Oil Price Shocks and Industrial Production: Is the Relationship Linear?*

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Abstract

This paper tests the three leading specifications of asymmetric and possibly nonlinear feedback from the real price of oil to U.S. industrial production and its sectoral components. We show that the evidence of such feedback is sensitive to the estimation period. Support for a nonlinear model is strongest for samples starting before 1973. Instead, using post-1973 data only, the evidence against symmetry becomes considerably weaker. For example, at the aggregate level, there is no evidence against the hypothesis of symmetric responses to oil price innovations of typical magnitude, consistent with results by Kilian and Vigfusson (2009) for U.S. real GDP. There is strong evidence of asymmetries at the disaggregate level, however, especially for industries that are energy intensive in production (such as chemicals) or that produce goods that are energy-intensive in use (such as transportation equipment). Our analysis suggests that these asymmetries may be obscured in the aggregate data and highlights the importance of developing multi-sector models of the transmission of oil price shocks.

Key Words: Asymmetry; oil price; net increase; shocks; industrial production; transmission.

JEL Classification: C32, E37, Q43.

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1 Introduction

Since the oil price shocks of the 1970s, many economists have considered unexpected oil price fluctuations as one of the main sources of fluctuations in macroeconomic aggregates. Linear models of the transmission of oil price shocks, however, cannot explain large fluctuations in U.S. real activity. This fact stimulated interest in models of an asymmetric and possibly nonlinear relationship between the real price of oil and U.S. real activity. For example, Loungani (1986) and Davis (1987a,b) emphasized asymmetries due to costly sectoral reallocation of resources. Mork (1989) observed that feedback from lagged real oil price increases appears negative and statistically significant, while the lagged feedback from oil price decreases is small and statistically insignificant. Given evidence in Hooker (1996) that Mork's model does not fit the data, Lee, Ni and Ratti (1995) and Hamilton (1996, 2003) made the case that empirical work needed to take account of the environment in which the oil price increases take place. Their preferred specification combined asymmetries in the transmission of oil price shocks with additional nonlinearities.[1]

By the beginning of the 2000s, a consensus had emerged in the literature regarding the nonlinear relationship between U.S. real economic activity and the price of oil, which in turn was thought to account for the seeming structural instability of linear models in the post-1986 era. Yet, recent work by Kilian and Vigfusson (2009) –henceforth KV– has called into question the view that unexpected oil price increases and decreases have an asymmetric effect on macroeconomic aggregates. They proved that the method commonly employed in the literature to evaluate the asymmetric and potentially nonlinear impact of oil price innovations produces inconsistent estimates and is likely to overestimate the impact

[1] Specifically, Lee, Ni and Ratti (1995) showed that oil price increases scaled by the standard deviation of recent volatility improved the fit of the predictive relationship between real GDP growth and relative to oil price changes. Similarly, Hamilton (1996, 2003) showed that a nonlinear transformation that records the net oil price increase over the previous 1-year or 3-year maximum improves the fit of a predictive model of real GDP growth.

of such shocks. They also showed that for a shock of typical magnitude the linear and symmetric model appears to provide a very good approximation to the responses of U.S. real GDP to innovations in the real price of oil.

Our paper builds on these methodological insights, but broadens the scope of the analysis. First, we focus on the relationship between the price of oil and U.S. industrial production on the grounds that asymmetries are likely to be more prevalent in industrial production data than in real GDP data. If oil price innovations involve a costly reallocation of capital and labor, for example, then concentrating on real aggregate GDP might obscure the nature of the reallocative effect (see for instance, Bresnahan and Ramey, 1993; Davis and Haltiwanger, 2001). Second, we conduct a comprehensive analysis of sectoral disaggregates of U.S. industrial production, including sectors that one would expect to be particularly sensitive to the price of oil ex ante. The response of aggregate data represents a weighted average of possibly symmetric and possibly asymmetric responses across sectors. Thus, an obvious concern is that the finding of a symmetric response at the aggregate level could obscure important asymmetries at the sectoral level driven by different degrees of energy intensity in use and production at the sectoral level (see, e.g., Lee and Ni 2002).

We investigate the three leading specifications of asymmetric and possibly nonlinear feedback from the real price of oil to U.S. industrial production: the percent increase specification of Mork (1989) and the 1-year and 3-year net oil price increase specifications of Hamilton (1996, 2003). We start by testing for asymmetries and nonlinearities in the slope of the reduced-form relationship between industrial production growth and the real price of oil. Our results for these traditional slope-based tests are consistent with Hamilton's (2010) and KV's finding that the reduced-form relationship between oil prices and economic activity appears nonlinear in some transformations of the price of oil. Rejections of the linear model are more prevalent for the net oil price increase. We then use the modified slope-based test proposed in KV obtaining similar or even stronger results.

None of the slope-based tests, however, directly address the question of how asymmetric the response functions of industrial production are to positive and negative innovations in the real price of oil. We address this question using the impulse response function –henceforth IRF– based test of symmetry proposed in KV. Overall, the IRF based test suggests strong evidence against the null of symmetric responses to innovations in the real price of oil using the 1947-2009 sample. There is considerable disagreement, however, as to which sectors are most affected, depending on the specification chosen. For example, Mork's specification shows statistically significant asymmetric responses in the automobile sector, even after accounting for the data mining involved in considering a large number of sectors, whereas the behavioral specifications of Hamilton (1996, 2003) do not.

There is reason to be cautious in interpreting these full-sample results, however, given evidence of a structural break in 1973 not only in the marginal distribution governing the real price of oil, but in the predictive relationship between the real price of oil and U.S. real economic activity (see Dvir and Rogoff, 2010, Kilian and Vigfusson, 2010). Using post-1973 data, the evidence against symmetric responses to oil price innovations becomes considerably weaker. For example, for aggregate industrial production, there is no evidence against the hypothesis of symmetric responses to oil price innovations of typical magnitude, consistent with results by KV for U.S. real GDP. Yet, there is strong evidence of asymmetries at the disaggregate level based on the 3-year net increase measure, especially for industries that are energy intensive in production (such as chemicals) or that produce goods that are energy-intensive in use (such as transit equipment). This finding is consistent with our conjecture that asymmetries at the sectoral level may be obscured in the aggregate data. No such evidence is found for the other two oil price specifications, however, and even for the 3-year net increase specification the response of the motor vehicles and parts sector, for example, does not appear asymmetric.

Our findings have important implications for the empirical literature regarding the effect of oil price shocks on industrial production. First, our results suggest that the response of industrial production growth to oil price innovations is asymmetric and nonlinear at least at the disaggregate level. Second, our results highlight the importance of developing multisector models of the transmission of oil price shocks. Third, our results are not consistent with standard theoretical explanations of asymmetries in the literature such as costly reallocation of labor or capital across sectors (see Hamilton, 1988) or asymmetries in the response of petroleum product prices to crude oil prices (Huntington, 1998), as these explanations rely on the asymmetry captured by Mork's (1989) oil price specification. The net oil price increase specifications in particular are not consistent with economic theory, but are based on (yet untested) behavioral arguments.

This paper is organized as follows. Section 2 discusses the data. In section 3 we use slope based tests to test whether nonlinear oil price measures have explanatory power for industrial production in a reduced-form model and to test for nonlinearity in a more general model. In section 4 we employ the impulse response based tests of symmetry of KV to further inquire about the effect of unanticipated oil price shocks on industrial production. Section 5 concludes.

2 Data

We follow Mork (1989) and Lee and Ni (2002) in measuring nominal oil prices by the composite refiners' acquisition cost when possible (i.e., from 1974 onwards), making adjustments to account for the price controls of the 1970s, and extrapolating the data from 1947 until 1974 by using the rate of growth of the producer price index. We then deflate the price of oil by the U.S. CPI. We use three different nonlinear transformations of the logarithm of the real oil price, o_t. First, Mork's (1989) oil price increase, which can be defined as:

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

This censoring of the oil price series was proposed by Mork (1989) after the 1985-86 fall in oil prices failed to lead to a boom in real GDP growth. He thus showed that whereas oil price increases preceded an economic recession; in contrast, he could not reject the null hypothesis that declines did not lead to expansions. Subsequently, Hooker (1996) and KV, among others, showed that this result vanishes in longer samples.

The second and third measures are the net oil price increase over the previous 12-month maximum (Hamilton, 1996)

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

and the net oil price increase over the previous 36-month maximum (Hamilton, 2003)

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

These nonlinear transformations are intended to filter out increases in the price of oil that represent corrections for recent declines, and have been commonly used in the literature on the macroeconomic effects of oil prices (see for instance Bernanke, Gertler and Watson, 1997; Davis and Haltiwanger, 2001; Lee and Ni, 2002). Note that in the text we report the results for the nonlinear transformations of the log of the real oil price. The results for the nonlinear transformation of the log of the nominal oil price (Hamilton 1996, 2003) are reported in the on-line appendix.[2]

To measure economic activity we use monthly data on the seasonally adjusted industrial production

[2] See Tables A.8-A.15 and A.22-A.29 in the on-line appendix, available at http://clas.wayne.edu/multimedia/usercontent/File/herrera/HLWappendix.pdf.

(IP) indices computed by the Board of Governors of the Federal Reserve. We report results for 37 indices of which 5 represent aggregates: total (or aggregate) IP index, manufacturing (SIC), manufacturing (NAICS), durable consumer goods and nondurable consumer goods. The total IP index measures the real output of the manufacturing, mining, and electric and gas utilities industries. The remaining 32 series represent both market and industry groups. Market groups comprise products and materials. Products include aggregates such as consumer goods, equipment and nonindustrial supplies, whereas materials correspond to inputs used in the manufacture of products. Industry groups include three-digit NAICS industries, and other industries that have traditionally been part of manufacturing such as newspaper, periodical, and books. The period spanned by the data varies across series depending on the availability of data on both oil prices and industrial production. Hence, the longest series span the period between January 1947 and September 2009, whereas the shortest series span the period between January 1986 and September 2009 (see Table A.1 of the on-line appendix for the period covered for each IP index).

3 Slope based tests of nonlinearity

3.1 Is the oil price-industrial production relation nonlinear?

In order to investigate whether the one-step ahead forecast of industrial production of sector i is linear in lags of oil prices we estimate the following reduced-form equation by OLS:

$$y_{i,t} = \alpha + \sum_{j=1}^{p} \phi_j y_{i,t-j} + \sum_{j=1}^{p} \beta_j x_{t-j} + \sum_{j=1}^{p} \gamma_j x_{t-j}^{\#} + u_{i,t} \tag{4}$$

where $y_{i,t}$ denotes the log growth in the industrial production index for sector i at time t, x_t is the log growth in oil prices without any transformation, $x_t^{\#}$ is one of the nonlinear measures of oil price increases described in section 2 ($x_t^{\#} = x_t^1$, x_t^{12}, x_t^{36}), $u_{i,t}$ is the residual for sector i at time t, and p is set equal to 12 months.[3] We then test the null hypothesis that the coefficients on the nonlinear measure are all equal to zero; that is, $\gamma_1 = \gamma_2 = ... = \gamma_{12} = 0$. Table 1 reports the p-values for the Wald test of joint significance for each of the three nonlinear measures of oil prices.

We start with the results for a test of symmetry; that is, the slope based test for the oil price increase, x_t^1, reported in the first panel in Table 1. At the 5% significance level, we reject the null of symmetry for 15 of the 37 industrial production indices. Of particular interest is the finding of asymmetry for chemicals and motor vehicles, industries that are either intensive in the use of energy in production or in the use by consumers. As can be seen in the first panel in Table 1, using the net oil price increase over the previous 12-month maximum, x_t^{12}, also provides evidence in favor of an asymmetry in the slope of the relationship between oil prices and industrial production. We reject the null of symmetry for 19 out of the 37 indices. Similarly, evidence of nonlinearity can be found for 25 indices using the net oil price increase over the previous 36-month maximum, x_t^{36}. This result mirrors similar results in Lee, Ni and Ratti (1995) and Hamilton (1996).

A couple of differences between the test results for the different measures of oil prices are worth noting. First, using Mork's oil price increase results in rejection of symmetry in the slope for 9 indices where one (or more) of the net oil price increase measures suggests symmetry. Second, whereas evidence of nonlinearity is not robust across measures of oil prices for the market group motor vehicles and parts, we do reject the null of linearity for all measures for motor vehicles. This result is consistent with the

[3]Our choice of twelve monthly lags is consistent with results in Hamilton and Herrera (2004), which suggest that using a smaller number of lags –as indicated by an information criterion such as the AIC or the BIC– is not enough to capture the dynamic effect of oil prices on economic activity.

common view that oil price increases have a significant negative effect on the automobile sector.

Overall, we do not find any evidence of asymmetry in the reduced-form equation (4) for apparel and leather goods, printing and related support industries, petroleum and coal products, pottery, ceramics and plumbing fixtures, clay product and refractory, and industrial machinery. Regardless of the oil price measure, the null of linearity is rejected for the total IP index, manufacturing (NAICS), nondurable consumer goods, foods and tobacco, paper products, and motor vehicles. For the remaining indices we find evidence of asymmetry for at least one of the oil price measures.

3.2 The effect of including contemporaneous regressors

KV propose a more powerful test of the null of symmetric slopes obtained by estimating a more general model of the oil price-macroeconomy relationship, which includes contemporaneous values of x_t and $x_t^{\#}$. Consider the data generating process for each of the IP series as being given by the bivariate dynamic model:

$$x_t = a_{10} + \sum_{j=1}^{12} a_{11,j} x_{t-j} + \sum_{j=1}^{12} a_{12,j} y_{i,t-j} + \varepsilon_{1t} \tag{5a}$$

$$y_{i,t} = a_{20} + \sum_{j=0}^{12} a_{21,j} x_{t-j} + \sum_{j=1}^{12} a_{22,j} y_{i,t-j} + \sum_{j=0}^{12} g_{21,j} x_{t-j}^{\#} + \varepsilon_{2t}. \tag{5b}$$

Note that since the errors are uncorrelated we can estimate only (5b) by OLS and then test the null hypothesis that $g_{21,0} = g_{21,1} = \cdots = g_{21,12} = 0$. The second panel in Table 1 reports the p-values for a Wald test of joint significance for each of the three nonlinear measures of oil prices.

Including the contemporaneous regressors provides stronger evidence of asymmetry. Using the oil price increase, x_t^1, we reject the null for 24 out of the 37 indices. Using x_t^{12} and x_t^{36} we reject the null of linearity for 23 and 24 indices, respectively. Regardless of the measure of oil prices, we reject the null of linearity for 15 indices. Only 5 indices (apparel and leather goods, petroleum and coal products, pottery, ceramics and plumbing fixtures, clay products and refractory, and industrial machinery) show no evidence of asymmetry. Interestingly, petroleum and coal products, an industry that is intensive in the use of oil in production, shows no evidence of asymmetry. This is possibly because both increases and decreases in the price of oil (the main production input) have a significant and symmetric effect through the direct requirement of oil in production, whereas the effect of the shock through indirect input-output linkages may be more asymmetric.

In brief, including the contemporaneous value of the oil price change and the nonlinear transformation of oil prices reveals more evidence of nonlinearity in the slope of the oil price-industrial production relation. This result is in line with KV's simulation evidence of an increase in power when contemporaneous terms are included in the economic activity equation.

4 Impulse response function based test

As was first noted by Balke, Brown and Yücel (2002), computing impulse responses in the textbook manner when one of the endogenous variables in the model is censored is problematic. KV show that the standard censored oil price VAR model is inherently misspecified, even if the data generating process is nonlinear and asymmetric, and cannot be consistently estimated. In addition, computing structural $IRFs$ from nonlinear models as in linear models ignores the fact that the effect of a structural oil price innovation depends on the recent history of the censored variable $x_t^{\#}$ and the magnitude of the shock ε_{1t} in (5a).[4] Moreover, KV show that evidence of asymmetry (or for that matter lack thereof) in the

[4]See, for instance, Gallant, Rossi and Tauchen (1993) and Koop, Pesaran and Potter (1996) in the context of reduced form models and Kilian and Vigfusson (2009) in the context of structural models.

reduced form slopes is not informative about the degree of asymmetry in the response of industrial production to an unanticipated oil price shock. We implement KV's impulse response based test. First, we compute structural IRFs, $I_y(h, \delta, \Omega^t)$, for a given horizon, h –conditional on the history Ω^t– that take into account the size of the shock, δ. Then, we average over all the histories to obtain the unconditional IRF, $I_y(h, \delta)$. We then compute the Wald test of the null of symmetric response functions:

$$I_y(h, \delta) = -I_y(h, -\delta) \text{ for } h = 0, 1, 2, ..., H.$$

See section 1 of the on-line appendix for details on the computation of the test. We report the results for one and two standard deviation shocks; we will refer to these shocks as typical and large, respectively.

4.1 Is the response of industrial production to oil price shocks linear and symmetric?

Tables 2 and 3 report the results corresponding to the test of symmetry of the IRF for the model (5) where $x_t^{\#} = x_t^1$. Results for a typical shock are reported in Table 2, whereas results for a large shock are reported in Table 3. To conserve space, the tables in this article report the test results for only four horizons ($h = 0, 1, 6, 12$). The number of rejections, noted hereafter, is based on all the horizons ($h = 0, 1, .., 12$) and thus might be smaller than the number of rejections found in Tables 2-5; they correspond to the number of rejections for all 13 horizons (i.e., $h = 0, 1, 2, ..., 12$) in Tables A.2-A.7 found in the on-line appendix (see section 2).[5]

[5]Impulse response functions for VARs using monthly data are typically computed for horizons of at least 12 months. Here, given the computational burden involved in computing the test for 37 indices and 3 oil price measures, we restrict ourselves to 12 months after the shock. See Tables A.2-A.7 of the on-line appendix at http://www.clas.wayne.edu/multimedia/usercontent/File/herrera/HLWappendix.pdf.

Contrary to the findings of KV for real GNP and unemployment on a shorter sample, we find evidence of asymmetry in the aggregate IP indices (total, manufacturing SIC, manufacturing NAICS) for at least 6 horizons if the size of the shock is one standard deviation. At a more disaggregate level, we find evidence of asymmetry at one or more horizons for 23 indices (see the first panel of Table 2 and Table A.2 in the on-line appendix). Based on the two standard deviation test we find ample evidence of asymmetry (see the first panel of Table 3 and Table A.5 of the on-line appendix). We reject the null of symmetry for 31 out of the 37 indices at the 5% significance level for at least one horizon. In particular, there is statistical evidence of asymmetry for manufacturing (NAICS) at all horizons, and for manufacturing (SIC) at all horizons but $h = 0, 4$. Only for non durable consumer goods, food, beverage and tobacco, textiles and products, petroleum and coal products, primary metal, and other transportation equipment are we not able to reject the null of symmetry.

Our finding of asymmetry in the response of the IP indices suggests that the oil price-industrial production relationship is nonlinear. However, it has been argued that measures of oil price shocks that take into account the environment in which the increase took place do a better job at capturing the nature of the nonlinearity (see for instance Lee, Ni and Ratti, 1995 and Hamilton, 1996, 2003). Hence, we re-estimate the model (5) where $x_t^{\#}$ is now defined as the net oil price increase over the previous 12-month maximum, x_t^{12}. We then compute the test of symmetry of the IRF to typical and large oil price shocks. The test results for a typical and large shock are reported in the second panel of Tables 2 and 3, respectively. Test results for all horizons $h = 0, 1, ..., 12$ are reported in Tables A.3 and A.6 of the on-line appendix.

Our test results suggest there is some evidence of nonlinearity in the response of industrial production when we use the net oil price increase over the previous 12-month maximum. For a typical shock, we reject the null of symmetry for 19 indices at one or more horizons. For large shocks, evidence of asymmetry is considerably stronger: we can reject the null of a symmetry for 34 indices at one or more horizons. Only for three indices –food, beverage and tobacco, periodicals, books and other, and pottery, ceramics and plumbing fixtures– is there no evidence of nonlinearity in the response to an oil price shock.

As a robustness check, we also compute the impulse response based tests for the net increase over the previous 36-month maximum ($x_t^{\#} = x_t^{36}$). The estimation results for a typical and a large shock are reported in the third panel of Tables 2 and 3, respectively. As can be seen by comparing the results for $x_t^{\#} = x_t^{12}$ and $x_t^{\#} = x_t^{36}$, the results for the 36-month maximum are somewhat weaker. For both a typical and a large oil price shock we can reject the null of symmetry for at least 14 of the indices at one or more horizons (See tables A.4 and A.7 of the on-line appendix). The main difference between the two measures is that we find less statistical evidence of a nonlinear effect using x_t^{36} than with x_t^{12} for sectors with samples that start in 1967 or later.[6]

But, how big is the difference between the response to positive and negative shocks? To illustrate the magnitude of this distance Figure 1 plots the responses $I_y(h, \delta)$ and $-I_y(h, -\delta)$ to a typical shock for the total IP index, manufacturing (SIC and NAICS), motor vehicles and parts, transit equipment, and chemical products. Figures A.1a - A.1e and A.2a - A.2e in the on-line appendix plot the responses for both a typical and a large shock for the total IP index, manufacturing, (SIC and NAICS), all the market groups, motor vehicles and parts, and all industry groups with data starting in 1972 or earlier. Note that to facilitate the comparison, we plot the response to a positive shock, $I_y(h, \delta)$, and the negative of the response to a negative shock, $-I_y(h, -\delta)$. The responses are measured in percentages and the horizontal axis represents months after the shock.

[6] Oil price shocks have a statistically significant effect only for 3 of the 10 sectors where we cannot reject the null of symmetry (textiles and products, electrical equipment and clay product and refractory).

As can be seen in Figure 1, the responses to a typical shock look very similar. Differences are noticeable mostly at short ($h < 5$) or long horizons ($h > 10$), especially for the total IP index and manufacturing (SIC and NAICS). For instance, depending on the nonlinear transformation of oil prices, at $h = 11$ the value of the response to a positive shock, $I_y(11, \delta)$ for the total IP is between 40% and 67% larger than the response to a negative shock, $-I_y(11, -\delta)$. Similarly, the difference for manufacturing SIC (NAICS) $I_y(11, \delta)$ is between 27% (17%) and 50% (26%) larger than $-I_y(11, -\delta)$, depending on the oil price measure. Results not reported herein- but available on the on-line appendix[7]– illustrate that for a large shock the initial difference between the two impulse responses might not seem large. Yet, for many indices the responses $I_y(h, \delta)$ and $-I_y(h, -\delta)$ diverge more as time passes. For instance, for the total IP and manufacturing (SIC and NAICS), the response to a positive shock is more than twice the size of the response to a negative shock at $h = 12$.

To summarize, we find evidence against the joint null of linearity and symmetry for most of the aggregates, most of the market groups and some of the industry groups. Furthermore, statistical evidence in favor of a nonlinear relationship between oil prices and industrial production appears to be stronger for the net oil price increase measure over the 12-month maximum (Hamilton 1996) than for the positive oil price change proposed by Mork (1989). These results suggest that inferring the effect of unanticipated oil price shocks on economic activity from the usual linear impulse response analysis might be flawed, especially for the aggregates and some sectors such as motor vehicles and chemicals. Departures from symmetry for a typical one standard deviation shock measured as the ratio of the positive to negative response range from 17% to 67% for the total IP index and the aggregates, depending on the nonlinear transformation. In contrast, a linear approximation might work well for the typical shocks in a number of industries.

[7]See Figures A.2a-A.2e in the on-line appendix.

4.2 The effect of dropping the pre-1973 data

The test results reported in the previous section suggest that contrary to what was found by KV for aggregate GDP data on a shorter sample, unexpected oil price increases and decreases appear to have an asymmetric effect on industrial production. Two possible explanations for such a difference –that cannot be directly tested– stem from differences in the computation of GDP and IP indices. First, whereas GDP is a measure of the value added in the economy, the IP index measures gross output. Second, the IP index excludes services, a sector that has gained importance over time in the U.S. economy and that being less energy intensive (in use and consumption) than manufacturing is less likely to exhibit a significant response to oil price shocks. A third (and testable) possible source of divergence is the difference in the sample period due to a structural break in the predictive relationship between the real price of oil and U.S. output in 1973 (see KV). Hence, in this section we report the results for the 1973:1-2009:9 subsample. Tables 4 and 5 report the results for these IRF based test for one and two standard deviations shocks at horizons $h = 0, 1, 6, 12$, respectively. Tables for horizons $h = 0, 1, 2, ..., 12$ are available in section 2 of the on-line appendix (see Tables A.16-A.21).

There are two reasons why we could expect these results to be different from the full sample. One is that the responses are likely to be different, given statistical evidence of a structural break in 1973. The other is that reducing the number of observations in the sample increases estimation uncertainty and, all else equal, would be expected to lower the power of tests and to reduce the number of rejections for the 1973-2009 subsample, if asymmetry holds. As we will show below, the loss of power alone cannot explain our findings.

For a typical shock, we find that the test statistic is significant at the 5% level for at least one horizon for 11, 7 and 10 of the 29 IP indices in the subsample using the oil price measure $x_t^{\#} = x_t^1, x_t^{12}, x_t^{36}$, respectively. (See Tables A.16-A.18 in section 2 of the on-line appendix). As it can be seen in Table 4, for the total IP index we are only able to reject the null of symmetry at the 10% level for $h = 1$ when we use the oil price increase ($x_t^{\#} = x_t^1$) or the net oil price increase with respect to the previous 12 months ($x_t^{\#} = x_t^{12}$). Evidence of asymmetry for manufacturing (SIC and NAICS) is also less prevalent and less consistent across oil price measures in the 1973:1-2009:9 subsample. Yet, as it is the case for the full sample, the number of rejections is considerably larger when we test for symmetry in the response to a large shock. We reject the null at the 5% level for 22, 27 and 12 of the 29 IP indices in the subsample using the oil price measure $x_t^{\#} = x_t^1$, x_t^{12}, x_t^{36}, respectively (See Tables A.19-A.21 in section 2 of the on-line appendix).

All in all, these results are consistent with KV's original conclusion that a linear model appears to provide a good approximation to the response of aggregate measures of economic activity to a typical real oil price innovation in post-1973 data. For large oil price innovations, however, nonlinear asymmetric models appear to provide a marginally better approximation to the response of both aggregate and sectoral IP indices to oil price shocks.

4.3 Should we interpret the sectoral rejections as evidence of nonlinearity at the aggregate level?

The results from the IRF based tests allow two interpretations. First, one could interpret the rejections as evidence against linearity in the response of a particular IP index to an oil price shock. That is, rejecting the null for a number of sectors would not be taken as evidence that the response of IP as a whole is nonlinear. Instead, one would consider this as evidence that the response of the particular sector is better approximated by a nonlinear model. Such an interpretation is straightforward and does not require additional discussion.

However, a second interpretation would take a large number of rejections as evidence against linearity in the response of aggregate production measured by the total IP index. Moreover, because the total IP index and the aggregates are constructed as a weighted average of the production indices (with weights that change over time), one may expect aggregation across industries to "average out" the nonlinearities if the number of rejections is small. Our estimation results appear to run against this view as in the full sample we reject the null of symmetry for the total IP index and for manufacturing but not for a large number of industries. To understand this result it is important to recall that the effect of a shock that affects a number of industries, such as an oil price increase, depends on two factors: the behavior of the sectoral weights and the degree of comovement across sectors. Work by Foerster, Sarte and Watson (2008) suggests that sectoral weights play little role in explaining the variability of the total IP index. Instead, they find that as in Shea (2002), variability of the total IP index is mainly driven complementarities in production, such as input-output linkages, which work as propagation mechanisms for aggregate and sectoral shocks. While quantifying the importance of these two factors is beyond the scope of our paper, our results in conjunction with Foerster, Sarte and Watson's (2008) findings suggest that the covariability among sectors plays an important role in explaining the response of the aggregates to oil price shocks.

4.4 The effect of data mining

One additional concern with interpreting the disaggregate results as evidence of asymmetry at the aggregate level is that there is an element of data mining involved. That is, such an interpretation would ignore the fact that we have conducted 37 Wald tests for each oil price measure. Conventional critical values do not account for repeated applications of the IRF based test to alternative IP indices.[8] To address this concern we simulate the null distribution of the supremum of the bootstrap test statistic across all disaggregates for each of the oil price measures.[9] Test statistics that are significant at 5% and 10% level are denoted by ** and *, respectively, in Tables 2-5.

As one would expect, accounting for data mining reduces the number of rejections. Using the full sample and a typical shock, we are still able to reject the null of symmetry at the 5% level for at least one horizon for the total IP index and SIC manufacturing across all oil price measures (see Table 2). Evidence of asymmetry is more prevalent for Mork's (1989) oil price increase ($x_t^{\#} = x_t^1$) than for the net oil price increase and it is consistent across at least two oil price measures for foods and tobacco, durable consumer goods, miscellaneous durable goods, and transit equipment.

Using the full sample and a large shock, and accounting for data mining, we are able to reject the null of symmetry at the 5% level for one horizon for the total IP index and SIC manufacturing using the net oil price increase over the previous 36-month maximum (see Table 3). In addition, at the 5% level we are able to reject the null of symmetry for at least one horizon for transit equipment using the net oil price increase over the previous 12-month maximum.

For the 1973-2009 subsample and a typical shock, evidence of asymmetry is found for at least one horizon using one of the oil measures for transit equipment, foods and tobacco, food, beverage and tobacco, petroleum and coal, plastics and rubber, and machinery; we are able to reject the null of symmetry for at least one horizon using one of the oil measures at the 5% level. However, once we account for data mining, we do not find any evidence of asymmetry using the subsample and a large

[8]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.

[9]The critical values that account for data mining are based on 100 pseudo series generated using the estimated coefficients for the subsample that covers all 37 indices for the full sample and 29 indices for the 1973-2009 subsample. For each series, we use 100 replications to obtain the conditional IRFs (R =100 in section 1 of the on-line appendix) and 100 bootstraps to get the test statistic.

shock. This finding illustrates that much of the evidence of asymmetries appears to be driven by data from the pre-1973 period. This is consistent both with the view that tests on the subsample have lower power against the null of symmetry and the view that there was a structural change in the transmission of oil price shocks in 1973.

5 Conclusions

The view that the oil price-output relationship is asymmetric and nonlinear has been questioned by KV. They showed that conventional censored oil price VAR studies of the macroeconomic effect of oil price shocks generally produce inconsistent estimates of the true effects of unanticipated increases in the price of oil due to the censoring applied to the oil price variable. Their paper stresses the importance of correctly specifying the model to be estimated, of using appropriate estimators, and of formally testing the dynamic effects of unexpected oil price changes on U.S. real GDP, when the underlying dynamic relationship is possibly asymmetric and/or nonlinear.

This paper explored these same issues in the context of monthly U.S. industrial production data. We first tested for nonlinearity in the slope of a reduced-form relation between domestic real economic activity and the real price of oil. We found evidence of asymmetric slopes for 15 of the 37 indices using the oil price increase, x_t^1, and for 19 (25) indices using the net oil price increase, x_t^{12} (x_t^{36}).

We also explored whether our findings are robust to the inclusion of the contemporaneous value of the oil price series, as suggested by KV. The results for this slope based test are very similar to those obtained using the forecasting equation. We find evidence of asymmetric slopes for 24 out of the 37 indices, using the oil price increase, x_t^1, and for 23 (24) IP indices using the net oil price increase over the previous 12 (36) month maximum.

Evidence of nonlinearity is even stronger when we use the IRF based test proposed by KV, in particular for the net oil price increase measures. We reject the null of symmetry for at least 70% of the IP indices for typical shocks and for most of the indices if the oil price shock is large. Departures from symmetry are economically significant for the typical shock, especially for the total IP index, manufacturing (SIC and NAICS) and sectors such as motor vehicles and chemicals. For larger shocks, departures from symmetry are economically significant for an additional number of industries. These results, however, become much weaker after accounting for the data mining that is inherent in evaluating many industrial production indices.

The baseline results are highly sensitive to whether pre-1973 data are included in the regression or not, possibly due to a structural break in the predictive relationship between the real price of oil and U.S. economic activity in 1973 (see, e.g., Kilian and Vigfusson, 2010). For the post-1973 period we find no evidence against the hypothesis that aggregate industrial production responds symmetrically to oil price innovations of typical magnitude, consistent with findings for real GDP growth in Kilian and Vigfusson (2009, 2010). Yet, there is strong evidence against the hypothesis of symmetric responses at the disaggregate level, even after accounting for data mining, for the 3-year net oil price increase specification. This finding is important because it shows that even on post-1973 data, the impulse response based test has sufficient power to detect departures from the joint null hypothesis of linearity and symmetry.

Like Kilian and Vigfusson (2010), we also find that there is statistically significant evidence of asymmetric aggregate responses to large oil price innovations in the 1973-2009 data. There is no evidence of corresponding significant rejections at the sectoral level in response to such large oil price innovations, however, perhaps because such shocks are rare and imprecisely estimated, undermining the power of the test.

Our findings have important implications for the empirical literature interested in estimating the effect of oil price shock on industrial production, as they indicate the relationship is nonlinear, at least at the sectoral level. Care must be taken in computing impulse response functions that correctly account for the nonlinearity of the oil price-industrial production relationship, especially for large shocks. All in all, while a linear model appears to provide a good approximation to the response of aggregate industrial production data, for all but the largest oil price innovations, this is not the case for several sectoral disaggregates. The fact that we find more evidence of asymmetry in the response of industrial production to oil price shocks at the disaggregate level than at the aggregate level, highlights the importance of developing multi-sector models of the transmission of oil price shocks. Moreover, the types of nonlinearities we found to fit the data do not seem consistent with standard theoretical explanations of asymmetries such as the costly reallocation of capital and labor (Hamilton, 1988) or energy complementarities (Shea, 2002) in industrial production. Our results suggest an important role for behavioral arguments in the transmission of oil price shocks. Such mechanisms to date have not been validated externally or formally modeled in a macroeconomic context. Finally, our work highlights that aggregation across sectors with very different responses might obscure the nature of the reallocative effect. For example, Edelstein and Kilian (2007) find no compelling evidence for an allocative effect on aggregate consumer spending and aggregate unemployment, which they attribute to the small share of the U.S. automobile industry in real GDP and employment. Foerster, Sarte and Watson (2008) suggest that the variability of the total IP index is mainly driven by sectoral comovement (i.e., input-output linkages) and not by the sector weights. Analyzing the importance of these two different factors in explaining where the asymmetry originates is a question that is left for future research.

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Table 1. Slope based test of nonlinearity

Sector	Forecasting Equation			Structural Equation		
	$x_t^\# = x_t^1$	$x_t^\# = x_t^{12}$	$x_t^\# = x_t^{36}$	$x_t^\# = x_t^1$	$x_t^\# = x_t^{12}$	$x_t^\# = x_t^{36}$
Total index	**0.00**	**0.04**	**0.00**	**0.00**	**0.01**	**0.00**
Foods and tobacco	**0.00**	**0.01**	**0.00**	**0.00**	**0.01**	**0.00**
Clothing	**0.01**	0.12	0.77	**0.01**	0.11	0.69
Durable consumer goods	0.08	0.38	**0.04**	**0.02**	0.14	**0.04**
Miscellaneous durable goods	0.29	**0.01**	**0.01**	**0.03**	**0.00**	**0.00**
Nondurable consumer goods	**0.04**	**0.00**	**0.00**	**0.03**	**0.00**	**0.00**
Manufacturing (SIC)	**0.00**	0.08	**0.00**	**0.00**	**0.03**	**0.00**
Paper products	**0.01**	**0.02**	**0.04**	**0.01**	**0.01**	0.06
Chemical products	**0.00**	0.10	**0.00**	**0.00**	**0.03**	**0.00**
Transit equipment	0.18	0.11	**0.00**	0.17	0.10	**0.00**
Textiles materials	0.12	**0.03**	0.07	0.06	**0.01**	0.06
Paper materials	0.07	**0.03**	**0.02**	**0.03**	**0.00**	**0.01**
Chemical materials	0.07	**0.04**	**0.04**	0.07	**0.03**	**0.03**
Motor vehicles and parts	**0.00**	0.57	0.14	**0.00**	0.30	0.15
Food, beverage and tobacco	0.15	0.21	**0.00**	0.12	0.19	**0.00**
Textiles and products	0.66	**0.03**	0.10	0.48	**0.02**	0.11
Apparel and leather goods	0.50	0.15	0.45	0.26	0.15	0.39
Paper	0.08	**0.01**	**0.02**	**0.04**	**0.00**	**0.01**
Printing and related	0.06	0.19	0.42	**0.01**	**0.01**	0.20
Chemicals	**0.00**	0.12	0.16	**0.00**	0.10	0.08
Petroleum and coal	0.89	0.52	0.16	0.84	0.47	0.15
Plastics and rubber	0.15	**0.01**	**0.00**	**0.03**	**0.01**	**0.00**
Furniture	0.06	**0.01**	**0.03**	**0.00**	**0.00**	**0.02**
Primary metal	0.34	0.19	**0.02**	0.32	0.11	**0.00**
Fabricated metal	0.53	**0.00**	**0.00**	0.30	**0.00**	**0.00**
Machinery	0.11	**0.00**	**0.02**	**0.05**	**0.00**	**0.01**
Electrical equipment	0.07	**0.01**	**0.01**	**0.03**	**0.00**	**0.01**
Motor vehicles	**0.00**	**0.04**	**0.00**	**0.00**	**0.00**	**0.00**
Manufacturing (NAICS)	**0.01**	**0.05**	**0.00**	**0.00**	**0.02**	**0.00**
Newspaper	**0.01**	0.07	**0.00**	**0.01**	**0.02**	**0.00**
Periodical books and other	**0.03**	0.16	**0.00**	**0.04**	0.14	**0.01**
Pottery, ceramics and plumbing	0.10	0.79	0.83	0.11	0.85	0.80
Glass and glass products	**0.00**	**0.00**	0.18	**0.00**	**0.00**	0.26
Clay product and refractory	0.36	0.37	0.62	0.33	0.33	0.70
Industrial machinery	0.09	0.18	0.30	0.06	0.08	0.20
Other transportation equipment	0.30	**0.00**	**0.01**	0.24	**0.00**	**0.01**
Navigational, measuring and other	**0.01**	0.19	**0.00**	**0.00**	0.16	**0.00**

Note: This table reports the p-values for a Robust Wald Test of the joint significance of the lags of $x_t^\#$ in the reduced-form equation (4).

Table 2. IRF based test of symmetry to 1 s.d. shock - Full sample

	$x_t^{\#} = x_t^1$				$x_t^{\#} = x_t^{12}$				$x_t^{\#} = x_t^{36}$			
Sector	0	1	6	12	0	1	6	12	0	1	6	12
Total index	_0.10_	_0.06_	__0.04__	__0.04**__	__0.00**__	__0.00**__	__0.02**__	__0.00**__	0.55	0.14	_0.06*_	__0.00**__
Foods and tobacco	0.29	0.14	__0.04__	0.16	0.34	0.33	__0.00**__	__0.00**__	0.51	0.77	0.11	__0.01**__
Clothing	__0.02__	__0.04__	_0.07_	0.27	0.16	0.36	__0.02**__	__0.01**__	0.66	0.79	0.96	0.75
Durable consumer goods	__0.03__	__0.04__	_0.08_	0.16	__0.00**__	__0.00**__	__0.00**__	__0.00**__	0.44	_0.09_	_0.06*_	__0.01**__
Miscellaneous durable goods	__0.00**__	__0.01__	_0.07_	0.18	__0.00**__	__0.00**__	__0.03**__	__0.01**__	0.32	_0.08_	_0.09*_	__0.03**__
Nondurable consumer goods	0.20	0.27	0.11	0.35	0.11	_0.07_	__0.01**__	__0.00**__	0.93	0.35	0.11	_0.06**_
Manufacturing (SIC)	__0.05__	__0.01__	__0.03__	_0.07**_	__0.00**__	__0.00**__	__0.01**__	__0.01**__	0.47	_0.09_	__0.05*__	__0.00**__
Paper products	0.21	0.30	__0.05__	_0.10*_	0.39	0.63	_0.09*_	0.17**	0.95	0.87	0.70	_0.09**_
Chemical products	0.85	0.22	0.16	_0.09*_	__0.02__	__0.03__	0.11*	_0.10**_	0.60	0.26	_0.09*_	0.20*
Transit equipment	0.42	__0.04__	__0.03__	_0.08**_	0.28	__0.00**__	__0.01**__	__0.00**__	0.60	0.73	__0.03**__	__0.00**__
Textiles materials	_0.08_	__0.01__	__0.02**__	0.13	__0.04__	0.11	0.47	0.44	__0.05__	0.11	0.42	0.53
Paper materials	_0.08_	__0.03__	0.21	0.23	__0.01__	__0.04__	0.13	0.48	0.15	0.34	0.50	0.66
Chemical materials	0.71	__0.00**__	__0.02**__	_0.07**_	0.60	__0.03__	0.27	0.32	0.92	0.15	0.35	0.49
Motor vehicles and parts	0.68	__0.01__	__0.00**__	__0.00**__	0.27	__0.04__	0.23	0.37	0.64	__0.05__	0.29	0.66
Food, beverage and tobacco	0.47	0.16	0.14	0.57	0.70	0.82	0.58	0.89	0.37	_0.07_	0.12	0.41
Textiles and products	0.11	_0.09_	0.42	0.68	0.18	0.28	0.52	0.78	0.88	0.11	0.49	0.88
Apparel and leather goods	__0.03__	_0.08_	0.32	0.62	0.55	0.80	0.43	0.69	0.91	0.44	0.53	0.44
Paper	0.11	__0.02__	0.16	0.48	_0.10_	0.24	0.50	0.83	0.17	0.26	0.40	0.78
Printing and related	__0.01__	__0.03__	0.11	0.29	__0.02__	_0.06_	0.32	0.76	0.11	0.22	0.64	0.83
Chemicals	0.69	__0.00**__	__0.00**__	__0.02**__	0.54	0.20	0.57	0.75	0.32	__0.03__	_0.08*_	0.31*
Petroleum and coal	0.26	0.17	0.75	0.96	0.18	0.14	0.75	0.88	__0.03__	_0.07_	_0.06*_	0.35
Plastics and rubber	__0.03__	_0.07_	0.39	_0.09*_	0.20	0.37	0.74	0.67	0.70	0.26	0.26	0.30*
Furniture	__0.01__	__0.04__	0.17	0.45	__0.02__	_0.06_	0.35	0.65	_0.07_	0.18	0.35	0.54
Primary metal	0.32	0.19	0.61	0.83	0.11	__0.04__	0.34	0.73	_0.07_	0.18	0.35	0.54
Fabricated metal	_0.09_	__0.04__	0.29	0.68	_0.06_	__0.04__	0.43	0.68	0.10	__0.05__	0.33	0.57
Machinery	_0.09_	__0.03__	0.17	0.56	0.16	_0.06_	0.39	0.64	0.11	_0.06_	0.22	0.47
Electrical equipment	_0.07_	0.17	0.43	0.12*	_0.08_	0.15	0.62	0.57	0.25	0.35	0.78	0.81
Motor vehicles	0.46	__0.01__	_0.08_	0.27	__0.04__	__0.04__	0.39	0.73	0.99	__0.04__	0.33	0.75
Manufacturing (NAICS)	_0.06_	__0.00__	__0.02*__	0.12*	_0.07_	_0.08_	0.51	0.87	0.60	_0.07_	0.33	0.62
Newspaper	0.96	0.27	0.17	0.55	0.14	0.21	0.50	0.89	0.12	0.13	0.34	0.80
Periodical books and other	0.36	0.17	0.25	0.68	0.41	0.69	0.80	0.98	0.62	0.16	0.45	0.81
Pottery, ceramics and plumbing	0.30	_0.06_	0.12	0.39	0.37	0.59	0.70	0.95	0.65	0.72	0.83	0.99
Glass and glass products	0.16	0.28	0.25	0.62	0.24	0.38	0.79	0.85	0.46	0.75	0.93	0.98
Clay product and refractory	0.76	0.32	0.42	0.85	0.17	0.27	0.62	0.91	0.61	0.36	0.80	0.96
Industrial machinery	0.26	0.16	0.42	0.78	__0.04__	0.12	0.58	0.67	0.12	0.30	0.51	0.70
Other transportation equipment	0.26	0.28	0.54	0.85	0.96	0.77	0.50	0.84	0.41	0.58	0.68	0.94
Navigational, measuring and other	0.11	0.27	0.20	0.48	0.91	0.35	0.76	0.82	0.72	0.25	0.35	0.63

Notes: Tests are based on 1000 simulations of model (5) . 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 3. IRF based test of symmetry for 2 s.d. shock - Full sample

	$x_t^{\#} = x_t^1$				$x_t^{\#} = x_t^{12}$				$x_t^{\#} = x_t^{36}$			
Sector	0	1	6	12	0	1	6	12	0	1	6	12
Total index	0.15	*0.10*	*0.06*	**0.01**	**0.00**	**0.00**	**0.00**	**0.00**	0.20	**0.01**	**0.04**	**0.00****
Foods and tobacco	0.34	0.21	*0.06*	*0.10*	0.38	0.44	**0.00**	**0.00**	0.17	**0.03**	**0.00**	**0.00***
Clothing	**0.02**	**0.05**	**0.04**	0.13	0.16	0.38	**0.01**	**0.00**	0.35	0.64	0.72	0.38
Durable consumer goods	**0.04**	**0.04**	*0.06*	*0.06*	**0.00**	**0.00**	**0.00**	**0.00**	0.12	**0.01**	*0.06*	**0.00***
Miscellaneous durable goods	**0.01**	**0.02**	0.11	0.20	**0.00**	**0.00**	**0.01**	**0.00**	**0.03**	**0.00**	*0.07*	**0.00**
Nondurable consumer goods	0.24	0.35	0.15	0.34	0.11	*0.10*	**0.00**	**0.00**	0.86	**0.03**	**0.00**	**0.00***
Manufacturing (SIC)	*0.07*	**0.02**	**0.04**	**0.04**	**0.00**	**0.00**	**0.00**	**0.00**	0.11	**0.00**	**0.04**	**0.00****
Paper products	0.27	0.38	**0.03**	**0.01**	0.39	0.56	**0.01**	**0.00**	0.79	0.41	0.13	**0.01**
Chemical products	0.86	0.26	0.20	**0.04**	**0.02**	**0.04**	0.24	**0.00**	*0.08*	*0.06*	*0.08*	**0.04**
Transit equipment	0.47	*0.08*	**0.01**	**0.00**	0.39	**0.01**	**0.00**	**0.00****	*0.07*	**0.01**	**0.03**	**0.00**
Textiles materials	*0.10*	**0.01**	**0.01**	**0.05**	**0.01**	**0.05**	*0.07*	**0.00**	**0.04**	0.13	0.21	**0.03**
Paper materials	*0.09*	**0.02**	0.12	**0.03**	**0.00**	**0.01**	**0.01**	**0.00**	0.15	0.28	0.38	0.14
Chemical materials	0.72	**0.00**	**0.00**	**0.00**	0.59	**0.00**	**0.01**	**0.00***	0.91	*0.10*	**0.05**	**0.00**
Motor vehicles and parts	0.71	**0.00**	**0.00**	**0.00**	0.24	**0.00**	**0.00**	**0.00**	0.66	**0.01**	**0.03**	0.12
Food, beverage and tobacco	0.49	0.17	*0.07*	0.29	0.65	0.77	*0.09*	0.11	0.38	*0.06*	*0.06*	0.21
Textiles and products	0.12	*0.09*	0.27	0.35	0.11	0.12	0.11	**0.02**	0.89	*0.07*	0.33	0.47
Apparel and leather goods	**0.02**	*0.06*	*0.08*	*0.10*	0.46	0.71	0.11	*0.07*	0.96	0.46	0.39	0.45
Paper	0.11	**0.01**	*0.08*	0.11	**0.02**	*0.06*	**0.03**	**0.01**	0.16	0.33	0.41	0.53
Printing and related	**0.00**	**0.01**	**0.01**	**0.02**	**0.00**	**0.00**	**0.00**	**0.00**	*0.07*	0.11	0.20	0.46
Chemicals	0.72	**0.00**	**0.00**	**0.00**	0.47	**0.04**	0.15	**0.00**	0.35	**0.01**	**0.04**	0.12
Petroleum and coal	0.30	0.19	0.77	0.96	0.12	**0.04**	0.45	0.23	**0.02**	*0.08*	0.11	0.20
Plastics and rubber	**0.03**	*0.07*	0.26	**0.00**	*0.07*	0.13	*0.08*	**0.00**	0.71	0.27	**0.02**	*0.10*
Furniture	**0.01**	**0.02**	**0.04**	*0.08*	**0.00**	**0.00**	**0.00**	**0.00**	*0.06*	0.16	0.13	0.17
Primary metal	0.36	0.20	0.51	0.69	*0.06*	**0.01**	**0.01**	**0.01**	**0.03**	*0.10*	0.15	0.27
Fabricated metal	0.11	**0.04**	0.18	0.40	**0.01**	**0.00**	**0.01**	**0.00**	*0.10*	**0.01**	0.13	0.21
Machinery	*0.09*	**0.02**	**0.05**	0.25	*0.08*	**0.00**	**0.00**	**0.00**	*0.07*	**0.01**	*0.06*	0.11
Electrical equipment	*0.08*	0.18	0.32	**0.01**	**0.02**	**0.01**	*0.09*	**0.00**	0.23	0.29	0.44	0.45
Motor vehicles	0.46	**0.01**	**0.01**	**0.01**	**0.00**	**0.01**	**0.00**	**0.00**	0.99	**0.02**	*0.06*	0.17
Manufacturing (NAICS)	**0.05**	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**	**0.01**	**0.00**	0.59	**0.01**	**0.03**	0.13
Newspaper	0.96	0.24	**0.00**	**0.00**	*0.06*	**0.02**	**0.03**	0.13	0.11	**0.01**	**0.04**	0.24
Periodical books and other	0.32	*0.09*	**0.00**	**0.03**	0.30	0.51	0.11	0.14	0.61	*0.07*	0.21	0.60
Pottery, ceramics and plumbing	0.28	**0.03**	**0.00**	**0.00**	0.24	0.26	0.12	0.50	0.60	0.76	0.83	0.99
Glass and glass products	0.12	0.19	**0.00**	**0.00**	0.11	*0.08*	**0.00**	**0.01**	0.41	0.63	0.43	0.72
Clay product and refractory	0.75	0.24	*0.07*	0.27	*0.09*	**0.04**	0.11	0.14	0.59	0.19	0.69	0.85
Industrial machinery	0.25	*0.10*	**0.03**	**0.04**	**0.01**	**0.01**	**0.03**	**0.01**	*0.10*	0.14	0.39	0.36
Other transportation equipment	0.22	0.17	0.16	0.25	0.96	0.70	**0.02**	**0.00**	0.38	0.62	0.38	0.81
Navigational, measuring and other	*0.10*	0.25	**0.04**	**0.04**	0.94	0.16	0.15	**0.01**	0.71	0.19	0.11	0.26

Notes: Tests are based on 1000 simulations of model (5) . 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 4. IRF based test of symmetry to 1 s.d. shock - 1973-2009 subsample

	$x_t^{\#} = x_t^1$				$x_t^{\#} = x_t^{12}$				$x_t^{\#} = x_t^{36}$			
Sector	0	1	6	12	0	1	6	12	0	1	6	12
Total index	0.14	*0.06*	*0.07*	0.18	0.12	*0.09*	0.50	0.74	0.88	0.18	0.65	0.80
Foods and tobacco	0.29	0.13	0.31	0.57	0.42	0.62	0.77	0.96	0.28	0.11	*0.06***	0.33
Clothing	*0.09*	0.20	0.47	0.71	0.86	0.50	0.47	0.71	0.80	0.25	0.34	0.67
Durable consumer goods	0.11	*0.08*	0.13	0.27	0.22	0.30	0.84	0.94	0.99	*0.08*	0.22	0.66
Miscellaneous durable goods	**0.02**	*0.07*	0.51	0.81	*0.07*	0.12	0.44	0.78	0.15	0.13	0.26	0.63
Nondurable consumer goods	0.13	0.29	0.53	0.75	0.31	0.59	0.65	0.92	0.41	0.26	0.76	0.97
Manufacturing (SIC)	*0.09*	**0.03**	0.11	0.42	0.14	*0.06*	0.39	0.74	0.53	*0.06*	0.21	0.26
Paper products	0.15	0.33	*0.06*	0.29	0.42	0.49	0.42	0.66	0.69	0.37	0.21	0.47
Chemical products	0.68	0.17	0.14	0.28	0.22	0.44	0.76	0.97	0.19	0.28	0.29	0.62
Transit equipment	0.50	0.12	0.14	0.38	0.23	0.13	0.43	0.48	**0.02***	**0.00****	**0.01****	**0.00****
Textiles materials	0.14	*0.06*	0.19	0.46	*0.07*	0.16	0.34	0.70	0.20	0.29	0.20	0.48
Paper materials	*0.07*	**0.02**	0.22	0.29	**0.04**	0.11	0.44	0.86	0.31	0.31	0.30	0.72
Chemical materials	0.65	**0.01**	*0.08*	0.22	0.46	0.12	0.40	0.69	0.79	0.20	*0.08*	0.26
Motor vehicles and parts	0.71	**0.02**	*0.07*	0.20	0.27	0.12	0.52	0.73	0.34	**0.02***	0.11	0.39
Food, beverage and tobacco	0.25	0.13	0.24	0.54	0.32	0.48	0.63	0.90	0.35	0.12	**0.03****	0.24
Textiles and products	0.18	*0.07*	0.42	0.76	0.93	0.78	0.60	0.74	0.81	0.19	0.46	0.82
Apparel and leather goods	*0.10*	0.25	0.59	0.82	**0.03**	*0.10*	0.44	0.87	0.89	0.50	0.68	0.84
Paper	**0.05**	**0.02**	0.18	0.37	**0.04**	0.11	0.44	0.81	0.27	0.24	0.19	0.59
Printing and related	*0.07*	*0.08*	0.37	0.80	0.17	*0.10*	0.46	0.74	*0.10*	0.21	0.44	0.66
Chemicals	0.79	**0.00**	**0.03**	0.11	*0.06*	*0.09*	0.36	0.75	0.35	*0.07*	*0.08*	0.22*
Petroleum and coal	0.27	0.12	0.61	0.95	0.27	0.38	0.73	0.92	**0.05**	*0.06*	**0.01****	*0.10***
Plastics and rubber	*0.07*	0.18	0.64	0.63	**0.03**	0.11	0.44	0.75	0.96	0.31	0.20	*0.07***
Furniture	**0.03**	*0.09*	0.38	0.55	**0.03**	0.11	0.44	0.75	0.11	0.16	0.26	0.54
Primary metal	0.52	0.20	0.54	0.81	**0.05**	**0.05**	0.40	0.63	*0.06*	0.15	0.21	0.13*
Fabricated metal	0.16	0.19	0.67	0.92	0.19	**0.03**	0.29	0.71	0.18	0.11	0.15	0.33
Machinery	*0.10*	*0.06*	0.25	0.61	*0.07*	0.15	0.70	0.87	*0.08*	0.14	*0.09*	0.11**
Electrical equipment	0.13	0.28	0.75	0.32	*0.07*	0.15	0.70	0.87	0.20	0.39	0.68	0.37
Motor vehicles	0.88	**0.03**	0.15	0.32	0.17	*0.09*	0.54	0.81	0.94	*0.08*	0.13	0.46
Manufacturing (NAICS)	*0.10*	**0.03**	0.12	0.43	0.16	*0.06*	0.39	0.74	0.57	*0.06*	0.20	0.26

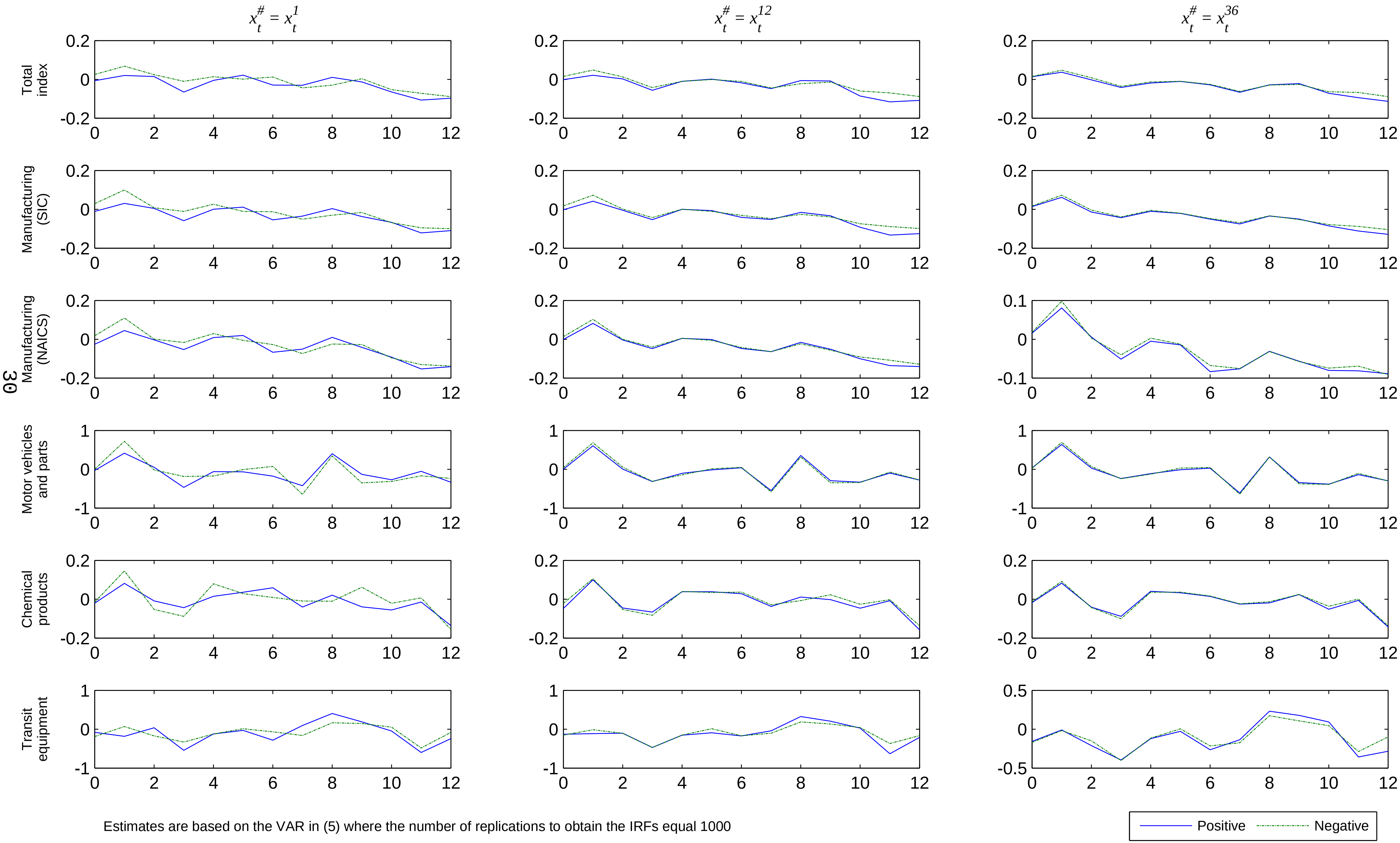
Notes: Tests are based on 1000 simulations of model (5) . p-values are based on the χ^2_{H+1}. Bold and italics denote significance at the 5% and 10% level, respectively. ** and * denote significance after accounting for data mining at the 5% and 10% level, respectively.

Table 5. IRF based test of symmetry for 2 s.d. shock - 1973-2009 subsample

	$x_t^{\#} = x_t^{1}$				$x_t^{\#} = x_t^{12}$				$x_t^{\#} = x_t^{36}$			
Sector	0	1	6	12	0	1	6	12	0	1	6	12
Total index	**0.01**	**0.01**	**0.02**	**0.00**	0.24	*0.06*	0.23	**0.03**	0.67	**0.03**	**0.05**	*0.09*
Foods and tobacco	0.26	0.51	0.57	0.66	0.64	0.89	0.29	0.54	0.30	0.17	0.12	0.36
Clothing	*0.06*	0.14	*0.08*	*0.08*	0.84	0.37	0.11	**0.03**	0.88	0.27	0.37	0.63
Durable consumer goods	*0.09*	**0.03**	**0.00**	**0.00**	*0.07*	**0.00**	**0.03**	*0.07*	0.67	*0.09*	0.25	0.35
Miscellaneous durable goods	**0.01**	**0.04**	0.27	0.46	**0.01**	**0.00**	**0.01**	**0.00**	0.17	*0.06*	0.20	0.38
Nondurable consumer goods	0.11	0.24	0.35	0.53	0.22	0.44	**0.02**	**0.02**	0.53	0.20	0.28	0.69
Manufacturing (SIC)	*0.06*	**0.00**	**0.00**	**0.02**	**0.04**	**0.00**	**0.01**	**0.00**	0.56	**0.02**	**0.03**	*0.10*
Paper products	0.16	0.34	**0.00**	**0.01**	0.31	0.34	**0.01**	**0.01**	0.77	0.43	*0.06*	0.13
Chemical products	0.70	0.12	**0.01**	**0.00**	0.11	0.23	0.43	0.38	0.29	0.29	0.38	0.65
Transit equipment	0.54	*0.10*	**0.01**	**0.01**	0.18	**0.03**	**0.02**	**0.00**	*0.06*	**0.03**	0.12	*0.09*
Textiles materials	0.14	**0.04**	**0.03**	**0.05**	**0.01**	**0.04**	**0.01**	**0.00**	0.23	0.43	0.39	0.65
Paper materials	*0.07*	**0.01**	0.16	*0.08*	**0.01**	**0.02**	**0.03**	**0.01**	0.31	0.49	0.37	0.60
Chemical materials	0.66	**0.00**	**0.01**	**0.00**	0.38	**0.01**	**0.05**	**0.01**	0.79	*0.06*	**0.05**	*0.06*
Motor vehicles and parts	0.72	**0.00**	**0.00**	**0.00**	0.23	**0.03**	**0.01**	*0.07*	0.49	**0.04**	*0.06*	0.31
Food, beverage and tobacco	0.28	*0.10*	*0.07*	0.11	0.22	0.32	**0.03**	*0.09*	0.37	0.17	*0.06*	0.26
Textiles and products	0.18	**0.04**	0.19	0.41	*0.06*	0.12	**0.01**	**0.00**	0.89	0.20	0.42	0.63
Apparel and leather goods	*0.06*	0.18	0.17	0.23	0.94	0.70	0.21	*0.06*	0.98	0.58	0.64	0.78
Paper	**0.04**	**0.01**	*0.07*	*0.06*	**0.00**	**0.00**	**0.01**	**0.01**	0.28	0.44	0.28	0.50
Printing and related	**0.04**	**0.03**	0.11	0.26	**0.01**	**0.00**	**0.00**	**0.01**	0.11	0.18	0.20	0.50
Chemicals	0.80	**0.00**	**0.00**	**0.00**	0.11	**0.01**	**0.05**	*0.07*	0.42	**0.02**	*0.07*	0.13
Petroleum and coal	0.29	0.11	0.59	0.92	**0.02**	**0.03**	**0.02**	**0.03**	**0.04**	0.11	0.11	0.25
Plastics and rubber	*0.07*	0.19	0.49	*0.07*	0.20	0.23	**0.04**	**0.00**	0.95	0.33	*0.06*	**0.03**
Furniture	**0.02**	*0.06*	*0.09*	0.11	**0.00**	**0.01**	**0.00**	**0.00**	*0.09*	0.21	0.21	0.36
Primary metal	0.54	0.19	0.52	0.64	*0.09*	**0.04**	0.11	**0.05**	*0.06*	0.13	*0.10*	0.15
Fabricated metal	0.16	0.14	0.54	0.80	**0.01**	**0.00**	**0.00**	**0.00**	0.20	**0.04**	0.23	0.45
Machinery	*0.08*	**0.04**	*0.09*	0.17	*0.07*	**0.00**	**0.00**	**0.00**	*0.09*	**0.05**	0.18	0.21
Electrical equipment	0.13	0.25	0.56	**0.04**	**0.02**	**0.02**	0.12	**0.00**	0.21	0.31	0.28	0.41
Motor vehicles	0.89	**0.01**	**0.01**	**0.00**	0.11	**0.00**	**0.01**	*0.06*	0.96	*0.07*	**0.04**	0.17
Manufacturing (NAICS)	*0.07*	**0.00**	**0.00**	**0.02**	*0.06*	**0.00**	**0.01**	**0.00**	0.60	**0.03**	**0.04**	0.11

Notes: Tests are based on 1000 simulations of model (5) . 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.

Figure 1: Impulse response to two standard deviation positive and negative shocks to the real oil price (percentage)



Estimates are based on the VAR in (5) where the number of replications to obtain the IRFs equal 1000