncertainty about oil prices on investments, as shown in Herrera, Lagalo and Wada (2012). It is also shown in Kellogg (2010) who shows that oil companies respond to changes in expected price volatility by adjusting their drilling activity by a magnitude consistent with the optimal response prescribed by theory. This is explained by the real option theory, which suggests that increased uncertainty about the price of oil, measured by expected volatility of the real price of oil, tends to depress current investments.

Regarding the financial market evidence of asymmetry is still ambiguous. While some researchers during the last decade found that oil price increases and decreases are likely to have asymmetric effects on the stock market, in the sense that boosts in oil prices have a negative impact on stock market, while declines in oil prices do not necessarily have a positive impact (see e.g. Ciner 2001, Park and Ratti, 2008, Sadorsky, 1999). Others as Alsalman and Herrera (2013) find no evidence of asymmetry for aggregate stock returns, and only very limited evidence for the industry-level portfolios. However, only a few papers address the effect of uncertainty in oil prices on stock returns. Elyasiani, Mansur and Odusami (2011) examine the impact of changes in the oil returns and oil return volatility on excess stock returns and return volatilities of thirteen U.S. industries using the GARCH (1,1) model. They show that oil price fluctuations constitute a systematic asset price risk at the industry level. For several European countries, but not for the U.S., Park and Ratti (2008) show that an increase in oil price volatility significantly depresses real stock returns. They also show little evidence of asymmetric effects on real stock returns of positive and negative oil price shocks for oil importing European countries. Sadorsky (1999) finds that oil price volatility generated by a GARCH (1,1) process have a significantly negative impact on the U.S. real stock returns. He also suggests that the response of the stock market to oil price shocks is asymmetric.

This study distinguishes itself from the previous studies within the energy and financial market literature through three important directions. First, we use a bivariate GARCH–in-mean VAR model to examine the effect of oil price uncertainty on the U.S. real stock returns. Results show that uncertainty about the real price of oil has a positive but insignificant effect on the U.S. real stock returns. This suggests that the volatility in oil prices does not play an important role on corporate cash flow and/or discount rates.

Second, we simulate the response of real stock returns to positive and negative oil price shocks to study whether the responses to positive and negative shocks are symmetric or asymmetric, after accounting for the effects of oil price uncertainty. The impulse responses indicate that the responses to positive and negative shocks are symmetric, in that energy price increases and decreases are perceived to have opposite sign but equal magnitude effects on the U.S. financial markets.

Third, since results at the aggregate level might hide important effects of oil price volatility at the sectoral level, we examine the oil uncertainty effects on sectoral stock markets, and investigate whether the relationship between oil prices and sectoral stock returns is symmetric. Investigating the effect of oil price shocks at a sectoral level is important for a number of reasons. First, as we mentioned before, evidence regarding the presence (or absence) of asymmetry differs among sectors and in the aggregate. Second, Fama and French (1997), among others, show that returns and volatility at the sectoral level offer important information about the return and volatility process at the aggregate level. Similarly, Hong et al. (2007) also recognize the importance of sectoral returns to give information about the movements of aggregate stock returns. Accordingly, it is important to examine the effect of oil price uncertainty on stock returns across industries especially during periods of instabilities in oil prices; so that investors can adjust their portfolios accordingly.

The results show that uncertainty about the real price of oil has no effect on the U.S. real stock returns across industries. This might suggest that other hidden variables drive the stock market returns across industries as shown in King et al. (1994) who try to identify the causes for stock volatility through observable factors such as oil prices, interest rates and industrial production, and unobservable factors that are not captured by published statistics. Their results show little support for the observable economic variables, whereas the unobservable uncertainty contributes to the variability in stock returns. Thus, except for decisions about oil drilling in Alaska or Texas (see Kellogg 2010), for instance, variations in oil prices don't seem to have important effects on other sectors of the economy where oil prices represent a small share of corporate cash flow.

The findings can also be explained by the ability of companies to hedge against fluctuations in oil prices or by the ability of most companies across sectors to transfer the higher cost of oil to customers (see Hammoudeh et al (2010) and Elyasiani et al (2011)).

This paper is organized as follows. Section 2 describes the data. Section 3 illustrates the bivariate GARCH-in-mean model. Section 4 presents the empirical results. Section 5 provides evidence across industries. We conclude in section 6.

3.2. Data Description

This paper uses monthly data spanning the period between January 1973 and December 2009, to examine the effect of volatility in real oil prices on the U.S. real stock returns. As a measure of the price of oil, we use the U.S. refiner's acquisition cost of imported crude oil. The nominal price of oil is deflated by the U.S. consumer price index (CPI).

The data on monthly nominal stock returns were obtained from Kenneth French's database available on his webpage[8]. To measure aggregate U.S. stock return, we use the excess return on the market, which is defined as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks from the Center for Research in Security Prices (CRSP) minus the one-month Treasury bill rate. In order to examine how the response of stock returns differs across industries, we use the industry level data made accessible by Kenneth French, constructed from the CRSP database[9]. We concentrate on industries that are expected to respond to fluctuations in oil prices (Petroleum and Natural Gas, Coal, Utilities, Automobiles and Trucks, Aircraft, Ships and Railroad Equipment, Retail,

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8 See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

9 The data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The file containing 49 industry portfolios is used.

Consumer Goods, Restaurants Hotels and Motels, Entertainment, Transportation, Chemicals, Paper Business Supplies, Rubber and Plastic Products, Steel, Precious Metals, Machinery, and Electrical Equipment), as in Kilian and Park (2009). A complete classification of the industries in terms of their Standard Industry Classification Code (SIC) is available in the appendix of this paper. We then compute real stock returns by taking the log of the nominal stock returns and subtracting the CPI inflation.

Because unit root tests reported in Table 1 suggest that real U.S. stock returns and the rate of growth of real oil prices are stationary, we estimate the log using the log change in the real oil price and the U.S. stock returns for the aggregate and the sectors of interest as in Kilian and Park (2009).

Table 2 presents summary statistics for the change in the real price of oil and the U.S. real stock returns at the aggregate and industry levels. The results indicate that oil growth and stock returns are skewed and that high excess kurtosis exists in the data that is substantially greater than 3. The kurtosis statistics indicate the existence of volatility persistence, which suggests that a GARCH model could do a good job at capturing the behavior of volatility in oil prices. Furthermore, Table 3 presents a χ^2 (2) Skewness-Kurtosis test for normality, which indicates that we reject the null hypothesis of normality at the 1% level for the change in real oil prices as well as the aggregate and sectoral U.S. real stock returns.

In Table 4, we report the results of Breusch-Godfrey LM test for serial correlation. The test indicates the existence of serial correlation in the residuals for the real oil price and the aggregate stock returns. However, when testing for serial correlation across industries, the results indicate the presence of significant serial dependence in most industry-level stock returns, except for chemicals, steel, electrical equipment, precious metal, coal, petroleum, utilities, and business supplies returns. We also report the results of Engle's (1982) LM test for ARCH effect in table 4.1. The test shows strong evidence of conditional heteroscedasticity in the real oil price and in aggregate stock returns. At the sectoral level, evidence of conditional heteroscedasticity is evident for entertainment, consumer goods, chemicals, steel, machinery, precious metal, coal, and petroleum.

3.3. Methodology

In this paper, we examine the effects of oil price uncertainty on U.S. stock returns by using a modified structural vector autoregression (VAR) to accommodate GARCH-in-Mean errors as in Elder (1995, 2004) and Elder and Serletis (2010). Hence, the volatility of oil price change is measured by the conditional variance of the oil price change forecast error as follows

$$By_t = \alpha + \sum_{i=1}^{p} \Gamma_i y_{t-i} + \Psi\sqrt{h_t} + \varepsilon_t, \qquad (1)$$

$$\varepsilon_t = H_t^{1/2} z_t \qquad (2)$$

where the vector y_t includes the change in the real price of oil and real U.S. stock returns, $\varepsilon_t\,|\Omega_{t-1} \sim$ *iid* N(0, H_t), Ω_{t-1} denotes the information set in period t-1, and H_t is a k x k conditional variance-covariance matrix, and

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix} \quad , \quad B = \begin{bmatrix} 1 & 0 \\ b & 1 \end{bmatrix} \quad , \quad h_t = \begin{bmatrix} h_{1t} \\ h_{2t} \end{bmatrix}$$

$$y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} \quad , \quad \alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \quad , \quad \varepsilon_t = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$$

$$\Gamma_i = \begin{bmatrix} \gamma_{11}^i & \gamma_{12}^i \\ \gamma_{21}^i & \gamma_{22}^i \end{bmatrix} \quad , \quad \Psi_j = \begin{bmatrix} \psi_{11}^j & \psi_{12}^j \\ \psi_{21}^j & \psi_{22}^j \end{bmatrix}$$

We identify the system by assuming that the structural shocks are uncorrelated, and by assuming that stock returns have no contemporaneous effect on oil price changes. This zero restriction (b_{12}) on one of the elements of B allows to have a just-identified model with $(n^2-n)/2$ restrictions.

A general form of the bivariate GARCH (p,q) variance function is presented in the work of Bollerslev, Engle, and Wooldridge (1988) and Engle and Kroner (1995) as

$$h_t = A + \sum_{q=1}^{Q} M_q vec(\varepsilon_{t-q}\varepsilon_{t-q}^{'}) + \sum_{p=1}^{P} N_p h_{t-p} \quad ,$$

$$Z_t \sim iid\ N(0, I),$$

$$\varepsilon_t = H_t^{1/2} Z_t$$

where A is N^2 x 1, M and N are N^2 x N^2, and $h_t = vec(H_t)$ with ½ $N(N+1)(N^2+N+1)$ different variance function parameters for p=q=1. Moreover, by imposing the normal identifying restriction that the structural disturbances are contemporaneously uncorrelated greatly reduces the parameters in the variance function (see Elder (2004)), so that the variance function is written as

$$diag(H_t) = A + \sum_{q=1}^{Q} M_q diag(\varepsilon_{t-q}\varepsilon_{t-q}^{'}) + \sum_{p=1}^{P} N_p diag(H_{t-p}), \quad (3)$$

Where the conditional variance depends only on its own squared errors and its own past conditional variances

$$\begin{bmatrix} H_{1,1(t)} \\ H_{2,2(t)} \end{bmatrix} = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} + \begin{bmatrix} M_{1,1} & M_{1,2} \\ M_{2,1} & M_{2,2} \end{bmatrix} \begin{bmatrix} e_{1(t-1)}^2 \\ e_{2(t-1)}^2 \end{bmatrix} + \begin{bmatrix} N_{1,1} & N_{1,2} \\ N_{2,1} & N_{2,2} \end{bmatrix} \begin{bmatrix} H_{1,1(t-1)} \\ H_{2,2(t-1)} \end{bmatrix}$$

Imposing additional restrictions that M and N are diagonal can reduce the number of parameters furthermore[10]. We thus follow Elder (2004) and Elder and Serletis (2010) and estimate the conditional variance H_t as a diagonal matrix with p=q=1 where the conditional variance depends merely on one-lagged squared errors and one-lagged conditional variances.

We estimate the model by full information maximum likelihood (FIML) by maximizing the log likelihood function

$$l_t = -(\frac{N}{2})\ln(2\Pi) + \frac{1}{2}\ln|B^2| - \frac{1}{2}\ln|H_t| - \frac{1}{2}(\varepsilon_t^{'} H_t^{-1} \varepsilon_t) \qquad (4)$$

with respect to the structural parameters B, α, Γ_1, …, Γ_p, Ψ, A, M. and N.

After estimating the model, we generate the impulse response functions to evaluate the effect of oil price uncertainty on the response of the U.S. stock returns to oil price shocks. We also plot the impulse response of real stock returns to positive and negative oil price shocks, to examine whether the responses to positive and negative shocks are symmetric

[10] These restrictions can be relaxed as appropriate given the researcher's specific interest in how the lagged volatility of one variable might relate to the conditional variance of another.

or asymmetric. The maximum likelihood estimates are used to simulate the impulse responses where the confidence intervals are generated by the Monte Carlo method with 1000 simulations, as illustrated in Elder (2003), and Elder and Serletis (2010).

3.4. Empirical Results

Before we present the estimation results, let us describe our model selection strategy. In order to select the number of lags in the mean equation (1), we use the SIC. According to this selection criterion we include only one lag of the oil price change and the stock returns in the conditional mean equation. Setting p=1 in the mean equation is sufficient to eliminate serial correlation and ARCH effects in the residuals as can be seen in the results of the LM test for residual serial correlation reported in table 5[11]. In addition, we use a low order GARCH (1,1) model, which proves to be adequate to remove conditional heteroscedasticity in the residuals. This is consistent with Bollerslev et al. (1992) suggestion that a GARCH (1,1) model performs well in capturing the behavior of time-varying volatility in most macroeconomic and finance series. Similarly, it falls in line with Sadorsky (1999) who points out that volatility computed from GARCH (1, 1) is the best fit in examining the relationship between oil prices and stock returns.

To evaluate the adequacy of the model, we report the results of LM tests for ARCH effects on the standardized residuals from the GARCH-in-Mean in Table 6. As can be seen from the Table, test statistics are statistically insignificant. This means that no ARCH effects are left in the model. In other words, a GARCH (1,1) appears to be a good representation of the conditional volatility process. Therefore, we estimate the bivariate GARCH-in-Mean VAR with one lag in the mean equation.

[11] Except for Automobile, Chemicals and Steel where we set p = 2, 7 and 10 respectively.

In order to measure the efficiency of the parameterized model in terms of predicting the data, we compare the Schwarz information criterion (SIC) for the GARCH-M VAR against the conventional homoskedastic VAR (see Table 7). The SIC for GARCH-M (5390.42) is significantly lower than that of the homoskedastic VAR (5564.31), which implies that our specification for the GARCH-M VAR is consistent with the data.

3.4.1 Oil Uncertainty Effect on the U.S. Aggregate Stock Returns

The parameter estimates for the free elements in the variance function are reported in Table 8. They show evidence of GARCH in the real price of oil and the real stock returns as the coefficients on the lagged conditional variance and the lagged squared errors are highly significant. These results indicate persistence in the volatility process for the real stock returns and the change in the real price of oil.

The point estimates for the free elements in Ψ from the structural VAR with bivariate GARCH-M represent the effect of oil price uncertainty on real stock returns. The null hypothesis is that the value of Ψ is zero. The results are reported in Table 9 where the coefficient on the standard deviation of real oil prices in the aggregate stock returns equation equals 0.029 with a t-statistic of 0.41, which indicates that we cannot reject the null hypothesis that the value of Ψ is zero. This implies that oil price uncertainty has no effect on aggregate stock returns in the U.S., as the effect is not statistically significant.

We then simulate the response of real stock returns to positive and negative oil price shocks to study whether the responses to positive and negative shocks are symmetric or asymmetric, after accounting for the effects of oil price uncertainty. The impulse response functions presented in the first panel of Figure 1 show that the responses of aggregate stock returns increase immediately after a positive oil price shock and then die out in four months. However, the opposite is true for the responses of aggregate returns to negative oil shock, where the aggregate returns decrease immediately and dies out in four months. This suggests that the responses to positive and negative shocks are symmetric, in that energy price increases and decreases are perceived to have equal and opposite sign effects on the U.S. financial markets. Figure 1b compares the responses of stock returns to positive and negative shocks when oil uncertainty is accounted for (represented by the solid line), against those when oil price uncertainty is excluded from the stock return equation (represented by the dashed line where Ψ=0). The figures show that the responses of real stock returns to positive and negative oil price shocks when oil price uncertainty is accounted for are virtually identical to those where oil price uncertainty is excluded from the model. These figures suggest that uncertainty in oil prices has no effect on stock returns.

The findings that oil price uncertainty has no effect on the U.S. stock market can have five different explanations. First, it is likely that businesses in most sectors are able to hedge against oil price risk (see Elyasiani, Mansur and Odusami (2011)). Thus, fluctuations in oil prices could encourage the use of derivatives and future markets to hedge against oil price risk. Oil prices can fluctuate greatly from month to month, meaning that if oil-consuming industries bought oil at market price, the costs would also fluctuate greatly from month to month. Through the process of hedging, such industries greatly reduce their exposure to price fluctuations of oil.

Second, it is also likely that sectors do raise their prices to their customers more easily when uncertainty about the oil price change is greater, rather than when the oil price is stable (Hammoudeh, Yuan, Chiang, Nandha 2010). Thus, most of the higher costs will eventually have to be paid for by individuals, through higher prices on goods or services, or higher taxes. However, we don't have to forget the role of the government in protecting the consumers from the impacts of high oil prices. Thus, with high spending, low interest rates and low taxes, the government stimulates the economy leaving consumers with more money to spend.

Third, it might be that a boost in oil price affects a corporate cash flow positively or negatively depending on whether the firm is an energy producer or consumer. It might also affects the firm value through the effect on the discount rate and therefore on stock prices. Thus, it is possible that variations in oil prices do not have important effects on sectors of the economy where oil prices represent a small share of corporate cash flow.

Fourth, based on the efficient market hypothesis (EMH), securities in an efficient market are traded and priced on the basis of fully available information to the public. Thus, theoretically speaking, when investors face new information, such as changes in oil prices, some of them may under react while others may over react. In other words, it is likely that, since changes in oil prices are readily observable for market participants, this information is quickly incorporated in the stock prices and thus does not appear in monthly stock returns.

Fifth, the finding that oil price uncertainty has no effect on the U.S. stock market might be due to some limitations of the GARCH model. That is the conditional variance of the oil price might not capture other factors of uncertainty and thus might not be an appropriate proxy of oil price uncertainty. For instance, uncertainty in oil prices might not be only a function of the past oil price variance, but it might depend on whether sharp decreases (or increases) in oil prices were observed in the recent past. In other words, periods of sharp decrease in oil prices can lead to a reduction in the uncertainty about the future oil prices, thus making the conditional variance of oil prices a poor proxy for uncertainty. In addition, uncertainty caused by oil demand shocks might have different effects on stock returns than uncertainty caused by oil supply shocks (see Kilian and Park 2009).

3.5. Effect of Oil Uncertainty Across Industries

Based on the heterogeneity of the response of stock returns across industries to fluctuations in oil prices (see, for instance, Herrera, Lagalo and Wada 2011), and since results at the aggregate level might hide important effects of oil price volatility at the sectoral level, we examine the oil uncertainty effects on sectoral stock markets. As is the case for aggregate returns, the parameter estimates for the free elements in the variance function show evidence of GARCH in the real price of oil and the real stock returns across sectors, as the coefficients on the lagged conditional variance and the lagged squared errors are highly significant. These results indicate persistence in the volatility process for sectoral stock returns and the change in the real price of oil[12].

The point estimates for the free elements in Ψ from the structural VAR with bivariate GARCH-M represent the effect of oil price uncertainty on sectoral stock returns. The null hypothesis is that the value of Ψ is zero. The results reported in Table 9 suggest that uncertainty in oil prices has no effect on stock returns across all industries examined in

[12] To conserve space, these results are available upon request.

this paper, as the point estimates for the coefficient on oil price uncertainty are not statistically significant, which indicates that we cannot reject the null hypothesis that the value of Ψ is zero.

We then simulate the response of real stock returns across industries to positive and negative oil price shocks to study whether the responses to positive and negative shocks are symmetric or asymmetric, after accounting for the effects of oil price uncertainty. The impulse response functions presented in the appendix of the paper show that the responses to positive and negative shocks mirror each other, in that energy price increases and decreases are perceived to have equal and opposite sign effects on the U.S. sectoral returns. The figures in the appendix also compare the responses of stock returns to positive and negative shocks when oil uncertainty is accounted for (represented by the solid line), against those when oil price uncertainty is excluded from the stock return equation (represented by the dashed line where Ψ=0). The figures show that the responses of stock returns across industries to positive and negative oil price shocks when oil price uncertainty is accounted for are virtually identical to those where oil price uncertainty is excluded from the model. These figures suggest that uncertainty in oil prices has no effect on sectoral stock returns.

The results that the volatility of oil prices is irrelevant to some sectoral stock returns might not be surprising. Take for example the automobile sector; the uncertainty effect in oil prices might not lead to a drop in the number of motor vehicles sold. It might lead to consumers swapping from large energy-inefficient vehicles to small energy-efficient ones. Thus, the aggregate real consumption of automobiles may decrease but not the number of vehicles sold (see Hamilton (1988) and Bresnahan and Ramey (1993)).

Regarding construction machinery, the absence of an uncertainty effect can be explained by the view that with the increase in oil price volatility, demand for new homes increases since newer buildings are more energy efficient.

On the other hand, one way to reduce the exposure to fluctuations in oil prices is through the ability of companies to transfer the high price of oil to their customers which is easier to do when uncertainty about the price of oil is high, rather than when oil price is stable. However, although many sectors, such as consumer goods and utilities, manage to pass through the higher price of oil to consumers (see Hammoudeh, Yuan, Chiang, Nandha 2010), some sectors, such as the airline industry, fail to do so due to highly competitive market or high price elasticity of demand[13]. Thus, through the process of hedging, such sectors greatly reduce their exposure to oil price fluctuations.

Future markets and derivatives are two efficient ways of hedging against oil price volatility. The airline industry is one example where hedging against oil price volatility is prevalent and can help the more skilled companies to survive. While some airlines fail to pass through the high priced fuel to consumers, others like Southwest airlines survive by using a combination of futures, options and swaps to hedge against fuel price risk (Carter et al (2004)). Because of oil price volatility, airlines normally hedge most of their oil consumption; they buy call options to lessen their exposure to oil price risk.

Thus to protect themselves against oil price volatility, companies across sectors, mainly those that are energy intensive in use, are likely to hedge against fluctuations in oil prices, or transfer the higher cost of oil to customers. Adding to that, the absence of uncertainty effect of oil prices on stock returns across industries is shown graphically in

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[13] These are defensive sectors that are unaffected by the ups and downs in the economy.

the figures of the appendix, where the reactions of real stock returns to positive and negative oil price shocks when oil price uncertainty is accounted for are virtually identical to those where oil price uncertainty is excluded from the model. The figures also show that the effects of oil price increases are simply the reverse of oil price declines.

Alternatively, another explanation for the results showing that uncertainty in oil prices has no effect on stock returns can be related to the fact that this paper does not identify the source of the shock as in Kilian and Park (2009) and Ready (2012) who demonstrate that U.S. stock returns react differently to oil supply shocks than oil demand shocks. Kilian and park (2009) shows that the response of U.S. stock returns may differ greatly depending on whether the increase in the price of oil is driven by demand or supply shocks in the crude oil market. Additionally, Ready (2012) shows that oil supply shocks are shown to have a highly significant impact on U.S. stock prices. Thus, since different shocks in the crude oil market have different effects on U.S. stock returns, and since the relative importance of individual shocks in the price of oil evolves over time, testing the response of stock returns to variations in oil prices may be biased toward finding no statistical significant effect.

3.6. Conclusions

There is a broad literature exploring the relationship between the price of oil and the financial market; however, very little research has focused on the role of uncertainty in oil prices. This paper investigates the direct effect of oil price uncertainty on the U.S. stock returns at the aggregate and sectoral level using a bivariate GARCH–in-mean VAR model. Oil price uncertainty is measured by the conditional standard deviation of the one-lagged squared errors of the change in the price of oil. Because aggregating over a number of industry-level stock returns might hide important effects at the sectoral level, we also examine the effect of oil price uncertainty on sectoral stock markets.

Our estimation results show that uncertainty about the real price of oil has a positive but insignificant effect on the U.S. aggregate stock returns. As it is widely known, high priced fuel translates into high transportation and production cost, which could affect stock prices through their effect on the corporate cash flow. High oil prices could also affect expected interest rate and inflation rate, which in turn would influence the stock prices. However, our results suggest that the conditional volatility of the real price of oil has no effect on the U.S. stock returns. In other words, oil price shocks affect stock returns through the impact of an unexpected innovation to the conditional mean of the oil price change but not through shocks to the conditional volatility. This result is likely to be linked to the absence of an uncertainty effect of the real price of oil on corporate cash flow and discount rates. Moreover, by simulating the response of real stock returns to positive and negative oil price shocks, we show that the responses to positive and negative shocks are symmetric, in that energy price increases and decreases are estimated to have equal and opposite effects on the U.S. financial markets.

Because the effect of oil price shocks might differ across sectors, we investigate the effect of changes in oil price uncertainty on industry-level stock returns. In particular, sectoral response to oil price volatility might have important implications in understanding the market and in retaining efficient portfolio diversification. Our results show that uncertainty in oil prices has no effect on stock returns across all industries[14].

[14] Where uncertainty in oil prices shows a negative impact on oil intensive sectors such as transportation, utilities, automobile, aircraft, ship railroad, and consumer goods; however, the impact in not statistically significant.

The finding that uncertainty in oil prices has no effect on stock returns across all industries can be explained by the ability of most companies across sectors to transfer the higher cost of oil to customers, and by the ability of companies to hedge against fluctuations in oil prices. Moreover, testing the response of stock returns to variations in oil prices may be biased toward finding no statistical significant effect since this paper does not identify the source of the shock as some papers in the literature which demonstrate that U.S. stock returns react differently to oil supply shocks than oil demand shocks.

Table 3.1 Unit Root Test

Variable	DF-GLS
oil	-11.487
Aggregate	-13.011
Entertainment	-9.474
Consumer Goods	-12.088
Chemicals	-13.352
Rubber&plastic	-14.464
Steel	-13.513
Machinery	-12.663
Electrical Equipment	-12.224
Auto	-11.793
Aircraft	-9.976
Shipbuilding	-14.607
Precious metal	-14.16
Coal	-9.567
Petroleum	-14.014
Utilities	-10.802
Business Supplies	-11.647
Transportation	-8.663
Retail	-12.671
Restaurants	-10.61
5% CV	-2.882

Note: Using the log change in the real price of oil and the U.S. stock returns for the aggregate and the sectors of interest.

Table 3.2 Summary Statistics

Variable	Mean	Variance	Skewness	Excess kurtosis
oil	0.251	49.284	-0.493	8.372
Aggregate	-0.060	23.330	-0.838	5.741
Entertainment	0.427	66.103	-0.843	7.362
Consumer Goods	0.314	26.150	-0.572	5.231
Chemicals	0.443	34.511	-0.559	6.253
Rubber&plastic	0.448	39.977	-0.705	7.003
Steel	0.228	63.463	-0.796	6.503
Machinery	0.337	44.451	-0.997	7.309
Electrical Equipment	0.576	44.372	-0.646	6.045
Auto	0.179	53.119	-0.542	8.923
Aircraft	0.629	49.418	-0.883	6.215
Shipbuilding	0.325	53.498	-0.637	5.603
Precious metal	0.153	118.724	0.034	5.121
Coal	0.629	107.653	-0.211	5.222
Petroleum	0.621	31.259	-0.262	4.375
Utilities	0.463	18.038	-0.373	4.117
Business Supplies	0.432	34.751	-0.298	5.650
Transportation	0.391	36.618	-0.670	5.403
Retail	0.456	35.249	-0.554	5.970
Restaurants	0.393	42.978	-0.986	7.100

Notes: This table presents summary statistics for the change in the real price of oil and the U.S. real stock returns at the aggregate and industry levels. 18 sector stock indices are considered. The monthly sample period ranges from 1973:1 to 2009:12.

Table 3.3 Skewness/Kurtosis Tests for Normality

Variable	Pr(Skewness)	Pr(Kurtosis)	$chi^2(2)$	joint Prob>chi^2
oil	0.000**	0.000**	76.510	0.000**
returns	0.000**	0.000**	75.050	0.000**
entertainment	0.000**	0.000**	92.810	0.000**
consumer goods	0.000**	0.000**	48.900	0.000**
chemicals	0.000**	0.000**	60.280	0.000**
rubber	0.000**	0.000**	78.580	0.000**
steel	0.000**	0.000**	80.400	0.000**
machinery	0.000**	0.000**	104.910	0.000**
Electrical equipment	0.000**	0.000**	64.010	0.000**
auto	0.000**	0.000**	84.080	0.000**
aircraft	0.000**	0.000**	84.170	0.000**
shipbuild	0.000**	0.000**	58.080	0.000**
precious metals	0.769	0.000**	25.700	0.000**
coal	0.068	0.000**	30.260	0.000**
petroleum	0.024**	0.000**	20.600	0.000**
utilities	0.002**	0.001**	21.900	0.000**
business supplies	0.011**	0.000**	38.800	0.000**
transportation	0.000**	0.000**	58.030	0.000**
retail	0.000**	0.000**	56.760	0.000**
restaurant	0.000**	0.000**	101.940	0.000**

The p-value of 0.00 indicated in the table above denotes that it is significantly different from the kurtosis of a normal distribution at the 1% significance level. In addition, based on the skewness alone, we reject the hypothesis that the variables are normally distributed. ** denotes significance at the 5% level.

Table 3.4 Breusch-Godfrey LM test for autocorrelation

H0: no serial correlation

Variable	lags(p)	chi2	df	Prob > chi2
oil	1	104.363	1	0.000**
Aggregate	1	4.986	1	0.026**
Entertainment	1	14.240	1	0.000**
Consumer Goods	1	4.021	1	0.045**
Chemicals	1	1.289	1	0.256
Rubber&plastic	1	5.472	1	0.019**
Steel	1	2.195	1	0.138
Machinery	1	7.140	1	0.008**
Electrical Equipment	1	0.914	1	0.339
Auto	1	11.040	1	0.001**
Aircraft	1	7.238	1	0.007**
Shipbuilding	1	5.402	1	0.020**
Precious metal	1	0.923	1	0.337
Coal	1	2.200	1	0.138
Petroleum	1	0.611	1	0.435
Utilities	1	2.047	1	0.153
Business Supplies	1	0.304	1	0.581
Transportation	1	3.870	1	0.049**
Retail	1	12.124	1	0.001**
Restaurants	1	6.780	1	0.009**

Note: This table represents Breusch-Godfrey LM test for serial correlation in the data. ** denotes significance at the 1% level.

Table 3.4.1 Engle's (1982) LM test for ARCH effects

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Variable	lags(p)	chi2	df	Prob > chi2
oil	1	94.505	1	0.000**
Aggregate	1	4.946	1	0.026**
Entertainment	1	7.544	1	0.006**
Consumer Goods	1	23.685	1	0.000**
Chemicals	1	7.960	1	0.005**
Rubber&plastic	1	0.766	1	0.382
Steel	1	19.661	1	0.000**
Machinery	1	8.351	1	0.004**
Electrical Equipment	1	2.363	1	0.124
Auto	1	0.148	1	0.701
Aircraft	1	0.367	1	0.545
Shipbuilding	1	0.924	1	0.336
Precious metal	1	11.888	1	0.001**
Coal	1	16.525	1	0.000**
Petroleum	1	13.044	1	0.000**
Utilities	1	1.249	1	0.264
Business Supplies	1	0.096	1	0.756
Transportation	1	0.839	1	0.360
Retail	1	2.623	1	0.105
Restaurants	1	2.092	1	0.148

Note: This table tests for conditional heteroscedasticity in the data. ** denotes significance at the 1% level.

Table 3.5 LM tests for residual serial correlation

Real Stock Return	LM-Stat	Prob
aggregate	6.414	0.170
Aircraft	5.460	0.243
auto	6.143	0.189
Business Supplies	3.029	0.553
Chemicals	5.478	0.242
Coal	8.277	0.082
Consumer Goods	2.258	0.688
Electrical Equipment	6.955	0.138
Entertainment	3.917	0.417
Machinery	7.717	0.103
Petroleum & natural gas	4.858	0.302
Precious metal	4.742	0.315
restaurants	2.438	0.656
retail	8.304	0.081
rubber and plastic	2.780	0.595
shiprailroad	4.533	0.339
steel	3.786	0.436
transportation	3.612	0.461
utilities	3.044	0.550

Note: This table represents the tests for serial correlation in the residuals of the GARCH-in-Mean model.

Table 3.6 LM tests for arch effects on the standardized residuals from the GARCH-in-Mean

Real Stock Return	Test for Multivariate ARCH: Signif.	# of lags
aggregate	0.089	1
Aircraft	0.385	1
auto	0.349	1
Business Supplies	0.697	1
Chemicals	0.013	7
Coal	0.100	1
Consumer Goods	0.866	1
Electrical Equipment	0.611	1
Entertainment	0.579	1
Machinery	0.195	1
Petroleum & natural gas	0.024	1
Precious metal	0.767	1
restaurants	0.391	1
retail	0.109	1
rubber and plastic	0.835	1
shiprailroad	0.219	1
steel	0.012	10
transportation	0.340	1
utilities	0.497	1

Note: This table represents the tests for arch effects on the standardized residuals from the GARCH-in-Mean model.

Table 3.7 Model Specification Test

	Homoskedastic VAR	Bivariate GARCH-M VAR
Real Oil Price-Aggregate Stock Returns	5564.32	5390.43

Note: This table computes the Schwartz Information Criterion for the conventional homoskedastic VAR and the bivariate GARCH-in-Mean VAR.

Table 3.8 Parameter Estimates for the Variance Function

Equation	Conditional Variance	Constatnt	$\varepsilon_i(t-1)^2$	$H_{i,i}(t-1)$
Real Oil Price	$H_{1,1}(t)$	0.975**	0.380**	0.612**
		(2.962)	(8.932)	(14.040)
Aggregate Returns	$H_{2,2}(t)$	0.753*	0.122**	0.858**
		(1.905)	(4.262)	(28.177)

Notes: These are the parameter estimates for the free elements in M and N from the structural VAR with bivariate GARCH given by equations (1) and (2) with $\varepsilon t \sim N(0, Ht)$. Asymptotic t-statistics are in parentheses. ** denotes significance at the 5% level. * denotes significance at the 10% level.

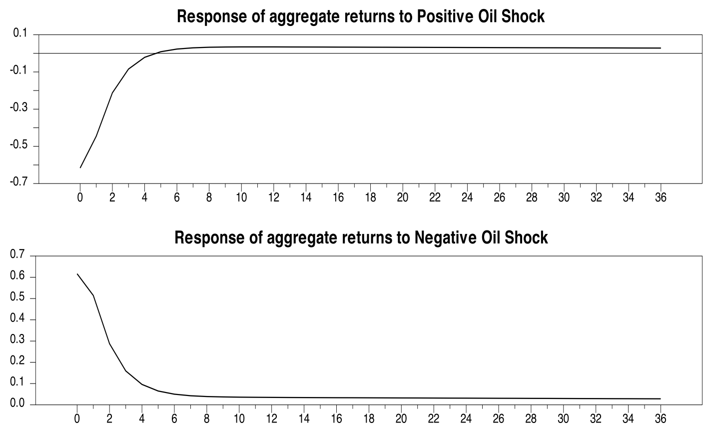
Table 3.9 Coefficient Estimates on Oil Volatility

Real Stock Return	Coef. on $H_{1,1}(t)^{1/2}$, oil volatility	T-stat
aggregate	0.029	0.414
Aircraft	-0.075	-0.816
Auto	-0.049	-0.530
Business Supplies	0.051	0.645
Chemicals	0.085	1.097
Coal	0.135	0.992
Consumer Goods	-0.029	-0.416
Electrical Equipment	-0.015	-0.155
Entertainment	-0.008	-0.074
Machinery	0.033	0.349
Petroleum & natural gas	-0.015	-0.196
Precious metal	0.024	0.159
restaurants	0.032	0.384
retail	0.110	1.435
rubber and plastic	0.008	0.090
shiprailroad	-0.101	-1.019
steel	0.110	0.950
transportation	-0.071	-0.839
utilities	-0.054	-0.961

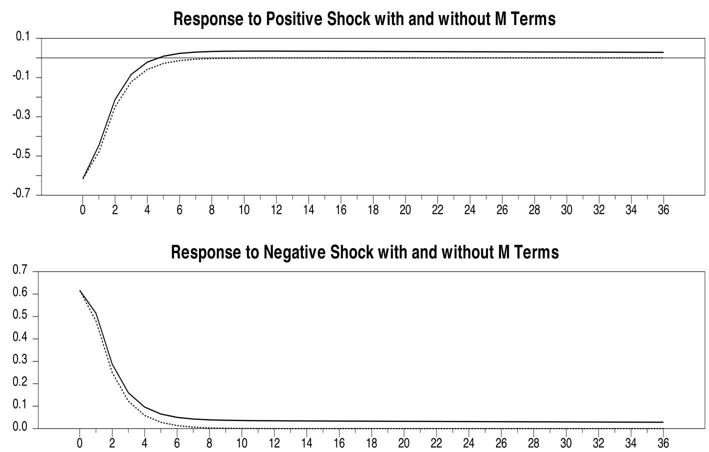
Notes: These are the coefficient estimates for the free elements in Ψ from the structural VAR with bivariate GARCH. H1,1(t)1⁄2 indicates the conditional standard deviation of the related measure of oil prices.

Figure 3(a-c): Impulse response functions

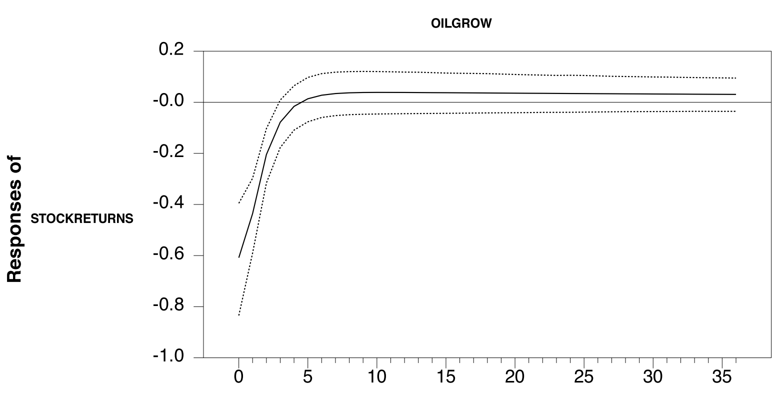
a)



b)



C)



Chapter 4: Does Uncertainty in Oil Prices Affect U.S. Stock Returns? Analysis under the Day of the Week Effect

Using high frequency data, this paper addresses the issue of uncertainty in oil prices and its effect on U.S. stock returns, taking into account the day of the week effect. We first examine the presence of seasonal effects in the mean and variance equations. The results suggest that the-day-of-the-week effect is present in both the mean and volatility equations. While the Wednesday dummy has a statistically significant effect on the conditional mean, Thursdays and Wednesdays appear to have the highest and the lowest aggregate returns volatilities, respectively. We then question the response of aggregate and industry-level stock returns to oil price uncertainty. We find that the U.S. stock market is sensitive to oil price variations not only at the aggregate level but also across some industries, such as chemicals, entertainment, and retail, where uncertainty in oil prices proves to have positive and statistically significant effect. The results also show that some sectors react against our expectations to fluctuations in oil prices. For instance, one might expect higher uncertainty in oil prices would lead to higher returns in the petroleum and natural gas sector, but not in transportation or automobiles sectors. Surprisingly, some sectors such as the retail and entertainment (unpredictably) seem to benefit from higher uncertainty in oil prices. On the other hand, unexpectedly many sectors, such as transportation, automobiles, consumer goods, aircraft, and many others, came out to be unaffected by variations in oil prices. The effects of crude oil price fluctuations on stock returns may not be as large and harmful as might be expected.

4.1 Introduction

The price of oil is one of the inputs that greatly impact the world economy because of its sensitivity on stock prices, and its importance as a sole input in the production of many sectors. Boosts in oil prices benefit some sectors in the economy while hurt others. For example, oil controls the automotive and aircraft sectors such as cars, trucks, airplanes and vessels. It also controls transportation sector in a way that a rise in oil prices, increases input prices for transportation companies and cut their earnings and profits, which in turn affects other firms in the market. On the other hand, energy firms generally gain from boosts in oil prices simply by increasing revenues. Therefore, fluctuations in oil prices can affect asset prices through their effect on expected earnings (Jones, Lelby and Paik 2004). The strength of this paper is in the fact that it provides investors and regulators important information about the response of stock returns to fluctuations in oil prices at the aggregate and sectoral level.

According to the academic literature, the relationship between oil prices and stock market is still mixed. While many researchers showed that boosts in oil prices play a significant role on the behavior of the stock returns (see among others, Kling 1985, Jones and Kaul 1996, Park and Ratti 2008, and Sadorsky 2011)[15], others had found that oil price shocks have no impact on stock returns (see among others, Chen, Roll and Ross (1986), Huang, Masulis, and Stoll (1996) and Wei (2003)). One explanation of these contrasting results is that none of the papers above mentioned identified the source of oil shock as in Kilian and Park (2009). By separating oil price shocks into demand and

15 These studies find that the impact of oil price shock on stock returns is negative.

supply shocks, Kilian and Park found that different types of shocks might have different effects on U.S. stock markets.

These diverse results in the literature question the effect of uncertainty and volatility in oil prices on stock returns. During the last decade, only a few papers have addressed the issue of oil price volatility and its effect on the financial market. While boosts in oil prices tend to have a negative impact on stock returns, mainly on sectors that are energy intensive in use; the effect of fluctuations in oil prices on the U.S. stock returns is still mixed. Park and Ratti (2008) show that an increase in oil price volatility has no effect on U.S. real stock returns, where the effect is insignificant. Using an asymmetric BEKK model on weekly data for the aggregate stock markets of Japan, Norway, Sweden, and U.K., Agren (2006) examines volatility spillover from oil prices to stock markets. Except for Swedish stock market, the paper indicates the presence of volatility spillover for all stock markets. Using a GARCH (1,1) model, Sadorsky (2001) proves that the effect of oil price volatility on U.S. real stock returns is negative. Elyasiani, Mansur and Odusami (2011) examine the effect of changes in oil returns and oil return volatility on excess stock returns and returns volatilities of thirteen U.S. industries using the GARCH (1,1) model. They show that oil price fluctuations constitute a systematic asset price risk at the industry level.

This paper first examines the effect of oil price uncertainty on stock returns. To the best of our knowledge, there are only a limited number of studies that address this question (e.g., Elyasiani, Mansur and Odusami (2011)). However, none of these papers address this question based on a structural VAR model that is altered to fit GARCH-in-mean errors where uncertainty about oil prices is presented by the standard deviation of the one-step-ahead forecast error. This paper contributes to this literature by directly testing for the effect of oil price uncertainty on stock returns using a GARCH-in-Mean model.

Moreover, considering seasonality in risk and returns is essential for financial managers and analysts. For instance, detecting a particular pattern in volatility might assist investors in making decisions based on both return and risk (Kiymaz and Berument, 2003). Thus, the presence of seasonal effects (calendar anomalies) in stock returns has been widely examined in the financial literature. A number of studies have shown that there are dissimilarities in the allocation of stock returns for each day of the week (see among others, French (1980), Keim and Stambaugh (1984), and Rogalski (1984)). Several papers in the financial literature examine the seasonal effect using the GARCH framework (see among others, Bayar and Kan (2001), Kiymaz and Berument, (2003), Yalcin and Yucel (2006), and Sales and Caro (2006)). To the best of our knowledge, no work has examined the day-of-the-week effect in the crude oil market using GARCH models. This paper attempts to fill this gap.

While some of the papers in the literature examined variability in oil prices and its effect on stock returns (Sadorsky (2001), Park and Ratti (2008), Elyasiani, Mansur and Odusami (2011)), none has tested for the possible existence of seasonal variation in volatility, such as the day of the week effect or the month of the year effect. Hence, in order to make rational investment decisions, investors need to know whether there are variations in volatility of stock returns by the day of the week. This seasonal effect has been extensively examined in the financial literature, which report the existence of the day of the week effect in stock market volatility. Kiymaz and Berument (2003), for instance, show that the day of the week effect appears in both the return and volatility equations.

Using daily data on aggregate and sectoral level U.S. stock returns, this paper investigates the effect of oil price uncertainty on the stock market. We employ a modified structural vector autoregression (VAR) that fits GARCH-in-Mean errors as in Elder (1995, 2004) and Elder and Serletis (2010) and take into account the day of the week effect. The volatility of oil price change is measured by the conditional variance of the oil price change forecast error.

This paper distinguishes itself from previous studies in the energy and financial market literature in three major points. First, we use a bivariate GARCH–in-mean VAR model to examine the effect of oil price uncertainty on the U.S. stock returns. Based on the results of Elder and Serletis (2010) for production, we would expect our results to show a negative effect of higher oil price volatility on the U.S. stock returns[16]. However, the findings show that uncertainty about the price of oil has a positive and statistically significant effect on U.S. stock returns. This suggests that the volatility in oil prices does play an important role on corporate cash flow and/or discount rates. The results also propose that some sectors benefit from the variations in oil prices more than others.

Second, since results at the aggregate level might hide important effects of oil price volatility at the sectoral level, we examine the oil uncertainty effects on sectoral stock markets. Fama and French (1997), among others, show that returns and volatility at the sectoral level present significant information about the return and volatility procedure at the aggregate level. Similarly, Hong et al. (2007) also identify the importance of sectoral

[16] Elder and Serletis (2010) found that volatility in oil prices has a negative and statistically significant effect on aggregate output.

returns in providing information about the changes in aggregate stock returns. Accordingly, it is important to examine the effect of oil price uncertainty on stock returns across industries especially during periods of instabilities in oil prices; so that investors can adjust their portfolios accordingly. The sectoral response to uncertainty in oil prices seems to be heterogeneous. Our results show that uncertainty in oil prices plays a significant and positive effect on chemicals (in line with Elyasiani et al (2011)), electrical equipment, entertainment, precious metal, restaurants, retail, and rubber and plastic. However, variations in oil prices don't seem to have important effects on other sectors of the economy where oil prices seem to represent a small share of corporate cash flow (e.g., aircraft, automobiles, transportation, consumer goods). Thus, even though one could think that energy-intensive sectors (e.g., transportation, automobiles) are anticipated to lose from higher uncertainty in oil prices, while energy sectors (e.g., petroleum and natural gas) are expected to benefit from variations in oil prices, the results suggest that the impact of changes in oil prices on stock returns might also depend on the ability of some industries to pass on the increase in oil prices to customers better than other industries, or by the practice of the right financial derivative to hedge against or profit from this volatility.

Third, we address the issue of uncertainty in oil prices and its effect on U.S. stock returns, taking into account the day of the week effect. At the aggregate level, the results show that the day-of-the-week effect is present in both the mean and variance equations, where the highest volatility occurs on Thursdays and the lowest volatility occurs on Wednesdays. Except for electrical equipment, sectors that are positively affected by the uncertainty in oil prices show that the day of the week effect is present in the mean, variance, or both equations. Moreover, the highest volatility occurs on Mondays for chemicals (insignificant) and entertainment, and on Thursdays for electrical equipment (insignificant), restaurants, retail, and rubber and plastic. The lowest volatility is presented on Mondays for electrical equipments, Tuesdays for entertainment and restaurants, and Wednesdays for chemicals, precious metals, retail, and rubber and plastic. With the exception of that of chemicals, the results are statistically insignificant. The results also show that the day of the week is present in the mean, variance or both equations for the other sectors of the economy that are not significantly affected by oil price volatility.

This paper is organized as follows. Section 2 describes the data and specifies the model. Section 3 presents the empirical results. Section 4 provides evidence across industries. We conclude in section 5.

4.2 Data Description and Model Specification

To investigate the effect of oil price volatility, we use daily data spanning the period between January 3, 1986 and December 30, 2011. As a measure of oil prices we use the daily spot price on West Texas Intermediate (WTI) crude oil. We consider U.S. aggregate stock returns, as well as stock returns for a number of industries that are expected to respond to changes in oil prices (see Kilian and Park, 2008). To measure aggregate U.S. stock returns, we use the excess return on the market, which is defined as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks from the Center for Research in Security Prices (CRSP) minus the one-month Treasury bill rate.

In order to examine how the response of stock returns differs across industries, we use the industry level data made accessible by Kenneth French, constructed from the CRSP database[17]. As mentioned above, we concentrate on industries that are expected to respond to fluctuations in oil prices; these industries are: aircraft, automobile, business supplies, chemicals, coal, consumer goods, electrical equipment, entertainment, machinery, petroleum & natural gas, precious metal, restaurants, retail, rubber and plastic, ships and railroad equipment, steel, transportation, and utilities stock returns. After matching daily stock returns with the corresponding oil prices, we ended up with 6,528 daily observations. Because the DF-GLS tests suggest that we cannot reject the null of a unit root in the oil price and in stock prices at a 5% significance level (See Table 1), we use the first differences of the logged variables. That is, we used the percentage rate of growth in nominal spot prices and the daily stock returns.

Most of the studies on the day-of-the-week effect discussed in the literature have investigated the impact of the day-of-the-week in the mean return (see among others, Cross (1973), French (1980), Gay and Kim (1987), and Aggarwal and Rivoli (1989)). However, it is possible that different days of the weeks could exhibit a different conditional variance. Thus, we include daily dummies both in the mean and in the variance equations.

In this paper, we test the effects of oil price uncertainty on the U.S. stock returns by using a structural vector autoregression (VAR) adjusted to fit GARCH-in-Mean errors as in Elder (1995, 2004) and Elder and Serletis (2010). Hence, the volatility of the oil price change is measured by the conditional variance of the oil price change forecast error.

[17] The data are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The file containing 49 industry portfolios is used.

This model, presented below, has the advantage that it allows to directly test the effect of oil price uncertainty on stock returns.

$$By_t = \alpha + \sum_{i=1}^{p} \Gamma_i y_{t-i} + \Psi\sqrt{h_t} + \varepsilon_t, \qquad (1)$$

$$\varepsilon_t = H_t^{1/2} z_t \qquad (2)$$

where the vector y_t includes the change in the price of oil and U.S. stock returns, $\varepsilon_t \,|\Omega_{t-1} \sim$ *iid* $N(0, H_t)$, Ω_{t-1} denotes the information set in period t-1, and H_t is a k x k conditional variance-covariance matrix.

We identify the system by assuming that the structural shocks are uncorrelated, and by assuming that stock returns have no contemporaneous effect on oil price changes. This zero restriction (b_{12}=0) on one of the elements of B allows to have a just-identified model with $(n^2-n)/2$ restrictions.

The variance function is specified as

$$diag(H_t) = A + \sum_{q=1}^{Q} M_q diag(\varepsilon_{t-q}\varepsilon'_{t-q}) + \sum_{p=1}^{P} N_p diag(H_{t-p}), \quad (3)$$

Imposing additional restrictions that M and N are diagonal can reduce the number of parameters furthermore[18]. We thus follow Elder (2004) and Elder and Serletis (2010) and estimate the conditional variance H_t as a diagonal matrix.

In order to control for the day of the week effect, we introduce the day of the week

[18] These restrictions can be relaxed as appropriate given the researcher's specific interest in how the lagged volatility of one variable might relate to the conditional variance of another.

dummy variables in both the mean and variance equations. Thus the model is specified as

$$BY_t = \alpha_0 + \alpha_M M_t + \alpha_T T_t + \alpha_W W_t + \alpha_{TH} TH_t + \sum_{i=1}^{p} \Gamma_i y_{t-i} + \Psi\sqrt{h_t} + \varepsilon_t, \quad (4)$$

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 0 \\ b & 1 \end{bmatrix}, \quad h_t = \begin{bmatrix} h_{1t} \\ h_{2t} \end{bmatrix}$$

where $y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix}, \quad \Gamma_i = \begin{bmatrix} \gamma_{11}^i & \gamma_{12}^i \\ \gamma_{21}^i & \gamma_{22}^i \end{bmatrix}, \quad \Psi_j = \begin{bmatrix} \psi_{11}^j & \psi_{12}^j \\ \psi_{21}^j & \psi_{22}^j \end{bmatrix}, \varepsilon_t = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$

$$\alpha_0 = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix}, \alpha_M = \begin{bmatrix} \alpha_{1M} \\ \alpha_{2M} \end{bmatrix}, \alpha_T = \begin{bmatrix} \alpha_{1T} \\ \alpha_{2T} \end{bmatrix}, \alpha_W = \begin{bmatrix} \alpha_{1W} \\ \alpha_{2W} \end{bmatrix}, \alpha_{TH} = \begin{bmatrix} \alpha_{1TH} \\ \alpha_{2TH} \end{bmatrix},$$

and

$$diag(H_t) = \beta_0 + \beta_M M_t + \beta_T T_t + \beta_W W_t + \beta_{TH} TH_t + \sum_{q=1}^{q} \gamma_q diag(\varepsilon_{t-q}\varepsilon_{t-q}^{'}) + \sum_{p=1}^{p} \delta_p diag(H_{t-p}), (5)$$

where

$$\begin{bmatrix} H_{1,1(t)} \\ H_{2,2(t)} \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \beta_{1M} \\ \beta_{2M} \end{bmatrix} + \begin{bmatrix} \beta_{1T} \\ \beta_{2T} \end{bmatrix} + \begin{bmatrix} \beta_{1W} \\ \beta_{2W} \end{bmatrix} + \begin{bmatrix} \beta_{1TH} \\ \beta_{2TH} \end{bmatrix} + \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} \\ \gamma_{2,1} & \gamma_{2,2} \end{bmatrix} \begin{bmatrix} e_{1(t-1)}^2 \\ e_{2(t-1)}^2 \end{bmatrix} + \begin{bmatrix} \delta_{1,1} & \delta_{1,2} \\ \delta_{2,1} & \delta_{2,2} \end{bmatrix} \begin{bmatrix} H_{1,1(t-1)} \\ H_{2,2(t-1)} \end{bmatrix}$$

where H_t, γ_q and δ_p are diagonal.

We estimate the model by full information maximum likelihood (FIML) by maximizing the likelihood function given by

$$l_t = -(\frac{n}{2})\ln(2\Pi) + \frac{1}{2}\ln|B^2| - \frac{1}{2}\ln|H_t| - \frac{1}{2}(\varepsilon_t^{'} H_t^{-1} \varepsilon_t), (6)$$

with respect to the structural parameters B, , α_0, $\alpha_{M,}$ $\alpha_{T,}$ $\alpha_{W,}$ α_{TH}, Γ_1, …, Γ_p, Ψ, β_0, β_M, β_T, β_W, β_{TH}, $\gamma_{1,}$ and δ_1.

After entering the seasonal dummy variables into the models, we ended up with a GARCH(1,4) model to be the best fit at the aggregate level where p=1 in the variance equation and q=4 in the mean equation. However, at the sectoral level, the simple model GARCH(1,1) presented a good fit for automobile, chemicals, transportation, entertainment, precious metal, business supplies, and ship railroad stock returns; whereas, GARCH(1,4) proves to be the best fit for aircraft, coal, electrical equipment, rubber and plastic, machinery, steel, utilities, retail, petroleum and natural gas, and restaurants stock returns[19].

4.3. Empirical Results

Table 2 presents summary statistics for the change in the real price of oil and the U.S. real stock returns at the aggregate and industry levels. The results indicate that oil growth and stock returns are skewed and that high excess kurtosis exists in the data that is substantially greater than 3. Besides, excess skewness and kurtosis are present on each day of the week across all sectors. The kurtosis statistics indicate the existence of volatility persistence, which suggests that a GARCH model could do a good job at capturing the behavior of volatility in oil prices.

Descriptive statistics results in table 2 also show that, overall, average daily returns are positive for aggregate stock returns and across sectors. The highest returns are observed on Wednesdays for aggregate returns as well as for entertainment, consumer goods,

[19]The best fit for consumer goods is GARCH (1,6).

rubber & plastic, steel, machinery, business supplies, transportation, and retail, on Tuesdays for chemicals, electrical equipments, aircraft, and petroleum, On Thursdays for ships and railroad equipment, precious metal, coal, and restaurants, and on Mondays for automobiles and utilities. The lowest returns occur on Mondays for aggregate, entertainment, chemicals, rubber &plastic, steel, machinery, electrical equipment, aircraft, precious metal, coal, business supplies, transportation, retail, and restaurants returns, on Thursdays for consumer goods, automobiles, petroleum, and utilities, and on Tuesdays for ships and railroad equipment.

4.3.1 Effect of Uncertainty in Oil Prices on Aggregate Stock Returns

The point estimates for the free elements in Ψ from the structural VAR with bivariate GARCH-M represent the effect of oil price uncertainty on stock returns. The null hypothesis is that the value of Ψ is zero. The results are reported in Table 3 where the coefficient on the standard deviation of oil prices in the aggregate stock returns equation equals 0.024 with a t-statistic of 2.438, which indicates that we reject the null hypothesis that the value of Ψ is zero. This implies that uncertainty about the price of oil has a positive and statistically significant effect on U.S. stock returns.

Table 4 reports the results for the day of the week effect in both the mean (panel A) and variance (panel B) equations. We include four day-of-the-week dummy variables, Mondays, Tuesdays, Wednesdays and Thursdays. We exclude the dummy variable for Fridays to avoid the dummy variable trap. The results show that the day-of-the-week effect is present in both the mean and variance equations. Panel A of table 4 displays the estimates of the mean equation. The estimated coefficient of the Wednesdays' dummy variable for aggregate stock returns (0.04963) is positive and statistically significant at the 10% level, while the estimated coefficient is the lowest on Tuesdays (-0.01743), but it is statistically insignificant. In order to detect the existence of the day of the week effect in volatility, we allow the conditional variance to change for each day of the week. The results reported under panel B of table 4 show that the highest volatility occurs on Thursdays (0.08896) and the lowest volatility occurs on Wednesdays (-0.0664). Note that Wednesdays have the lowest mean (0.06064) and the lowest variance (1.18234).

The findings suggest that through progresses in financial instruments firms that are sensitive to changes in oil prices found ways to pass on oil price changes or risks to customers, or determined effective hedging strategies. In other words, the extremely high levels of price volatility that characterize the energy markets encourage investors to use derivatives and future markets in managing and hedging risk. Thus, during times of high oil volatility, traders choose sector stocks that match their lenience for volatility and use the right financial derivative to hedge against or profit from this volatility.

The results that oil price uncertainty has a positive effect on the U.S. stock market might also be the outcome of some limitations of the GARCH model. That is the conditional variance of the oil price might not capture other factors of uncertainty and thus might not be an appropriate proxy of oil price uncertainty. For instance, uncertainty in oil prices might not be only a function of the past oil price variance, but it might depend on whether sharp decreases (or increases) in oil prices were observed in the recent past. In other words, periods of sharp decrease in oil prices can lead to a reduction in the uncertainty about the future oil prices, thus making the conditional variance of oil prices a poor proxy for uncertainty. In addition, uncertainty caused by oil demand shocks might have different effects on stock returns than uncertainty caused by oil supply shocks (see Kilian and Park 2009).

4.4. Effect of Oil Uncertainty Across Industries

Based on the heterogeneity of the response of stock returns across industries to fluctuations in oil prices (see, for instance, Herrera, Lagalo and Wada 2011), and since results at the aggregate level might hide important effects of oil price volatility at the sectoral level, we examine the oil uncertainty effects on sectoral stock markets.

The point estimates for the free elements in Ψ from the structural VAR with bivariate GARCH-M represent the effect of oil price uncertainty on sectoral stock returns. The null hypothesis is that the value of Ψ is zero. The results reported in Table 3 suggest that uncertainty in oil prices have an important effect on stock returns across chemicals, electrical equipment, entertainment, precious metal, restaurants, retail, and rubber and plastic returns, as the point estimates for the coefficient on oil price uncertainty are positive and statistically significant except for precious metal which is negative and statistically significant at the 10% level. This indicates that we reject the null hypothesis that the value of Ψ is zero for the aforementioned sectors.

Based on the view that energy intensive sectors are expected to react negatively to high oil prices and energy sectors to react positively to high oil prices, we suspect that higher uncertainty in oil prices would lead to higher returns in the petroleum and natural gas sector, for instance, but not for transportation or automobiles sectors. Surprisingly, some sectors such as the retail and entertainment (unexpectedly) seem to benefit from higher uncertainty in oil prices. On the other hand, unexpectedly many sectors, such as transportation, automobiles, consumer goods, aircraft, and many others, came out to be unaffected by variations in oil prices. Explanations for the unexpected results are presented below.

While, Elyasiani, Mansur and Odusami (2011) show that building, chemical, transport equipment, air transportation, depository institution, and insurance industries are all positively affected by increased oil price volatility, our findings show that chemicals, electrical equipment, entertainment, restaurants, retail, and rubber and plastic returns benefit from increased oil price volatility. This can be explained, possibly, by the view that these sectors can pass on their prices to their consumers easier during periods of high uncertainty in oil prices rather than periods of stable oil prices. It might also be explained by the view that volatility of oil return could benefit firms in the oil-using sectors that are more expert in predicting oil price increases and able to realign their value creation strategies around it. Moreover, increased volatility in oil prices might encourage investors to switch from oil-related assets to other assets with the aim to reduce their risk exposure. This would result in an increase in the flow of funds into non-oil sectors and would increase their prices and stock returns.

The results for the day of the week effect across industries in both the mean (panel A) and variance (panel B) equations are reported in table 4. Except for electrical equipment, sectors that are positively affected by the uncertainty in oil prices show that the day of the week effect is present in the mean, variance, or both equations. Panel A of table 4 displays the estimates of the mean equation. Regarding the sectors that are positively affected by the uncertainty in oil prices, the estimated coefficients are the lowest on Tuesdays for chemicals (-0.01671), on Thursdays for electrical equipment (0.01156), and on Mondays for entertainment (-0.05058), precious metal (-0.224), restaurants (-0-0369), retail (-0.0246), and rubber and plastic (-0.04907), but they are statistically insignificant except for precious metal. This suggests that Mondays' returns are smaller than those of Fridays for precious metal. Moreover, the highest volatility seems to split among sectors, where the results for the variance equation show that the highest volatility occurs on Mondays for chemicals (insignificant) and entertainment, and on Thursdays for electrical equipment (insignificant), restaurants, retail, and rubber and plastic. The lowest volatility is presented on Mondays for electrical equipments, Tuesdays for entertainment and restaurants, and Wednesdays for chemicals, precious metals, retail, and rubber and plastic. With the exception of that of chemicals, the results are statistically insignificant.

All sectors are not equally exposed to oil price risk factors i.e. some sectors are significantly affected by uncertainty in oil prices while others are not. The results under table 3 also show that uncertainty in oil prices has no effect on stock returns across the rest of industries examined in this paper which are aircraft, automobiles, business supplies, coal, consumer goods, machinery, petroleum and natural gas, ships and railroad equipment, steel, transportation, and utilities, as the point estimates for the coefficient on oil price uncertainty are not statistically significant, which indicates that we cannot reject the null hypothesis that the value of Ψ is zero. This falls in line with Kilian and Park (2008) argument that: "Because any unexpected change in the real price of oil may be associated with higher expected volatility, whether the real price of oil goes up or down, this uncertainty effect may serve to amplify the effects of unexpected oil price increases and to offset the effects of unexpected oil price declines".

In addition, the result that the volatility of oil prices is irrelevant to some sectoral stock returns is insightful. Take for example the automobile sector; the uncertainty effect in oil prices might not lead to a drop in the number of motor vehicles sold. It might lead to consumers swapping from large energy-inefficient vehicles to small energy-efficient ones. Thus, the aggregate real consumption of automobiles may decrease but not the number of vehicles sold (see Hamilton (1988) and Bresnahan and Ramey (1993)). Regarding construction machinery, the absence of an uncertainty effect can be explained by the view that with the increase in oil price volatility, demand for new homes increases since newer buildings are more energy efficient. Furthermore, regarding utilities stocks, the uncertainty effect is insignificant probably because public utilities tend to be regulated, so their responses to crude oil market disturbances are further hushed (see Kilian and Park 2009).

On the other hand, one way to reduce the exposure to fluctuations in oil prices is through the ability of companies to transfer the high price of oil to their customers which is easier to do when uncertainty about the price of oil is high, rather than when oil price is stable. The transportation sector, for instance, reacts insignificantly to oil price changes, probably, since most of the firms in this sector pass their extra cost to customers. However, although many sectors, such as consumer goods and utilities, manage to pass through the higher price of oil to consumers (see Hammoudeh, Yuan, Chiang, Nandha 2010), some sectors, such as the airline industry, fail to do so due to highly competitive market or high price elasticity of demand[20]. Thus, through the process of hedging, such sectors greatly reduce their exposure to oil price fluctuations.

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[20] These are defensive sectors that are unaffected by the ups and downs in the economy.

The results also show that the day of the week effect is present in the mean, variance or both equations for the other sectors of the economy that are not significantly affected by oil price volatility. The estimates of the mean equation (See panel A of table 4) show that the estimated coefficients are lowest and statistically significant on Mondays for coal (-0.23535), ships and railroad equipment (-0.0928), steel (-0.2026) and transportation (-0.07122) suggesting that Monday's returns are smaller than those of Fridays, and on Thursdays for utilities (-0.0851) suggesting that Thursday's returns are smaller than those of Fridays. Furthermore, the results for the variance equation show that coal (0.4471), and machinery (0.10349) have significantly the highest volatility on Thursdays, whereas aircraft (-0.202), petroleum and natural gas (-0.1696), and utilities (-0.0519) have significantly the lowest volatility on Tuesdays, business supplies (-0.1521) on Wednesdays, and ships and railroad equipment (-0.27421) on Thursdays.

4.5. Conclusion

The estimation and analysis of the volatility and conditional correlations between oil prices and stock returns can provide useful information for investors, hedgers and government agencies that are concerned with the crude oil and stock markets, especially regarding optimal hedging across the two markets.

While our results show that uncertainty about the price of oil has a positive and statistically significant effect on U.S. aggregate stock returns. The fact that the effect is positive and significant for some sectors but insignificant for others appears to drive the result for the U.S. stock market. For example, chemicals, electrical equipment, entertainment, precious metal, restaurants, retail, and rubber and plastic are positively affected by variations in oil prices, whereas the other sectors, such as aircraft, automobiles, business supplies, coal, consumer goods, machinery, petroleum and natural gas, ships and railroad equipment, steel, transportation, and utilities, are insensitive to variations in oil prices.

The results show that the day-of-the-week effect for aggregate stock returns is present in both the mean (Wednesday effect) and variance equations where the highest volatility occurs on Thursdays. Regarding the sectors that are positively affected by the uncertainty in oil prices, the estimated coefficients are lowest on Tuesdays for chemicals, on Thursdays for electrical equipment, and on Mondays for entertainment, precious metal, restaurants, retail, and rubber and plastic, but they are statistically insignificant except for precious metal. This suggests that Monday’s returns are smaller than those of Fridays for precious metal. Moreover, the highest volatility seems to split among sectors, where the results for the variance equation show that the highest volatility occurs on Mondays for chemicals (insignificant) and entertainment, and on Thursdays for electrical equipment (insignificant), restaurants, retail, and rubber and plastic. The lowest volatility is presented on Mondays for electrical equipments, Tuesdays for entertainment and restaurants, and Wednesdays for chemicals, precious metals, retail, and rubber and plastic. With the exception of that of chemicals, the results are statistically insignificant.

Regarding the other sectors of the economy that are not significantly affected by oil price volatility, the results show that the estimated coefficients are lowest and statistically significant on Mondays for coal, ships and railroad equipment, steel, and transportation suggesting that Monday’s returns are smaller than those of Fridays, and on Thursdays for utilities suggesting that Thursday’s returns are smaller than those of Fridays.

Furthermore, the results for the variance equation show that coal, and machinery have significantly the highest volatility on Thursdays, whereas aircraft, petroleum and natural gas, and utilities have significantly lowest volatility on Tuesdays, business supplies on Wednesdays, and ships and railroad equipment on Thursdays. Thus, the statistical evidence clearly suggests the presence of seasonal effect.

Briefly, our findings show that the response of aggregate and industry-level stock returns to oil price uncertainty is mixed. We find that the U.S. stock market is sensitive to oil price variations not only at the aggregate level but also across some industries, such as chemicals, entertainment, and retail, where uncertainty in oil prices proves to have positive and statistically significant effect. The results also show that some sectors react against our expectations to fluctuations in oil prices. For instance, one might expect higher uncertainty in oil prices would lead to higher returns in the petroleum and natural gas sector, but not in transportation or automobiles sectors. Surprisingly, some sectors such as the retail and entertainment (unpredictably) seem to benefit from higher uncertainty in oil prices. On the other hand, unexpectedly many sectors, such as transportation, automobiles, consumer goods, aircraft, and many others, came out to be unaffected by variations in oil prices. Thus, the effects of crude oil price fluctuations on stock returns may not be as large and harmful as might be expected. Ultimately, the extremely high levels of price volatility that characterize the energy markets encourage investors to use derivatives and future markets in managing and hedging risk. Thus, during times of high oil volatility, traders choose sector stocks that match their lenience for volatility and use the right financial derivative to hedge against or profit from this volatility.

Table 4.1. Unit root test

Variable	DF-GLS
oil	-6.35
Aggregate	-7.879
Entertainment	-7.672
Consumer Goods	-10.69
Chemicals	-7.961
Rubber&plastic	-5.312
Steel	-7.247
Machinery	-8.861
Electrical Equipment	-9.237
Auto	-10.777
Aircraft	-4.527
Shipbuilding	-6.579
Precious metal	-6.908
Coal	-8.062
Petroleum	-5.531
Utilities	-6.856
Business Supplies	-13.512
Transportation	-9.667
Retail	-13.219
Restaurants	-10.514
5% CV	-2.834

Note: Using the log change in the nominal price of oil and the U.S. stock returns for the aggregate and the sectors of interest.

Table 4.2:Summary Statistics

	Monday	Tuesday	Wednesday	Thursday	all days
Aggregate					
mean	-0.0174515	0.0470216	0.0606404	0.0184446	0.026
S.D.	1.361246	1.160421	1.087354	1.148556	1.162
variance	1.852989	1.346577	1.182339	1.31918	1.351
skewness	-1.914878	0.5954692	-0.4056609	-0.365822	-0.673
kurtosis	33.24797	9.77847	13.2209	8.675256	18.636
Entertainment					
mean	-0.0378803	0.0815115	0.0906031	0.0493551	0.054
S.D.	2.051669	1.795407	1.802799	1.833597	1.820
variance	4.209345	3.223485	3.250083	3.362079	3.311
skewness	-1.681555	0.0123619	0.829807	-0.5097096	-0.379
kurtosis	24.51252	8.999424	17.3669	8.748224	15.626
Consumer Goods					
mean	0.0570955	0.0698362	0.1041772	0.0072231	0.047
S.D.	1.302457	1.23639	1.085349	1.138068	1.173
variance	1.696393	1.52866	1.177983	1.295199	1.375
skewness	-3.816859	-1.636759	0.5569055	-0.1061041	-1.447
kurtosis	66.14793	40.86441	14.73442	7.233339	34.309
Chemicals					
mean	0.0216748	0.0794043	0.0664557	0.0322458	0.050
S.D.	1.642246	1.385008	1.369925	1.458462	1.427
variance	2.696972	1.918246	1.876696	2.127112	2.037
skewness	-1.335338	0.4500275	-0.4731213	-0.5935224	-0.531
kurtosis	22.02765	8.327525	11.36699	9.831805	13.764
Rubber&plastic					
mean	-0.0212379	0.0383246	0.0860611	0.0736115	0.046
S.D.	1.451301	1.262525	1.230762	1.340049	1.291
variance	2.106275	1.593968	1.514775	1.795733	1.666
skewness	-1.77723	0.1140206	-0.0033322	-0.1677863	-0.561
kurtosis	23.55831	6.914278	9.829109	7.913188	12.785

Table 4.2 (continued)	Monday	Tuesday	Wednesday	Thursday	all days
Steel					
mean	-0.0891343	0.0277141	0.0487937	0.0318437	0.038
S.D.	2.231935	1.906353	1.92853	1.910666	1.935
variance	4.981535	3.634183	3.719228	3.650645	3.744
skewness	-0.9108458	0.6008222	-0.8766832	-0.3782437	-0.395
kurtosis	24.51983	9.553213	12.57387	10.05347	15.510
Machinery					
mean	0.0106392	0.0508637	0.1055026	0.0368892	0.050
S.D.	1.745538	1.47115	1.50399	1.581406	1.535
variance	3.046902	2.164281	2.261986	2.500844	2.358
skewness	-1.06961	0.2036438	-0.5015882	-0.0666677	-0.398
kurtosis	21.33848	7.176936	11.02731	8.575656	12.787
Electrical Equipment					
mean	0.0436165	0.1136039	0.0549367	0.0456373	0.060
S.D.	1.763157	1.576304	1.52618	1.608173	1.594
variance	3.108721	2.484734	2.329226	2.586221	2.542
skewness	-1.372168	0.52514	-0.2767409	0.2189738	-0.323
kurtosis	23.30255	6.642509	7.690404	8.113778	11.832
Auto					
mean	0.1194417	0.0604989	0.0684959	-0.0382777	0.034
S.D.	1.906632	1.632993	1.639845	1.73704	1.693
variance	3.635246	2.666667	2.689091	3.017308	2.867
skewness	-1.142355	0.3190687	-0.0465265	-0.1577799	-0.288
kurtosis	18.71741	7.09364	8.663883	8.529321	11.097
Aircraft					
mean	-0.0275162	0.0928369	0.0824646	0.0527086	0.051
S.D.	1.709663	1.414308	1.385637	1.45477	1.465
variance	2.922948	2.000267	1.919991	2.116355	2.147
skewness	-1.745757	0.7293179	-0.5141362	-0.3876236	-0.621
kurtosis	25.80154	11.89171	6.916539	7.504487	14.804

Table 4.2 (continued)	Monday	Tuesday	Wednesday	Thursday	all days
Shipbuilding					
mean	0.038843	0.0053239	0.0186001	0.0864264	0.040
S.D.	1.709018	1.646258	1.670035	1.596866	1.625
variance	2.920741	2.710164	2.789017	2.549982	2.640
skewness	-0.1344804	-0.2244356	-0.4367917	-0.0044837	-0.231
kurtosis	9.177628	7.425178	7.996764	5.653496	7.481
Precious metal					
mean	-0.1385518	0.0456292	0.086143	0.0989833	0.044
S.D.	2.539596	2.557995	2.533167	2.520145	2.516
variance	6.44955	6.543339	6.416936	6.351131	6.333
skewness	0.5244166	0.0632112	0.4839785	0.5065114	0.544
kurtosis	10.9825	13.46482	6.381372	6.539399	10.567
Coal					
mean	-0.0139644	0.018414	0.0540506	0.0545068	0.076
S.D.	2.871772	2.532565	2.669785	2.641037	2.617
variance	8.247076	6.413887	7.127749	6.975075	6.849
skewness	0.1880253	0.2105043	-0.5543528	-0.2927874	-0.082
kurtosis	12.09938	7.08199	11.59132	10.44885	10.594
Petroleum					
mean	0.0376456	0.0788757	0.0695383	-0.0041654	0.056
S.D.	1.711697	1.45591	1.522468	1.517334	1.510
variance	2.929906	2.119675	2.317909	2.302302	2.280
skewness	-0.4781978	0.5942993	-0.7307053	-0.4727772	-0.264
kurtosis	33.85125	8.585606	14.67438	11.88913	18.849
Utilities					
mean	0.0726294	0.0376322	0.0444527	0.0120561	0.043
S.D.	1.149342	1.010699	1.003903	1.032844	1.025
variance	1.320988	1.021513	1.00782	1.066766	1.051
skewness	0.2177755	0.2224108	-0.6726885	-0.2034731	-0.043
kurtosis	40.67406	16.28899	16.76999	12.62133	22.680

Table 4.2 (continued)	Monday	Tuesday	Wednesday	Thursday	all days
Business Supplies					
mean	0.0212783	0.0645048	0.0786225	0.0261533	0.041
S.D.	1.411137	1.205784	1.179602	1.271639	1.248
variance	1.991307	1.453914	1.39146	1.617065	1.557
skewness	-2.78893	0.2796324	-0.2441081	0.1366012	-0.766
kurtosis	43.42523	6.399095	9.684902	8.319178	19.160
Transportation					
mean	-0.0354126	0.0607372	0.0743783	0.0688391	0.043
S.D.	1.535203	1.308626	1.313369	1.393298	1.350
variance	2.356847	1.712503	1.724939	1.941278	1.823
skewness	-1.912149	0.2797332	-0.2776592	0.0206502	-0.563
kurtosis	26.33609	6.758242	7.585589	7.042904	13.321
Retail					
mean	0.0012055	0.0901713	0.1033433	0.052003	0.051
S.D.	1.512364	1.353054	1.282546	1.354971	1.351
variance	2.287245	1.830756	1.644925	1.835947	1.826
skewness	-1.675113	0.6853671	0.4547543	0.0446425	-0.290
kurtosis	22.53857	8.589672	11.2763	6.591228	12.795
Restaurants					
mean	0.0054126	0.0645272	0.0604542	0.0765099	0.051
S.D.	1.392339	1.202573	1.240928	1.321221	1.264
variance	1.938608	1.446182	1.539902	1.745624	1.597
skewness	-1.543037	0.1953086	0.4063863	0.0777423	-0.309
kurtosis	19.60158	7.661813	11.17301	5.113281	11.090

Table 4. 3. Coefficient Estimates on Oil Volatility

Real Stock Return	Coef. on $H_{1,1}(t)^{1/2}$, oil volatility	T-stat
aggregate	**0.024**	2.438
Aircraft	0.011	0.812
Auto	0.026	1.582
Business Supplies	0.018	1.618
Chemicals	*0.024*	1.828
Coal	0.003	0.199
Consumer Goods	0.019	1.603
Electrical Equipment	**0.030**	2.209
Entertainment	**0.037**	2.621
Machinery	0.005	0.419
Petroleum & natural gas	0.013	0.938
Precious metal	*-0.037*	-1.650
restaurants	**0.041**	3.033
retail	**0.044**	3.417
rubber and plastic	**0.037**	3.607
shiprailroad	-0.007	-0.436
steel	-0.006	-0.449
transportation	0.007	0.592
utilities	0.010	1.300

Notes: These are the coefficient estimates for the free elements in Ψ from the structural VAR with bivariate GARCH. $H_{1,1}(t)^{1/2}$ indicates the conditional standard deviation of the related measure of oil prices. Bold and italics denot significance at the 5% and 10% level, respectively.

Table 4.4(a). Day of the week effect in the mean and variance equations

	Aggregate	Aircraft	Auto	Business Supplies	Chemicals
Panel A Mean Equation					
Constant	-0.0016	0.0444	-0.0443	0.0177	0.0257
	(-0.05193)	(1.10197)	(-0.87562)	(0.48601)	(0.65586)
Monday	-0.0096	-0.0319	**0.1551**	0.0151	0.0153
	(-0.33215)	(-0.79768)	(3.00424)	(0.39053)	(0.38326)
Tuesday	-0.0174	0.0188	0.0690	-0.0024	-0.0167
	(-0.60543)	(0.48217)	(1.34424)	(-0.06555)	(-0.43402)
Wednesday	0.0496	**0.0870**	*0.0916*	0.0387	-0.0071
	(1.83477)	(2.19806)	(1.80296)	(1.06103)	(-0.18797)
Thursday	-0.0145	0.0331	-0.0412	-0.0363	-0.0121
	(-0.48251)	(0.86906)	(-0.80894)	(-0.98158)	(-0.3191)
Panel B Variance Equation					
Constant	0.0242	**0.1281**	0.0784	*0.0482*	**0.0933**
	(1.16101)	(3.10718)	(1.42814)	(1.76584)	(3.39041)
Monday	*-0.0522*	**-0.1513**	-0.0067	-0.0275	-0.0418
	(-1.7143)	(-2.46803)	(-0.07233)	(-0.61467)	(-0.98203)
Tuesday	-0.0109	**-0.2019**	0.0271	0.0033	-0.0787
	(-0.31224)	(-3.20205)	(0.29131)	(0.07317)	(-1.55131)
Wednesday	**-0.0664**	-0.0196	-0.0758	**-0.1521**	**-0.1240**
	(-2.74249)	(-0.30674)	(-0.88294)	(-4.2106)	(-2.57347)
Thursday	**0.0890**	-0.1457	-0.0792	0.0382	**-0.1165**
	(2.45255)	(-1.74658)	(-0.84226)	(0.80229)	(-2.63907)

Note: This table reports the estimates of mean and variance equations. T-statistics are reported in parentheses. Bold and italics denot significance at the 5% and 10% level, respectively.

Table 4.4(b).Day of the week effect in the mean and variance equations

	Coal	Consumer Goods	Electrical Equipment	Entertainment	Machinery
Panel A					
Mean Equation					
Constant	**0.1976**	0.0185	0.0132	0.0259	**0.0909**
	(3.46878)	(0.49984)	(0.29703)	(0.57706)	(2.28463)
Monday	**-0.2353**	0.0282	0.0219	-0.0506	-0.0394
	(-3.77649)	(0.84671)	(0.43951)	(-1.05189)	(-0.96511)
Tuesday	**-0.1451**	0.0048	0.0280	-0.0322	-0.0367
	(-2.49527)	(0.13867)	(0.56655)	(-0.67036)	(-0.93173)
Wednesday	**-0.1416**	**0.0795**	0.0366	0.0070	0.0406
	(-2.39886)	(2.44751)	(0.76418)	(0.15021)	(1.07385)
Thursday	**-0.1614**	0.0086	0.0116	-0.0303	*-0.0680*
	(-2.70178)	(0.25001)	(0.24426)	(-0.65424)	(-1.72155)
Panel B					
Variance Equation					
Constant	-0.0993	*0.0548*	0.0292	0.0572	0.0239
	(-1.10597)	(1.95898)	(0.61629)	(1.26131)	(0.68932)
Monday	-0.0539	-0.0689	-0.0605	**0.1837**	-0.0015
	(-0.39774)	(-1.33605)	(-0.81805)	(2.65947)	(-0.02603)
Tuesday	0.1373	0.0635	-0.0377	-0.1141	-0.0587
	(1.05947)	(1.54353)	(-0.42632)	(-1.4539)	(-1.00706)
Wednesday	0.0957	**-0.1417**	-0.0286	-0.0252	-0.0477
	(0.77982)	(-3.42991)	(-0.4775)	(-0.35696)	(-1.02835)
Thursday	**0.4471**	-0.0128	0.1088	-0.0977	*0.1035*
	(2.87619)	(-0.26515)	(1.33779)	(-1.35976)	(1.75256)

Note: This table reports the estimates of mean and variance equations. T-statistics are reported in parentheses. Bold and italics denot significance at the 5% and 10% level, respectively.

Table 4.4(c).Day of the week effect in the mean and variance equations

	Petroleum & natural gas	Precious metal	restaurants	retail	Rubber and Plastic
Panel A Mean Equation					
Constant	0.0675	**0.1784**	-0.0153	-0.0442	-0.0031
	(1.61608)	(2.47936)	(-0.36977)	(-1.09892)	(-0.0901)
Monday	0.0162	**-0.2242**	-0.0369	-0.0246	-0.0491
	(0.36631)	(-2.87993)	(-0.8852)	(-0.63969)	(-1.30699)
Tuesday	-0.0241	-0.0324	-0.0160	0.0142	-0.0478
	(-0.5879)	(-0.40646)	(-0.41419)	(0.35431)	(-1.30785)
Wednesday	-0.0030	0.0099	0.0393	**0.0972**	0.0197
	(-0.07487)	(0.12748)	(0.95674)	(2.62501)	(0.55455)
Thursday	*-0.0730*	-0.0511	0.0460	0.0434	0.0402
	(-1.77567)	(-0.74204)	(1.05904)	(1.10739)	(1.05326)
Panel B Variance Equation					
Constant	**0.1106**	*-0.1775*	-0.0141	-0.0393	**-0.1123**
	(3.15183)	(-1.73104)	(-0.34723)	(-1.16755)	(-3.48485)
Monday	-0.0808	**0.4409**	0.0503	0.0311	**0.1711**
	(-1.43759)	(2.26864)	(0.80916)	(0.55535)	(3.19226)
Tuesday	**-0.1696**	**0.9933**	-0.0170	*0.1049*	**0.1167**
	(-2.7457)	(5.19659)	(-0.26785)	(1.82939)	(2.22238)
Wednesday	*-0.0964*	-0.0915	0.0747	-0.0468	0.0699
	(-1.87873)	(-0.4281)	(1.24078)	(-1.10301)	(1.54701)
Thursday	-0.0856	0.0274	*0.1331*	**0.2396**	**0.3822**
	(-1.36873)	(0.13156)	(1.87288)	(4.38653)	(7.06723)

Note: This table reports the estimates of mean and variance equations. T-statistics are reported in parentheses. Bold and italics denot significance at the 5% and 10% level, respectively.

Table 4.4(d).Day of the week effect in the mean and variance equations

	Shiprailroad	Steel	Transportation	Utilities
Panel A Mean Equation				
Constant	**0.1358**	**0.1748**	**0.0850**	**0.0639**
	(2.58878)	(3.94441)	(2.12549)	(2.59133)
Monday	*-0.0929*	**-0.2026**	*-0.0712*	-0.0205
	(-1.73047)	(-4.1627)	(-1.72469)	(-0.7317)
Tuesday	-0.0885	**-0.1086**	-0.0455	0.0013
	(-1.67698)	(-2.30376)	(-1.1245)	(0.04702)
Wednesday	-0.0406	-0.0447	0.0145	-0.0132
	(-0.77585)	(-0.92244)	(0.35045)	(-0.491)
Thursday	-0.0292	**-0.1146**	-0.0221	**-0.0851**
	(-0.57321)	(-2.34864)	(-0.54905)	(-3.05807)
Panel B Variance Equation				
Constant	**0.1478**	**0.0890**	0.0536	0.0153
	(3.43285)	(2.14859)	(1.48134)	(0.97757)
Monday	-0.0219	-0.0783	0.0367	-0.0314
	(-0.26842)	(-1.06093)	(0.59888)	(-1.2703)
Tuesday	-0.1057	-0.1143	-0.0693	**-0.0519**
	(-1.06469)	(-1.45623)	(-1.18244)	(-2.10489)
Wednesday	-0.0052	-0.0703	-0.0377	0.0069
	(-0.05666)	(-1.25305)	(-0.72074)	(0.32055)
Thursday	**-0.2742**	-0.0163	0.0047	**0.0723**
	(-3.50969)	(-0.22493)	(0.0824)	(2.59292)

Note: This table reports the estimates of mean and variance equations. T-statistics are reported in parentheses. Bold and italics denot significance at the 5% and 10% level, respectively.

Chapter 5: Research Conclusions

Even though some might believe that shocks in crude oil prices have a drastic effect on the financial market, the relationship between changes in oil prices and stock returns is still not clear. These inconclusive findings could arise due to limitations in the linear models used in the literature since these models are not good enough in identifying asymmetries and nonlinear relationship between oil and stock returns. Thus, the contrasting results in the effect of oil price innovations on stock returns raise the question of whether the nature of the relationship might make a difference. Meaning that stock returns might respond differently to oil price increases and decreases. The divergent results in the literature also question the effect of uncertainty and variability in oil prices on stock returns. Thus, this research attempts to tackle these questions by testing for asymmetry in the response of U.S. stock returns, and by examining the effect of uncertainty and variability in oil prices on stock returns.

Using a simultaneous equation model that nests symmetric and asymmetric responses to positive and negative oil price innovations, we investigate whether the size and the sign of an oil price shock matter for the response of U.S. real stock returns. Estimation results suggested that a linear model fits the data well for aggregate returns, as well as for most industry-level portfolios. We find no evidence of asymmetry for aggregate stock returns, and only very limited evidence for the 49 industry-level portfolios studied in this research. We also examine whether the size of the shock matters in that doubling the size of the shock more (or less) than doubles the size of the response. Consistent with our finding that a linear model fits most of the industries, we conclude that the effect of a 2.s.d innovation is just double the magnitude of the impact of a 1.s.d innovation.

Additionally, we find no support for the assumption that shocks that exceed a threshold have an asymmetric effect on stock returns. We then explore whether our results are robust to specifying our model in terms of the nominal oil price. Our test results indicate a considerable increase in the number of rejections for the net oil price increase over the previous 12-month maximum, even after controlling for data mining.

This research also investigates the direct effect of oil price uncertainty on the U.S. stock returns at the aggregate and sectoral level using a bivariate GARCH–in-mean VAR model. Estimation results suggest that the conditional volatility of the real price of oil has no effect on the U.S. stock returns. In other words, oil price shocks affect stock returns through the impact of an unexpected innovation to the conditional mean of the oil price change but not through shocks to the conditional volatility. This result is likely to be linked to the absence of an uncertainty effect of the real price of oil on corporate cash flow and discount rates. Moreover, by simulating the response of real stock returns to positive and negative oil price shocks, we show that the responses to positive and negative shocks are symmetric, in that energy price increases and decreases are estimated to have equal and opposite effects on the U.S. financial markets.

Because the effect of oil price shocks might differ across sectors, we investigate the effect of changes in oil price uncertainty on industry-level stock returns. In particular, sectoral response to oil price volatility might have important implications in understanding the market and in retaining efficient portfolio diversification. Our results show that uncertainty in oil prices has no effect on stock returns across all industries. The absence of an uncertainty effect might be explained by the view that companies across sectors, the airline industry for instance, are likely to hedge against fluctuations in oil prices. It could also stem from the ability of most companies to transfer the higher cost of oil to customers.

The presence of seasonal effects (calendar anomalies) in stock returns has been widely examined in the financial literature. A number of studies have shown that there are dissimilarities in the allocation of stock returns for each day of the week (see among others, French (1980), Keim and Stambaugh (1984), and Rogalski (1984)). Therefore, using daily data on aggregate and sectoral level U.S. stock returns, we employ a modified structural vector autoregression (VAR) that fits GARCH-in-Mean errors as in Elder (1995, 2004) and Elder and Serletis (2010) and take into account the day of the week effect. The volatility of oil price change is measured by the conditional variance of the oil price change forecast error.

We find that the U.S. stock market is sensitive to oil price variations not only at the aggregate level but also across some industries, such as chemicals, entertainment, and retail, where uncertainty in oil prices proves to have positive and statistically significant effect. The results also show that some sectors react against our expectations to fluctuations in oil prices. For instance, one might expect higher uncertainty in oil prices would lead to higher returns in the petroleum and natural gas sector, but not in transportation or automobiles sectors. Surprisingly, some sectors such as the retail and entertainment (unpredictably) seem to benefit from higher uncertainty in oil prices. On the other hand, unexpectedly many sectors, such as transportation, automobiles, consumer goods, aircraft, and many others, came out to be unaffected by variations in oil prices. Thus, the effects of crude oil price fluctuations on stock returns may not be as large and harmful as might be expected. Ultimately, the extremely high levels of price volatility that characterize the energy markets encourage investors to use derivatives and future markets in managing and hedging risk. Thus, during times of high oil volatility, traders choose sector stocks that match their lenience for volatility and use the right financial derivative to hedge against or profit from this volatility.

Furthermore, it would be interesting to extend this research to a group of emerging and developing economies by applying these nonlinear models to estimate and forecast the response of stock returns to changes in crude oil prices. Another remarkable extension for this study is to identify the source of oil shock by separating oil price shocks into demand and supply shocks as in Kilian and Park (2009), and then use nonlinear techniques in testing for the response of stock returns to oil price innovations. This will clarify the reason behind the inconclusive finding in the literature.

Table 2A: Standard Industrial Classification (SIC) Codes for Industries

This appendix describes the industries included in each portfolio.

1 Agric Agriculture
    0100-0199 Agric production - crops
    0200-0299 Agric production - livestock
    0700-0799 Agricultural services
    0910-0919 Commercial fishing
    2048-2048 Prepared feeds for animals

2 Food Food Products
    2000-2009 Food and kindred products
    2010-2019 Meat products
    2020-2029 Dairy products
    2030-2039 Canned-preserved fruits-vegs
    2040-2046 Flour and other grain mill products
    2050-2059 Bakery products
    2060-2063 Sugar and confectionery products
    2070-2079 Fats and oils
    2090-2092 Misc food preps
    2095-2095 Roasted coffee
    2098-2099 Misc food preparations

3 Soda Candy & Soda
    2064-2068 Candy and other confectionery
    2086-2086 Bottled-canned soft drinks
    2087-2087 Flavoring syrup
    2096-2096 Potato chips
    2097-2097 Manufactured ice

4 Beer Beer & Liquor
    2080-2080 Beverages
    2082-2082 Malt beverages
    2083-2083 Malt
    2084-2084 Wine
    2085-2085 Distilled and blended liquors

5 Smoke Tobacco Products
    2100-2199 Tobacco products

6 Toys Recreation
    0920-0999 Fishing, hunting & trapping
    3650-3651 Household audio visual equip
    3652-3652 Phonographic records
    3732-3732 Boat building and repair
    3930-3931 Musical instruments
    3940-3949 Toys

7 Fun Entertainment
    7800-7829 Services - motion picture production and distribution
    7830-7833 Services - motion picture theatres

7840-7841 Services - video rental
7900-7900 Services - amusement and recreation
7910-7911 Services - dance studios
7920-7929 Services - bands, entertainers
7930-7933 Services - bowling centers
7940-7949 Services - professional sports
7980-7980 Amusement and recreation services (?)
7990-7999 Services - misc entertainment

8 Books Printing and Publishing
2700-2709 Printing publishing and allied
2710-2719 Newspapers: publishing-printing
2720-2729 Periodicals: publishing-printing
2730-2739 Books: publishing-printing
2740-2749 Misc publishing
2770-2771 Greeting card publishing
2780-2789 Book binding
2790-2799 Service industries for print trade

9 Hshld Consumer Goods
2047-2047 Dog and cat food
2391-2392 Curtains, home furnishings
2510-2519 Household furniture
2590-2599 Misc furniture and fixtures
2840-2843 Soap & other detergents
2844-2844 Perfumes cosmetics
3160-3161 Luggage
3170-3171 Handbags and purses
3172-3172 Personal leather goods, except handbags
3190-3199 Leather goods
3229-3229 Pressed and blown glass
3260-3260 Pottery and related products
3262-3263 China and earthenware table articles
3269-3269 Pottery products
3230-3231 Glass products
3630-3639 Household appliances
3750-3751 Motorcycles, bicycles and parts (Harley & Huffy)
3800-3800 Misc inst, photo goods, watches
3860-3861 Photographic equip (Kodak etc, but also Xerox)
3870-3873 Watches clocks and parts
3910-3911 Jewelry-precious metals
3914-3914 Silverware
3915-3915 Jewelers' findings, materials
3960-3962 Costume jewelry and notions
3991-3991 Brooms and brushes
3995-3995 Burial caskets

10 Clths Apparel
2300-2390 Apparel and other finished products
3020-3021 Rubber and plastics footwear
3100-3111 Leather tanning and finishing
3130-3131 Boot, shoe cut stock, findings
3140-3149 Footware except rubber

3150-3151 Leather gloves and mittens
3963-3965 Fasteners, buttons, needles, pins

11 Hlth Healthcare
8000-8099 Services - health

12 MedEq Medical Equipment
3693-3693 X-ray, electromedical app
3840-3849 Surg & med instru
3850-3851 Ophthalmic goods

13 Drugs Pharmaceutical Products
2830-2830 Drugs
2831-2831 Biological products
2833-2833 Medicinal chemicals
2834-2834 Pharmaceutical preparations
2835-2835 In vitro, in vivo diagnostics
2836-2836 Biological products, except diagnostics

14 Chems Chemicals
2800-2809 Chemicals and allied products
2810-2819 Industrial inorganical chems
2820-2829 Plastic material & synthetic resin
2850-2859 Paints
2860-2869 Industrial organic chems
2870-2879 Agriculture chemicals
2890-2899 Misc chemical products

15 Rubbr Rubber and Plastic Products
3031-3031 Reclaimed rubber
3041-3041 Rubber & plastic hose and belting
3050-3053 Gaskets, hoses, etc
3060-3069 Fabricated rubber products
3070-3079 Misc rubber products (?)
3080-3089 Misc plastic products
3090-3099 Misc rubber and plastic products (?)

16 Txtls Textiles
2200-2269 Textile mill products
2270-2279 Floor covering mills
2280-2284 Yarn and thread mills
2290-2295 Misc textile goods
2297-2297 Nonwoven fabrics
2298-2298 Cordage and twine
2299-2299 Misc textile products
2393-2395 Textile bags, canvas products
2397-2399 Misc textile products

17 BldMt Construction Materials
0800-0899 Forestry
2400-2439 Lumber and wood products
2450-2459 Wood buildings-mobile homes
2490-2499 Misc wood products

2660-2661 Building paper and board mills
2950-2952 Paving & roofing materials
3200-3200 Stone, clay, glass, concrete etc
3210-3211 Flat glass
3240-3241 Cement hydraulic
3250-3259 Structural clay prods
3261-3261 Vitreous china plumbing fixtures
3264-3264 Porcelain electrical supply
3270-3275 Concrete gypsum & plaster
3280-3281 Cut stone and stone products
3290-3293 Abrasive and asbestos products
3295-3299 Non-metalic mineral products
3420-3429 Handtools and hardware
3430-3433 Heating equip & plumbing fix
3440-3441 Fabicated struct metal products
3442-3442 Metal doors, frames
3446-3446 Architectual or ornamental metal work
3448-3448 Pre-fab metal buildings
3449-3449 Misc structural metal work
3450-3451 Screw machine products
3452-3452 Bolts, nuts screws
3490-3499 Misc fabricated metal products
3996-3996 Hard surface floor cover

18 Cnstr Construction
1500-1511 Build construction - general contractors
1520-1529 Gen building contractors - residential
1530-1539 Operative builders
1540-1549 Gen building contractors - non-residential
1600-1699 Heavy Construction - not building contractors
1700-1799 Construction - special contractors

19 Steel Steel Works Etc
3300-3300 Primary metal industries
3310-3317 Blast furnaces & steel works
3320-3325 Iron & steel foundries
3330-3339 Prim smelt-refin nonfer metals
3340-3341 Secondary smelt-refin nonfer metals
3350-3357 Rolling & drawing nonferous metals
3360-3369 Non-ferrous foundries and casting
3370-3379 Steel works etc
3390-3399 Misc primary metal products

20 FabPr Fabricated Products
3400-3400 Fabricated metal, except machinery and trans eq
3443-3443 Fabricated plate work
3444-3444 Sheet metal work
3460-3469 Metal forgings and stampings
3470-3479 Coating and engraving

21 Mach Machinery
3510-3519 Engines & turbines
3520-3529 Farm and garden machinery

3530-3530 Constr, mining material handling machinery
3531-3531 Construction machinery
3532-3532 Mining machinery, except oil field
3533-3533 Oil field machinery
3534-3534 Elevators
3535-3535 Conveyors
3536-3536 Cranes, hoists
3538-3538 Machinery
3540-3549 Metalworking machinery
3550-3559 Special industry machinery
3560-3569 General industrial machinery
3580-3580 Refrig & service ind machines
3581-3581 Automatic vending machines
3582-3582 Commercial laundry and drycleaning machines
3585-3585 Air conditioning, heating, refrid eq
3586-3586 Measuring and dispensing pumps
3589-3589 Service industry machinery
3590-3599 Misc industrial and commercial equipment and mach

22 ElcEq Electrical Equipment
3600-3600 Elec mach eq & supply
3610-3613 Elec transmission
3620-3621 Electrical industrial appar
3623-3629 Electrical industrial appar
3640-3644 Electric lighting, wiring
3645-3645 Residential lighting fixtures
3646-3646 Commercial lighting
3648-3649 Lighting equipment
3660-3660 Communication equip
3690-3690 Miscellaneous electrical machinery and equip
3691-3692 Storage batteries
3699-3699 Electrical machinery and equip

23 Autos Automobiles and Trucks
2296-2296 Tire cord and fabric
2396-2396 Auto trim
3010-3011 Tires and inner tubes
3537-3537 Trucks, tractors, trailers
3647-3647 Vehicular lighting
3694-3694 Elec eq, internal combustion engines
3700-3700 Transportation equipment
3710-3710 Motor vehicles and motor vehicle equip
3711-3711 Motor vehicles & car bodies
3713-3713 Truck & bus bodies
3714-3714 Motor vehicle parts
3715-3715 Truck trailers
3716-3716 Motor homes
3792-3792 Travel trailers and campers
3790-3791 Misc trans equip
3799-3799 Misc trans equip

24 Aero   Aircraft
3720-3720 Aircraft & parts

3721-3721 Aircraft
3723-3724 Aircraft engines, engine parts
3725-3725 Aircraft parts
3728-3729 Aircraft parts

25 Ships Shipbuilding, Railroad Equipment
3730-3731 Ship building and repair
3740-3743 Railroad Equipment

26 Guns   Defense
3760-3769 Guided missiles and space vehicles
3795-3795 Tanks and tank components
3480-3489 Ordnance & accessories

27 Gold   Precious Metals
1040-1049 Gold & silver ores

28 Mines Non-Metallic and Industrial Metal Mining
1000-1009 Metal mining
1010-1019 Iron ores
1020-1029 Copper ores
1030-1039 Lead and zinc ores
1050-1059 Bauxite and other aluminum ores
1060-1069 Ferroalloy ores
1070-1079 Mining
1080-1089 Mining services
1090-1099 Misc metal ores
1100-1119 Anthracite mining
1400-1499 Mining and quarrying non-metalic minerals

29 Coal   Coal
1200-1299 Bituminous coal

30 Oil   Petroleum and Natural Gas
1300-1300 Oil and gas extraction
1310-1319 Crude petroleum & natural gas
1320-1329 Natural gas liquids
1330-1339 Petroleum and natural gas
1370-1379 Petroleum and natural gas
1380-1380 Oil and gas field services
1381-1381 Drilling oil & gas wells
1382-1382 Oil-gas field exploration
1389-1389 Oil and gas field services
2900-2912 Petroleum refining
2990-2999 Misc petroleum products

31 Util   Utilities
4900-4900 Electric, gas, sanitary services
4910-4911 Electric services
4920-4922 Natural gas transmission
4923-4923 Natural gas transmission-distr
4924-4925 Natural gas distribution
4930-4931 Electric and other services combined

4932-4932 Gas and other services combined
4939-4939 Combination utilities
4940-4942 Water supply

32 Telcm Communication
4800-4800 Communications
4810-4813 Telephone communications
4820-4822 Telegraph and other message communication
4830-4839 Radio-TV Broadcasters
4840-4841 Cable and other pay TV services
4880-4889 Communications
4890-4890 Communication services (Comsat)
4891-4891 Cable TV operators
4892-4892 Telephone interconnect
4899-4899 Communication services

33 PerSv Personal Services
7020-7021 Rooming and boarding houses
7030-7033 Camps and recreational vehicle parks
7200-7200 Services - personal
7210-7212 Services - laundry, cleaners
7214-7214 Services - diaper service
7215-7216 Services - coin-op cleaners, dry cleaners
7217-7217 Services - carpet, upholstery cleaning
7219-7219 Services - laundry, cleaners
7220-7221 Services - photo studios, portrait
7230-7231 Services - beauty shops
7240-7241 Services - barber shops
7250-7251 Services - shoe repair
7260-7269 Services - funeral
7270-7290 Services - misc
7291-7291 Services - tax return
7292-7299 Services - misc
7395-7395 Services - photofinishing labs (School pictures)
7500-7500 Services - auto repair, services
7520-7529 Services - automobile parking
7530-7539 Services - auto repair shops
7540-7549 Services - auto services, except repair (car washes)
7600-7600 Services - Misc repair services
7620-7620 Services - Electrical repair shops
7622-7622 Services - Radio and TV repair shops
7623-7623 Services - Refridg and air conditioner repair
7629-7629 Services - Electrical repair shops
7630-7631 Services - Watch, clock and jewelry repair
7640-7641 Services - Reupholster, furniture repair
7690-7699 Services - Misc repair shops
8100-8199 Services - legal
8200-8299 Services - educational
8300-8399 Services - social services
8400-8499 Services - museums, galleries, botanic gardens
8600-8699 Services - membership organizations
8800-8899 Services - private households
7510-7515 Services - truck, auto rental and leasing

34 BusSv Business Services
2750-2759 Commercial printing
3993-3993 Signs, advertising specialty
7218-7218 Services - industrial launderers
7300-7300 Services - business services
7310-7319 Services - advertising
7320-7329 Services - credit reporting agencies, collection services
7330-7339 Services - mailing, reproduction, commercial art
7340-7342 Services - services to dwellings, other buildings
7349-7349 Services - cleaning and builging maint
7350-7351 Services - misc equip rental and leasing
7352-7352 Services - medical equip rental
7353-7353 Services - heavy construction equip rental
7359-7359 Services - equip rental and leasing
7360-7369 Services - personnel supply services
7374-7374 Services - computer processing, data prep
7376-7376 Services - computer facilities management service
7377-7377 Services - computer rental and leasing
7378-7378 Services - computer maintanence and repair
7379-7379 Services - computer related services
7380-7380 Services - misc business services
7381-7382 Services - security
7383-7383 Services - news syndicates
7384-7384 Services - photofinishing labs
7385-7385 Services - telephone interconnections
7389-7390 Services - misc business services
7391-7391 Services - R&D labs
7392-7392 Services - management consulting & P.R.
7393-7393 Services - detective and protective (ADT)
7394-7394 Services - equipment rental & leasing
7396-7396 Services - trading stamp services
7397-7397 Services - commercial testing labs
7399-7399 Services - business services
7519-7519 Services - trailer rental and leasing
8700-8700 Services - engineering, accounting, research, management
8710-8713 Services - engineering, accounting, surveying
8720-8721 Services - accounting, auditing, bookkeeping
8730-8734 Services - research, development, testing labs
8740-8748 Services - management, public relations, consulting
8900-8910 Services - misc
8911-8911 Services - engineering & architect
8920-8999 Services - misc
4220-4229 Warehousing and storage

35 Hardw Computers
3570-3579 Office computers
3680-3680 Computers
3681-3681 Computers - mini
3682-3682 Computers - mainframe
3683-3683 Computers - terminals
3684-3684 Computers - disk & tape drives
3685-3685 Computers - optical scanners

3686-3686 Computers - graphics
3687-3687 Computers - office automation systems
3688-3688 Computers - peripherals
3689-3689 Computers - equipment
3695-3695 Magnetic and optical recording media

36 Softw Computer Software
7370-7372 Services - computer programming and data processing
7375-7375 Services - information retrieval services
7373-7373 Computer integrated systems design

37 Chips Electronic Equipment
3622-3622 Industrial controls
3661-3661 Telephone and telegraph apparatus
3662-3662 Communications equipment
3663-3663 Radio TV comm equip & apparatus
3664-3664 Search, navigation, guidance systems
3665-3665 Training equipment & simulators
3666-3666 Alarm & signaling products
3669-3669 Communication equipment
3670-3679 Electronic components
3810-3810 Search, detection, navigation, guidance
3812-3812 Search, detection, navigation, guidance

38 LabEq Measuring and Control Equipment
3811-3811 Engr lab and research equipment
3820-3820 Measuring and controlling equipment
3821-3821 Lab apparatus and furniture
3822-3822 Automatic controls - Envir and applic
3823-3823 Industrial measurement instru
3824-3824 Totalizing fluid meters
3825-3825 Elec meas & test instr
3826-3826 Lab analytical instruments
3827-3827 Optical instr and lenses
3829-3829 Meas and control devices
3830-3839 Optical instr and lenses

39 Paper Business Supplies
2520-2549 Office furniture and fixtures
2600-2639 Paper and allied products
2670-2699 Paper and allied products
2760-2761 Manifold business forms
3950-3955 Pens pencils and office supplies

40 Boxes Shipping Containers
2440-2449 Wood containers
2640-2659 Paperboard containers, boxes, drums, tubs
3220-3221 Glass containers
3410-3412 Metal cans and shipping containers

41 Trans Transportation
4000-4013 Railroads-line haul
4040-4049 Railway express service

4100-4100 Transit and passenger trans
4110-4119 Local passenger trans
4120-4121 Taxicabs
4130-4131 Intercity bus trans (Greyhound)
4140-4142 Bus charter
4150-4151 School buses
4170-4173 Motor vehicle terminals, service facilities
4190-4199 Misc transit and passenger transportation
4200-4200 Motor freight trans, warehousing
4210-4219 Trucking
4230-4231 Terminal facilities - motor freight
4240-4249 Transportation
4400-4499 Water transport
4500-4599 Air transportation
4600-4699 Pipelines, except natural gas
4700-4700 Transportation services
4710-4712 Freight forwarding
4720-4729 Travel agencies, etc
4730-4739 Arrange trans - freight and cargo
4740-4749 Rental of railroad cars
4780-4780 Misc services incidental to trans
4782-4782 Inspection and weighing services
4783-4783 Packing and crating
4784-4784 Fixed facilities for vehicles, not elsewhere classified
4785-4785 Motor vehicle inspection
4789-4789 Transportation services

42 Whlsl Wholesale
5000-5000 Wholesale - durable goods
5010-5015 Wholesale - autos and parts
5020-5023 Wholesale - furniture and home furnishings
5030-5039 Wholesale - lumber and construction materials
5040-5042 Wholesale - professional and commercial equipment and supplies
5043-5043 Wholesale - photographic equipment
5044-5044 Wholesale - office equipment
5045-5045 Wholesale - computers
5046-5046 Wholesale - commerical equip
5047-5047 Wholesale - medical, dental equip
5048-5048 Wholesale - ophthalmic goods
5049-5049 Wholesale - professional equip and supplies
5050-5059 Wholesale - metals and minerals
5060-5060 Wholesale - electrical goods
5063-5063 Wholesale - electrical apparatus and equipment
5064-5064 Wholesale - electrical appliance TV and radio
5065-5065 Wholesale - electronic parts
5070-5078 Wholesale - hardware, plumbing, heating equip
5080-5080 Wholesale - machinery and equipment
5081-5081 Wholesale - machinery and equipment (?)
5082-5082 Wholesale - construction and mining equipment
5083-5083 Wholesale - farm and garden machinery
5084-5084 Wholesale - industrial machinery and equipment
5085-5085 Wholesale - industrial supplies
5086-5087 Wholesale - machinery and equipment (?)

5088-5088 Wholesale - trans eq except motor vehicles
5090-5090 Wholesale - misc durable goods
5091-5092 Wholesale - sporting goods, toys
5093-5093 Wholesale - scrap and waste materials
5094-5094 Wholesale - jewelry and watches
5099-5099 Wholesale - durable goods
5100-5100 Wholesale - nondurable goods
5110-5113 Wholesale - paper and paper products
5120-5122 Wholesale - drugs & propietary
5130-5139 Wholesale - apparel
5140-5149 Wholesale - groceries & related prods
5150-5159 Wholesale - farm products
5160-5169 Wholesale - chemicals & allied prods
5170-5172 Wholesale - petroleum and petro prods
5180-5182 Wholesale - beer, wine
5190-5199 Wholesale - non-durable goods

43 Rtail Retail
5200-5200 Retail - bldg material, hardware, garden
5210-5219 Retail - lumber & other building mat
5220-5229 Retail
5230-5231 Retail - paint, glass, wallpaper
5250-5251 Retail - hardward stores
5260-5261 Retail - nurseries, lawn, garden stores
5270-5271 Retail - mobile home dealers
5300-5300 Retail - general merchandise stores
5310-5311 Retail - department stores
5320-5320 Retail - general merchandise stores (?)
5330-5331 Retail - variety stores
5334-5334 Retail - catalog showroom
5340-5349 Retail
5390-5399 Retail - Misc general merchandise stores
5400-5400 Retail - food stores
5410-5411 Retail - grocery stores
5412-5412 Retail - convenience stores
5420-5429 Retail - meat, fish mkt
5430-5439 Retail - fruite and vegatable markets
5440-5449 Retail - candy, nut, confectionary stores
5450-5459 Retail - dairy product stores
5460-5469 Retail - bakeries
5490-5499 Retail - miscellaneous food stores
5500-5500 Retail - auto dealers and gas stations
5510-5529 Retail - auto dealers
5530-5539 Retail - auto and home supply stores
5540-5549 Retail - gasoline service stations
5550-5559 Retail - boat dealers
5560-5569 Retail - recreational vehicle dealers
5570-5579 Retail - motorcycle dealers
5590-5599 Retail - automotive dealers
5600-5699 Retail - apparel & acces
5700-5700 Retail - home furniture and equipment stores
5710-5719 Retail - home furnishings stores
5720-5722 Retail - household appliance stores

5730-5733 Retail - radio, TV and consumer electronic stores
5734-5734 Retail - computer and computer software stores
5735-5735 Retail - record and tape stores
5736-5736 Retail - musical instrument stores
5750-5799 Retail
5900-5900 Retail - misc
5910-5912 Retail - drug & proprietary stores
5920-5929 Retail - liquor stores
5930-5932 Retail - used merchandise stores
5940-5940 Retail - misc
5941-5941 Retail - sporting goods stores, bike shops
5942-5942 Retail - book stores
5943-5943 Retail - stationery stores
5944-5944 Retail - jewelry stores
5945-5945 Retail - hobby, toy and game shops
5946-5946 Retail - camera and photo shop
5947-5947 Retail - gift, novelty
5948-5948 Retail - luggage
5949-5949 Retail - sewing & needlework stores
5950-5959 Retail
5960-5969 Retail - non-store retailers (catalogs, etc)
5970-5979 Retail
5980-5989 Retail - fuel & ice stores (Penn Central Co)
5990-5990 Retail - retail stores
5992-5992 Retail - florists
5993-5993 Retail - tobacco stores
5994-5994 Retail - newsdealers
5995-5995 Retail - computer stores
5999-5999 Retail stores

44 Meals Restaurants, Hotels, Motels
5800-5819 Retail - eating places
5820-5829 Restaurants, hotels, motels
5890-5899 Eating and drinking places
7000-7000 Hotels, other lodging places
7010-7019 Hotels motels
7040-7049 Membership hotels and lodging
7213-7213 Services - linen

45 Banks Banking
6000-6000 Depository institutions
6010-6019 Federal reserve banks
6020-6020 Commercial banks
6021-6021 National commercial banks
6022-6022 State banks - Fed Res System
6023-6024 State banks - not Fed Res System
6025-6025 National banks - Fed Res System
6026-6026 National banks - not Fed Res System
6027-6027 National banks, not FDIC
6028-6029 Banks
6030-6036 Savings institutions
6040-6059 Banks (?)
6060-6062 Credit unions

6080-6082 Foreign banks
6090-6099 Functions related to deposit banking
6100-6100 Nondepository credit institutions
6110-6111 Federal credit agencies
6112-6113 FNMA
6120-6129 S&Ls
6130-6139 Agricultural credit institutions
6140-6149 Personal credit institutions (Beneficial)
6150-6159 Business credit institutions
6160-6169 Mortgage bankers
6170-6179 Finance lessors
6190-6199 Financial services

46 Insur Insurance
6300-6300 Insurance
6310-6319 Life insurance
6320-6329 Accident and health insurance
6330-6331 Fire, marine, property-casualty ins
6350-6351 Surety insurance
6360-6361 Title insurance
6370-6379 Pension, health, welfare funds
6390-6399 Insurance carriers
6400-6411 Insurance agents

47 RlEst Real Estate
6500-6500 Real estate
6510-6510 Real estate operators
6512-6512 Operators - non-resident buildings
6513-6513 Operators - apartment buildings
6514-6514 Operators - other than apartment
6515-6515 Operators - residential mobile home
6517-6519 Lessors of real property
6520-6529 Real estate
6530-6531 Real estate agents and managers
6532-6532 Real estate dealers
6540-6541 Title abstract offices
6550-6553 Real estate developers
6590-6599 Real estate
6610-6611 Combined real estate, insurance, etc

48 Fin Trading
6200-6299 Security and commodity brokers
6700-6700 Holding, other investment offices
6710-6719 Holding offices
6720-6722 Investment offices
6723-6723 Management investment, closed-end
6724-6724 Unit investment trusts
6725-6725 Face-amount certificate offices
6726-6726 Unit inv trusts, closed-end
6730-6733 Trusts
6740-6779 Investment offices
6790-6791 Miscellaneous investing
6792-6792 Oil royalty traders

6793-6793 Commodity traders
6794-6794 Patent owners & lessors
6795-6795 Mineral royalty traders
6798-6798 REIT
6799-6799 Investors, NEC

49 Other Almost Nothing
4950-4959 Sanitary services
4960-4961 Steam, air conditioning supplies
4970-4971 Irrigation systems
4990-4991 Cogeneration - SM power producer

Figure A.1 a-f: Response to one standard deviation positive and negative innovation in the real oil price change

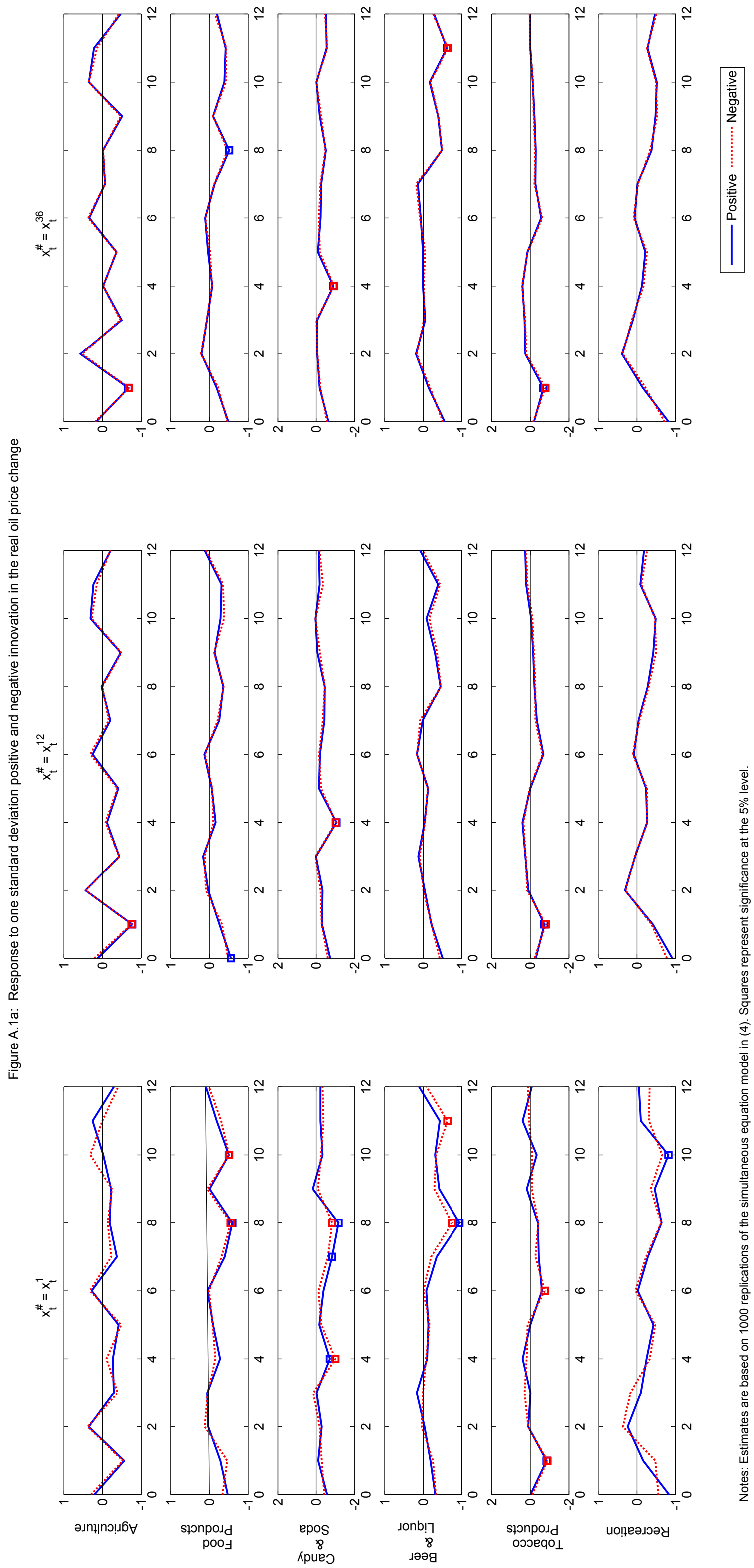


Figure A.1 a-f: Response to one standard deviation positive and negative innovation in the real oil price change

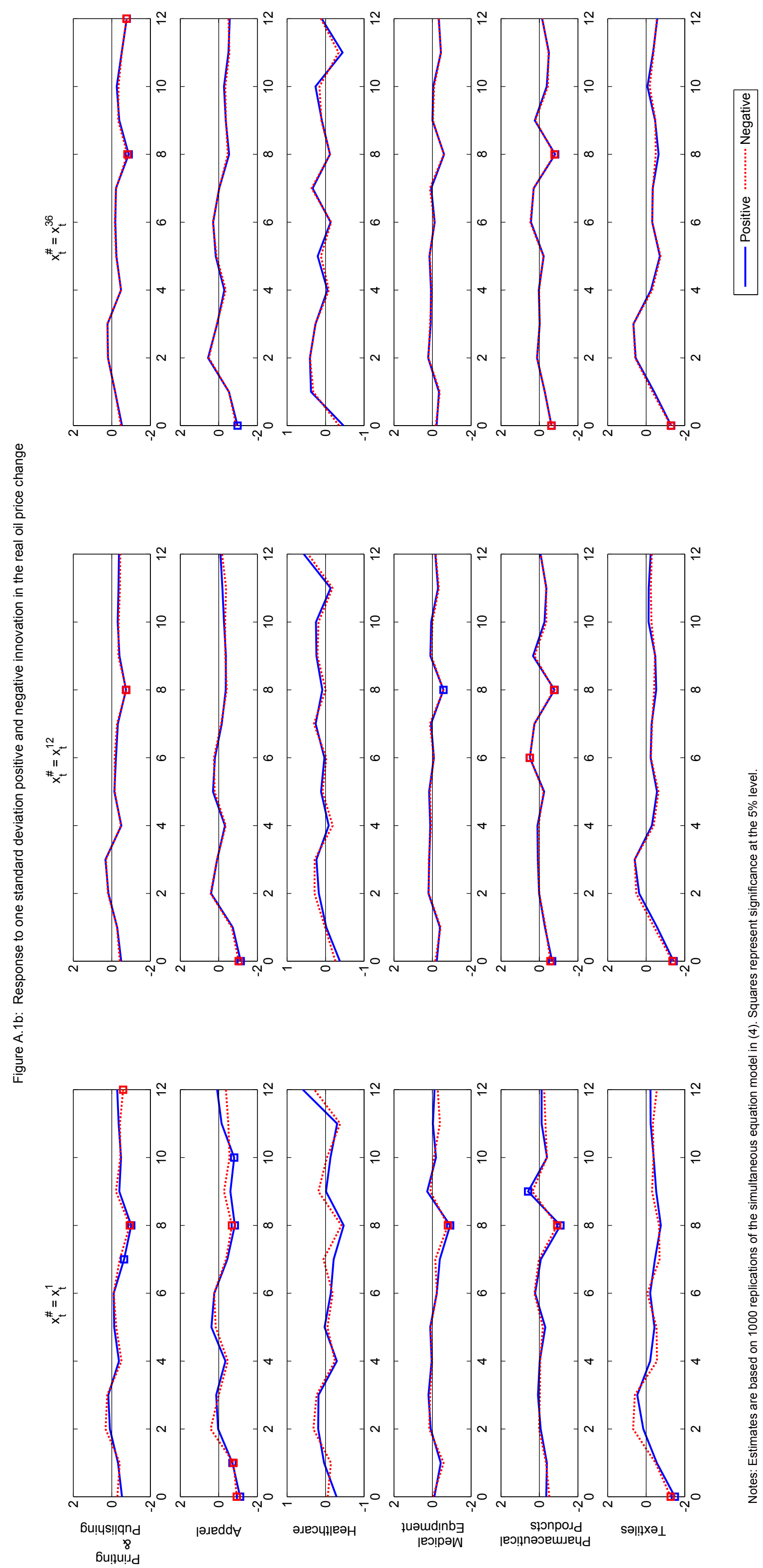


Figure A.1 a-f: Response to one standard deviation positive and negative innovation in the real oil price change

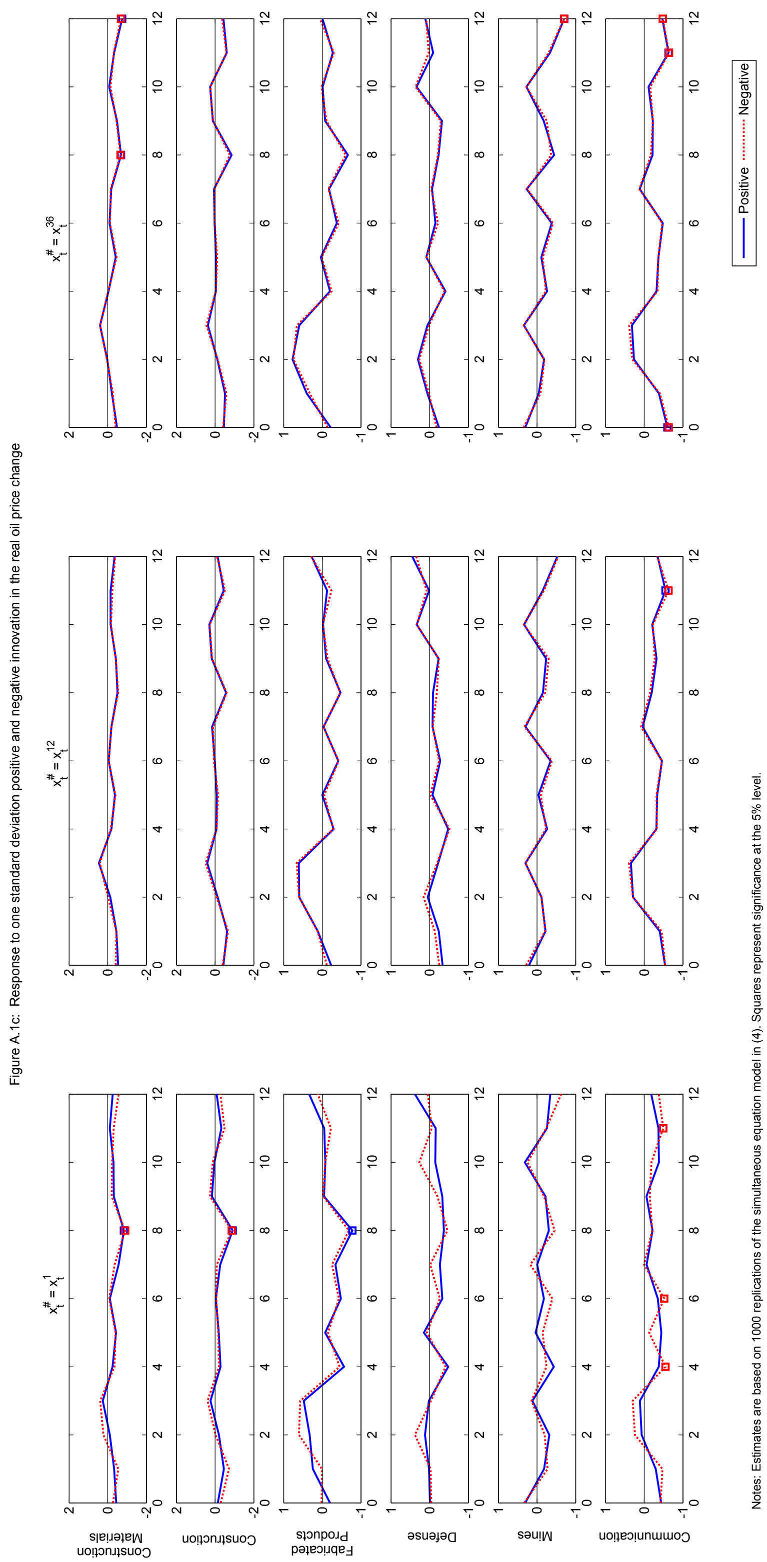


Figure A.1 a-f: Response to one standard deviation positive and negative innovation in the real oil price change

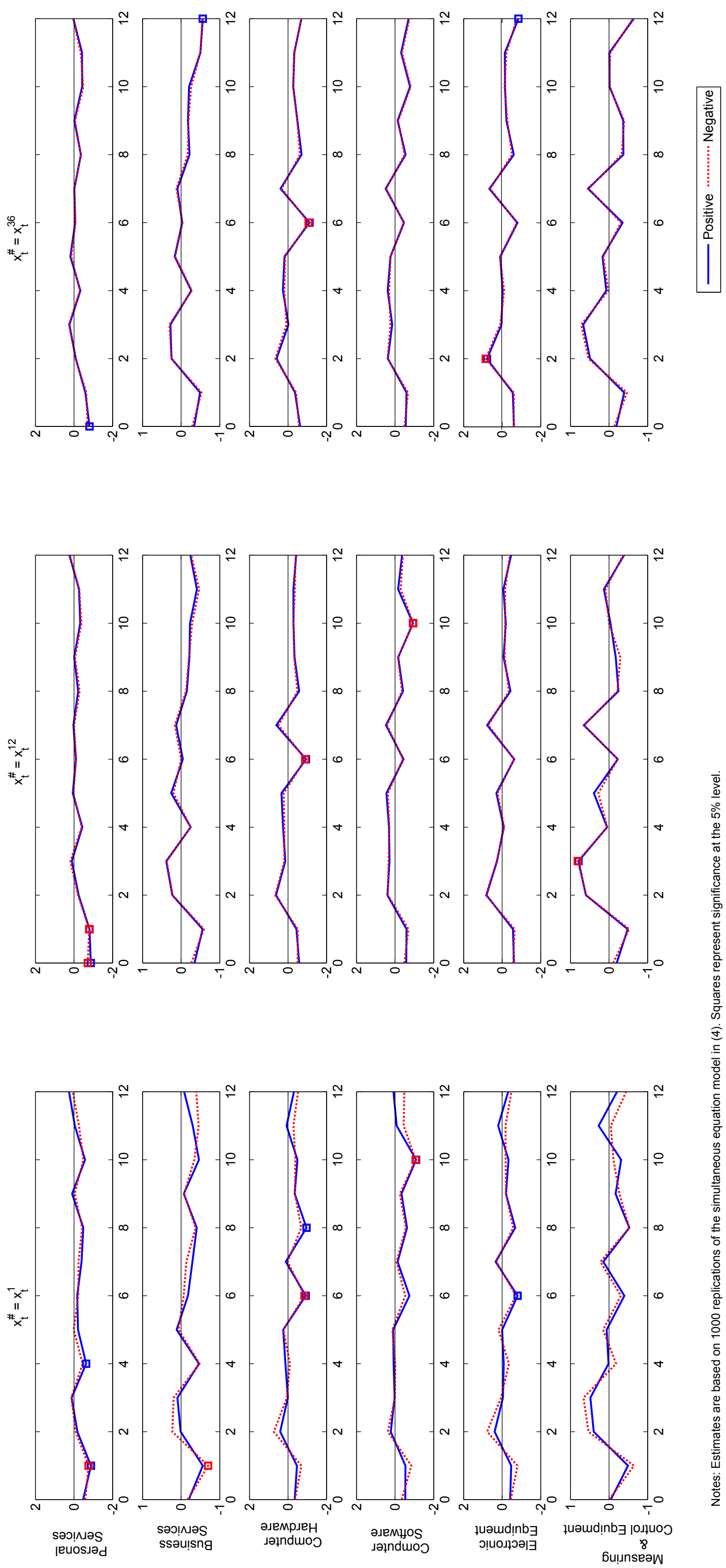


Figure A.1d : Response to one standard deviation positive and negative innovation in the real oil price change

Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.1 a-f: Response to one standard deviation positive and negative innovation in the real oil price change

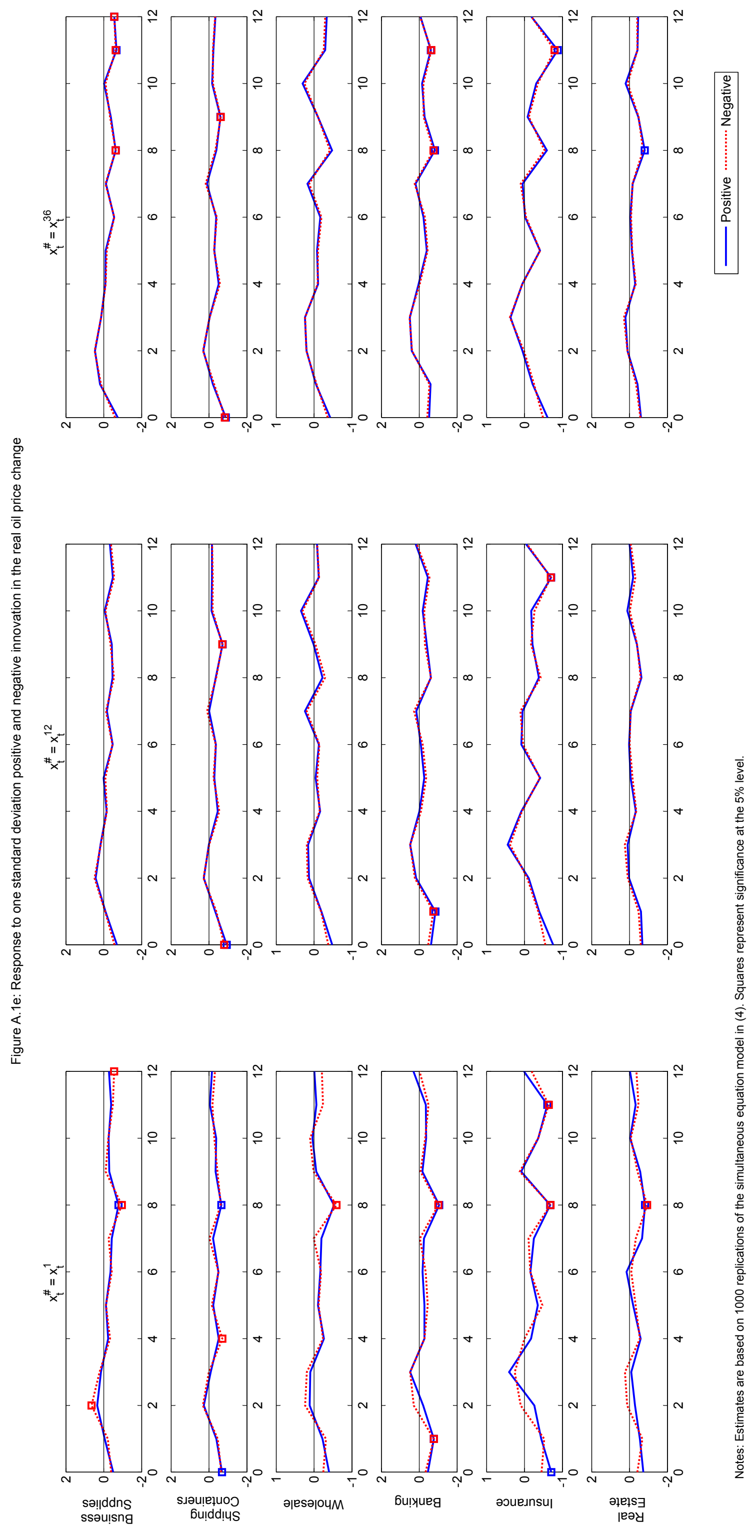
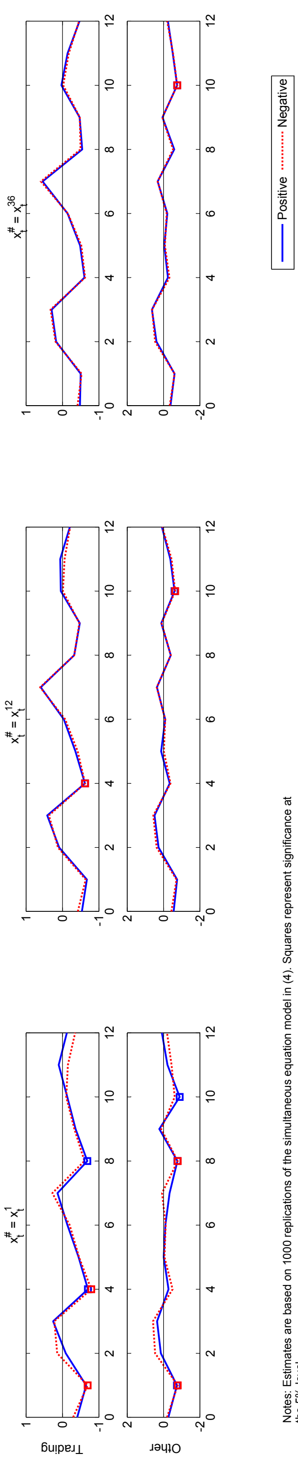


Figure A.1 a-f: Response to one standard deviation positive and negative innovation in the real oil price change

Figure A.1f: Response to one standard deviation positive and negative innovation in the real oil price change

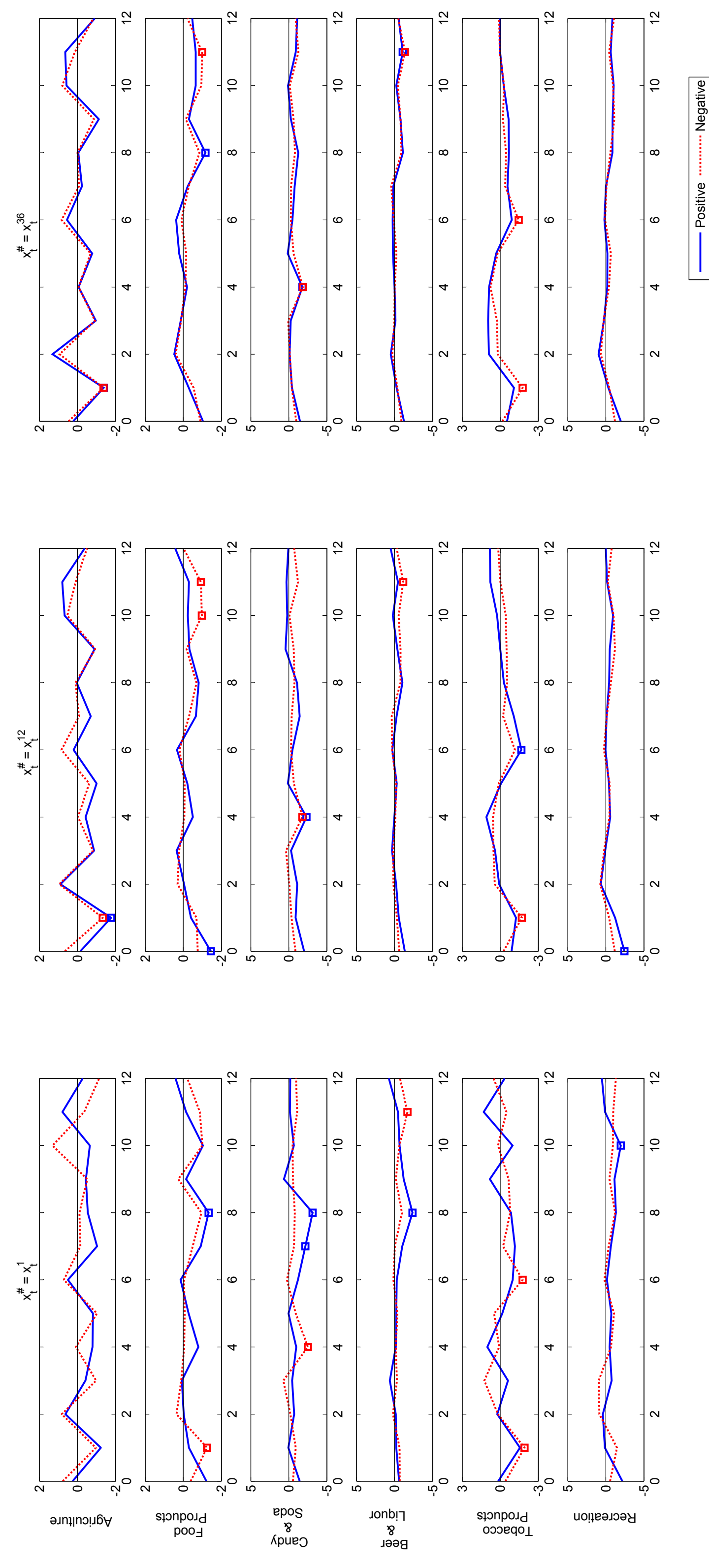


Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Other: - Sanitary services
- Steam, air conditioning supplies
- Irrigation systems
- Cogeneration - SM power producer

Figure A.2 a-f: Response to two standard deviation positive and negative innovation in the real oil price change

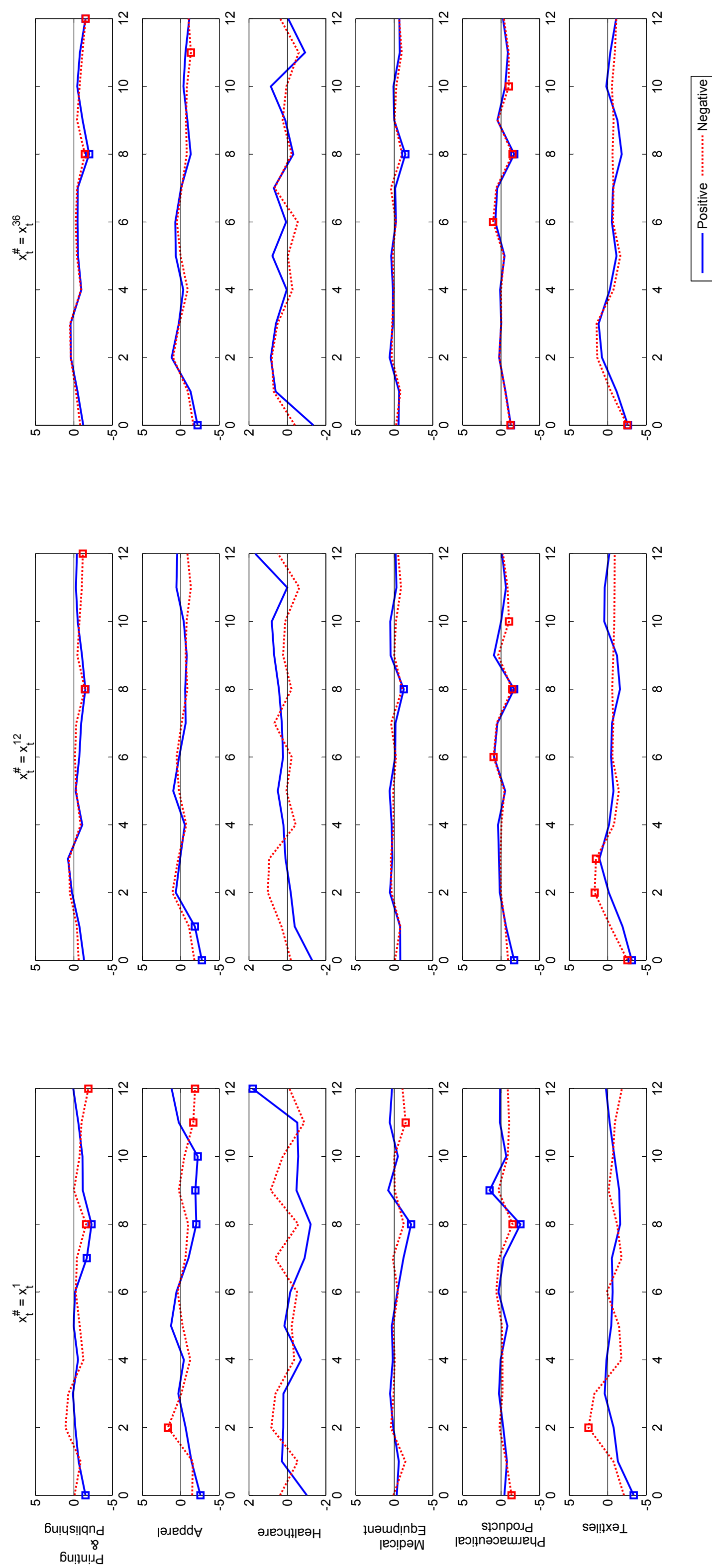
Figure A.2a: Response to two standard deviation positive and negative innovation in the real oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.2 a-f: Response to two standard deviation positive and negative innovation in the real oil price change

Figure A.2b: Response to two standard deviation positive and negative innovation in the real oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.2 a-f: Response to two standard deviation positive and negative innovation in the real oil price change

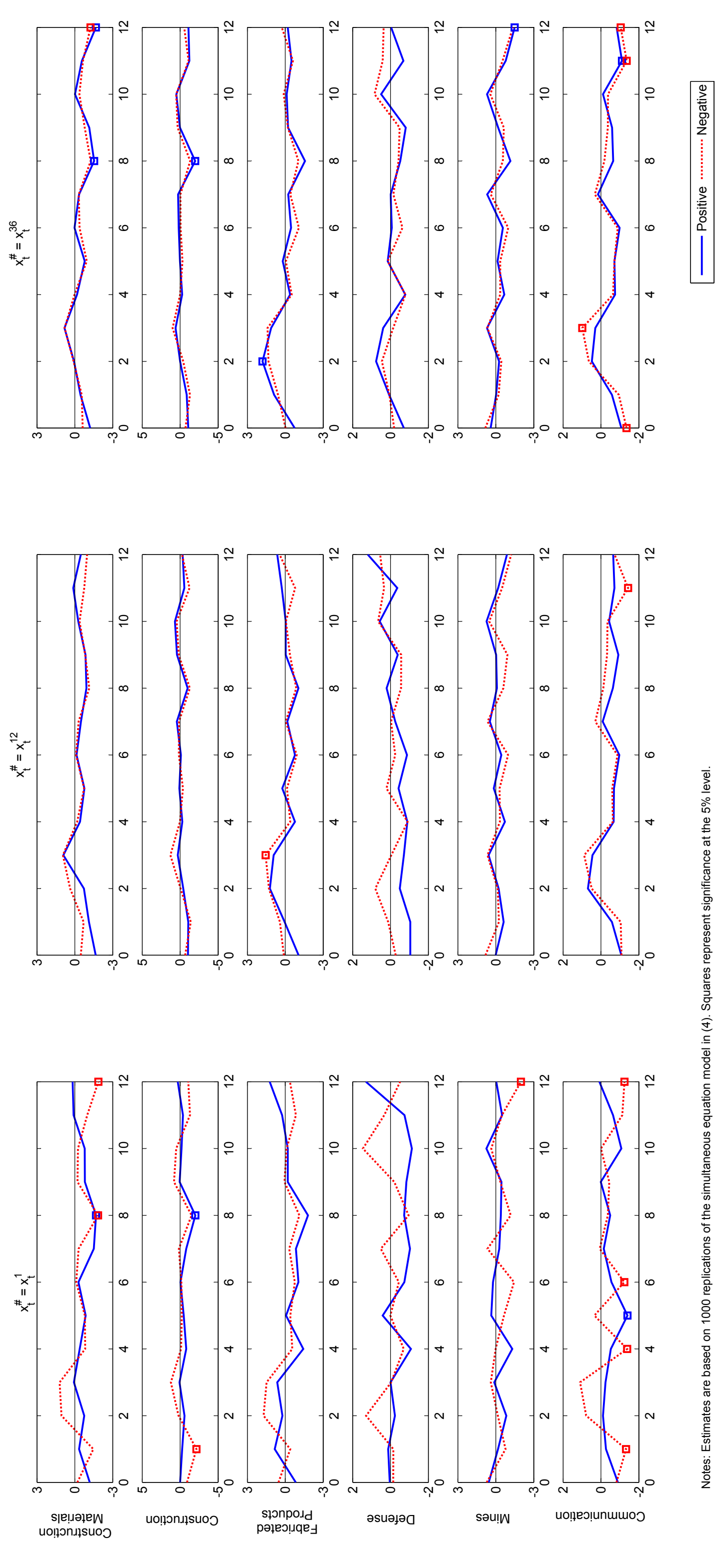


Figure A.2c: Response to two standard deviation positive and negative innovation in the real oil price change

Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.2 a-f: Response to two standard deviation positive and negative innovation in the real oil price change

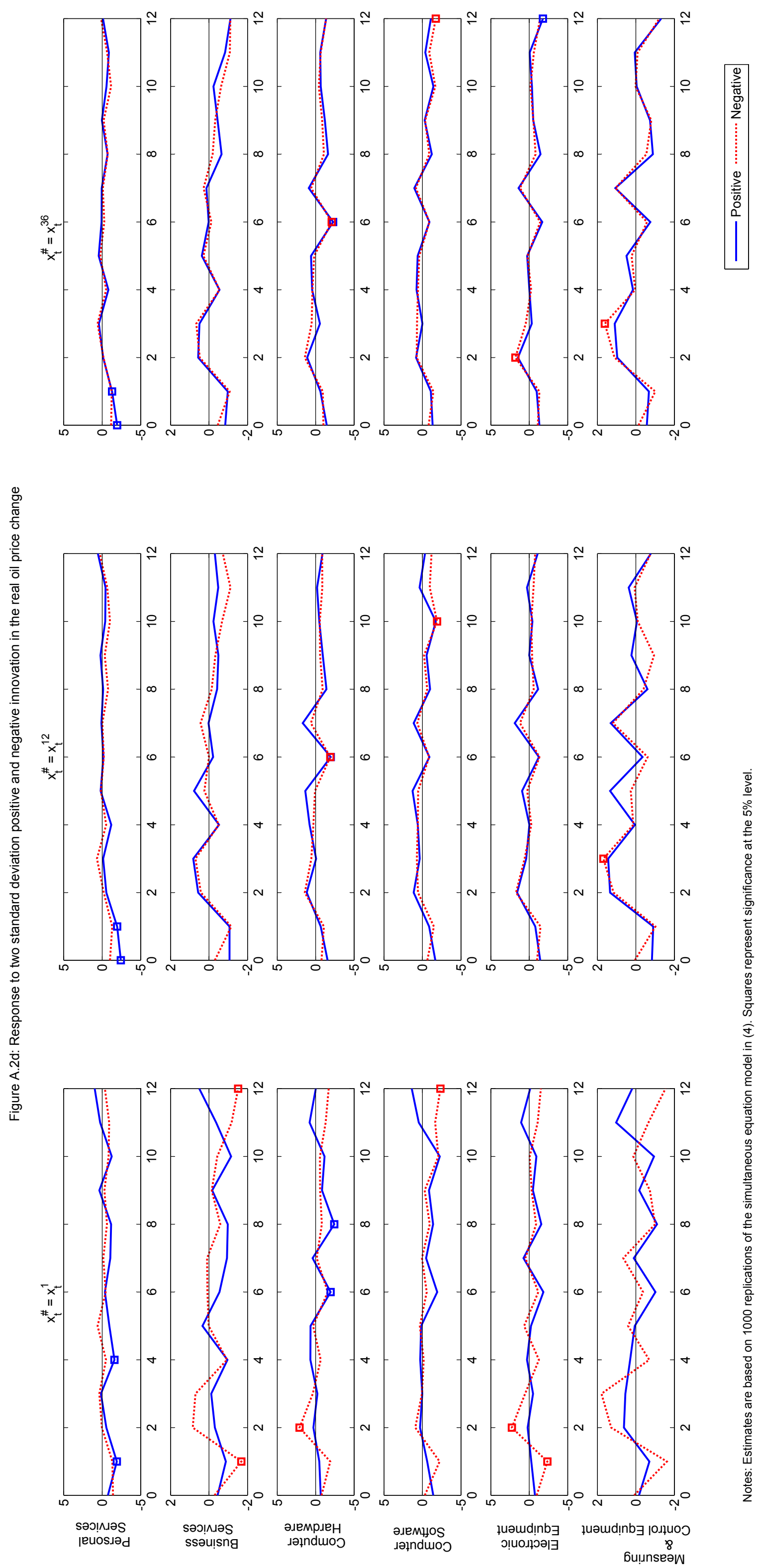
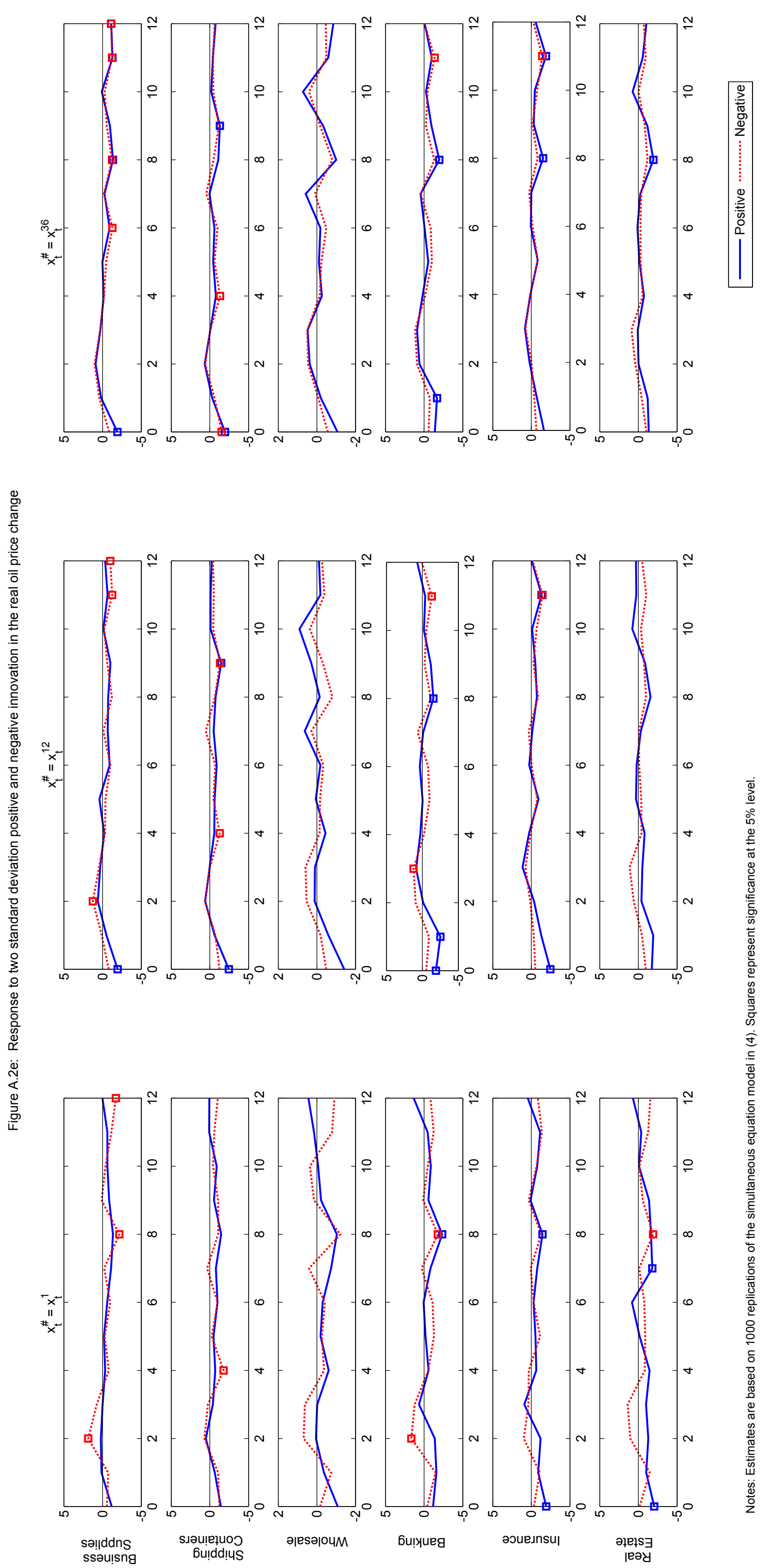


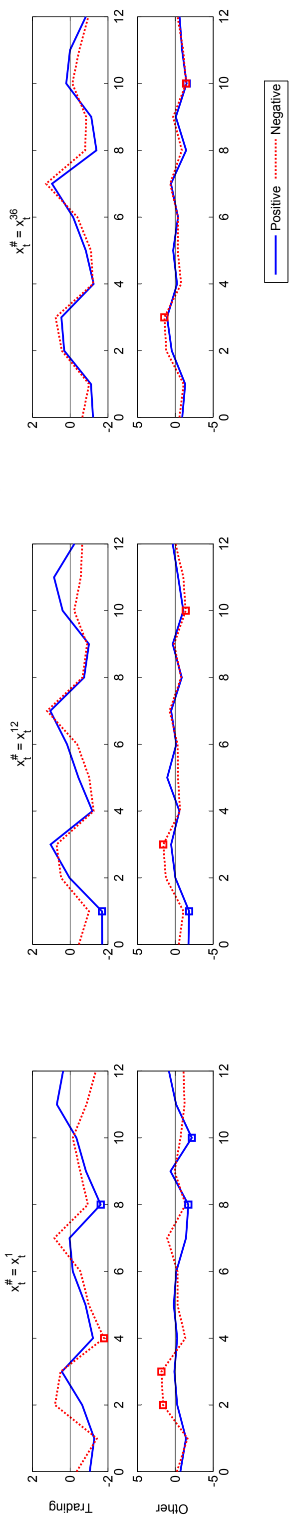
Figure A.2 a-f: Response to two standard deviation positive and negative innovation in the real oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.2 a-f: Response to two standard deviation positive and negative innovation in the real oil price change

Figure A.2f: Response to two standard deviation positive and negative innovation in the real oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Other: - Sanitary services
- Steam, air conditioning supplies
- Irrigation systems
- Cogeneration - SM power producer

Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

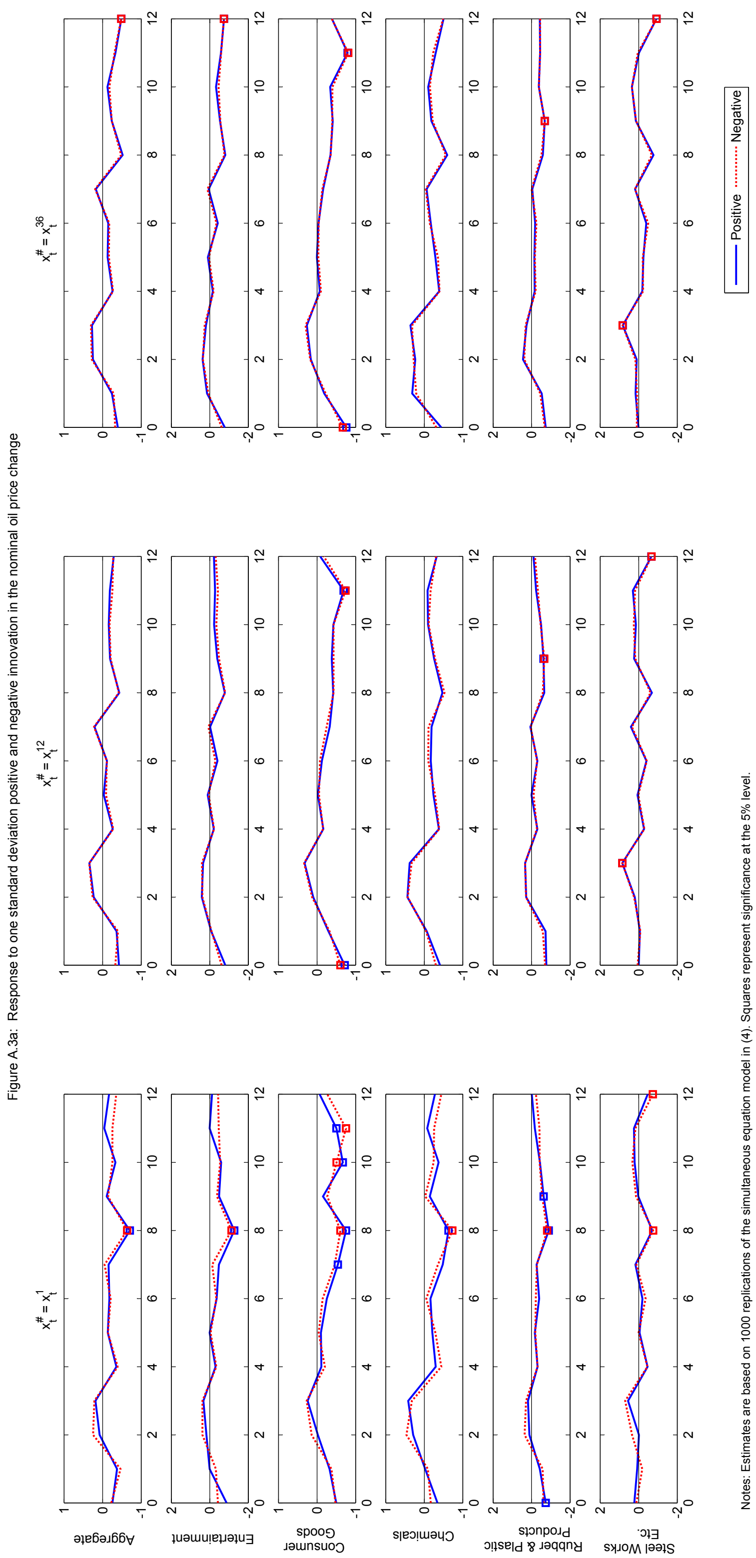


Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

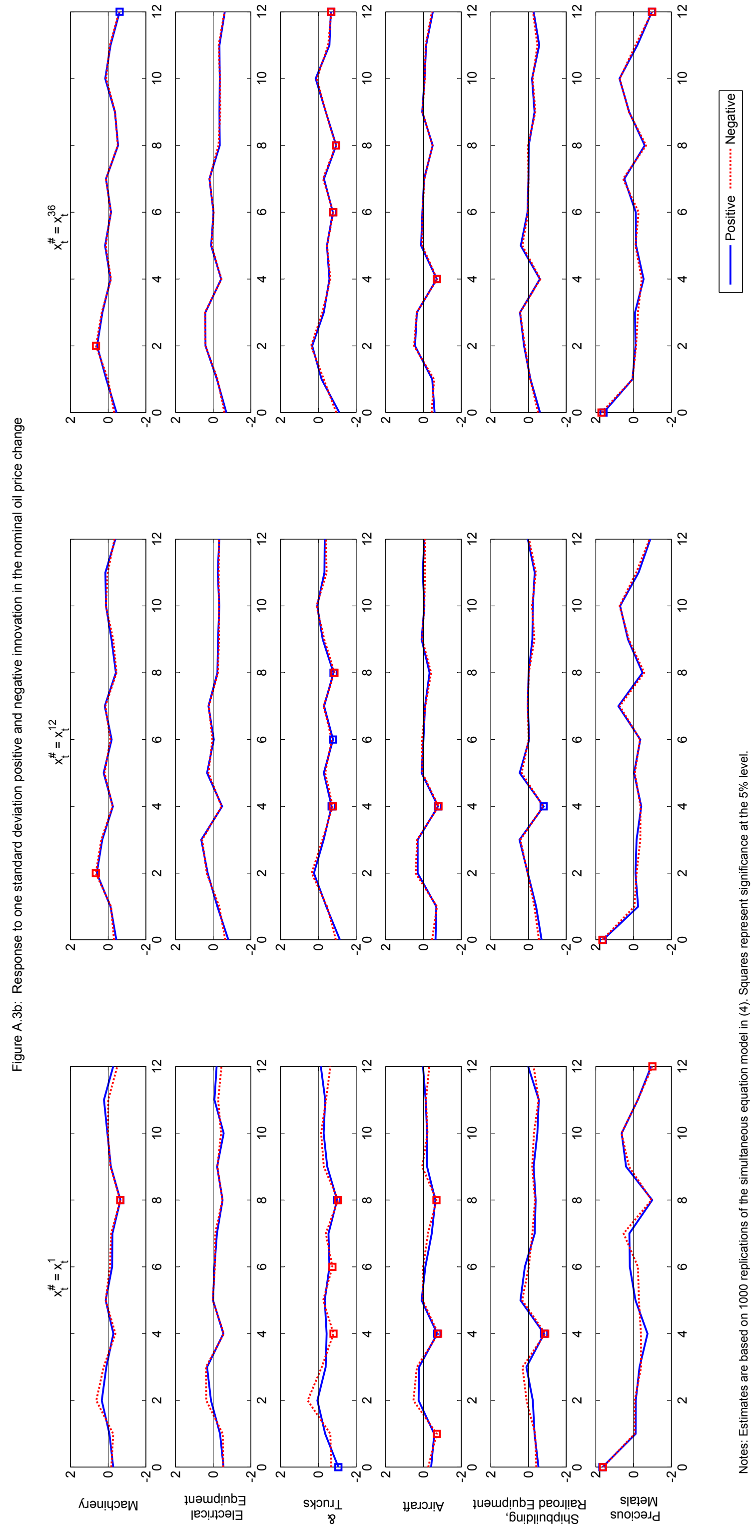
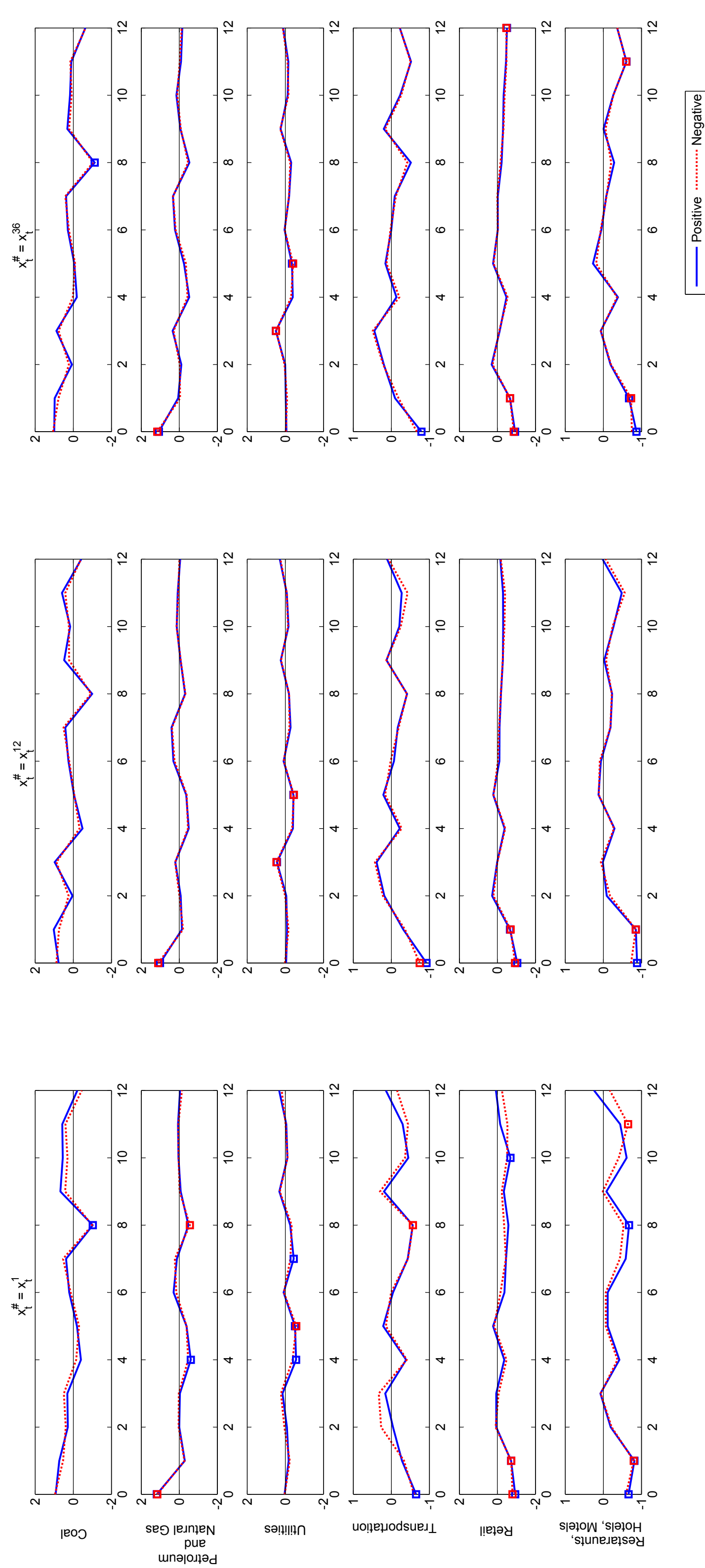


Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

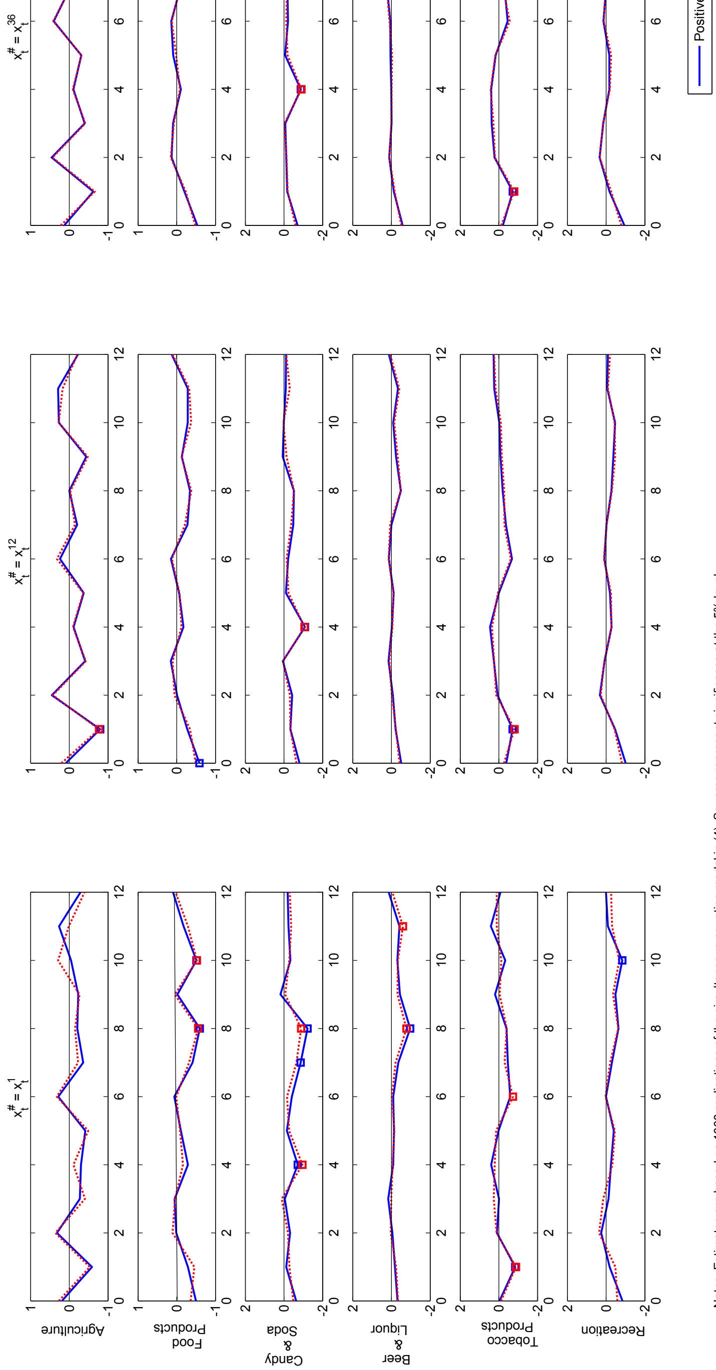
Figure A.3c: Response to one standard deviation positive and negative innovation in the nominal oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

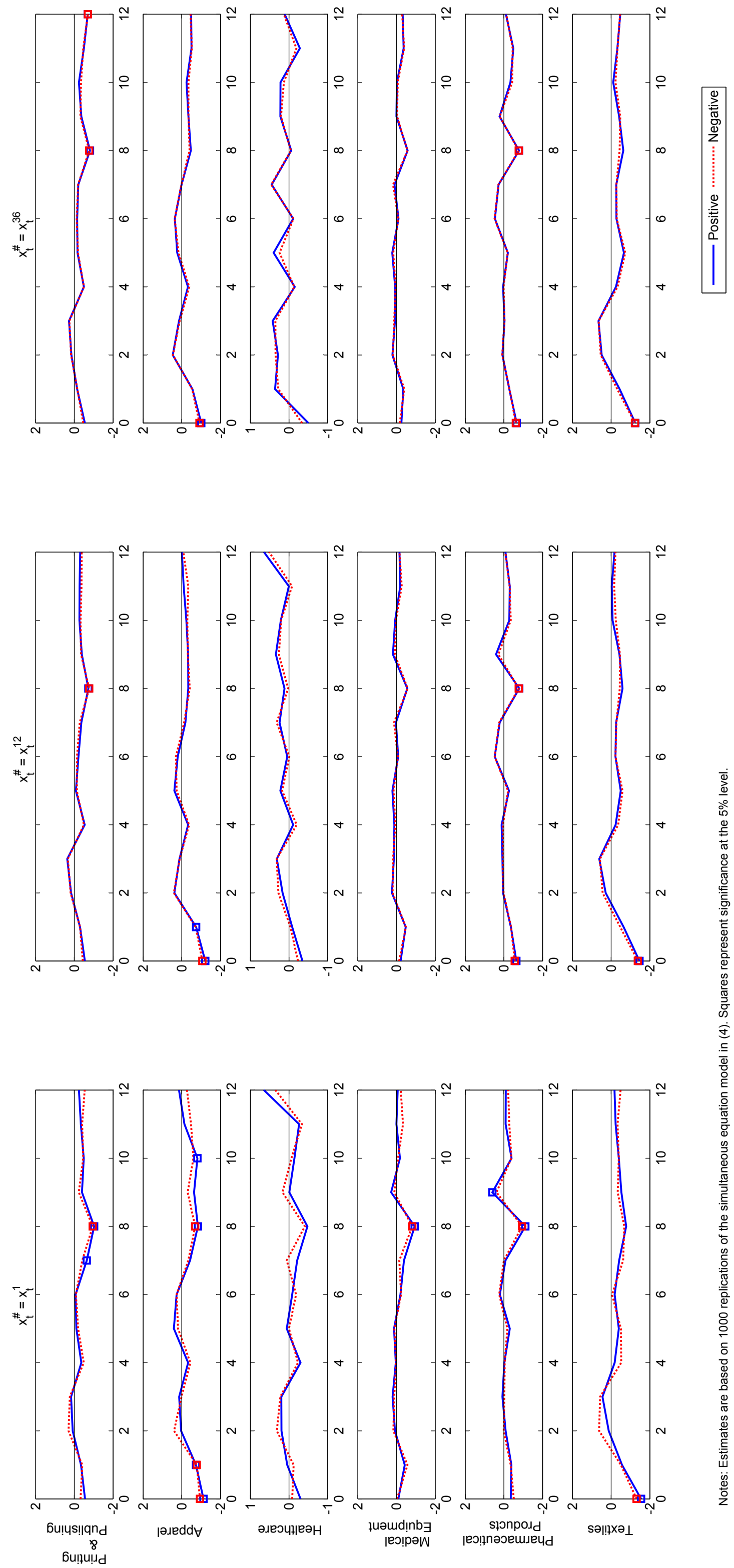
Figure A.3d: Response to one standard deviation positive and negative innovation in the nominal oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

Figure A.3e: Response to one standard deviation positive and negative innovation in the nominal oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

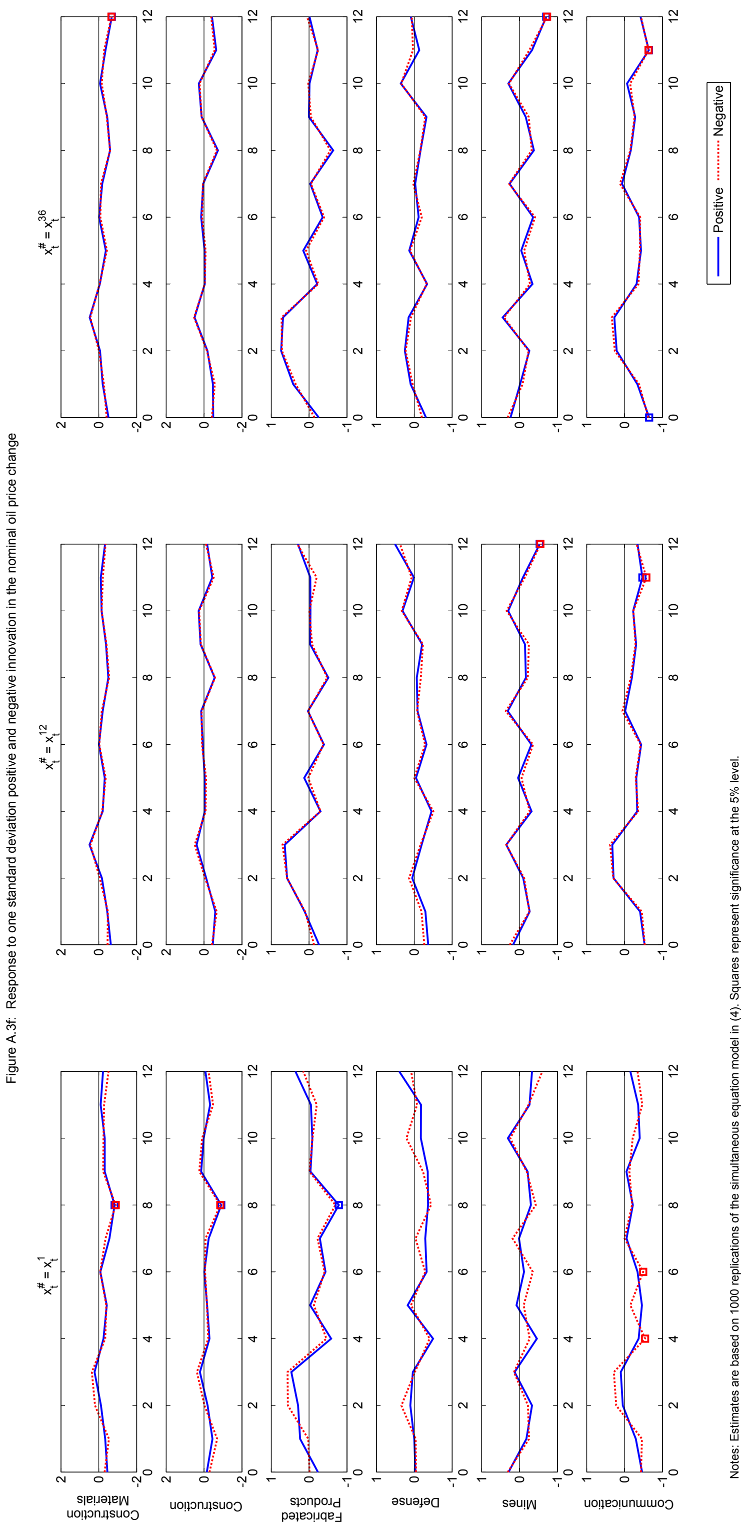


Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

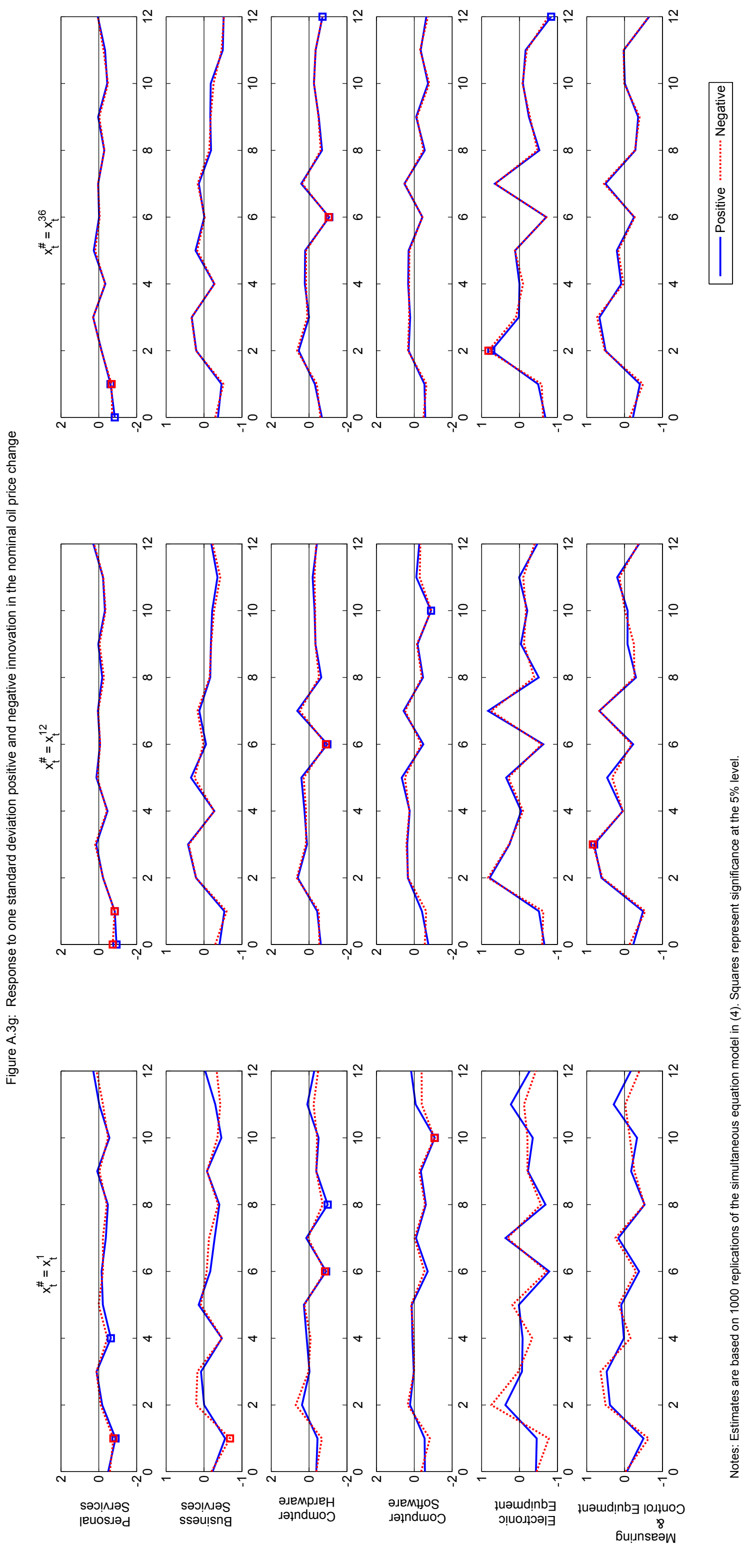


Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

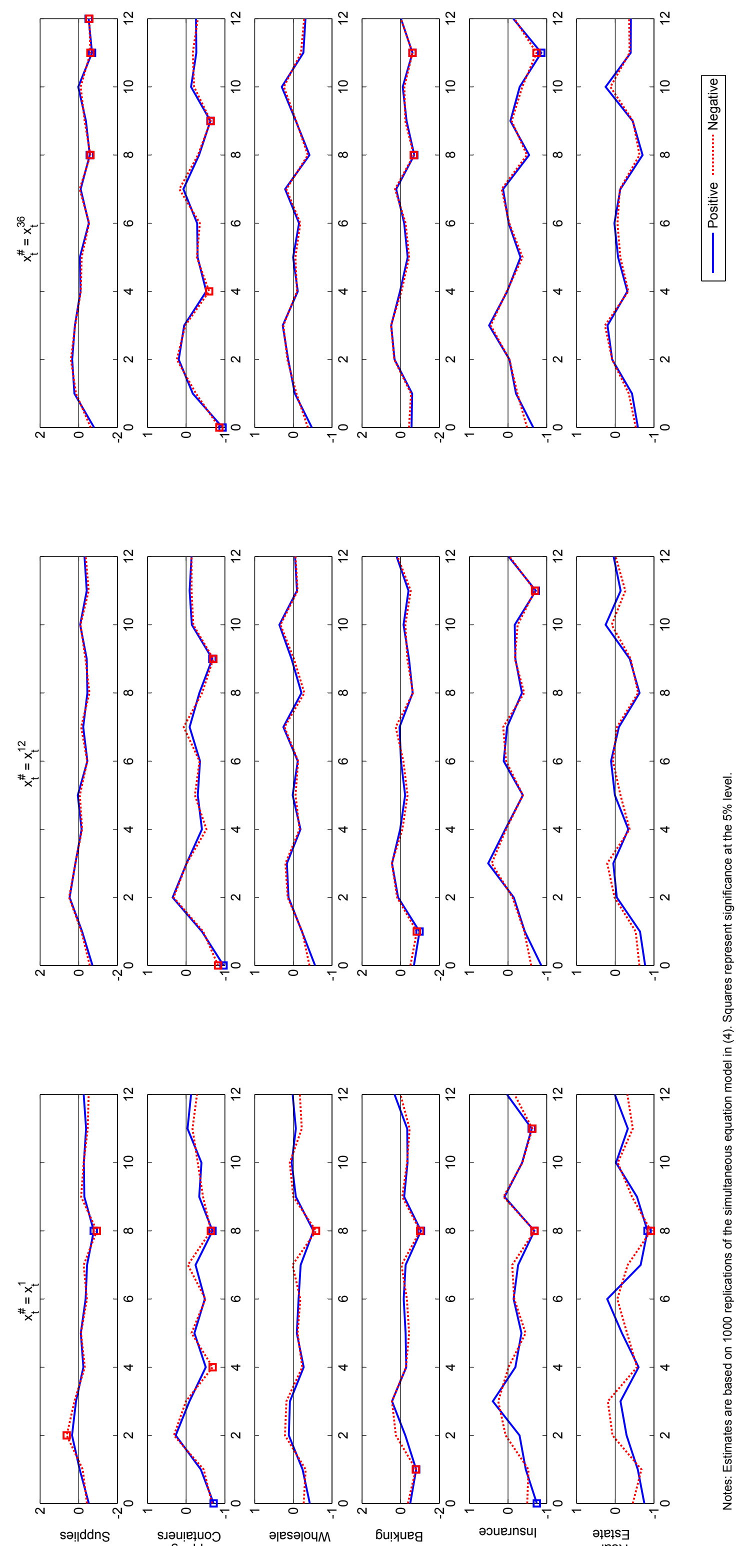
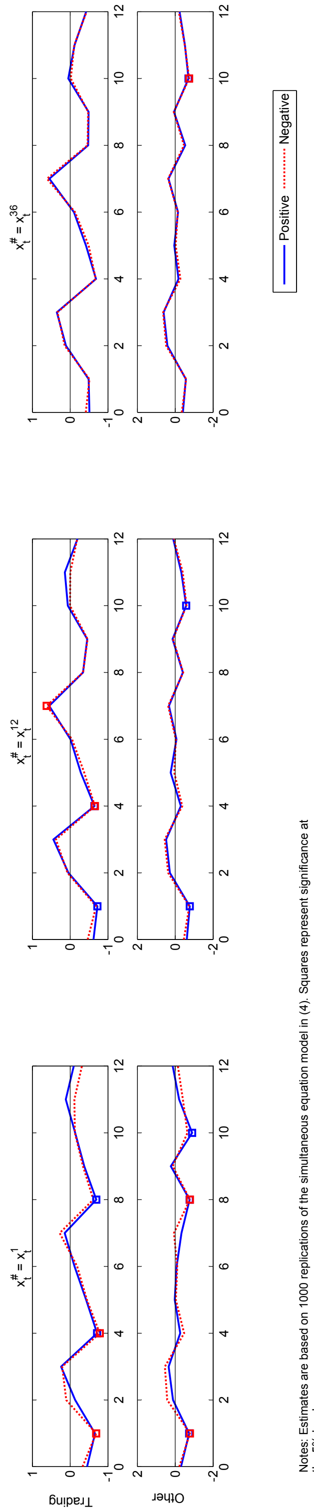


Figure A.3h: Response to one standard deviation positive and negative innovation in the nominal oil price change

Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.3 a-i: Response to one standard deviation positive and negative innovation in the nominal oil price change

Figure A.3i: Response to one standard deviation positive and negative innovation in the nominal oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Other: - Sanitary services
- Steam, air conditioning supplies
- Irrigation systems
- Cogeneration - SM power producer

Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

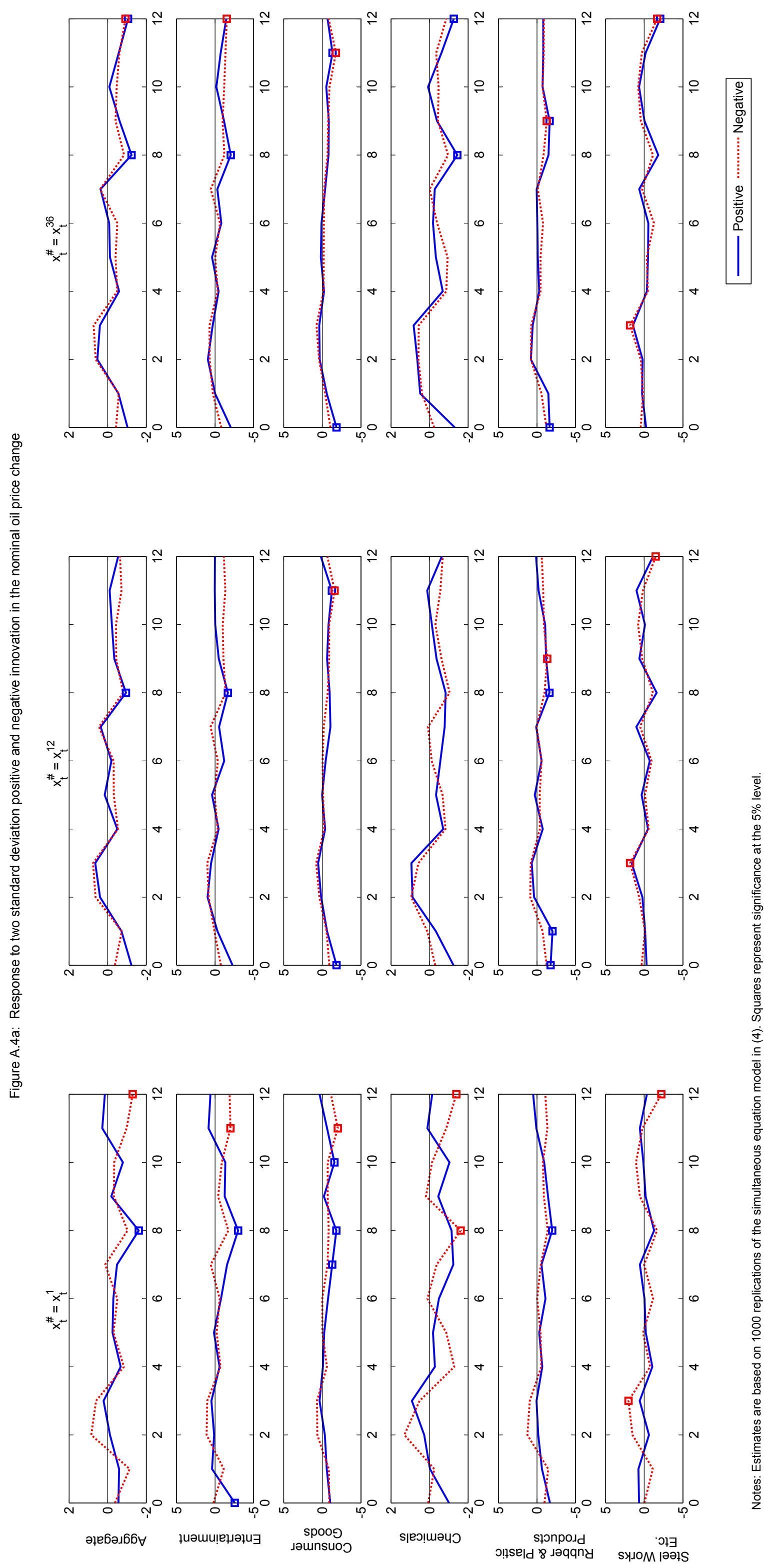
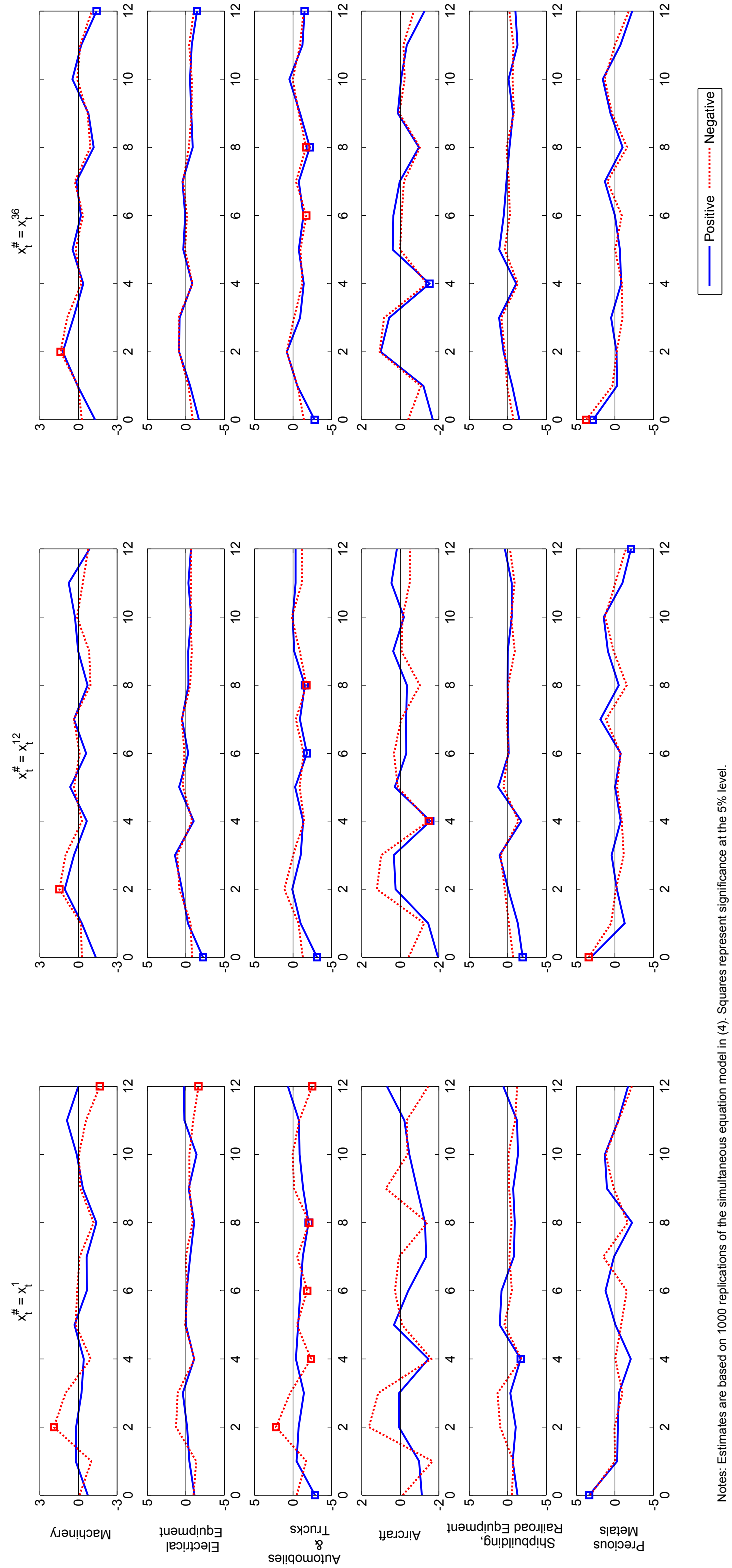


Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

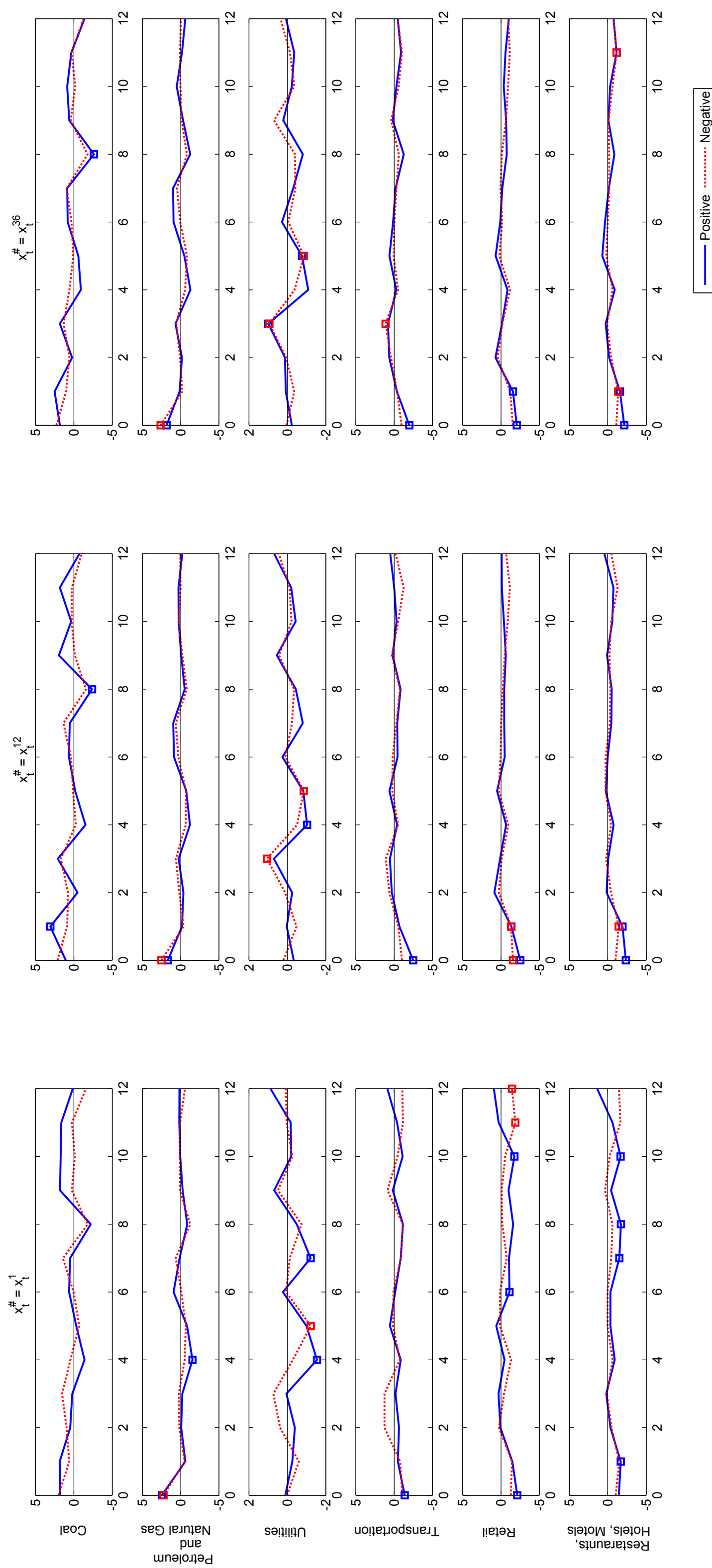
Figure A.4b: Response to two standard deviation positive and negative innovation in the nominal oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

Figure A.4c: Response to two standard deviation positive and negative innovation in the nominal oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

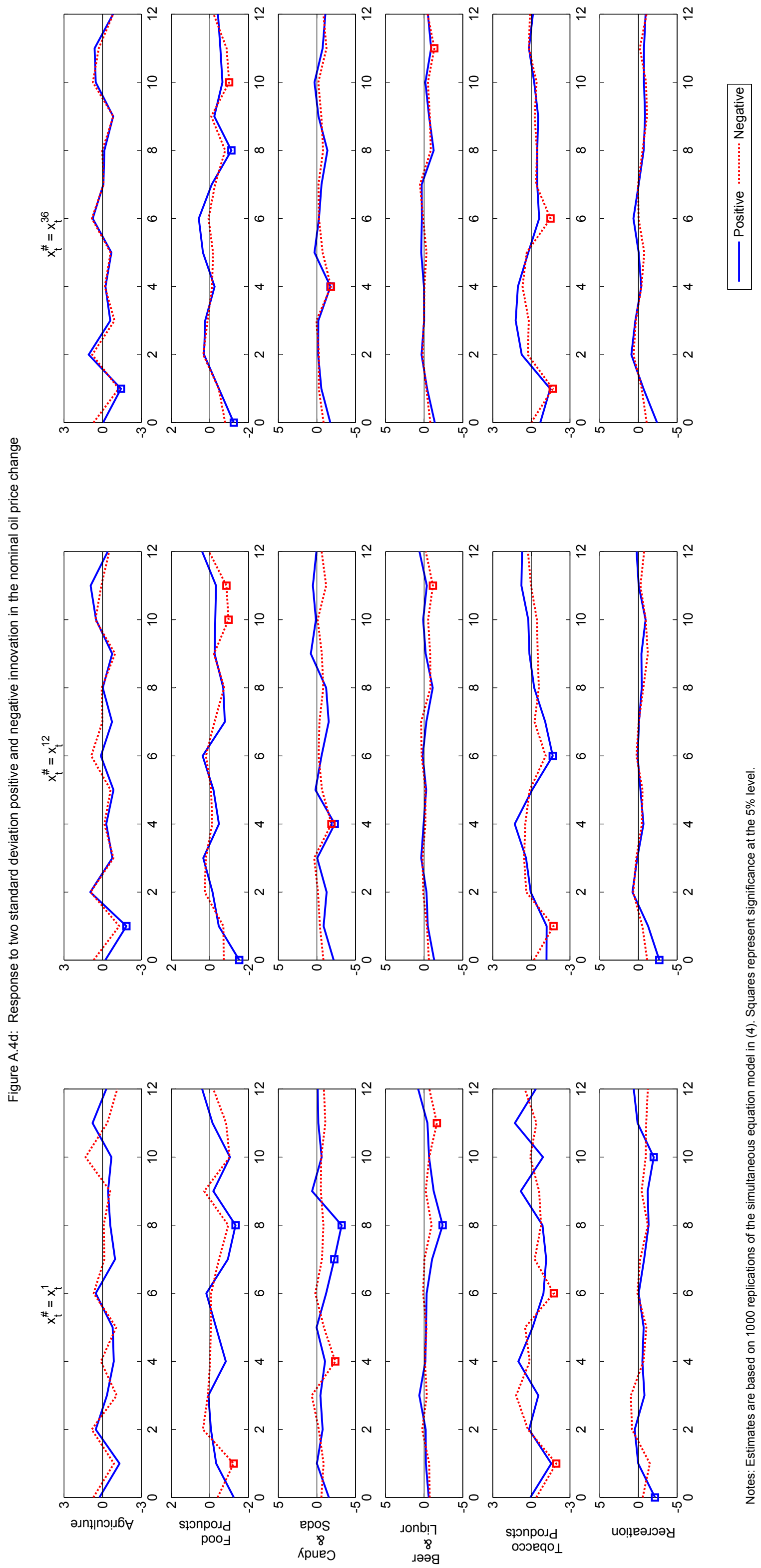


Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

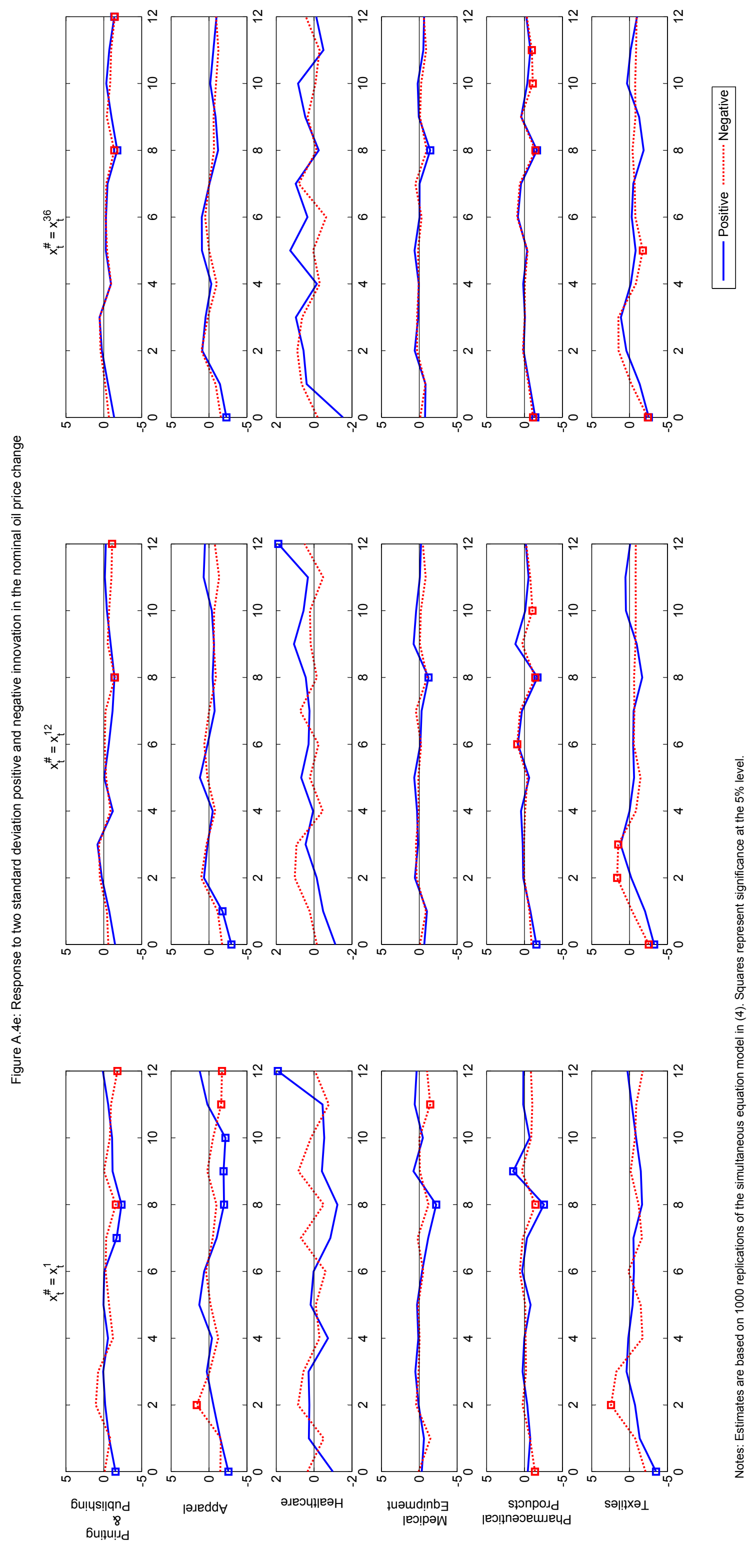
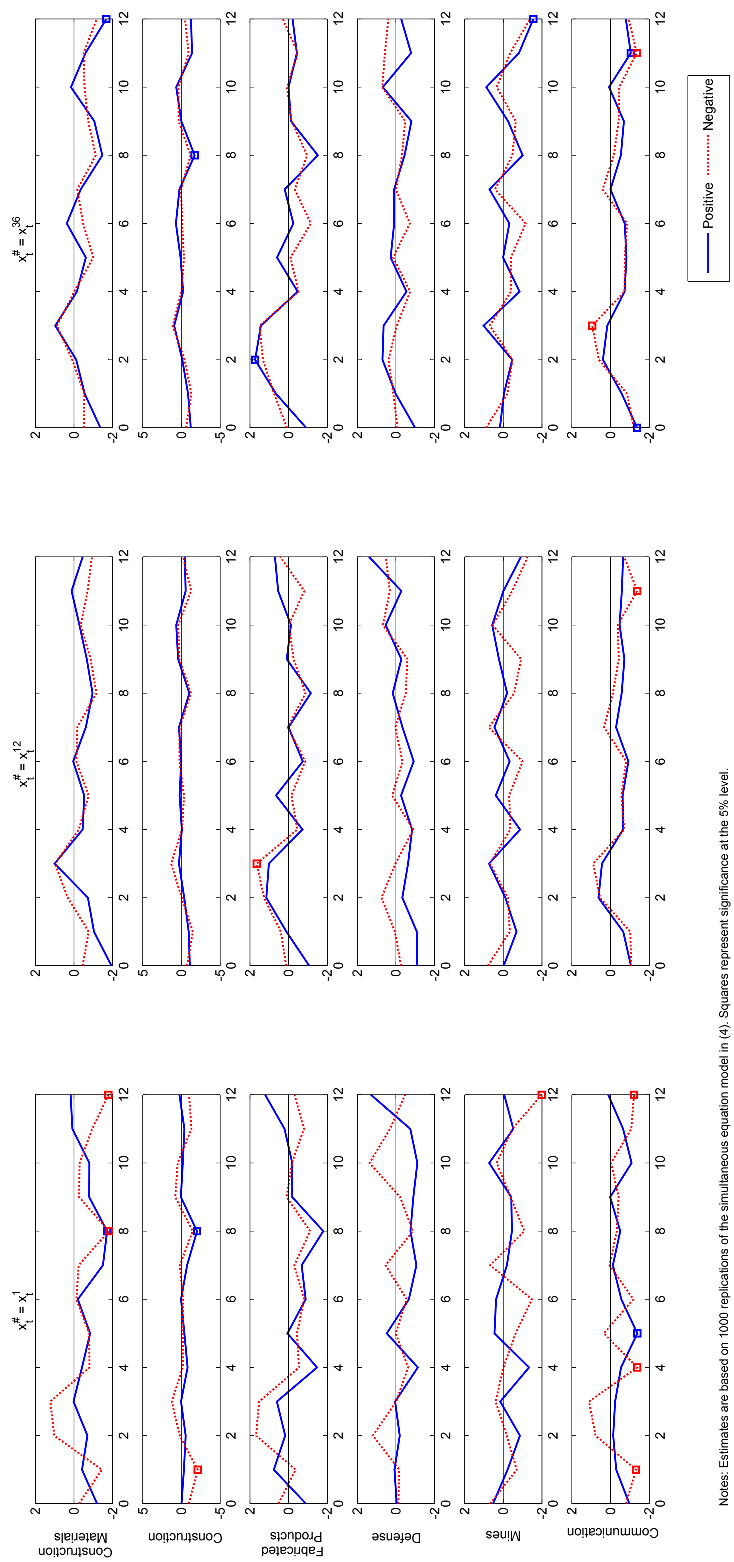


Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

Figure A.4f: Response to two standard deviation positive and negative innovation in the nominal oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

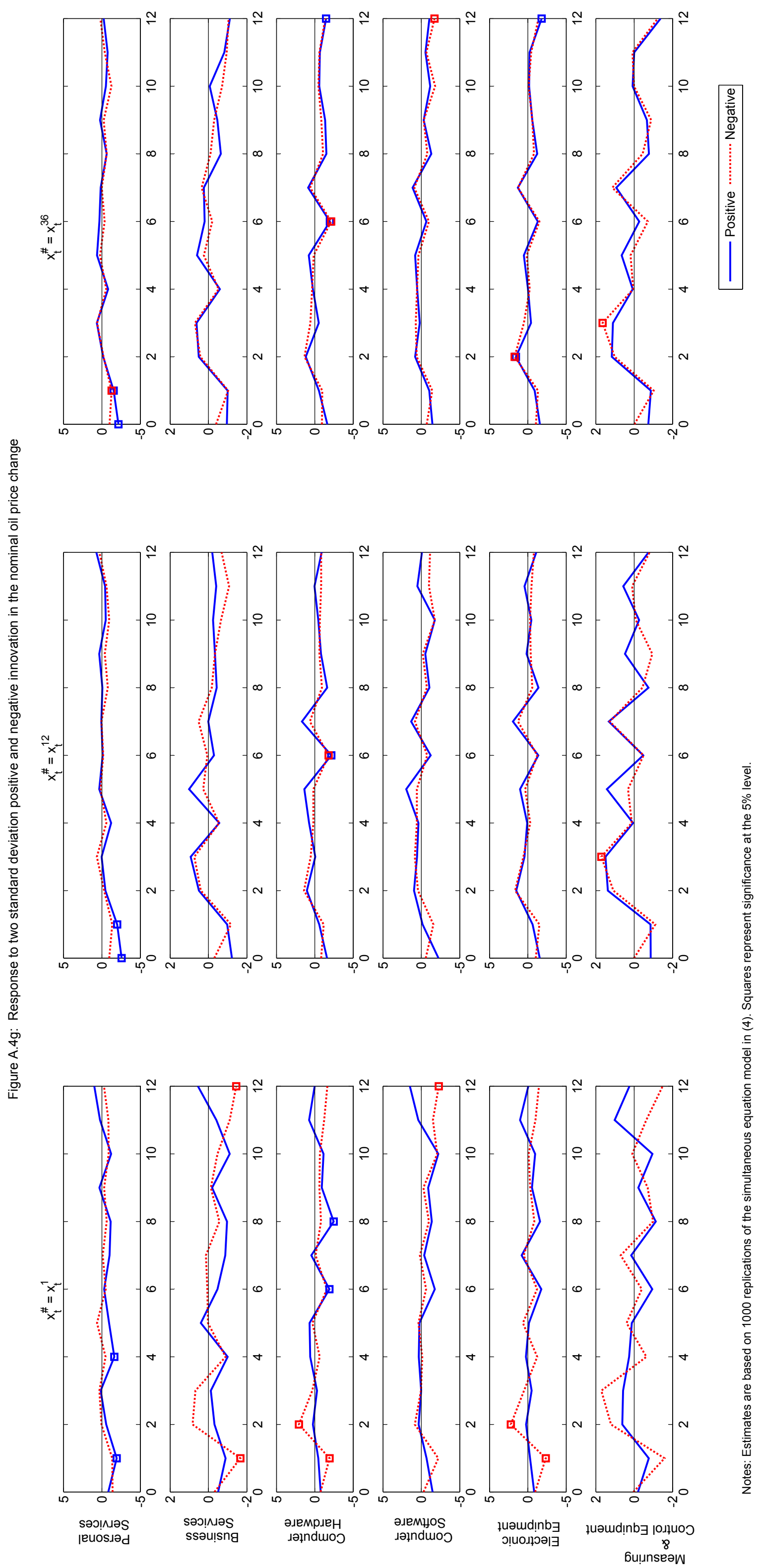


Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

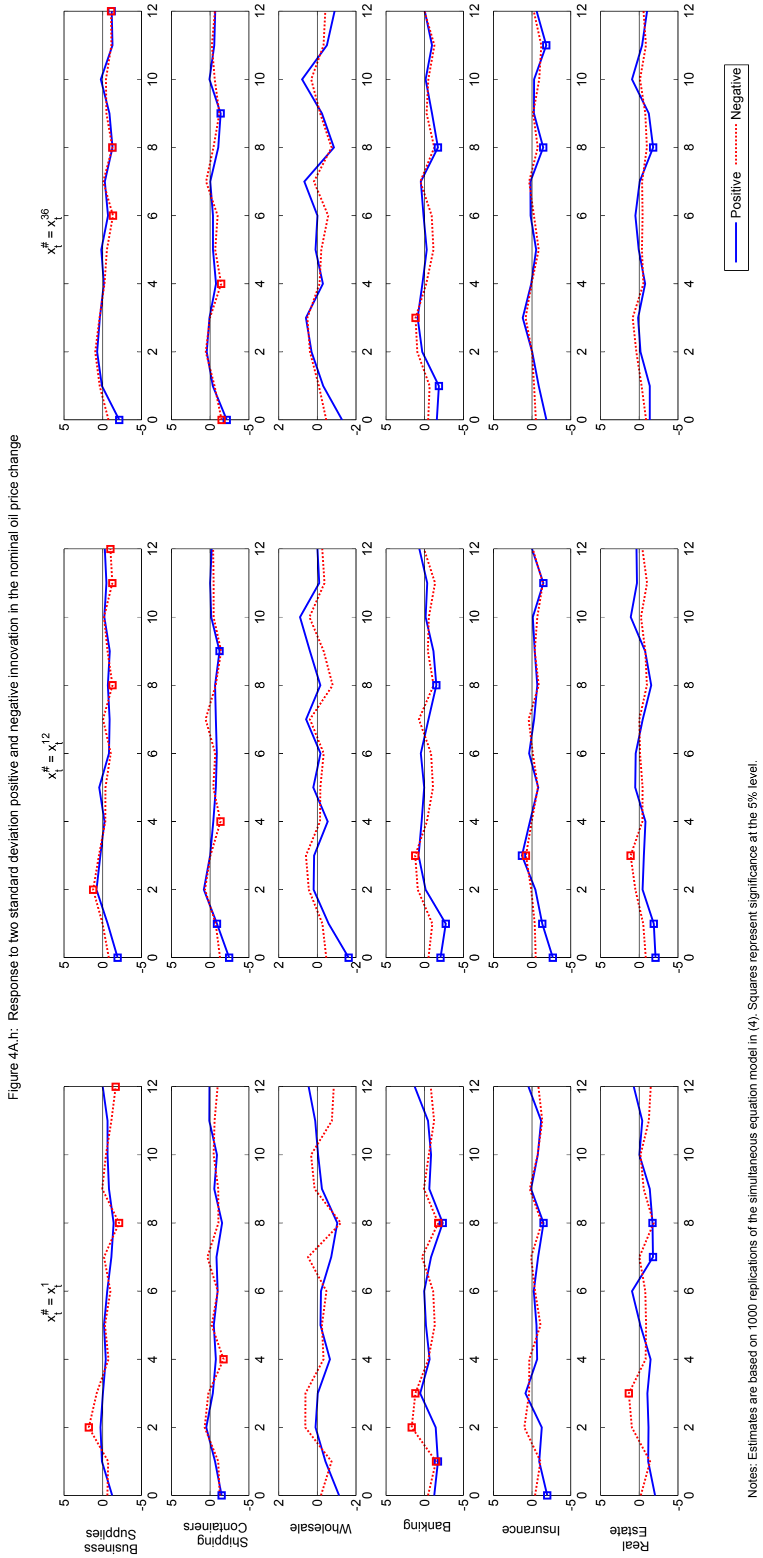
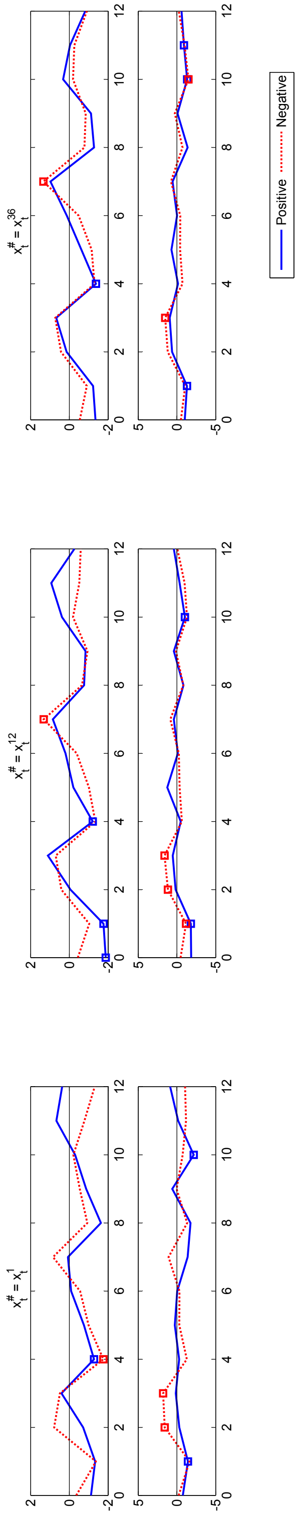


Figure A.4 a-i: Response to two standard deviation positive and negative innovation in the nominal oil price change

Figure A.4i: Response to two standard deviation positive and negative innovation in the nominal oil price change



Notes: Estimates are based on 1000 replications of the simultaneous equation model in (4). Squares represent significance at the 5% level.

Other: - Sanitary services
- Steam, air conditioning supplies
- Irrigation systems
- Cogeneration - SM power producer

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ABSTRACT

ESSAYS ON THE EFFECTS OF OIL PRICE SHOCKS ON THE U.S. STOCK RETURNS

by

ZEINA N. ALSALMAN

December 2013

Advisor: Dr. Ana María Herrera

Major: Economics

Degree: Doctor of Philosophy

This research investigates the effect of changes in oil prices and oil price volatility on the U.S. stock returns. The first essay tests whether the sign and the size of oil price shocks matter for the U.S. stock returns. The results suggest a linear model provides a good approximation to the response of real stock returns to real oil price innovations. However, this is not the case when the model is specified in terms of the nominal price of crude oil. Using a modified structural VAR to accommodate GARCH-in-Mean errors, the second essay studies the direct effects of oil price uncertainty on the U.S. stock returns at the aggregate and sectoral levels. We also simulate the response of U.S. stock returns to positive and negative oil price shocks, to examine whether the responses to positive and negative shocks are symmetric. Estimation results suggest that there is no statistically significant effect of oil price volatility on the U.S. stock returns. Moreover, the impulse responses indicate that oil price increases and decreases have symmetric effects on the U.S. stock returns. Using high frequency data, the third essay addresses the issue of uncertainty in oil prices and its effect on U.S. stock returns, taking into account the day of

the week effect. The results suggest that the-day-of-the-week effect is present in both the mean and volatility equations. The results also show that the U.S. stock market is sensitive to oil price variations not only at the aggregate level but also across some industries, such as chemicals, entertainment, and retail, where uncertainty in oil prices proves to have positive and statistically significant effect.

AUTOBIOGRAPHICAL STATEMENT

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FIELDS OF SPECIALIZATION

Macroeconomics, Energy Economics, Macro-Finance, International Economics, Time Series Analysis, Corporate Finance.

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Credit Analyst, National Bank of Kuwait, Lebanon, 2004-2005
Accountant, Boury Manufacturing and Trading Co, Beirut, Lebanon, 2003
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- American Economic Association, January 2013
- Southern Economic Association, November 2011
- Midwest Economic Association, March 2011

AFFILIATIONS

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AWARDS AND HONORS

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