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) 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 of such shocks. They also showed that for a shock of typical magnitude the linear and

[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.

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), which can be motivated directly from economic theory, and the 1-year and 3-year net oil price increase specifications of Hamilton (1996, 2003) whose motivation is behavioral. We start by testing for asymmetries and nonlinearities in the coefficients of the reduced-form relationship between industrial production growth and the percentage change in the real price of oil using data since 1947. Our results for these traditional slope-based tests are consistent with Hamilton's (2010) and Kilian and Vigfusson's (2009) finding that the reduced-form relationship between oil prices and economic activity appears nonlinear in some transformations of the price of oil. As suggested by previous studies, rejections of the linear model are more prevalent when we use measures of oil prices that filter out not only decreases in the price, but also increases that corrected for previous declines. We then repeat this analysis based on the modified slope-based test proposed in Kilian and Vigfusson (2009) with similar or even stronger results. Our empirical findings are consistent with Kilian and Vigfusson's (2009) findings that slope based tests that include the contemporaneous terms may have higher power than traditional slope based tests.

None of the slope-based tests, however, directly addresses 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 the latter question based on the impulse response function (IRF) based test of symmetry proposed in Kilian and Vigfusson (2009). We show that the IRF based tests may reject the null of symmetric response functions even when slope based tests do not reject the null of symmetric slopes. Overall, the impulse response 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 only, 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 Kilian and Vigfusson (2009) for U.S. real GDP. In response to shocks of the same magnitude, there is strong evidence of asymmetries at the disaggregate level based on the 3-year net increase measure, 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 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.

Recent work by Edelstein and Kilian (2009), Kilian (2009), and Blanchard and Galí (2010) suggests that the effect of oil price shocks on economic activity during the 2000s have been muted compared to the 1970s. Likewise, there has been evidence that the nonlinear relationship uncovered by Mork (1989), for example, has not been stable over time (see Hooker 1996; Hamilton 1996; Kilian and Vigfusson 2009). This raises the question of whether the nonlinear reduced form relationships we document have been stable over time. As a further robustness check, we therefore test whether the coefficients on the censored oil price have changed, while the other coefficients remain unchanged. To this end, we implement Qu and Perron's (2007) test for multiple breaks of unknown timing. Our test results suggest that there is little evidence of a structural change in the coefficients that govern the effect of the nonlinear oil price variable on industrial production growth (i.e., breaks are estimated for at most 7 out of the 37 indices). In the few cases where breaks are estimated, they tend to be located in the mid-1980s or the late 1990s.

Our findings have important implications for the empirical literature regarding the effect of oil price shocks on industrial production. First, our test 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 test results highlight the importance of developing multisector models of the transmission of oil price shocks. Third, our test 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. Embedding such behavioral explanations into macroeconomic models of the transmission of oil price shocks will require a different class of theoretical models of the transmission of oil price shocks.

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 (section 3.1) and to test for nonlinearity in a more general model (section 3.2). In section 4 we employ the impulse response based tests of symmetry of Kilian and Vigfusson (2009) to further inquire about the effect of unanticipated oil price shocks on industrial production. Section 5 addresses the issue of structural stability of the nonlinear oil parameters by applying Qu and Perron's (2007) test for multiple breaks of unknown timing. Section 6 concludes.

2 Data

To study the relationship between oil price shocks and economic activity we use monthly data on oil prices and industrial production indices. 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. To make our results comparable to Kilian and Vigfusson (2009) we 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. The first of these measures is Mork's (1989) oil price increase, which can be defined as:

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

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 Kilian and Vigfusson (2009), among others, showed that this result vanishes in longer samples.

The second measure used in our paper is the net oil price increase over the previous 12-month maximum (Hamilton, 1996)

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

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

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

The last two 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, 2002; Lee and Ni, 2002). Note, however, that in the text we report the results for the nonlinear transformations of the log of the real oil price whereas the results for the nonlinear transformation of the log of the nominal oil price, as originally proposed by Hamilton (1996, 2003) are reported in section 3 of the on-line appendix.[2]

To measure economic activity we use monthly data on the seasonally adjusted industrial production (IP) indices computed by the Board of Governors of the Federal Reserve; the reference period is 2002. 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 used in this paper 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 1 for the period covered for each IP index). IP indices have been frequently used by both researchers and policy-makers to assess the current state of the economy and to study business cycles and inventory behavior (see for example, Hamilton and Lin, 1996, and Terasvirta and Anderson, 1992).[3]

[2] See Tables A.7-A.14 and A.21-A.28 in section 3 of the on-line appendix, available at http://clas.wayne.edu/multimedia/usercontent/File/herrera/HLWappendix.pdf.

[3] Another measure of output ($Y4$) commonly used by economists stems directly from the inventory identity, which states that output equals the sum of sales plus the change in inventories. Sales and inventories for manufacturing, wholesale and retail trade are reported by the Bureau of Economic Analysis (BEA) at a monthly frequency. In theory, both the $Y4$ measure and the IP indices measure the same underlying economic variable; that is, the output produced by firms during a given month. However, work by Miron and Zeldes (1989) suggests that both series have different time series properties making it difficult in practice to compare the results obtained by using these two

3 Slope based tests of nonlinearity

Is the oil price-industrial production relation nonlinear? In this section we take a first step in answering this question by implementing two types of slope based tests. First, we inquire whether nonlinear measures of oil prices have explanatory power for the rate of growth of industrial production in a standard predictive equation, once we have controlled for the rate of growth of oil prices. Then, we follow Kilian and Vigfusson (2009) and implement a slope based test of nonlinearity where, in addition to lags of oil prices, the contemporaneous value of the oil price change and the nonlinear transformation enter in the industrial production equation.

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 ordinary least squares:

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

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

different measures. Whereas literature on the Great Moderation and on the effect of oil prices has more commonly used the $Y4$ measure (see for instance McConnell and Perez-Quiros, 2000; Irvine and Schuh, 2005; and Herrera and Pesavento 2005, 2009), this measure suffers from a historical discontinuity due to the replacement of the Standard Industrial Classification (SIC) as the standard used in classifying business establishment with the North American Industry Classification System (NAICS) in 1997. As a result, there is no exact correspondence between the 2-digit SIC manufacturing industries used in the literature on the Great Moderation and the NAICS data currently reported by the BEA. This discontinuity in the data renders it ineffectual for our purpose of exploring the functional form and structural stability of the effect of oil price shocks on manufacturing activity, especially given our interest in the evolution of this relationship during the past decade.

is set equal to 12 months.[4] 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 2 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 column of the first panel in Table 2. At the 5% significance level, we reject the null of symmetry for 15 of the 37 industrial production indices. In particular, the test results provide evidence of asymmetry in the reduced form slope for oil price increases and decreases when using the total IP index, manufacturing (NAICS and SIC), non durable consumer goods, two market groups (foods and tobacco, and clothing), and nine industry groups (paper products, chemical products, motor vehicles and parts, chemicals, motor vehicles, newspaper publishers, periodicals, books and other publishers, glass and glass products, and navigational and other instruments). All in all, there appears to be some evidence of asymmetry for a number of manufacturing industries. 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.

Consider now the possibility that an alternative transformation of oil prices does a better job at capturing the nonlinearity in the reduced-form equation, as suggested by Hamilton (1996, 2003). As can be seen in the second column of the first panel in Table 2, 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 at the 5% level. 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} (see

[4] 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.

last column of the first panel in Table 2). 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 several indices where one (or more) of the net oil price increase measures suggests symmetry. These are clothing, manufacturing (SIC), chemical products, motor vehicles and parts, chemicals, newspaper publishers, periodicals, books, and other publishers, glass and glass products, and navigational and other instruments. Second, note that 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 at the 5% significance level for the industry group of motor vehicles. This result is consistent with the common view that oil price increases have a significant negative effect on the automobile sector (see Hamilton, 2009).

Summing up, 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. The sectors for which the null of linearity is rejected regardless of the oil price measure are 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

Kilian and Vigfusson (2009) propose a more powerful test of the null of symmetric slopes that could be obtained by estimating a more general model of the oil price-macroeconomy relationship, which would include contemporaneous values of x_t and $x_t^{\#}$. Hence, consider the data generating process for each of the IP series as being given by the following 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 $g_{21,0} = g_{21,1} = \cdots = g_{21,12} = 0$. In other words, we test whether the coefficients on the nonlinear measure of oil prices are all equal to zero in equation (5b). The second panel in Table 2 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 us with stronger evidence of asymmetry. In fact, for 24 out of the 37 indices we reject the null hypothesis that the coefficients on the contemporaneous value and on the lags of the oil price increase, x_t^1, are all equal to zero at the 5% significance level. Using x_t^{12}, we reject the null of linearity for 23 indices, whereas, by using x_t^{36} we are able to find evidence of nonlinearity for 24 indices.

Regardless of the measure of oil prices, we reject the null of linearity for 15 indices: the total IP index, manufacturing (SIC and NAICS), foods and tobacco, miscellaneous durable goods, non-durable consumer goods, chemical products, paper materials, paper, plastics and rubber products, furniture and related products, machinery, electrical equipment, motor vehicles, and newspaper publishers. 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. Indeed computations based on the 1999 input-output tables suggest that the direct (total) crude petroleum and natural gas requirement per dollar of production is 0.48 (0.76) for petroleum products versus 0.09 (0.27) for chemicals, the industry with the second highest direct and total requirements.

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. That is, the number of indices for which we reject the null of symmetry increases slightly for both the oil price increase and the net oil price increase over the previous 12-month maximum. This result is in line with Kilian and Vigfusson's (2009) simulation evidence of an increase in power when contemporaneous terms are included in the economic activity equation.

However, it has been shown by Kilian and Vigfusson (2009) that evidence of asymmetry (or for that matter lack thereof) in the reduced form slopes is not informative about the degree of asymmetry in the response of industrial production to an unanticipated oil price shock. In many applied studies in the literature it is these responses that are the central object of interest. For that reason, in the following section, we compute the impulse response based test of symmetry for the different transformations of the oil price.

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. As shown in Kilian and Vigfusson (2009), there are two distinct problems. One is 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. The other is that 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).[5] To avoid this problem we follow Kilian and Vigfusson (2009) and specify an encompassing multivariate dynamic model that allows for possible nonlinearities. We then compute structural impulse response functions for a given horizon, h –conditional on the history Ω^t– that take into account the size of the shock, δ. We will denote these conditional $IRFs$ by $I_y\left(h, \delta, \Omega^t\right)$. Then, averaging over all the histories provides us with the object of interest, that is the unconditional IRF, $I_y\left(h, \delta\right)$. We then compute the Wald test of the null of symmetric response functions, as proposed in Kilian and Vigfusson (2009):

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

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.

[5] 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.

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

As a first pass at the question of nonlinearity we examine whether the response of industrial production to oil price increases and decreases is linear and symmetric. Tables 3 and 4 report the results corresponding to the test of symmetry of the impulse response function for the model (5) where $x_t^{\#}$ represents the positive change in oil prices. That is $x_t^{\#} = x_t^1$ is defined as in equation (1) and first proposed by Mork (1989). Results for a one standard deviation (typical) shock are reported in Table 3, whereas results for a two standard deviation (large) shock are reported in Table 4. To conserve space, the tables in this article report the test results for only four horizons ($h = 0, 1, 6, 12$). Test results for all 13 horizons (i.e., $h = 0, 1, 2, ..., 12$) can be found in section 3 of the on-line appendix.[6] 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 3-6; they correspond to the number of rejections in Tables A.1-A.6 found in the on-line appendix (see section 3).

Contrary to the findings of Kilian and Vigfusson (2009) for real GNP and unemployment on a shorter sample, we find evidence of asymmetry for 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 20 indices (see the first panel of Table 3 and Table A.1 in the on-line appendix). Based on the two standard deviation test we find ample evidence of asymmetry (see the first panel of Table 4 and Table A.4 of the on-line appendix). We reject the null of symmetry for 31 out of the 37 indices at the 5%

[6] 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.1-A.6 of the on-line appendix at http://www.clas.wayne.edu/multimedia/usercontent/File/herrera/HLWappendix.pdf.

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 $h = 0, 4$. Evidence of asymmetry for horizons such that $h > 0$ is also found for chemical materials, textiles materials, motor vehicles and parts, chemicals, motor vehicles, and pottery ceramics and plumbing fixtures. The null of symmetry is also rejected for printing and related at all horizons. Only for one of the market groups (non durable consumer goods) and five of the industry groups (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 to oil price increases and decreases 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, to test whether the net oil price increase (Hamilton 1996, 2003) has additional explanatory power, we estimate the model (5) where $x_t^{\#}$ is now defined as the net oil price increase over the previous 12-month maximum (i.e., $x_t^{\#} = x_t^{12}$ as defined in equation (2)). We then compute the test of symmetry of the impulse response function to typical and large oil price shocks. The test results for a one standard deviation and a two standard deviation shock to this net oil price increase are reported in the second panel of Tables 3 and 4, respectively. Test results for all horizons $h = 0, 1, ..., 12$ are reported in Tables A.2 and A.5 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 can reject the null of symmetry at the 5% significance level for 19 indices at one or more horizons. In general, we fail to reject the null at a 10% level for more disaggregated NAICS sectors with samples that start in 1967 or later, such as foods, beverage and tobacco, textiles and products, apparel and leather goods, chemicals, petroleum and coal, plastics and rubber, newspaper, periodicals, books and others, pottery, ceramics, and plumbing fixtures, glass and glass products, clay product and refractory, other transportation equipment and navigational, measuring, electromedical, and control instruments. For large shocks, evidence of asymmetry is considerably stronger: we can reject the null of a symmetry at the 5% significance level 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 3 and 4, respectively. As can be seen by comparing the results for a net oil price increase over the 12-month previous maximum (second panel of Tables 3 and 4) and the 36-month maximum (third panel of Tables 3 and 4), 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.3 and A.6 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.

We should note here that oil price shocks do not have a statistically significant effect for most of the ten sectors where we cannot reject the null of symmetry at the 5% level (i.e., food, beverage and tobacco, textiles and products, electrical equipment, newspaper, periodical, books and other publisher, pottery ceramics and plumbing, clay product and refractory, glass and glass products, other transportation equipment, navigational, measuring and other instruments). Among these sectors, only for textiles and products, electrical equipment and clay product and refractory do oil price shocks have a statistically significant impact about 8 or more months after the shock.

But, how big is the difference between the response to positive and negative shocks? To illustrate the magnitude of this distance Figures 1a-1e plot the responses $I_y(h, \delta)$ and $-I_y(h, -\delta)$ to a typical 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. Figures A.1a-A.1e in the on-line appendix plot the responses for a large (2 standard deviation) shock. 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.

As can be seen in Figures 1a-1e 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, let us focus on the response to a net oil price

[7] See Figures A.1a-A.1e in the on-line appendix.

increase with respect to the 12-month maximum at $h = 12$, as it is for this horizon and measure that we get more rejections of the null of linearity. Among the industry groups for which we reject the null of symmetry, the ratio of the positive to negative response, $I_y(h, \delta)/I_y(h, -\delta)$, ranges from 1.1 for motor vehicles and parts to 9.0 for transit equipment, and it equals 3.9 for motor vehicles. In fact, for the three aggregates (total, manufacturing SIC, and manufacturing NAICS) the response to a positive shock is more than twice the size of the response to a negative shock.

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.

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 Kilian and Vigfusson (2009) 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. Whereas we consider IP indices starting in 1947:1, the data in Kilian and Vigfusson (2009) begin in 1973. This reflects Kilian and Vigfusson's concern that there was a structural break in the predictive relationship between the real price of oil and U.S. output in 1973. Hence, in this section we report the results obtained using the 1973:1-2009:9 subsample for the indices with full samples starting prior to 1973. Tables 5 and 6 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 3 of the on-line appendix (see Tables A.15-A.20).

There are two reasons that we would expect these results to be potentially 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 (one standard deviation), 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.15-A.17 in section 3 of the on-line appendix). As it can be seen in Table 5, 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 (two standard deviations) 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.18-A.20 in section 3 of the on-line appendix).

All in all, these results are consistent with Kilian and Vigfusson's (2009) 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 very 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. This difference is driven by the extension of the sample beyond Kilian and Vigfusson's (2009) sample period. Kilian and Vigfusson (2010) report similar results for real GDP growth on data for 1973-2009.

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. In other words, rejecting the null for a number of sectors would not be taken as evidence that the response of industrial production 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 (e.g., manufacturing) are constructed as a weighted average of the production indices (with weights that change over time) for a large number of sectors, 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 by comovement across sectors. That is, variability in the total IP index is mainly due to 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. It is interesting to note, however, that there is no exact correspondence between the share of the industry in the total IP index and the economic significance of the departure from symmetry. For instance, using 2008 value added the Board of Governors of the Federal Reserve reports that chemicals and food, beverages and tobacco are the NAICS industries with the highest participation in industrial production (10.92 and 9.93, respectively). Whereas we cannot reject the null of symmetry for food, beverages and tobacco, we find evidence of asymmetry for chemicals where the ratio of the positive to the negative response for a one standard deviation shock at $h = 12$ ranges between 0.83 and 1.04 depending on the nonlinear transformation.

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 3-6.

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 3). 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

[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.

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 4). 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. Evidence of asymmetry is found at the 10% level for foods and tobacco, durable consumer goods, nondurable consumer goods, and chemical materials for at least one horizon and one of the oil measures.

For the 1973-2009 subsample and a typical shock, evidence of asymmetry is found at the 5% level for 3 horizons for transit equipment using the net oil price increase over the previous 36-month maximum. Additionally, for 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. For motor vehicles and parts, chemicals and primary metal, we reject the null at the 10% level. However, once we account for data mining, we do not find any evidence of asymmetry using the subsample and a large 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 Structural stability of the oil price-industrial production relation

An issue that received a great deal of attention in the literature is the structural stability of the oil price-macroeconomy relationship. As we mentioned in the introduction, at the beginning of the 2000s, the consensus in the literature appeared to be that the structural instability found in the relation –following the sharp price declines of 1985-86– was due to misspecification of the nonlinear relation as linear. However, recent work by Blanchard and Galí (2010) suggests that the effect of oil price shocks on economic activity during the 2000s have been muted compared to the 1970s. This recent strand of literature that explores the increased resiliency of the economy to oil price shocks is closely related to the literature on the Great Moderation. Possibly for this reason, recent studies into the nature of the change in the oil price-macroeconomy split the data into two sub-samples around the mid-1980s.[10] Splitting the data in this fashion is consistent with the estimated break date in output volatility and with the mid-1980s collapse of the oil market. Yet, to the best of our knowledge, there is no empirical evidence suggesting that this date may also correspond to a structural break in the *nonlinear* relationship between oil prices and economic activity.

Thus, as a further robustness check, in this section we investigate whether the nonlinear relationship has been stable over time. We focus particularly on the stability of the parameters associated with the nonlinear measure of oil prices; in other words, we test whether the coefficients on the censored oil price have changed while the other coefficients remain unchanged. To this end, we utilize the structural break test by Qu and Perron (2007). Their test has two advantages over Andrews' (1993) test employed by Hooker (1996) to explore the instability in the oil price-macroeconomy relationship.[11] First, it allows the researcher to test for multiple (instead of single) breaks of unknown timing. Second, it has the benefit of applying to a system of equations such as the multivariate dynamic models estimated in this paper.

Qu and Perron's (2007) test for multiple breaks of unknown timing is computed in the following

[10] During the 2000s, economic activity in a number of countries appeared to have been stable in the face of oil price hikes of a magnitude comparable to the shocks in the 1970s. This behavior has bolstered a line of research into the sources of the change in the oil price-macroeconomy relationship. Possible explanations for the increased resiliency of the economy to oil price increases include changes in the composition of oil prices (Kilian, 2009), a smaller share of oil in production (Edelstein and Kilian, 2009), more flexible labor markets (Blanchard and Galí, 2010), and better monetary policy (Leduc and Sill, 2004; Herrera and Pesavento, 2009; Kilian and Lewis, 2010).

[11] Using rolling Granger causality tests and Andrews (1993) structural break test, Hooker (1996) provided evidence that the oil price-macroeconomy relationship broke down after the collapse of the oil market in the 1980s.

manner.[12] Consider the system (5) where lags of a nonlinear transformation of oil prices, $x_t^{\#}$, enter the industrial production growth equation. Rewrite equation (5b) as

$$y_t = z_t' S \beta_j + u_t,$$

where $z_t' = \left[1, x_t, x_{t-1}, \ldots, x_{t-p}, y_{t-1}, \ldots, y_{t-p}, x_t^{\#}, \ldots, x_{t-p}^{\#}\right]$ is a $1 \times (3p+3)$ vector, $S = I_{3p+3}$,

$$\underbrace{\beta_j'}_{1\times(3p+3)} = \left[\begin{array}{ccccccccc} a_{20,j} & \vdots & a_{21,p,j} & \vdots & a_{22,p} & g_{21,0,j} & \vdots & g_{21,p,j} \end{array}\right],$$

and j indicates the j^{th} regime. Parameters $g_{21,0,j}, g_{21,2,j}, \ldots, g_{21,p,j}$ are allowed to change, while the others are not.[13] For more details, see section 2 of the on-line appendix.

We start by testing for one structural break ($m = 1$) or two regimes ($j = 2$) using the $SupLR$ test. Then, we proceed to the case with two breaks, thereby allowing three regimes in the sample periods. The null hypothesis in both cases is no-break; while the alternative hypotheses are one break and two breaks, respectively. Therefore, a test statistic that is higher than the critical value means that we reject the null hypothesis of no-break, against m (= 1 or 2) breaks.[14]

Test results for the three nonlinear measures of oil prices are reported in Table 7 for $m = 1$ and in Table 8 for $m = 2$. Comparing the results for the structural break test using different nonlinear measures of oil prices reveals three interesting results. First, regardless of the nonlinear transformation there is little evidence of a structural break in the coefficients that govern the

[12] GAUSS codes are available from Pierre Perron's website: http://people.bu.edu/perron/code/multivariate-breaks.rar.

[13] Hence, it can be denoted $a_{20}, \ldots, a_{22,p}$ instead of $a_{20,j}, \ldots, a_{22,p,j}$. See section 2 of the on-line appendix for details.

[14] Qu and Perron (2007) recommend a minimum length of the segment for the test to be 20% of the (whole) sample size. However, our oil price data include frequent zeros, often resulting in a non-invertible variance-covariance matrix of the estimator. To avoid computational infeasibility caused by non-invertible matrices, we skip such segments by using a Gauss command "trap 1."

nonlinear effect of oil price shocks. We reject the null of no break in favor of the alternative of one break for 6, 0 and 3 out of the 37 indices using x_t^1, x_t^{12}, and x_t^{36}, respectively (see Table 7). For the same measures of $x_t^{\#}$ the number of rejections for $m = 2$ are 7, 4 and 2 (see Table 8).

Second, the most evidence of a structural break is obtained when we use the oil price increase ($x_t^{\#} = x_t^1$). But, as we mentioned above, even for this measure we only find breaks for a small number of sectors. This finding is consistent with results in the literature that suggest the net oil price increase is better at capturing the nonlinearity in the oil price-macroeconomy relationship, and thus less likely to show structural instability.

Finally, in the cases where there is evidence of a break when $m = 1$, the break date is estimated in the 1980s. For most indices where two breaks are estimated, one break is estimated in the early 1980s and the second break is estimated in the 1990s. In brief, results from Qu and Perron's (2007) test suggest there is little evidence of structural change in the g_i parameters. This is especially the case for the net oil price increase with respect to the previous 36-month maximum. This result, combined with ample evidence of asymmetry using the impulse response based tests, suggests that the net oil price increase over the previous 36-month maximum does a good job at capturing the nature of the relationship between oil prices and industrial production.

We end this section with a caveat. The majority of the literature on the stability of the relationship between oil prices and economic activity tests whether the coefficients on the oil price measure change over time, conditional on the coefficients on economic activity being stable. Here, we restrict the test to the coefficients on the nonlinear transformation of oil prices given that we are interested in the importance of nonlinearities in the response of industrial production to oil price shocks. Obviously, such a test does not directly address the issue raised by Edelstein and Kilian (2009), Herrera and Pesavento (2009) and Blanchard and Galí (2010), among others, that the effect of oil prices on economic activity has been muted in recent years. Test results not reported herein –but available from the on-line appendix (see Tables A.29 and A.30) – reveal a larger number of rejections when we test for structural stability of all the coefficients on the oil variables (i.e. the lags on percentage change in oil prices, x_t, and on the nonlinear transformation, $x_t^{\#}$). Evidence of structural instability is more prevalent for Mork's oil price increase than for the net oil price increase and when we allow for two possible regimes ($m = 1$). Hence, splitting the data in two (or three) sub-samples around the mid-1980s (as is done in the above listed studies) might prove to be a better avenue to explore such change in the response to oil price shocks.

6 Conclusions

In the past two decades, a consensus had emerged in the literature that the oil price-output relationship is asymmetric and nonlinear. This consensus recently has been questioned by Kilian and Vigfusson (2009) who 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 both at the aggregate level and at the sectoral level. We started by testing 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 out of the 37 indices, where we reject the null that the coefficient on the lags of the oil price increase regressor, x_t^1, are all equal to zero at the 5% significance level. Moreover, as Hamilton (1996, 2003) suggests, taking into account the environment in which the oil price increase took place affects the strength of the evidence against the null hypothesis of symmetric slopes. For 19 (25) of 37 IP indices we reject the null of linearity at the 5% significance level using the net oil price increase, x_t^{12} $\left(x_t^{36}\right)$.

We also explored whether our findings are robust to the inclusion of the contemporaneous value of the oil price series, as suggested by Kilian and Vigfusson (2009). The results for these slope based tests are very similar to those obtained using the forecasting equation. We find evidence of asymmetric slope coefficients for 24 out of the 37 indices, where we reject the null that the coefficient on the contemporaneous value and lags of the oil price increase, x_t^1, are all equal to zero at the 5% significance level. For 23 (24) of 37 IP indices we reject the null of linearity at the 5% significance level using the net oil price increase over the previous 12 (36) month maximum.

The evidence of nonlinearity is even stronger when we use the impulse response based test proposed by Kilian and Vigfusson (2009), in particular for the net oil price increase measures. Unlike slope-based tests, this test directly evaluates the degree of asymmetry of the responses of industrial production to positive and negative oil price innovations and may produce different results. We reject the null of symmetry for at least 70% of the industrial production indices for typical shocks and for most of the indices if the oil price shock is large. Nonlinearity appears to be somewhat more prevalent across tests for industries that are intensive in the use of energy by consumers, such as transportation equipment, or in production, such as chemicals. It is also prevalent for sectors for which motor vehicles represent an important demand factor such as rubber and plastic products. Departures from symmetry are economically significant for the typical one standard deviation 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. There is little agreement across different nonlinear specifications, however, on which sectors are responding asymmetrically. These results, moreover, become much weaker after accounting for the data mining that is inherent in evaluating many industrial production indices.

The baseline results also are highly sensitive to whether pre-1973 data are included in the regression or not. There is clear evidence of 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). There is strong evidence against the hypothesis of symmetric responses at the disaggregate level, however, even after accounting for data mining, for the 3-year net oil price increase specification. We reject the null of symmetric responses in response to oil price innovations of typical magnitude for 6 of 28 sectors at the 1-year horizon. 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. Many of the industries that exhibit asymmetric responses are intensive in energy in use or production. Interestingly, however, some industries which one would have suspected of exhibiting asymmetric responses such as the motor vehicles and parts sector, show no sign of asymmetry at a 5% significance level.

Like Kilian and Vigfusson (2010), we also find that there is statistically significant evidence of asymmetric aggregate responses to unusually large oil price innovations in the 1973-2009 data. That result appears to be driven by the inclusion of data from the financial crisis of 2008. 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. Finally, we find very little evidence of a structural break in the parameters that govern the nonlinear effect of oil prices on industrial production. As expected, we estimate structural breaks for more IP indices (6 and 7 out of 37 for $m = 1, 2$, respectively) when using Mork's (1989) oil price increase than when we use the net oil price increase with respect to the previous 12- or 36-month maximum.

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 modelled 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. Industry Code and Sample Period

Sector	Industry code	Sample period
Total Industrial Production	B50001	1947:1-2009:9
Foods and tobacco	B51211	1947:1-2009:9
Clothing	B51212	1947:1-2009:9
Durable consumer goods	B51100	1947:1-2009:9
Miscellaneous durable goods	B51123	1947:1-2009:9
Non durable consumer goods	B51200	1947:1-2009:9
Manufacturing (SIC)	B00004	1947:1-2009:9
Paper products	B51214	1954:1-2009:9
Chemical products	B51213	1954:1-2009:9
Transit equipment	B52110	1954:1-2009:9
Textiles materials	B53210	1967:1-2009:9
Paper materials	B53220	1967:1-2009:9
Chemical materials	B53230	1967:1-2009:9
Motor vehicles and parts	G3361T3	1967:1-2009:9
Food, beverage and tobacco	G311A2	1972:1-2009:9
Textiles and products	G313A4	1972:1-2009:9
Apparel and leather goods	G315A6	1972:1-2009:9
Paper	G322	1972:1-2009:9
Printing and related support industries	G323	1972:1-2009:9
Chemicals	G325	1972:1-2009:9
Petroleum and coal products	G324	1972:1-2009:9
Plastics and rubber products	G326	1972:1-2009:9
Furniture and related products	G337	1972:1-2009:9
Primary metal	G331	1972:1-2009:9
Fabricated metal products	G332	1972:1-2009:9
Machinery	G333	1972:1-2009:9
Electrical equipment, appliance, and components	G335	1972:1-2009:9
Motor vehicles	G3361	1972:1-2009:9
Manufacturing (NAICS)	GMF	1972:1-2009:9
Newspaper publishers	G51111	1986:1-2009:9
Periodical, books, and other publishers	G51112T9	1986:1-2009:9
Pottery, ceramics, and plumbing fixtures	G32711	1986:1-2009:9
Glass and glass products	G3272	1986:1-2009:9
Clay products and refractory	G3271	1986:1-2009:9
Industrial machinery	G3332	1986:1-2009:9
Other transportation equipment	N3369	1986:1-2009:9
Navigational, measuring, electromedical and control instruments	G3345	1986:1-2009:9

Table 2. Slope based test of nonlinearity: Real Prices

	Forecasting Equation			Structural Equation		
Sector	$x_t^{\#} = x_t^1$	$x_t^{\#} = x_t^{12}$	$x_t^{\#} = x_t^{36}$	$x_t^{\#} = x_t^1$	$x_t^{\#} = x_t^{12}$	$x_t^{\#} = x_t^{36}$
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 inst.	**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 3. 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 inst.	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 4. 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 inst.	*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 5. 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 6. 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.

Table 7: Qu and Perron SupLR test for structural change ($m = 1$)

Oil price measure	$x_t^{\#} = x_t^1$		$x_t^{\#} = x_t^{12}$		$x_t^{\#} = x_t^{36}$	
Sector	SupLR	Break date	SupLR	Break date	SupLR	Break date
Total index	30.48		21.20		24.41	
Foods and tobacco	46.36		14.56		21.38	
Clothing	19.02		30.03		14.65	
Durable consumer goods	10.02		7.57		12.61	
Miscellaneous durable goods	35.64		20.45		11.41	
Nondurable consumer goods	35.59		27.26		18.97	
Manufacturing (SIC)	32.62		20.42		20.53	
Paper products	40.91		28.09		n.a.	
Chemical products	37.09		18.60		n.a.	
Transit equipment	19.37		38.12		n.a.	
Textiles materials	35.35		17.98		29.61	
Paper materials	35.88		30.23		22.18	
Chemical materials	41.50		26.23		34.93	
Motor vehicles and parts	13.03		7.10		9.47	
Food, beverage and tobacco	39.92		32.57		16.23	
Textiles and products	29.82		22.47		35.48	
Apparel and leather goods	28.10		23.48		30.24	
Paper	40.76		36.60		29.88	
Printing and related	16.76		11.45		22.69	
Chemicals	**51.64**	1980-7	29.13		22.26	
Petroleum and coal	16.84		13.44		39.75	
Plastics and rubber	**82.24**	1983-4	48.68		**58.66**	1983-4
Furniture	48.19		29.34		29.95	
Primary metal	26.73		15.25		25.66	
Fabricated metal	**50.79**	1983-4	26.94		**49.74**	1991-7
Machinery	25.95		22.55		18.31	
Electrical equipment	**62.90**	1985-12	45.91		47.85	
Motor vehicles	**52.60**	1982-10	16.38		28.02	
Manufacturing (NAICS)	**72.57**	1983-1	48.46		28.23	
Newspaper	27.95		31.54		31.55	
Periodical books and other	35.29		41.30		20.22	
Pottery, ceramics and plumbing	37.58		30.34		42.00	
Glass and glass products	20.47		29.23		**49.74**	2005-2
Clay product and refractory	29.55		19.63		35.59	
Industrial machinery	17.22		14.06		21.44	
Other transportation equipment	12.77		25.66		22.07	
Navigational, measuring and other inst.	17.68		25.23		15.12	

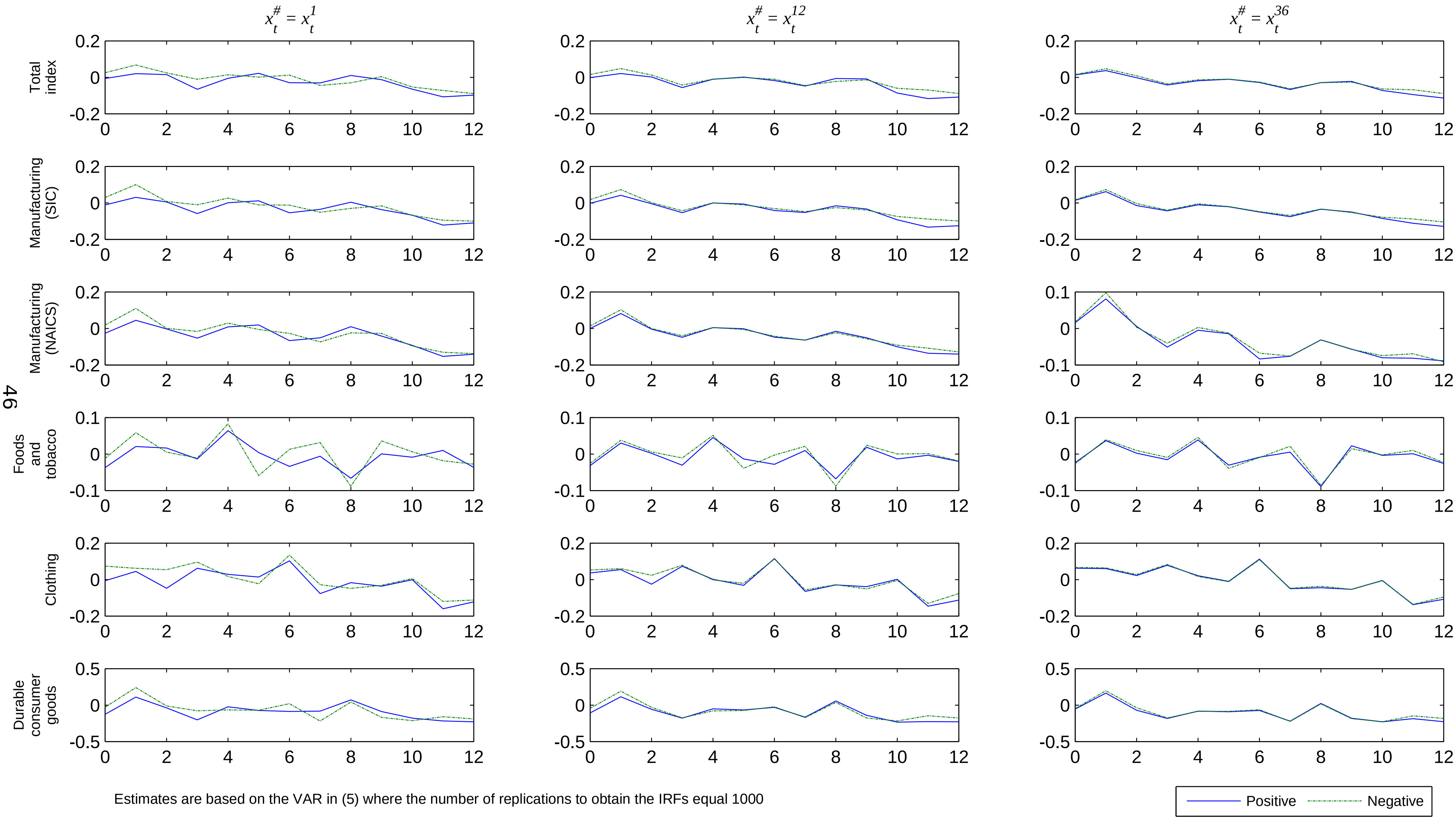
Note: The critical value for the 5% significance level is 49.43. n.a. denotes cases where, due to the large number of zeros in the oil price measure, the test statistic cannot be computed because the regressor matrix for one or more sub-samples has less than full rank.

Table 8: Qu and Perron SupLR test for structural change ($m = 2$)

Oil price measure	$x_t^{\#} = x_t^1$		$x_t^{\#} = x_t^{12}$		$x_t^{\#} = x_t^{36}$	
Sector	SupLR	Break dates	SupLR	Break dates	SupLR	Break dates
Total index	43.01		41.93		42.54	
Foods and tobacco	57.30		43.04		43.30	
Clothing	43.87		42.43		38.33	
Durable consumer goods	42.80		23.93		39.69	
Miscellaneous durable goods	55.48		47.76		23.91	
Nondurable consumer goods	41.75		41.98		29.86	
Manufacturing (SIC)	41.40		42.76		42.39	
Paper products	49.74		35.41		n.a.	
Chemical products	53.03		37.93		n.a.	
Transit equipment	49.39		57.50		n.a.	
Textiles materials	58.92		40.27		48.81	
Paper materials	51.75		42.07		39.96	
Chemical materials	**81.17**	1984-12, 2000-11	59.80		62.01	
Motor vehicles and parts	**77.95**	1985-12, 1998-8	**70.76**	1985-12, 1998-9	60.37	
Food, beverage and tobacco	55.79		48.74		44.56	
Textiles and products	47.50		38.53		42.74	
Apparel and leather goods	58.70		44.99		50.33	
Paper	57.04		55.78		52.70	
Printing and related	31.27		31.15		36.98	
Chemicals	67.93		**70.67**	1984-2, 2001-9	21.11	
Petroleum and coal	23.34		26.09		48.22	
Plastics and rubber	**96.96**	1983-3,1994-10	59.95		**77.41**	1984-6, 1993-11
Furniture	61.84		50.06		60.75	
Primary metal	62.54		44.76		39.10	
Fabricated metal	**74.03**	1983-1, 1993-5	54.29		**68.77**	1991-2, 1998-6
Machinery	55.54		32.56		44.42	
Electrical equipment	**71.79**	1985-12, 1999-3	60.35		65.90	
Motor vehicles	**74.39**	1983-2, 1995-12	63.36		52.38	
Manufacturing (NAICS)	**86.16**	1983-1, 1997-12	63.32		51.32	
Newspaper	59.77		50.23		65.20	
Periodical books and other	59.93		59.31		44.60	
Pottery, ceramics and plumbing	65.59		**71.76**	1999-6, 2004-3	64.40	
Glass and glass products	33.67		**74.58**	1992-4, 2005-2	65.01	
Clay product and refractory	54.19		40.63		67.31	
Industrial machinery	38.07		20.99		39.59	
Other transportation equipment	30.50		53.35		40.65	
Navigational, measuring and other inst.	27.01		21.93		33.75	

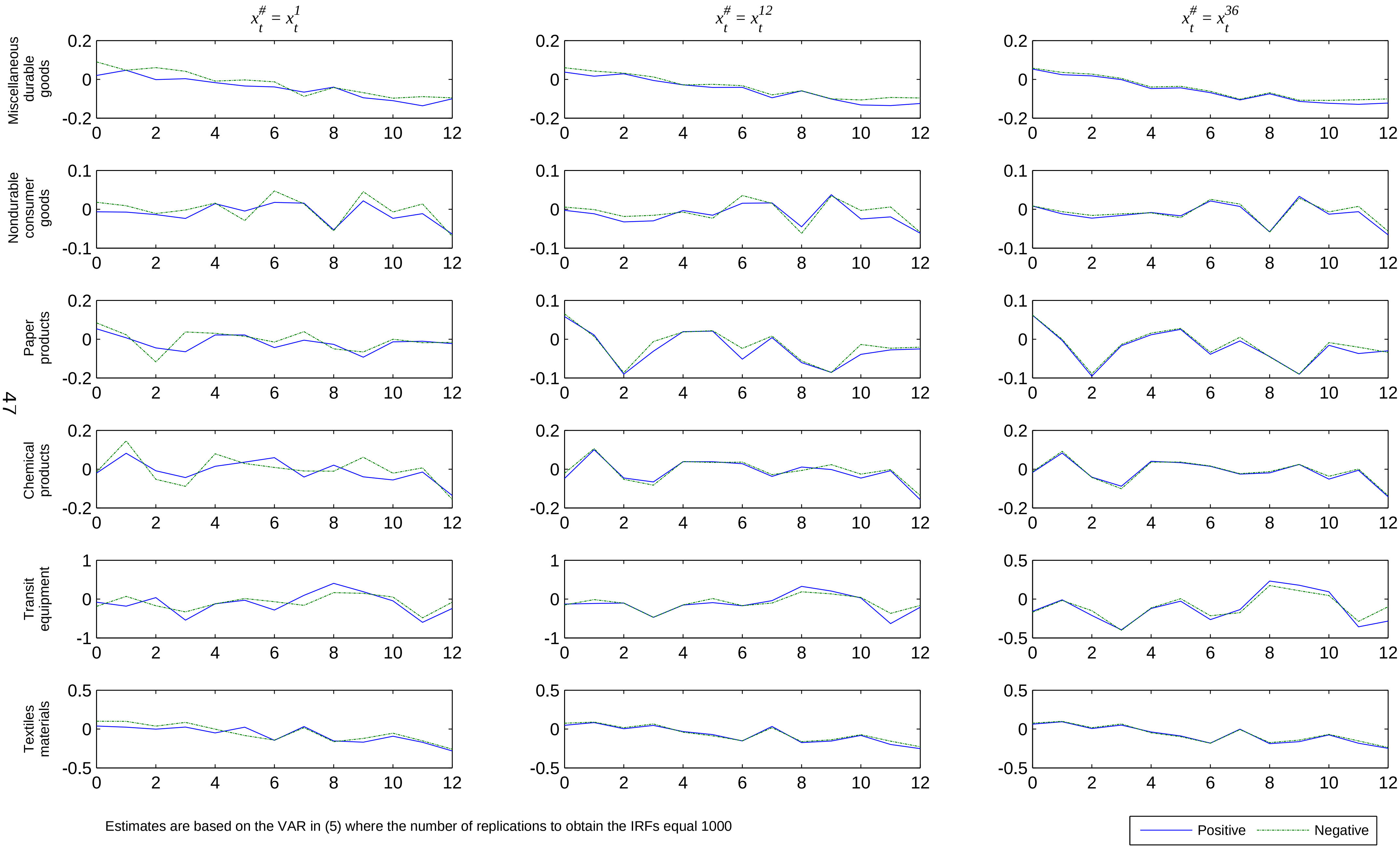
Notes: The critical value for the 5% significance level is 68.045. n.a. denotes cases where, due to the large number of zeros in the oil price measure, the test statistic cannot be computed because the regressor matrix for one or more sub-samples has less than full rank.

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



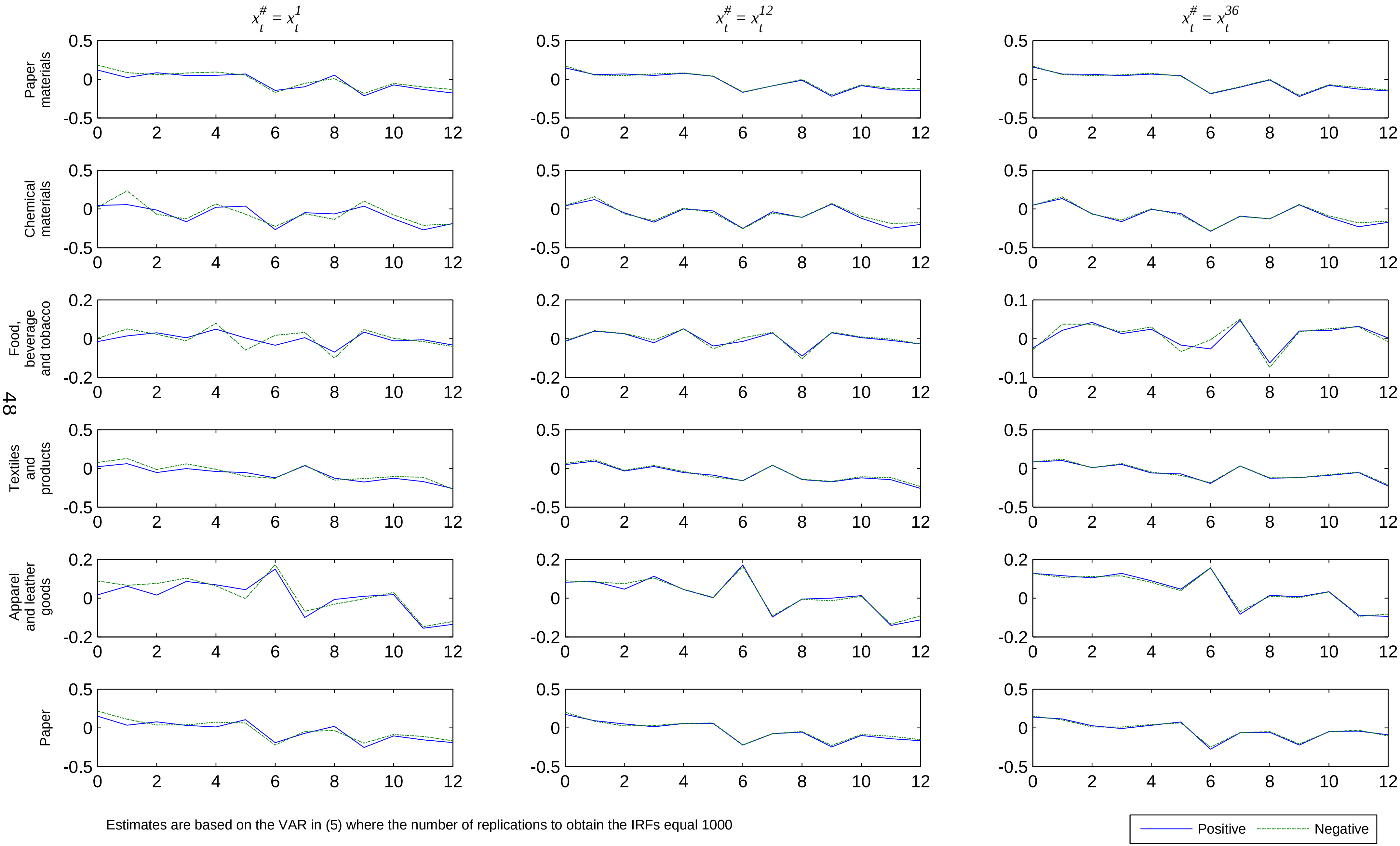
Estimates are based on the VAR in (5) where the number of replications to obtain the IRFs equal 1000

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



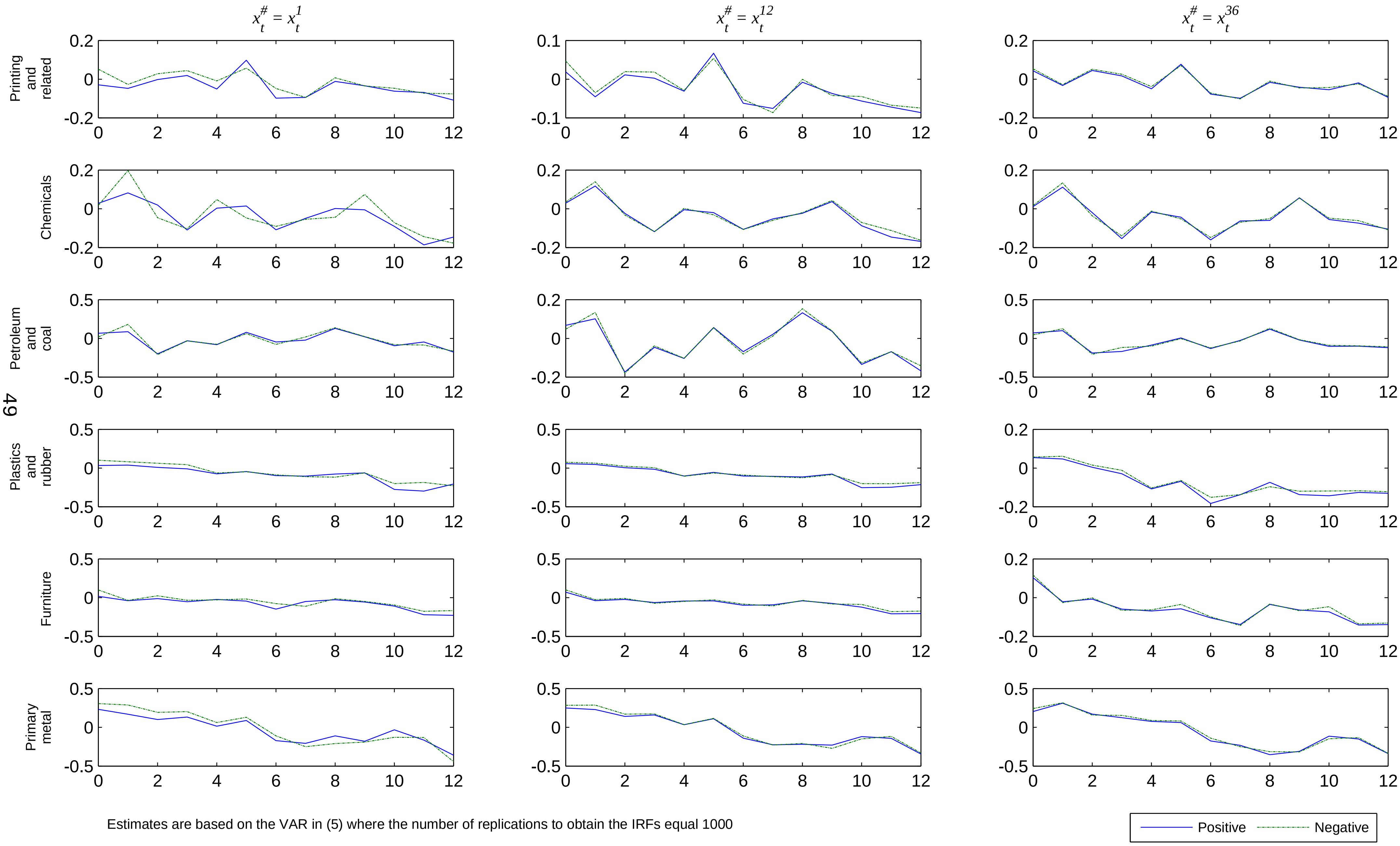
Estimates are based on the VAR in (5) where the number of replications to obtain the IRFs equal 1000

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



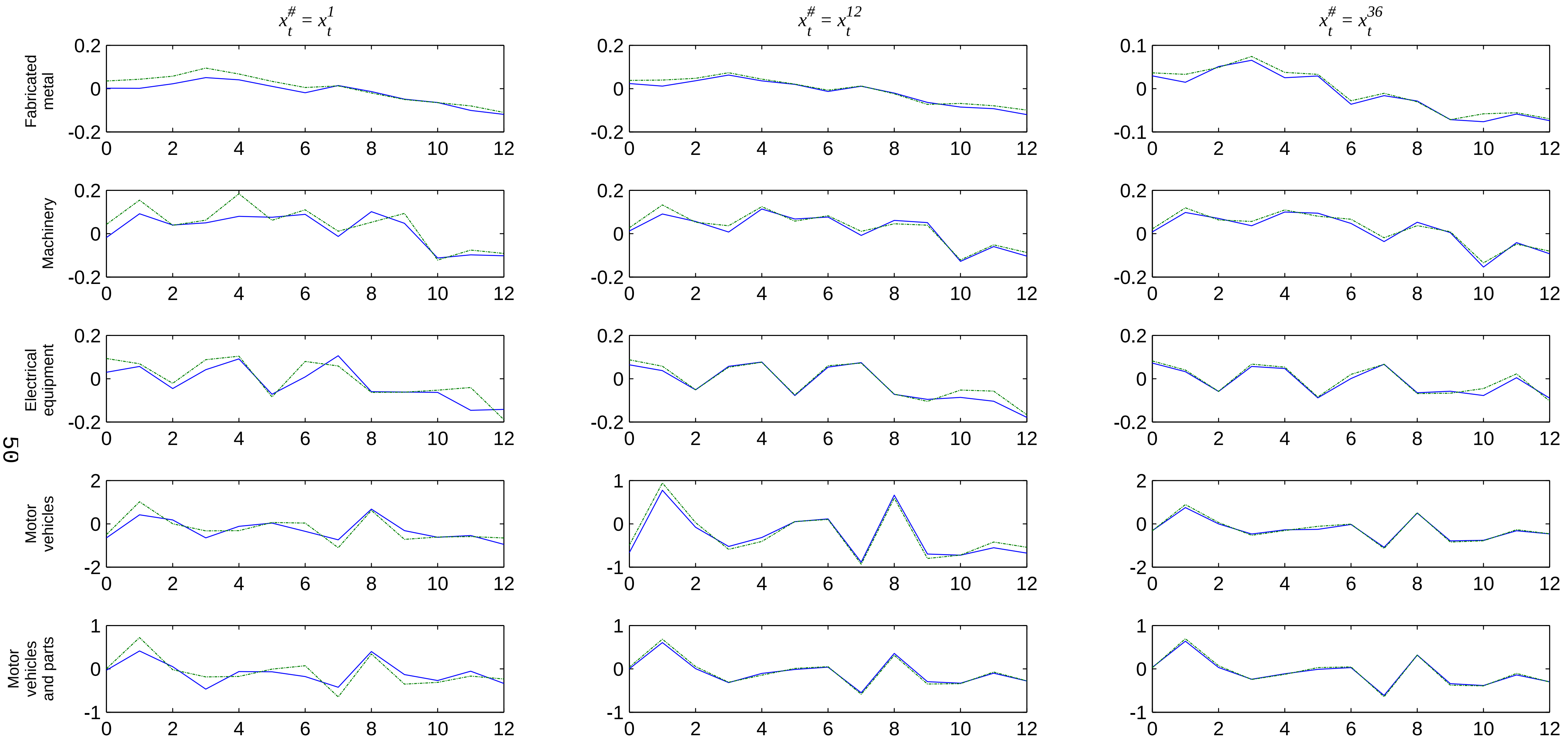
Estimates are based on the VAR in (5) where the number of replications to obtain the IRFs equal 1000

Figure 1d: Impulse response to one 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

Figure 1e: Impulse response to one 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