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Industry effects of oil price shocks: re-examination*

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Abstract: Sectoral responses to oil price shocks help determine how these shocks are transmitted through the economy. Textbook treatments of oil price shocks often emphasize negative supply effects on oil importing countries. By contrast, the seminal contribution of Lee and Ni (2002) has shown that almost all U.S. industries experience oil price shocks largely through a reduction in their respective demands. Only industries with very high oil intensities face a supply-driven reduction. In this paper, we re-examine this seminal finding using two additional decades of data. Further, we apply updated empirical methods, including structural factor-augmented vector autoregressions, that take into account how industries are linked among themselves and with the remainder of the macro-economy. Our results confirm the original finding of Lee and Ni that demand effects of oil price shocks dominate in all but a handful of U.S. industries.

Key words: oil price shocks; SVAR; FAVAR; industry supply and demand
JEL codes: E30, Q43.

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1 Introduction

This paper re-examines the existing evidence on the effects of oil price shocks on U.S. manufacturing industries. Oil price shocks have been historically interpreted as negative supply shocks (e.g. Kim and Loungani 1992, Rotemberg and Woodford 1996, Finn 2000). Since energy is an intermediate input, a rise in the price of oil increases the costs of producing goods and services, thereby reducing supply. Conventional wisdom until the millennium therefore focused on oil price shocks as negative supply shocks. This direct cost mechanism was expected to prevail in the aggregate economy as well as at the industry-level.

In a seminal article, Lee and Ni (2002)[1] discovered that industry responses to oil price shocks did not generally conform to the conventional wisdom. Supply effects were dominant only in a limited number of industries with very high shares on energy costs (petroleum refineries, chemicals). Most of the other industries, including the automobile industry, experienced oil price shocks primarily through demand channels. It was the energy share in production that largely determined if an industry experienced oil price shocks as net demand shocks, rather than net supply shocks. Their formal econometric assessment of the relative importance of the supply and demand effects of oil price shocks relied on the joint dynamics of industry output and prices. Interestingly, the inference from the econometric models was corroborated by the narrative accounts expressed by industry experts in trade journals during the oil crises of 1973-74 and 1978-81.

Since then, the literature has documented the importance of demand channels in the transmission of oil price shocks. A reduction in demand can be caused by a terms of trade shock that reduces the disposable income of consumers in the oil importing economy (e.g. Kilian (2008), Hamilton (2009), Edelstein and Kilian (2009)), a fall in the demand for final goods that are energy-intensive in consumption (e.g. Wei (2013)), a change in the composition of demand (e.g. Ramey and Vine (2011)), increased uncertainty about future oil prices (e.g. Bernanke (1983), Elder and Serletis (2010)) and endogenous monetary policy responses to oil price shocks (e.g. Bernanke et al. (1997), Leduc and Sill (2004)). In addition, industry supply and demand can be affected by sectoral shifts and costly factor reallocation (e.g. Hamilton (1988), Davis and Haltiwanger (2001)).

The results of LN have enhanced the economic profession's understanding of the transmission of oil price shocks, particularly in the U.S. economy. The influence of this seminal finding is evidenced

[1] We will denote Lee and Ni (2002) by LN thereafter.

by the 442 citations it has received in Google Scholar at the time of writing this article. At the same time, the *Journal of Monetary Economics*, where the article was originally published, claims 161 citations in published articles. However, there are several reasons to believe that the relative strengths of supply and demand effects may have changed since 1997, the end of the LN's data sample. First, improvements in energy efficiency in production technologies have likely weakened the input cost effects of oil price shocks. Second, the U.S. dependence on the imported oil has fallen, suggesting that the degree to which global oil prices show up as terms of trade shocks may have diminished. Third, reduced energy-intensities of consumer durable goods may have lowered oil price demand elasticities of those goods. Fourth, the extent to which monetary authorities react to oil price shocks may have changed. Finally, the structure of U.S. industrial production and the nature of interindustry relations have evolved over time. For example, shale oil extraction technology requires lower adjustment cost in changing the flow of production or investment than conventional oil.

Given the reasons above, it is worthwhile to re-examine the original findings of LN to see whether the pattern of industry responses to oil price shocks still holds, and whether there are substantive differences in the strengths of the demand and supply effects of oil price shocks across different industries and across time. We therefore (i) replicate the method of LN, (ii) extend it to a more recent sample and (iii) supplement their approach with an alternative empirical framework.

The econometric results of LN are based on structural vector autoregression (SVAR) models. For each industry, a separate model is set as a block-recursive structural VAR in which industry-specific output and price are added to a common macroeconomic block. The model identifies industry effects of oil price shocks, controlling for the effects of other macroeconomic shocks. The approach of LN is able to offer some insights on contemporaneous effects of oil price shocks on industry demand and supply in a large number of industries.

A possible limitation of the original LN's approach was to assess effects of oil price shocks on one industry at a time. Even though interindustry connections were one of the motivating factors for LN's analysis, it was "not feasible to incorporate all industries in one model" (LN, p. 831) with the econometric methods of the late 1990s. We address this limitation by using factor-augmented vector autoregression (FAVAR) models.

Our FAVAR models combine all industry variables in a single common block and estimate factors that determine industry comovement. It is well known that the behavior of U.S. industries is rather synchronized over the business cycle (e.g. Christiano and Fitzerald (1998)). If the common industry dynamics are important, then the estimated impulses responses from the SVAR models of LN will be consistent but biased. The FAVAR framework can further be extended to consider a large set of macroeconomic indicators. This property resolves a problem of choosing the most relevant macro-variables. In addition, it also allows us to comment on the origin of demand effects.

Our key identifying assumption, which is also consistent with that in LN, is that oil price changes are predetermined with respect to the U.S. macroeconomy at monthly frequency. This assumption is maintained in all empirical specifications of the paper. It implies that oil price shocks drive innovations to the oil price, while other shocks can influence the oil price with a delay of a month. The assumption of oil price being predetermined has been widely used in both empirical and theoretical work (e.g. Rotemberg and Woodford (1996), Edelstein and Kilian (2007), Blanchard and Gali (2007), Blanchard and Riggi (2013)). More importantly, it has some empirical support. For example, Hamilton (1983, 1985) argues that the historical behaviour of the crude oil price prior to the 1980s was explained by events exogenous to the U.S. economy. Kilian and Vega (2011) formally test the hypothesis of oil price predetermination and find no convincing evidence of feedback from U.S. macro-variables to monthly innovations in energy prices.

Overall, our results support the original findings of LN even with the updated sample, a new econometric framework and alternative oil price measures. Reductions in demand remain the key transmission mechanism via which oil price shocks affect U.S. manufacturing industries. Supply effects dominate only in the industries with very high energy costs.

The rest of the paper is organized as follows. Section 2 reviews our empirical framework. Section 3 describes the data. Section 4 presents the replication results from the SVAR models. Section 5 discusses the results from several FAVAR specifications. Section 6 concludes.

2 The empirical framework

A starting point of the analysis is a reduced-form VAR with N variables Y_t,

$$Y_t = c + B(L)\,Y_t + \varepsilon_t. \tag{1}$$

The N-dimensional vector c has constant terms. $B(L)$ is a matrix of polynomials of the lag operator L. The vector of error terms ε_t has a zero mean and the variance-covariance matrix Ω. Elements of Y_t are partitioned into two subvectors Y_{1t} and Y_{2t} with dimensions N_1 and N_2.

$$Y_t = \begin{bmatrix} Y_{1t} \\ Y_{2t} \end{bmatrix}, c = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix}, B(L) = \begin{bmatrix} B_{11}(L) & B_{12}(L) \\ B_{21}(L) & B_{22}(L) \end{bmatrix},\ \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix},\ \Omega = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix}.$$

The SVAR and FAVAR approaches differ in their choice of the variables, as explained below.

Identification of oil price shocks is based on a structural representation

$$A_0 Y_t = A_0 c + A_0 B(L) Y_t + u_t, \tag{2}$$

$$u_t \equiv A_0 \varepsilon_t,\ E(u_t) = 0,\ E\left(u_t' u\right) = I \tag{3}$$

where A_0 is an invertible $N \times N$ matrix. The structural shocks u_t are orthogonal to each other, with the unitary variance matrix. This section summarizes the restrictions imposed on A_0 and discusses identification and estimation of SVAR and FAVAR models. The key identification assumption is that the oil price is predetermined with respect to current changes in the U.S. economy.

2.1 The SVAR approach of LN

LN propose a non-recursive identification strategy that fully identifies structural shocks. In their model, a set of Y_{1t} macro-variables includes a money stock measure, a short-term interest rate, an aggregate price index, a long-term interest rate, industrial production and an oil price measure ($N_1 = 6$). The vector Y_{2t} consists of industry-specific output and price measures ($N_2 = 2$). There are N^2 elements in the matrix A_0, but only $N(N+1)/2$ independent moments in the variance-covariance matrix Ω. Since $A_0^{-1} A_0 = \Omega$, the full identification of the structural shocks requires at least $N(N-1)/2$ restrictions on A_0. For identification purposes, the matrix A_0 and the structural shocks u_t are partitioned into the macro and industry elements, as in

$$A_0 = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, u_t = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix},\ E\left(u_t u_t'\right) = \begin{bmatrix} I_1 & 0 \\ 0 & I_2 \end{bmatrix},$$

where the identity matrices I_1 and I_2 have dimensions $N_1 \times N_1$ and $N_2 \times N_2$. The restrictions are chosen as follows.

First, the oil price is assumed to be predetermined with respect to U.S. macroeconomic and industry-specific variables within a month. This means that the only non-zero element in the oil price equation in the matrix A_0 corresponds to the oil price shock. The oil price, however, is allowed to respond to other U.S. macro-shocks in the following months.

As mentioned early, the assumption that oil price changes are predetermined is supported by the results of Kilian and Vega (2011). It is worthwhile to note that LN do not identify the origin of oil price shocks. Dynamic responses of economic variables to oil price shocks are known to differ depending on whether oil price changes are triggered by supply shocks or by demand shocks in energy markets (e.g. Kilian 2009). However, incorporating global energy markets into the structural model of LN is not straightforward, and we do not attempt to do so. Our identified oil price shocks thus reflect the influence of the unknown composition of supply and demand shocks in energy markets. As in Edelstein and Kilian (2007, 2009), the impulse responses, reported in LN and in our paper, are best viewed as an average of historical responses to oil price shocks of the different origin over the sample period.

Second, it is assumed that the macro-variables do not respond to industry-specific shocks contemporaneously: $A_{12} = 0$. Further, the lagged effects of the industry shocks on the macro-variables are also excluded by imposing the zero restrictions $B_{12}(L) = 0$. The block-recursive structure of $B(L)$ is not critical for identification. However, combined with the assumption on A_{12}, it enables the estimation of all macro-block parameters (c_1, B_{11}, Ω_{11} and A_{11}) independently from the industry data. As a result, the identified macroeconomic shocks remain the same across the VAR models for different industries (see section 4.1 in LN for details). We have found that the block-recursive restrictions on B_{12} were supported by likelihood ratio tests in all but one case. Even in that exceptional case, the estimated covariance of macro-variables Ω_{11} was not substantially altered by the presence of the industry-specific variables.[2]

Third, identification of other macroeconomic shocks relies on the "information-based" approach, developed by Sims (1994), Gordon and Leeper (1994) and Sims and Zha (2006). LN hypothesize that the macro-block is driven by the structural shocks in money demand, money supply, price setting, bond yield and aggregate demand, in addition to oil price shocks. The shocks are identified via exclusion restrictions imposed on A_{11}. This matrix determines the relationship between the structural shocks u_{1t} and the residuals ε_{1t} from (1). The exclusion restrictions correspond to the views that (i) the money supply does not respond to current output and the price level, due to the publication lag for these series; (ii) the money demand is determined by the level of prices, aggregate income and short-term interest rates; (iii) the goods market does not react to current

[2]The exception was the apparel industry in 1972:1-1997:9. LN rejected the block-recursiveness of B_{12} for most industries, but that did not have much impact on the estimate of Ω_{11}. The differences in our results are likely to be attributed to the differences in the samples and the data.

money disturbances, and (iv) long bond rates reflect the term structure of interest rates and react quickly to any new information. These structural equations are detailed in section 4.2 in LN.

Overall, the non recursive identification strategy of LN imposes 16 zero restrictions on the elements of the A_{11} matrix. The model has one overidentification restriction. The 20 parameters of A_{11} are estimated with the maximum likelihood method from the 21 independent moments of the OLS-based estimate $\hat{\Omega}_{11}$. In addition, macroeconomic theory gives guidance for the signs of 17 elements of A_{11}. While the sign restrictions are not used in the estimation, they are nevertheless useful for detecting any major flaws with identification.

The final set of restrictions applies to $A_{21}\varepsilon_{1t} + A_{22}\varepsilon_{2t} = u_{2t}$, i.e., the two equations with industry variables. Conditional on the macro-variables, the residuals of the output and price equations in the reduced-form VAR y_i and p_i are related to the structural shocks u_{yi} and u_{pi} as

$$c_{21}m + c_{22}r + c_{23}cpi + c_{24}b + c_{25}ip + c_{26}oil + c_{27}y_i + c_{28}p_i = u_{yi}, \tag{4}$$

$$c_{29}m + c_{30}r + c_{31}cpi + c_{32}b + c_{33}ip + c_{34}oil + c_{35}y_i + c_{36}p_i = u_{pi}, \tag{5}$$

where the coefficients c_{kl} represent the corresponding elements of A_{21} and A_{22}. These equations correspond to the equations (9) and (10) in LN.

Equations (4) and (5) are viewed as defining the contemporaneous demand and supply relations in industry i. The price elasticities of output are given by $-c_{28}/c_{27}$ and $-c_{36}/c_{35}$. The identification in LN is motivated by a restriction that the product of these elasticities should be negative. This non-linear restriction is difficult to estimate. We follow an approximation procedure, proposed by LN. Specifically, we first estimate the reduced-form VAR and divide the logarithms of industrial output and price by their respective standard deviations of the VAR residuals from the output and price equations. We then use the scaled data to estimate the modified equations (4) and (5) under the restriction that $\tilde{c}_{35} = -\theta\tilde{c}_{28}$, $\theta > 0$.[3] In the structural VAR with the scaled data, the product of the price elasticities of the rescaled output is approximately $-1/\theta$. The parameters of the SVAR for the original data are recovered from the SVAR estimates for the scaled data. The value of the positive hyper-parameter θ is fixed to 2 for all industries.[4]

A classification of equations (4) and (5) as supply and demand is useful to understanding the industry effects of oil price shocks. This classification is based on the signs of the estimated

[3]The tildes are added to the structural coefficients to differentiate between the model with the scaled data.

[4]LN show that the estimation results are not materially affected by alternative values of θ.

coefficients $\hat{c}_{28}$ and $\hat{c}_{35}$. Since $\hat{c}_{27}$ and $\hat{c}_{36}$ are positive by construction, $\hat{c}_{28} < 0$ implies that equation (4) is a supply equation, while equation (5) describes industry demand. If $\hat{c}_{28} > 0$, supply and demand are given by (5) and (4).

Following LN, we also tried two separate exclusion restrictions for the off-diagonal elements of A_{22} for the shorter replication sample. The restriction $c_{28} = 0$ implied that output in (4) was perfectly price inelastic. The restriction $c_{35} = 0$ assumed that output in (5) was perfectly price elastic. We found that the estimates of the matrix A_{21} as well as the industry responses to the oil price shocks were not materially affected by the different industry identification assumptions.

2.2 The FAVAR approach

A FAVAR model augments the VAR model (1) with a dynamic factor model. The model postulates the existence of K unobservable factors F_t that drive comovement of M economic variables X_t,

$$X_t = \Lambda F_t + e_t, \tag{6}$$

where Λ is an $M \times K$ matrix of factor loadings. The $M \times 1$ vector of error terms e_t has mean zero and satisfy the cross-correlation restrictions defined in Stock and Watson (2002). The factors can be viewed as capturing the influence of unobserved shocks, common to all the variables in X_t. Error terms reflect idiosyncratic shocks. The vector of factors F_t defines the vector Y_{2t} in the VAR part of the model. We choose the composition of Y_{1t} and X_t in two different ways.

The first model, IND-FAVAR, is a natural extension of the LN's approach to incorporate industry interconnections. Y_{1t} keeps the six macro-series from LN. X_t contains output and price series of all industries. Unlike the two series that are specific to each industry, Y_{2t} includes the estimated factors that govern comovement across the industries. Thus, $N_1 = 6$, $N_2 = K$ and $M = 28$. If the industry interconnections are important then the estimated impulse response functions from a SVAR that only includes industry-specific output and price for a particular industry will be biased.

The second model, FULL-FAVAR, is motivated by a monetary FAVAR of Bernanke et al. (2005). Y_{1t} includes only the oil price measure ($N_1 = 1$). X_t consists of our industry variables plus a balanced panel of 120 monthly macroeconomic variables used by Bernanke et al. (2005) ($M = 148$). All the LN's variables (except for the oil price) are a part of the balanced panel. Even though the FULL-FAVAR model is not directly comparable with the SVAR of LN, it has several advantages. First, the behaviour of all industries is studied jointly, allowing for industry linkages. Second, possible feedbacks between industry and macro-variables are accommodated. Third, by including a large set of variables, the model avoids an arbitrary choice of the key macroeconomic indicators. No single series can accurately measure unobservable economic concepts, such as 'economic activity' or 'supply-side drivers.' In this context, a large FAVAR data set is more likely to adequately capture these economic concepts. Fourth, analyzing a large data set simultaneously can also help understand the transmission of oil price shocks. Finally, the factor block of the macro-variables in Bernanke et al. (2005) is shown to capture well the information about U.S. real activity and prices.

We estimate the FAVAR model, defined by (1) and (6), following a two-step procedure of Bernanke et al. (2005). During the first step, factors in (6) are estimated by the principle component analysis. When the number of variables in the factor block and the sample size are large, the principal component estimator of the factors consistently estimates F_t up to premultiplication by an arbitrary nonsingular $K \times K$ matrix. This identification problem is solved by choosing a standard restriction $\Lambda'\Lambda/M = I$. This arbitrary normalization implies that the estimated factors do not have a direct economic interpretation. However, the choice of normalization is inconsequential. We have found that the comovement among the variables in the IND-FAVAR and FULL-FAVAR models can be well captured by four and eight factors, respectively.

In the second step, the factors are put into the factor-augmented VAR (1). We identify oil price shocks recursively, by placing the oil price measure first in the VAR. As noted earlier, this assumption implies that innovations in the oil prices are not affected contemporaneously by innovations in any other variable. The VARs include a constant and 12 lags of the endogenous variables. The estimated factors are "generated regressors." The uncertainty in the factor estimation is taken into account in computing the bootstrap confidence intervals.[5]

The principal components are estimated from stationary data, so all series in the factor blocks are transformed to induce stationarity. Industry output and price series enter in log-differences, demeaned and normalized by their standard deviations. The other variables and their transformations are listed in Appendix 1 of Bernanke et al. (2005). For comparability with the SVAR analysis, we recover and report the impulse responses of the log-levels of industry series.

[5] We use the non-overlapping block bootstrap of Forni and Gambetti (2010) for FULL-FAVAR. This method does not work well for IND-FAVAR because the VAR includes non-stationary series. For that model, we rely on the standard residual-based bootstrap.

3 Data

LN work with the monthly data from 1959:1 to 1997:9. Due to the availability of industry data, our main results are based on two samples. The first sample, 1972:1-1997:9, overlaps with the sample of LN. The second sample, 1972:1-2017:2, spans the recent data. The data were retrieved primarily from Haver and the databases of the Federal Reserve of St. Louis and Philadelphia.

The benchmark oil price variable is the net oil price increase (NOI) of Hamilton (1999), as in LN. The measure is defined as the percentage change of the oil price over the maximum value of the preceding year if the price of the current month exceeds the previous year's maximum, and zero otherwise.[6] The oil price series selected for the construction of the NOI is refiners' acquisition cost of crude oil (composite) after 1974:1 and the producer price index (PPI) for crude petroleum, adjusted for the effects of the price controls in the 1970s, as in Mork (1989), which we denote as RAC.[7] For robustness, we also use three alternative oil price variables: (i) the RAC series, (ii) the RAC series adjusted by the PPI for all commodities (RACR), and (iii) the WTI series, equal to the West Texas Intermediate spot oil price until 2013:7 and Cushing WTI spot price after.

The macro-blocks in the SVAR model of LN and in the IND-FAVAR model include the M2 money stock, the 3-month treasury bill rate, the Consumer Price Index (CPI), the interest rates on 10-year treasury notes, industrial production (IP) and an oil price variable. All data are seasonally adjusted. The original data set of LN is not available. Given that macro-variables go through revisions (e.g. Kozicki (2004)), we use historical data for M2, CPI and IP that were available in January 1999 to replicate the results for the macro-block. The macroeconomic series in the FULL-FAVAR model are the same as in Bernanke et al. (2005).

LN selected 14 manufacturing industries with different oil-intensities. Partly due to a switch from the Standard Industry Classification (SIC) system to the North American Industry Classification System (NAICS), industry-level data prior to 1972 are no longer available on a consistent basis. Thus, our industry matching has been hindered by a number of definitional, classificational and statistical changes. In particular, we were unable to find the exact NAICS match for the electronic machinery and office and computing machines industries. These industries were substituted with electrical equipment except appliances and computer and peripheral equipment. Table 1 summarizes the concordance between LN's and NAICS industries. The order of the industries here and in

[6] LN divide the measure by 100, to avoid large discrepancies in the scales of the estimated structural parameters.
[7] The use of Ramey-Vine (2011)'s full cost of gasoline instead of NOI had minimal effects on our results.

the rest of the paper follows that in LN, by decreasing total oil and gas costs.

Table 1: Industry concordance and costs of oil and natural gas for each dollar of sale in 2007

Industry in LN	Industry in the 2007 NAICS code	Direct cost	Total cost
Petroleum refinery	Petroleum refneries (32411)	0.683	1.868
Industrial chemical and synthetic materials	Chemical manufacturing (325)	0.052	0.261
Paper	Paper products (322)	0.010	0.118
Rubber and plastic	Rubber and plastic products (326)	0.007	0.185
Nonferrous metals	Nonferrous metals (3313 and 3314)	0.004	0.103
Iron and steel	Iron and still products (3311 and 3312)	0.005	0.115
Lumber products	Wood products (321)	0.009	0.089
Apparel	Apparel manufacturing (315)	0.001	0.053
Household furniture^{s}	Household and institutional furniture and kitchen cabinet manufacturing (3371)	0.001	0.077
Household appliance	Household appliance (3352)	0.001	0.073
Automobile	Motor vehicles and parts (3361-3363)	0.001	0.067
Electronic machinery^{A}	Electrical equipment except appliances (3351, 3353 and 3359)	0.001	0.044
Construction machinery	Construction machinery (33312)	0.005	0.065
Office and computing machines^{B}	Computer and peripheral equipment (3341)	0.001	0.039

Notes: Direct and total costs correspond to direct and total requirements for the products produced by the NAICS industries 211000, 324110, 324121 and 324122 in industry production costs. The calculations are based on the detailed Industry-by-Commodity Direct and Total Requirement tables from 2016 Survey of Current Business. The order of the industries follows Lee and Ni (2002). Industries with the superscripts ^{A} and ^{B} do not have direct NAICS equivalents.

Table 1 also reports two indicators of oil-intensity of production. Direct combined costs of oil and natural gas correspond to the dollar amount spent by an industry on oil and gas products to produce a dollar of the industry's output. The total costs represent the sum of direct and indirect purchases of oil and natural gas to produce a dollar of industry's output. For example, total requirements of oil and gas for automobile production include energy costs to produce the aluminum, which was used in the production of the car's engine and frame.

Table 1 shows that the patterns of industry energy requirements in 2007 were relatively similar to that in 1977, reported by LN. Petroleum refineries and chemical manufacturing remain the largest petroleum users. For example, the chemical industry spends 26.1 cents on oil and gas for each dollar of revenue, out of which only 5.2 cents are direct costs. The total costs for petroleum refineries even exceeds the industry revenue. Total cost shares are much larger, which may suggest that energy content of intermediate inputs may amplify the supply side effects of oil price shocks.

Industry matching for output and prices is further complicated by the fact IP and PPI are produced by different statistical agencies (the Board of Governors and the Bureau of Economic Analysis). When the PPI for a particular industry is not reported at the industry level for the whole sample, we rely on the PPI by commodity. Even though the PPIs by commodity are based on a unique classification, there is a relatively close correspondence between industries and commodities they produce, at the level of our industry aggregation. The nominal prices are converted into real terms using the PPI of all commodities.

4 Replication results

This section discusses our best attempt to replicate the findings of LN. We were rather successful in reproducing their results for the macro-block of the identified SVAR. In replicating the industry results, we faced a challenge of data availability. As explained in the previous section, our data differed in the time coverage and industry compositions. Our estimated patterns of industry responses to oil price shocks were not completely identical to that in the original study of LN. Yet, we confirm their main conclusions: reduction in supply has consistently dominated the industry adjustment to positive oil price shocks only in highly oil-intensive industries, while reduction in demand has historically played an important role in explaining the effects of the oil shocks in the majority of the industries.

4.1 The macro-block from the non-recursive SVAR

In replicating the results of LN for the six macroeconomic variables, we first analyze the parameter estimates for the variance-covariance matrix of the VAR residuals $\hat{\Omega}_{11}$ and the structural matrix $\hat{A}_{11}$. Similar to LN, all VAR models include a constant and 12 lags of the endogenous variables. The confidence intervals are computed using the bootstrap-after-bootstrap method of Kilian (1998). We reproduce LN's estimates of the macro-block parameters in Tables 2 and 3, and report our replication of these statistics with the 1999-vintage data and the same sample period. We then focus on the effects oil price shocks on IP. Since monetary policy shocks are not central to our analysis, we delegate the discussion of these shocks to the Appendix. Overall, we are able to closely match the estimates of the macro-block.

Table 2: Variance-correlation matrix of residuals of the macro-variables (1959:1-1997:9)

	M2	INT3	CPI	LB	IP	HOILG
A. Statistics from Table 4 of Lee and Ni (2002)						
M2	3.33e-006	-0.103	-0.023	0.017	0.043	0.070
INT3		0.137	0.103	0.571	0.190	0.021
CPI			2.96e-005	0.154	0.013	0.166
LB				0.054	0.159	0.010
IP					4.00e-005	-0.065
HOILG						3.64e-004
B. Estimates based on the 1999-vintage data						
M2	3.51e-006	-0.109	-0.032	0.018	0.034	0.049
INT3		0.158	0.110	0.576	0.186	-0.029
CPI			3.48e-006	0.156	0.006	0.154
LB				0.063	0.159	-0.030
IP					4.89e-005	-0.070
HOILG						4.20e-004

Notes: The diagonal elements correspond to the variances of the reduced-form residuals from the VAR with six macro-variables. The off-diagonal elements are the correlation coefficients.

The size and the signs of the variances and correlations in Table 2 are comparable to each other, except for the variance of the CPI residuals.[8] Table 3 summarizes the estimates of the structural macro-block parameters in a matrix form. As in LN, the signs of all coefficients are consistent with prior economic theory predictions. Although the coefficients in panel B are less precisely estimated than in panel A, the magnitude of the estimates is similar in most cases.[9] Our standard errors are bootstrap-based, which may explain the differences with LN's estimates.

Figure 1 plots the impulse responses of industrial production to a positive oil price shock. The size of the shock is set to be identical to one standard deviation of the oil price innovations reported by LN ($u_{oil} = 0.019$). The dynamic path of IP on the left panel of Figure 1 bears a strong similarity with LN's original results. Output declines significantly ten month after the shock. The peak effect of -0.36% occurs in the sixteen month, after which output starts to recover. In comparison, LN

[8]Although the correlations between the residuals from the oil price and interest rate equations are of the opposite signs, they are not statistically significant.

[9]By comparing the reported impulse responses and the estimates in Gordon and Leeper (1994), we have discovered that the coefficients on r and m in the money supply equation in Table 5 of LN should be switched.

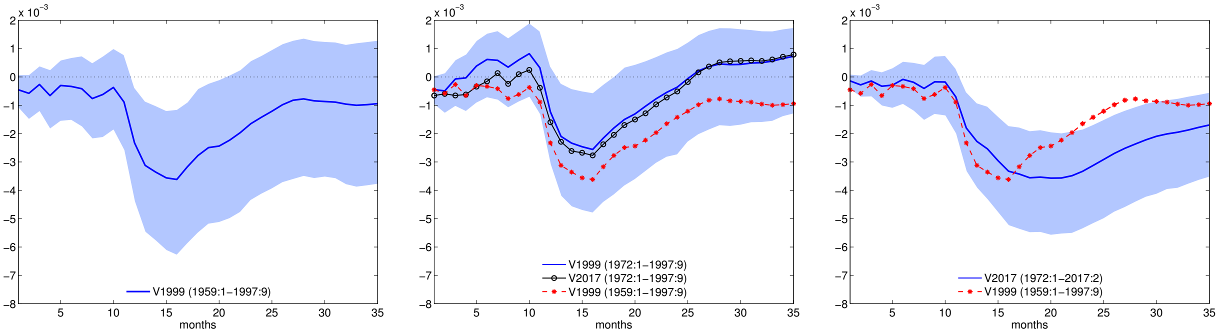
Table 3: Estimates of the structural parameters of the macro-block (1959:1-1997:9)

	m	*r*	*cpi*	*lb*	*ip*	*oil*
A. Statistics from Table 5 of Lee and Ni (2002), 1959:1-1997:9						
MD	194.93 (157.32)	2.70 (0.23)	-53.52 (28.77)		-32.32 (7.55)	
MS	-460.33 (165.45)	1.34 (1.38)		-2.00 (2.46)		2.80 (2.80)
PS			589.48 (19.59)		-3.74 (10.72)	-8.87 (2.49)
LB	-243.56 (218.41)	-1.48 (0.92)	-80.24 (29.00)	4.92 (1.02)	-8.40 (7.86)	2.63 (2.86)
AO					158.43 (5.26)	3.37 (2.46)
OP						52.37 (1.74)
B. Estimates based on the 1999-vintage data, 1959:1-1997:9						
MD	270.26 (274.13)	2.38 (1.95)	-46.06 (56.33)		-27.50 (23.55)	
MS	-356.87 (291.99)	1.84 (1.82)		-2.76 (3.07)		1.60 (3.83)
PS			542.35 (39.29)		-2.45 (8.74)	-7.69 (2.99)
LB	-305.00 (233.24)	-0.89 (1.36)	-80.65 (77.24)	4.12 (3.46)	-10.54 (17.48)	3.29 (4.52)
AO					143.39 (6.35)	3.40 (4.36)
OP						48.82 (20.88)

Notes: The numbers in parantheses are standard errors, taken from LN for panel A and boostrap-based for panel B. For the ease of reading, the zeros for the exclusion restrictions are replaced by empty cells. The row names correspond to the following structural equations: MD = money demand, MS = money supply, PS = aggregate price setting, LB = long bond rate, AO = aggregate output, OP = oil price. The column names denote the reduced-form VAR residuals.

estimate output decline in the range of 0.35-0.40%. The transitory effects from the oil price increase tend to dissipate within a year. The middle panel of Figure 1 demonstrates that the results for IP generally hold in the 1972-97 sample. This panel also shows that historical data revisions had a minimal impact on the estimated IP responses. Finally, the right panel reveals that oil price shocks have more persistent effects in our full sample.

Figure 1: IP responses to an oil price increase (non-recursive SVAR model)

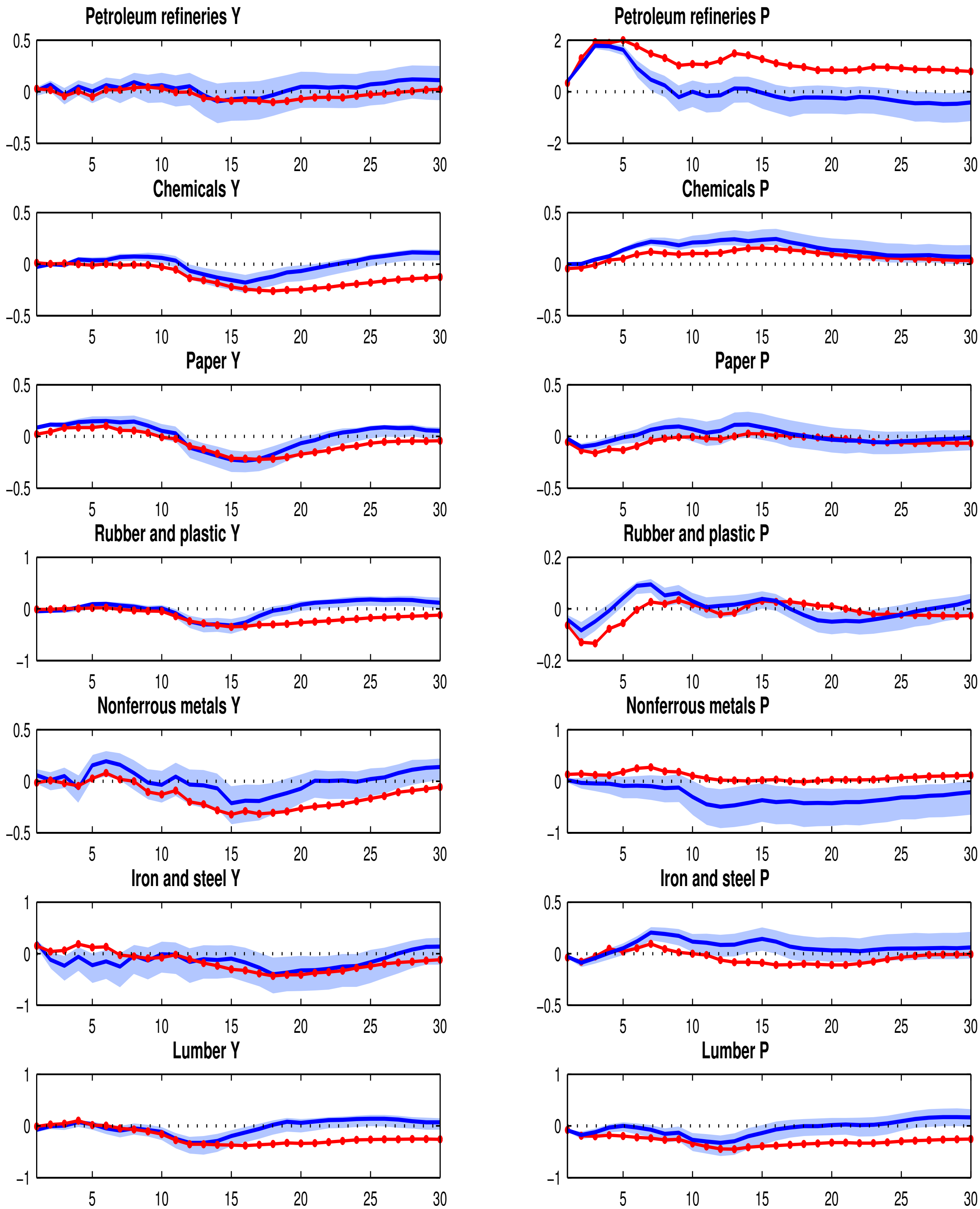


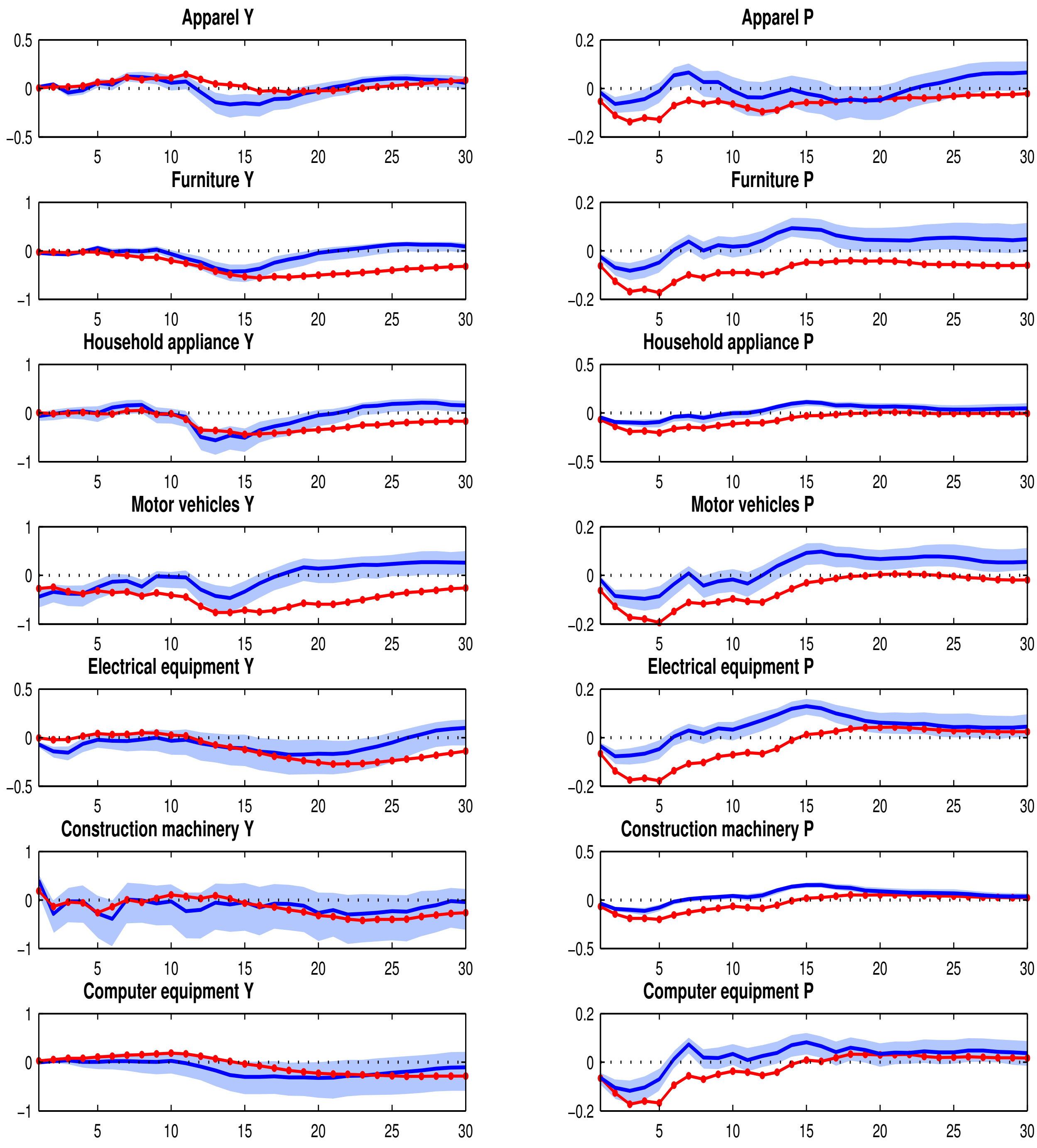
Notes: The impulse responses are estimated with the non-recursive model of Lee and Ni (2002). The size of the shock u_{oil}=0.019. The shaded areas are the 16 and 84 percentile bootstrap confidence bands for the impulse responses that are represented by the solid lines. V1999 and V2017 indicate the vintage of the data used in the estimation. The sample periods are in parentheses.

4.2 The industry results from the non-recursive SVAR

The key novelty of LN was to document the relative importance of supply and demand effects of oil price shocks in U.S. industries. The structural identification of equations (4) and (5) allowed them to identify contemporaneous effects of oil prices shocks on industry supply and demand. Yet, the main inference was based on the impulse responses of industry output and prices. Our discussion of the industry results thus focuses on the dynamic responses. We comment on the structural parameter estimates at the end of this subsection.

Figure 2: Impulse responses of industry-level output and price to a one percent oil price shock (non-recursive SVAR; 1972:1-1997:9 and 1972:1-2017:2)





Notes: The solid lines with shaded areas are the median impulse responses (in percent) and the 16 and 84 percentile bootstrap confidence bands for 1972-1997. The lines with circles are the responses for 1972-2017.

Figure 2 plots the impulse responses of industry output and price measures, Y and P, to a one percent oil price shock. The solid lines with the shaded areas correspond to the 1972:1-1997:9 period, which overlaps with LN's sample. For comparison, the lines with circles represent the impulse responses in the extended sample. The confidence bands are omitted for clarity of the figure. Table 4 records peak output and price responses, while Table 5 describes the pattern of industry effects of oil price shocks.

Oil price shocks affect industries differently through various supply and demand channels. For example, higher production costs, reduced discretionary income of consumers, increased uncertainty about the future path of oil prices, monetary policy tightening in anticipation of higher prices, in the aftermath of the oil price shock will all have negative effects on industry's production. However, it is also possible for an industry to experience positive supply and demand effects. Industry supply can increase if the higher energy costs are offset by inflows of labor and capital. Demand effects may be positive for industries that produce energy-efficient products.

Table 4: Peak responses of industry output and price to a one percent shock to the net oil price increase measure (non-recursive SVAR).

	1959:1-1997:9		1972:1-1997:9		1972:1-2017:2	
Industry	Y peak	P peak	Y peak	P peak	Y peak	P peak
Petroleum refin.	0	$+^*$	-0.09	1.78*	-0.10*	1.99*
Chemicals	$-^*$	$+^*$	-0.18*	0.22*	-0.26*	0.15*
Paper	$-^*$	Mixed	-0.24*	-0.10*	-0.22*	-0.16*
Rubber & plastic	$-^*$	Mixed	-0.33*	-0.08* & 0.09*	-0.35*	-0.13*
Nonferr. metals	$-^*$	$-^*$	-0.21*	-0.50*	-0.32*	0.27*
Iron & steel	$-^*$	Mixed	-0.40*	0.20*	-0.43*	-0.08*
Lumber	$-^*$	$-^*$	-0.33*	-0.33*	-0.38*	-0.45*
Apparel	$-^*$	$-^*$	-0.17*	-0.06*	0.16*	-0.14*
Furniture	$-^*$	$-^*$	-0.43*	-0.08* & 0.09*	-0.56*	-0.17*
Househ. appl.	$-^*$	$-^*$	-0.56*	-0.10* & 0.11*	-0.44*	-0.20*
Motor vehicles	$-^*$	$-^*$	-0.47*	-0.10* & 0.10*	-0.77*	-0.19*
Electrical equip.	$-^{*A}$	Mixed^A	-0.18*	0.13*	-0.27*	-0.18*
Constr. machin.	-	Mixed	-0.39	-0.11* & 0.15*	-0.42*	-0.20*
Computer equip.	$+^{*B}$	$-^{*B}$	-0.32	-0.12*	-0.29*	-0.17*

Notes: The responses are in percent. The stars indicate that the peak responses are significant, based on one standard error confidence bands. Columns 2 and 3 are from Table 7 in Lee and Ni (2002). "+" and "-" denote positive and negative responses. "0" means the peak responses are negligible."Mixed" or two peak values are reported when the positive and negative responses are of similar magnitudes. The subscripts ^{A} and ^{B} denote the electronic machinery and office and computing machines industries in LN (2002).

Table 5: Dominant effects of oil price shocks on U.S. industries: summary

	LN method			FVAR		Alter. oil prices		
Industry	1959-97	1972-97	1972-2017	IND	FULL	RAC	RACR	WTI
Petroleum refin.	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$
Chemicals	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$	$\downarrow S$
Paper	$\downarrow D, \downarrow S$	$\downarrow D$	$\downarrow D$	$\uparrow S \downarrow D$	$\uparrow S$	$\downarrow D$	$\downarrow D$	$\downarrow D$
Rubber & plastic	$\downarrow D, \downarrow S$	$\downarrow D, \downarrow S$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow S$	$\downarrow D$
Nonferr. metals	$\downarrow D$	$\downarrow D$	$\downarrow S$	$\downarrow S$	$\downarrow S$	indet	indet	indet
Iron & steel	$\downarrow D, \downarrow S$	$\downarrow S$	$\downarrow D$	$\uparrow D, \downarrow S$	indet	indet	indet	indet
Lumber	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	indet	$\downarrow D$
Apparel	$\downarrow D$	$\downarrow D$	$\uparrow S$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$
Furniture	$\downarrow D$	$\downarrow D, \downarrow S$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$
Househ. appl.	$\downarrow D$	$\downarrow D, \downarrow S$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$
Motor vehicles	$\downarrow D$	$\downarrow D, \downarrow S$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$
Electrical equip.	$\downarrow D, \downarrow S^A$	$\downarrow S$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$
Constr. machin.	indet	indet	$\downarrow D, \downarrow S$	$\uparrow S$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow S$
Computer equip.	$\uparrow S^B$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$	$\downarrow D$

Notes: The dominant effects of oil price shocks are inferred from the signs of the peak impulse responses of industry output and price. The arrows $\downarrow$ and $\uparrow$ show a reduction and an increase in the demand D or supply S. The dominant effects are called indeterminate (indet) if there is a large degree of uncertainty about the parameter estimates. The subscripts ^{A} and ^{B} denote the electronic machinery and office and computing machines industries in LN (2002) The estimation period is 1971:1-2017:2, unless stated otherwise.

Our results in Figure 2 and Table 4 corroborate the evidence of LN that oil price shocks tend to reduce industrial production.[10] The impulse responses of output in the shorter sample have many similarities with the results of LN, despite the differences in the industry data composition and periods. Output dynamics are relatively synchronized across most of the industries. With an exception of motor vehicles and parts, output responses are typically small and often insignificant for about ten months. Inventory buildups likely act as an initial shock absorber, explaining a delay in these responses. As the industry adjusts, production declines and reaches its trough some time between 13 to 18 months. The negative effects of oil price shocks on production are transitory, and output usually recovers by the end of the second year. In the full sample, however, the effects on oil price shocks become more persistent (except in the apparel industry).

The responses of producer prices to oil prices shocks can signal the relative strengths of supply and demand effects. LN rely on the peak responses to identify the type of oil price shock effects on

[10]The peak effect of ouput is positive only in the apparel industry in the full sample.

each industry. According to their classification, the dominant effect is on the supply side if output and price move in the opposite direction. The dominant effect is on the demand side if output and price move in the same direction. In the case when the positive and negative peak responses are of comparable magnitudes, the effects are mixed.

In contrast to output responses, price responses to oil price shocks tend to be more heterogeneous across the time periods and industries. This heterogeneity may arise when the strength of supply and demand channels varies across industries. It may also reflect changes in the underlying causes of oil price shocks. Since we do not identify supply and demand shocks in the global oil market, our oil price shocks can be viewed as an unknown combination of such shocks.

Figure 2 implies that many impulse responses are similar to those in the original study of LN. However, we do find important differences for the final goods industries[11] in the shorter sample. The initial significant price decline in those industries, within the first four months of the oil price shock, is followed by the price increase. The price typically peaks around the fifteen months mark, after which the effects of the shock dissipate. Thus, in contrast to LN, we find that supply effects of oil price shocks for the furniture, household appliances and motor vehicles and parts industries were as equally important as supply effects in the shorter sample (1972-97).

Demand effects of oil price shocks become more evident in the full sample. There are no double-peaked price responses, and producer prices fall significantly in ten out of fourteen industries. Only three energy-intensive industries (petroleum refineries, chemicals and nonferrous metals), experience oil price shocks as negative supply shocks. This conclusion supports the statistical as well as narrative evidence presented by LN based on econometric models and trade journals.

The impulse responses are based on the estimates of the structural parameters in A_0 and VAR coefficients. Table 6 in LN reports the parameter estimates of the contemporaneous effects of oil price shocks on U.S. industries. Due to a large number of the coefficients, we reproduce this table along with our parameter estimates in the Appendix. Instead, we highlight two main results here. First, similar to LN, we find that the coefficients c_{28} and c_{35} are rather small. As discussed in section 2.1, the signs of these coefficients determine the identification of (4) and (5) as supply and demand. The parameter estimates imply one of the two possibilities: (i) the industry demand curve is nearly vertical and supply curve is nearly horizontal; (ii) the industry demand curve is nearly

[11] Apparel, furtniture, household appliance, motor vehicles, electrical equipment, construction machinery and computer equipment.

horizontal and supply curve is nearly vertical. Second, the implied contemporaneous output and price elasticities with respect to oil price shocks are rather small and often insignificant. This property can also be seen from the impact responses on Figure 2.

5 Extensions

In this section, we first focus on the industry effects of oil price shocks estimated with the FAVAR models. These models take inter-industry connections into account and provide additional insights on the oil price shock transmission. We next evaluate if the pattern of industry output and price responses to oil price shocks is robust to the use of alternative oil price measures. We conclude the section with a discussion of different demand effects of oil price shocks.

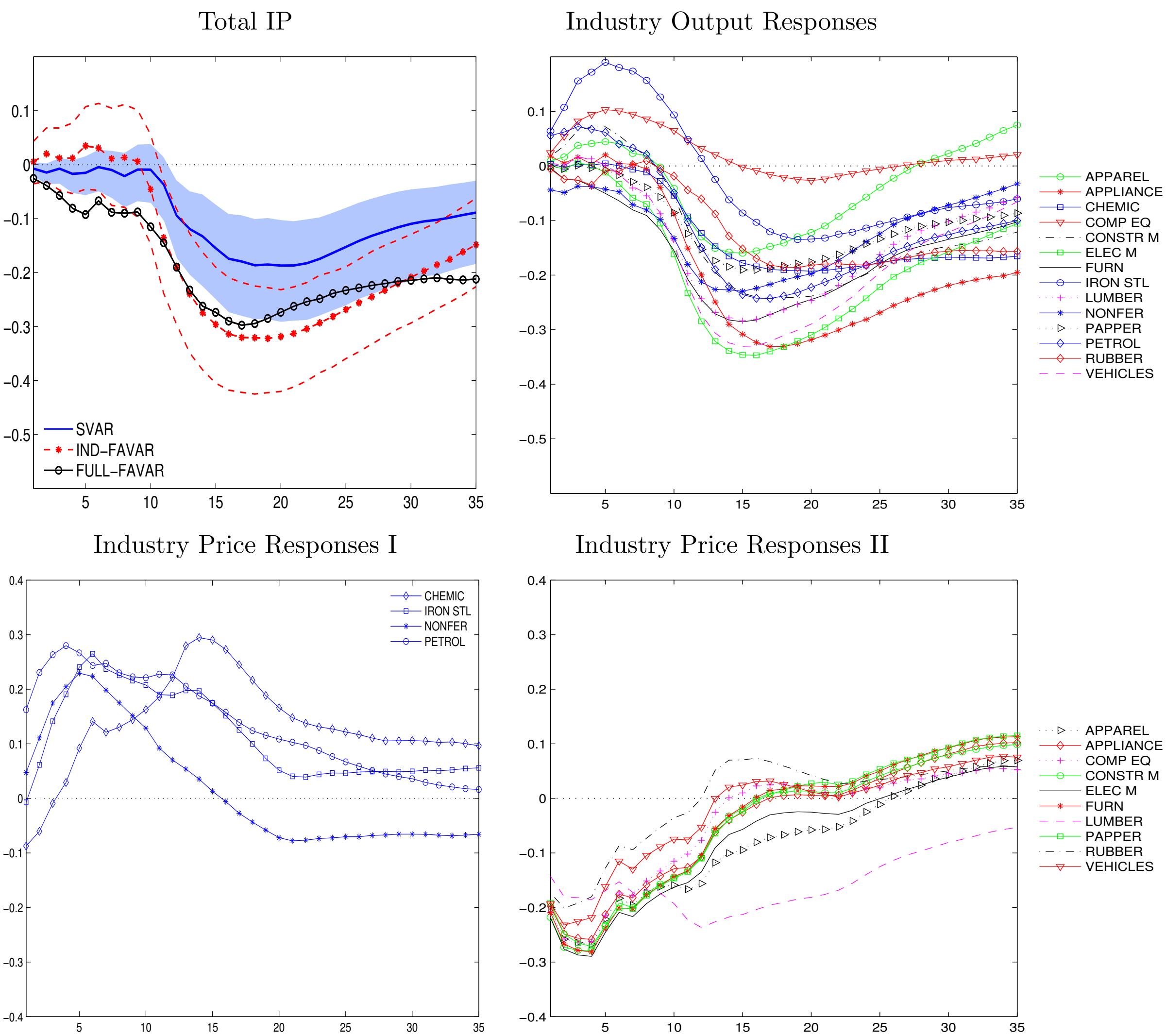
5.1 Results from the FAVAR models

One advantage of the FAVAR framework is its ability to take into account industry interactions. If such interactions are important in explaining industry responses to oil price shocks, then the SVAR results from Section 4 will be consistent but biased.

We find that the common industry factors do contain additional information, relative to industry-specific SVARs. The upper left panel of Figure 3 demonstrates this result for total IP. Even though the shape of the impulses responses is relatively similar across the models, the magnitude of the FAVAR estimates is larger. All three models predict a delayed production response of around ten months. When the estimated responses are significant, they are on the order of 0.1 percentage points larger in the FAVAR models. These results are consistent with the view that industry inter-connections can amplify the effects of macroeconomic shocks (e.g. Bouakez et al. (2009), Acemoglu et al. (2012)). Our results at the industry level suggest that the price responses in the SVARs are underestimated for the final goods industries. While output responses show some differences across the models, there is no clear pattern in the bias.

Figure 3 also plots industry output and prices responses obtained from the IND-FAVAR model. An increase in the price of oil generally has a negative impact on industrial production, with the peak response occurring some time between fifteen to twenty months. Price responses exhibit even a larger degree of synchronization. Higher oil prices increase producer prices only in the four energy-intensive industries (petroleum refineries, chemicals, iron and steel and nonferrous metals). In all other industries, prices fall quickly and remain low for about a year after the shock.

Figure 3: Output and price responses to a one percent oil price shock (IND-FAVAR; 1972:1-2017:2)



Notes: The figure plots median impulse responses (in percent) to a one percent increase in Hamilton's net oil price increase measure. The lines with the stars and dashed lines on the upper left panel are the responses and the 16 and 84 percentile bootstrap confidence bands for the IND-FAVAR model with four factors. The solid lines with the shaded areas are the responses and the confidence bands from the non-recursive SVAR model. The black line with circles represents the estimates from the FULL-FAVAR model with eight factors. The other panels report industry output and price responses from the IND-FAVAR model.

Table 6: Peak responses of industry output and price to a one percent shock to a oil price measure (FVAR method; 1972:1-2017:2).

	IND-FAVAR		FULL-FAVAR		RAC		RACR	
Industry	Y peak	P peak	Y peak	P peak	Y peak	P peak	Y peak	P peak
Petroleum refin.	-0.19*	0.28*	-0.05	0.35*	-0.13	0.14*	-0.43	0.94*
Chemicals	-0.33*	0.29*	-0.25*	0.10	-0.43*	0.13	-0.60*	1.61
Paper	0.07*&-0.24*	-0.20*	0.08*	-0.27*	-0.26*	-0.18*	-0.18	-0.15*
Rubber & plastic	-0.33*	-0.23*	-0.24*	-0.31*	-0.31*	-0.19*	-0.39*	3.45*
Nonferr. metals	-0.19*	0.23*	-0.12*	0.06*	0.06	-0.26*	-0.37	0.25
Iron & steel	0.19*&-0.13*	0.26*	0.07*&-0.11	-0.06	-0.15	-0.17	0.32	5.06*
Lumber	-0.28*	-0.24*	-0.18*	-0.28*	-0.28*	-0.15*	1.01	-0.51*
Apparel	-0.16	-0.27*	-0.03*	-0.36*	-0.40	-0.20*	-0.64*	-0.23*
Furniture	-0.35*	-0.29*	-0.31*	-0.37*	-0.35*	-0.22*	-0.49	-0.25*
Househ. appl.	-0.29*	-0.28*	-0.12*	-0.34*	-0.21*	-0.20*	-0.13	-0.21*
Motor vehicles	-0.23*	-0.27*	-0.16*	-0.32*	-0.10	-0.20*	-0.16	-0.33*
Electrical equip.	-0.24*	-0.28*	-0.31*	-0.35*	-0.15	-0.23*	-0.44	-0.25*
Constr. machin.	0.10*	-0.26*	-0.07	-0.32*	-0.07	-0.21*	-0.10	-0.31*
Computer equip.	-0.19*	-0.26*	-0.28*	-0.32*	-0.07*	-0.20*	-0.01	-0.29*

Notes: The responses are in percent. The stars indicate that the peak responses are significant, based on one standard error confidence bands. Two peak values are reported when the positive and negative responses are of similar magnitudes. The IND-FAVAR and FULL-FAVAR models use the NOI oil price variable. The RAC and RARC models are identical to the FULL-FAVAR, except for the oil price measure.

Minimal differences in the estimated paths of total IP from the small and large FAVARs in Figure 3 suggest that the IND-FAVAR may capture the common industry dynamics, relevant for the effects of oil price shocks. The FULL-FAVAR model leads to relatively similar conclusions about the dominant industry effects (see Tables 5 and 6). The estimated impulse responses of industry output and prices for the FULL-FAVAR model are qualitatively similar, albeit less precise. The average correlation coefficients for output (price) responses between the two FAVAR models is 0.87 (0.82). We report the impulses responses and the confidence intervals for both models, in comparison with the SVAR, in the Appendix. Taken together, our FAVAR results confirm the findings of LN that oil price shocks have dominant demand effects in most of the U.S. manufacturing industries (see Table 5).

5.2 The impact of alternative oil prices

The net oil price increase (NOI) measure is a non-linear transformation of the oil price. It has been put forward to capture three distinct ideas. First, firms and consumers respond only to large increases in the price of oil. Second, they do not respond to net decreases in the price of oil, and hence the net decreases can be omitted from the model. Put differently, the economic responses to oil price shocks are asymmetric. Finally, the transformation presumes that it is the nominal, rather than the real price of oil, that matters for the transmission of oil price shocks.

The net oil price increase is based on behavioral arguments, and is not derived explicitly from theoretical models. Further, the evidence on asymmetric effects of oil price shocks is mixed. A number of authors confirm this property (e.g. Mork (1989); Hamilton (2003); Davis and Haltiwanger (2001), Herrera et al. (2011)), while others reject (e.g. Kilian and Vigfusson (2011 and 2013)). In this section, we evaluate the robustness of the industry patterns to the use of alternative oil prices. To this end, we re-estimate the FULL-FAVAR model with three oil price measures and the full data sample.

The first two measures, RAC and the WTI spot prices, are expressed in current dollars. Despite large similarities, these two series reflect changes in the costs of energy to a different degree. We expect that fluctuations in the spot price may be less relevant for firms' production decisions, due to the existence of contracts with energy providers and hedging options. The choice of the last measure, RACR, is motivated by predictions of economic theory that firms' responses to changes in the real and nominal costs of energy may be different.

Table 6 reports the peak output and price responses for the RAC and RARC models. The industry impulse responses to an increase in the alternative oil price variables, in comparison with the results from the FULL-FAVAR with the NOI price, are plotted in the Appendix.

Several comparisons stand out. First, the impulse responses of total IP to oil price shocks are very similar across the large FAVAR models with four alternative price series. The responses to the change in the real price of oil, however, are estimated less precisely. Second, there are no substantive quantitative differences in the estimates and the confidence bands between the models with the nominal prices RAC and WTI. Output responses are often insignificant and generally estimated less precisely, relative to the model with Hamilton's net oil price increase. Yet, the statistical significance of the peak price responses is generally not affected. Fourth, there is even larger parameter uncertainty for the model with shocks to the real price of oil RACR.

Finally, the models with nominal and real oil prices exhibit some disagreement related to the strengths of the supply and demand effects in the paper, rubber and plastic, lumber and nonferrous metals industries. These industries produce largely intermediate goods and have above average energy cost shares. Identifying changes in those industries as largely supply or demand-driven is particularly difficult. The inference is sensitive to the method used as well as to the sample periods. Interestingly, LN also report mixed prices effects, and find evidence for reduction in both supply and demand.

5.3 Discussion and implications

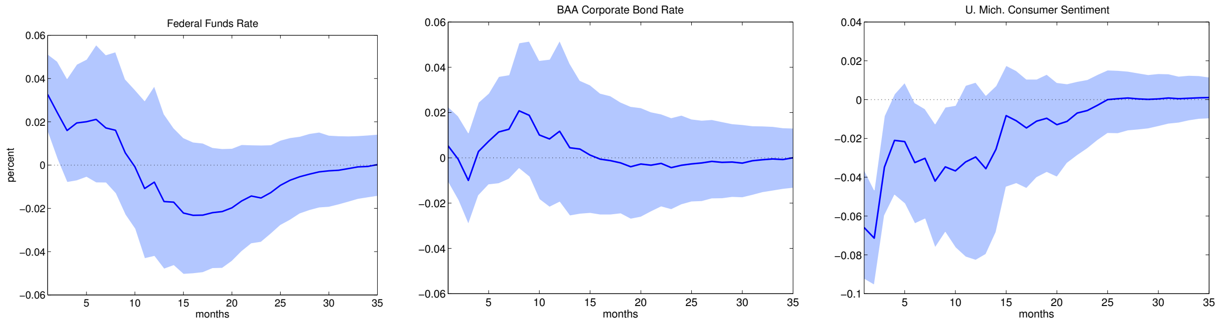
Output responses to oil price shocks follow a very similar pattern across industries and mimic the path of total IP. Production declines with a delay of about ten months but recovers relatively quickly (typically by the end of the second year). The analysis of the industry price dynamics reveals that the reduction in production after an oil price shock is often triggered by negative demand rather than negative supply effects. In this subsection, we explore the data structure of the FULL-FAVAR model to obtain some insights on the origin of the negative demand effects.

The discretionary income effect is viewed as the main transmission channel of oil price shocks by policy-makers and oil experts (e.g. Edelstein and Kilian (2009), Hamilton (2009), Yellen (2011, 2015)). Baumeister and Killian (2016) explain that oil price shocks are terms of trade shocks that alter domestic spending in the U.S. economy. An increase in the price of oil leads to higher prices of gasoline. Since the demand for gasoline is price inelastic, a positive oil price shock acts like an unanticipated tax for consumers. This "oil tax" is repatriated outside the U.S., the net oil importer, rather than re-circulated within the economy. A positive shock to oil prices thus reduces consumers' real disposable income, leading to a fall in consumption.

The discretionary income effect of oil price shocks on private consumption is a negative demand shock for final goods producers, such as motor vehicles and electronic products. Our results suggest that not only industries producing final products but also producers of intermediate goods may experience negative demand effects (e.g. lumber, iron and steel) . The discretionary channel alone will not be sufficient to explain reduced demand for intermediate products.

Interindustry input-output connections, emphasized by LN, provide a possible explanation for why a fall in demand for final goods is passed to intermediate goods producers. Narrative accounts

Figure 4: Impulse responses of monetary policy indicators and consumer sentiment a one percent oil price shock (FULL-FAVAR; 1972:1-2017:2)



Notes: The shaded areas are the 16 and 84 percentile bootstrap confidence bands.

of industry experts expressed in trade journals and reported by LN provide concrete examples. For instance, demand for steel and nonferrous metals plummeted after a sharp decline in demand for automobiles during the two oil crises.

Additional negative demand effects have been proposed in the literature. First, oil price shocks can reduce demand for final goods that are complementary to energy consumption (Wei (2013)). Second, changes in the composition of industry demand can adversely affect the industry in total (Ramey and Vine (2011)) Third, uncertainty about future price of oil is likely to lead firms and consumers to postpone major purchases, thereby reducing industry demand (Bernanke (1983), Elder and Serletis (2010)). Finally, negative demand effects may be triggered by monetary policy tightening, put in place in anticipation of future inflation (e.g. Bernanke et al. (1997), Leduc and Sill (2004)).

The last two possible mechanisms of oil price transmission will likely affect both final goods and intermediate goods producers. Figure 4 provides some support for these mechanisms. A rise in oil prices leads to an increase of the federal funds rate as well as of the BAA corporate bond rate, suggesting a general tightening of lending conditions across the board. At the same time, the University of Michigan Consumer Sentiment index falls. Lower consumer sentiment may in turn reduce consumers' willingness to spend and decrease aggregate and industry demands further.

6 Conclusion

This paper analyzed the dynamic effects of oil price shocks on U.S. industries. Identification of the effects of oil price shocks on industry-level output and price was based on two econometric approaches. The first approach closely followed the work of Lee and Ni (2002). For the replication purposes, we estimated a series of fully identified SVAR models, focusing on one industry at a time.

The second approach was based on a FAVAR framework. FAVAR models combined all industry variables in a single common block and isolated economic dynamics via common factors. Economic agents typically consider a wide range of economic and financial variables when taking a decision. Sparse VAR miss this rich set of interlinkages between variables that underlie agents decisions. In our context, the inter-industry dependence as well as dependence on a number of different economic concepts, such as the status of the labour market or credit availability, were missing in a sparse VAR. The FAVAR model delivered the results for a large number of variables in one consistent framework.

Our results showed that LN's baseline findings are robust to the use of different econometric models, sample periods and oil price series. Oil price shocks are transmitted largely through supply channels only in the industries with high oil and energy intensities. Most of the other industries experience oil price shocks primarily through reduction in demand. Several explanations have been put forward in the literature to explain how oil price shocks can reduce industry and aggregate demand. Future work could investigate the quantitative relative importance of the two channels in a more structural framework.

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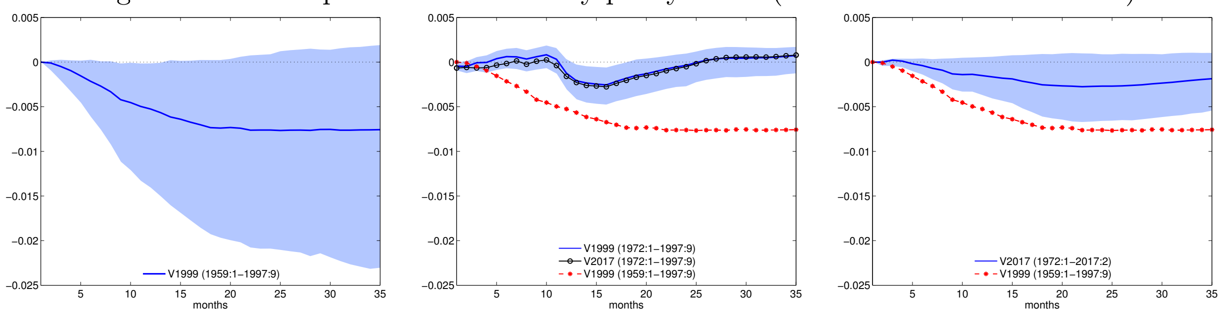
A Additional replication results for the non-recursive SVAR

A.1 Monetary policy shocks in the SVAR model

Figure A.1 plots the responses of industrial production to a contractionary monetary policy shock that are obtained with the non-block-recursive model of Lee and Ni (2002). The size of the shock u_{ms}=0.137 is inferred from Tables 4 and 5 in Lee and Ni (2002). The shaded areas are one standard deviation bootstrap confidence bands. The legends V1999 and V2017 indicate the vintage of the data used in the estimation. The sample period is in parentheses. The impulse responses in the

Figure A.1: IP responses to a monetary policy shock (non-recursive SVAR model)



1959-1997 sample with the 1999-vintage data capture the shape and the magnitude of the impulse responses reported on Figure 1 in Lee and Ni (2002). As in many other VAR models, the effects of the policy shock accumulate gradually, with the maximal impact at around 18 months. The estimated responses are significant during a very short period. Since the confidence bands were not reported in LN, it is hard to say whether they experienced the same problem.

The middle and the right panels report the estimates for the two periods that we use for replicating industry results. In both cases, the estimated response for the LN's sample is represented by the red lines with stars. The model predicts smaller but more precisely estimated effects of monetary policy shocks on industrial production for the 1972:1-1997:9 sample. The predicted effects are even less significant in the full sample. However, this sample, from 1972:1 to 2017:2, encompasses the Great Recession and a prolonged period of unconventional monetary policy.

The most important point to note is that possible differences in the estimated coefficients and effects of monetary policy shocks do not have an effect on the results related to oil price shocks.

A.2 Industry-level estimates of the SVAR model

Table A. 1 reproduces the statistics from Table 6 in Lee and Ni (2002) and reports our estimates of the same structural parameters.

Table A.1: Estimated contemporaneous effects of oil price shocks on industrial demand and supply.

Industry / Model	Demand/Supply	Oil price coeff (ste)	Output coeff (ste)	Price coeff (ste)
1. Petroleum refineries				
Lee and Ni (2002)	Demand (9)	3.046 (2.733)	67.996 (3.485)	0.140 (2.370)
	Supply (10)	-16.091 (2.714)	-0.484 (4.107)	41.982 (1.395)
1972:1-1997:9	Demand (9)	-2.467 (5.068)	53.301 (25.385)	2.233 (7.089)
	Supply (10)	-6.214 (4.311)	-14.082 (44.704)	16.855 (9.218)
1972:1-2017:2	Supply (9)	-1.983 (1.706)	53.588 (18.335)	-0.338 (3.364)
	Demand (10)	-3.660 (2.402)	2.528 (25.185)	14.025 (4.947)
2. Chemicals				
Lee and Ni (2002)	Supply (9)	-3.326 (2.684)	92.300 (4.475)	-7.938 (8.056)
	Demand (10)	-2.220 (2.724)	10.424 (5.289)	134.541 (4.505)
1972:1-1997:9	Demand (9)	1.914 (3.470)	138.019 (38.767)	15.670 (35.672)
	Supply (10)	-1.122 (3.927)	-27.033 (61.540)	158.479 (49.112)
1972:1-2017:2	Demand (9)	-1.872 (2.290)	115.031 (40.281)	8.004 (39.558)
	Supply (10)	5.097 (3.482)	-11.979 (59.209)	139.688 (51.540)
3. Paper				
Lee and Ni (2002)	Supply (9)	-2.497 (2.611)	53.557 (2.560)	-11.521 (11.091)
	Demand (10)	-0.971 (2.524)	6.594 (3.174)	188.983 (6.324)
1972:1-1997:9	Supply (9)	-8.832 (5.496)	77.220 (30.754)	-7.026 (39.170)
	Demand (10)	0.484 (6.682)	8.213 (45.785)	131.711 (57.178)
1972:1-2017:2	Supply (9)	-1.490 (1.982)	81.049 (28.312)	-6.023 (29.088)
	Demand (10)	2.936 (2.094)	8.677 (41.908)	125.108 (46.629)
4. Rubber and plastic				
Lee and Ni (2002)	Demand (9)	-1.598 (2.710)	60.384 (2.773)	9.510 (11.794)
	Supply (10)	0.584 (2.895)	-5.043 (3.127)	216.311 (7.220)
1972:1-1997:9	Demand (9)	0.672 (3.555)	81.133 (30.880)	8.422 (50.437)
	Supply (10)	5.594 (4.777)	-7.506 (44.953)	182.151 (70.175)
1972:1-2017:2	Supply (9)	0.774 (2.090)	87.210 (28.991)	-0.429 (31.434)
	Demand (10)	5.232 (2.990)	0.540 (39.543)	154.215 (50.523)

Table A.1 *(continued)*

Industry / Model	Demand/Supply	Oil price coeff (ste)	Output coeff (ste)	Price coeff (ste)
5. Nonferrous metals				
Lee and Ni (2002)	Supply (9)	-3.469 (2.641)	58.488 (2.597)	-1.218 (5.003)
	Demand (10)	-3.623 (3.234)	1.590 (3.266)	80.968 (2.692)
1972:1-1997:9	Demand (9)	-3.544 (4.454)	31.540 (13.187)	4.980 (15.707)
	Supply (10)	-1.674 (4.588)	-7.034 (22.184)	46.651 (21.953)
1972:1-2017:2	Demand (9)	0.446 (2.557)	34.892 (13.296)	1.975 (10.635)
	Supply (10)	-5.186 (3.157)	-3.648 (19.647)	38.229 (15.443)
6. Iron and steel				
Lee and Ni (2002)	Demand (9)	-4.204 (2.628)	28.176 (1.339)	2.341 (9.680)
	Supply (10)	3.143 (3.058)	-0.750 (1.551)	160.039 (5.321)
1972:1-1997:9	Demand (9)	-7.991 (4.190)	26.016 (9.285)	1.034 (32.189)
	Supply (10)	2.159 (5.888)	-0.438 (13.622)	119.492 (46.041)
1972:1-2017:2	Demand (9)	-2.698 (2.011)	24.000 (10.934)	14.967 (31.881)
	Supply (10)	3.019 (4.489)	-11.039 (23.514)	66.678 (36.410)
7. Lumber				
Lee and Ni (2002)	Demand (9)	2.168 (2.589)	58.351 (2.903)	23.252 (5.452)
	Supply (10)	6.219 (2.879)	-29.317 (3.437)	88.834 (3.429)
1972:1-1997:9	Demand (9)	1.688 (4.098)	47.081 (22.157)	26.529 (49.394)
	Supply (10)	4.262 (5.756)	-36.018 (67.061)	72.127 (44.872)
1972:1-2017:2	Demand (9)	1.249 (2.538)	53.162 (24.388)	20.411 (39.954)
	Supply (10)	3.530 (3.003)	-29.511 (57.768)	77.559 (42.205)
8. Apparel				
Lee and Ni (2002)	Supply (9)	0.719 (2.824)	80.132 (3.673)	-7.707 (13.154)
	Demand (10)	0.653 (3.005)	4.648 (3.966)	252.048 (8.392)
1972:1-1997:9	Supply (9)	-3.244 (4.030)	90.020 (47.794)	-19.011 (82.014)
	Demand (10)	0.783 (5.008)	18.834 (81.251)	182.401 (106.947)
1972:1-2017:2	Demand (9)	-0.234 (2.301)	70.181 (21.166)	2.036 (27.499)
	Supply (10)	3.805 (2.492)	-2.175 (29.377)	154.693 (47.766)
9. Household furniture				
Lee and Ni (2002)	Demand (9)	3.400 (2.620)	67.827 (3.267)	5.899 (12.710)
	Supply (10)	5.327 (2.580)	-3.220 (3.470)	252.261 (8.390)
1972:1-1997:9	Supply (9)	0.250 (3.474)	85.045 (41.202)	-25.942 (81.536)
	Demand (10)	3.535 (4.566)	24.212 (76.097)	187.607 (103.087)
1972:1-2017:2	Supply (9)	2.187 (2.042)	81.120 (22.042)	-4.251 (26.752)
	Demand (10)	4.999 (3.162)	5.159 (32.469)	153.989 (44.861)

Table A.1 *(continued)*

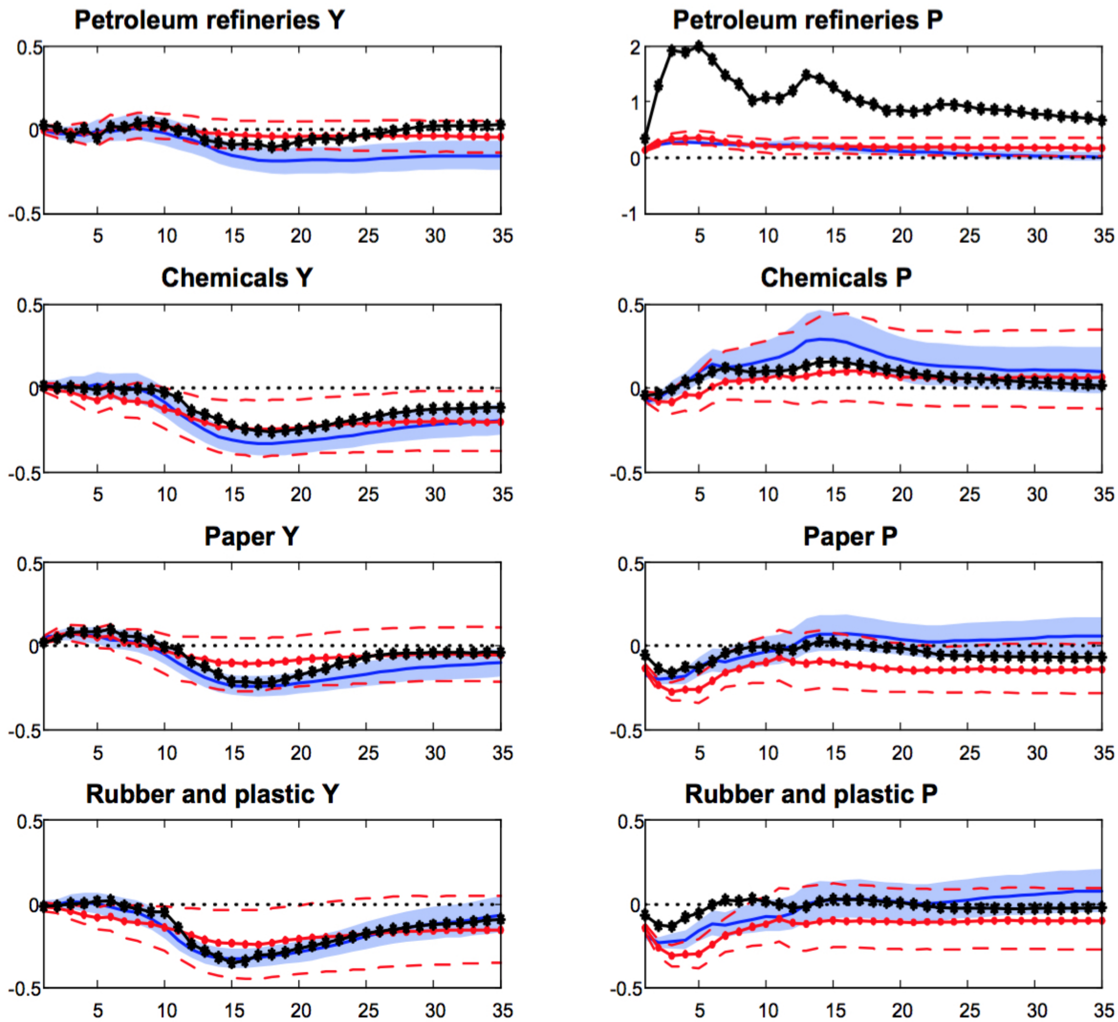
Industry / Model	Demand/Supply	Oil price coeff (ste)	Output coeff (ste)	Price coeff (ste)
10. Household appliance				
Lee and Ni (2002)	Demand (9)	-3.216 (2.700)	28.502 (1.353)	8.530 (16.086)
	Supply (10)	5.697 (2.570)	-1.848 (1.742)	270.725 (9.010)
1972:1-1997:9	Demand (9)	-0.420 (4.174)	29.530 (12.297)	10.712 (59.932)
	Supply (10)	7.714 (5.640)	-3.563 (19.933)	184.362 (83.534)
1972:1-2017:2	Supply (9)	-0.474 (2.607)	31.478 (9.908)	-1.927 (28.816)
	Demand (10)	5.822 (2.932)	0.935 (13.979)	148.017 (48.012)
11. Automobile				
Lee and Ni (2002)	Demand (9)	6.693 (2.610)	16.410 (0.709)	13.210 (9.555)
	Supply (10)	0.112 (3.306)	-2.450 (0.886)	162.552 (5.493)
1972:1-1997:9	Supply (9)	9.851 (6.083)	33.229 (10.898)	-0.933 (42.143)
	Demand (10)	1.935 (5.928)	0.348 (15.729)	162.405 (56.122)
1972:1-2017:2	Demand (9)	6.725 (3.992)	29.231 (11.320)	7.558 (39.042)
	Supply (10)	3.423 (2.790)	-3.267 (16.878)	139.390 (57.720)
12. Electronic Machinery [A]				
Lee and Ni (2002)	Demand (9)	0.101 (2.987)	108.553 (4.821)	21.108 (15.536)
	Supply (10)	4.855 (3.306)	-15.736 (5.791)	270.590 (9.130)
1972:1-1997:9	Demand (9)	2.860 (3.623)	91.443 (29.102)	5.433 (48.549)
	Supply (10)	5.724 (4.106)	-5.033 (44.972)	205.739 (72.306)
1972:1-2017:2	Supply (9)	0.234 (2.159)	93.380 (26.079)	-4.960 (26.856)
	Demand (10)	5.640 (2.384)	6.864 (37.160)	158.134 (46.092)
13. Construction Machinery				
Lee and Ni (2002)	Demand (9)	-3.491 (2.796)	33.444 (1.662)	15.741 (13.185)
	Supply (10)	6.007 (2.526)	-4.686 (1.963)	227.373 (7.623)
1972:1-1997:9	Demand (9)	-5.297 (4.226)	10.949 (4.863)	15.317 (57.350)
	Supply (10)	6.025 (7.330)	-2.190 (8.198)	167.548 (82.864)
1972:1-2017:2	Supply (9)	-2.192 (2.298)	12.620 (3.606)	-2.531 (23.309)
	Demand (10)	5.046 (1.993)	0.538 (4.959)	141.503 (41.068)
14. Office Machinery [A]				
Lee and Ni (2002)	Demand (9)	0.498 (3.710)	42.440 (2.073)	0.063 (11.815)
	Supply (10)	8.938 (3.188)	-0.001 (2.292)	232.092 (7.711)
1972:1-1997:9	Supply (9)	-1.026 (4.855)	68.017 (33.494)	-11.565 (52.289)
	Demand (10)	8.266 (5.629)	11.666 (52.745)	139.643 (74.468)
1972:1-2017:2	Demand (9)	-1.433 (1.676)	61.435 (12.287)	2.100 (15.385)
	Supply (10)	4.660 (2.090)	-2.310 (16.924)	129.193 (25.457)

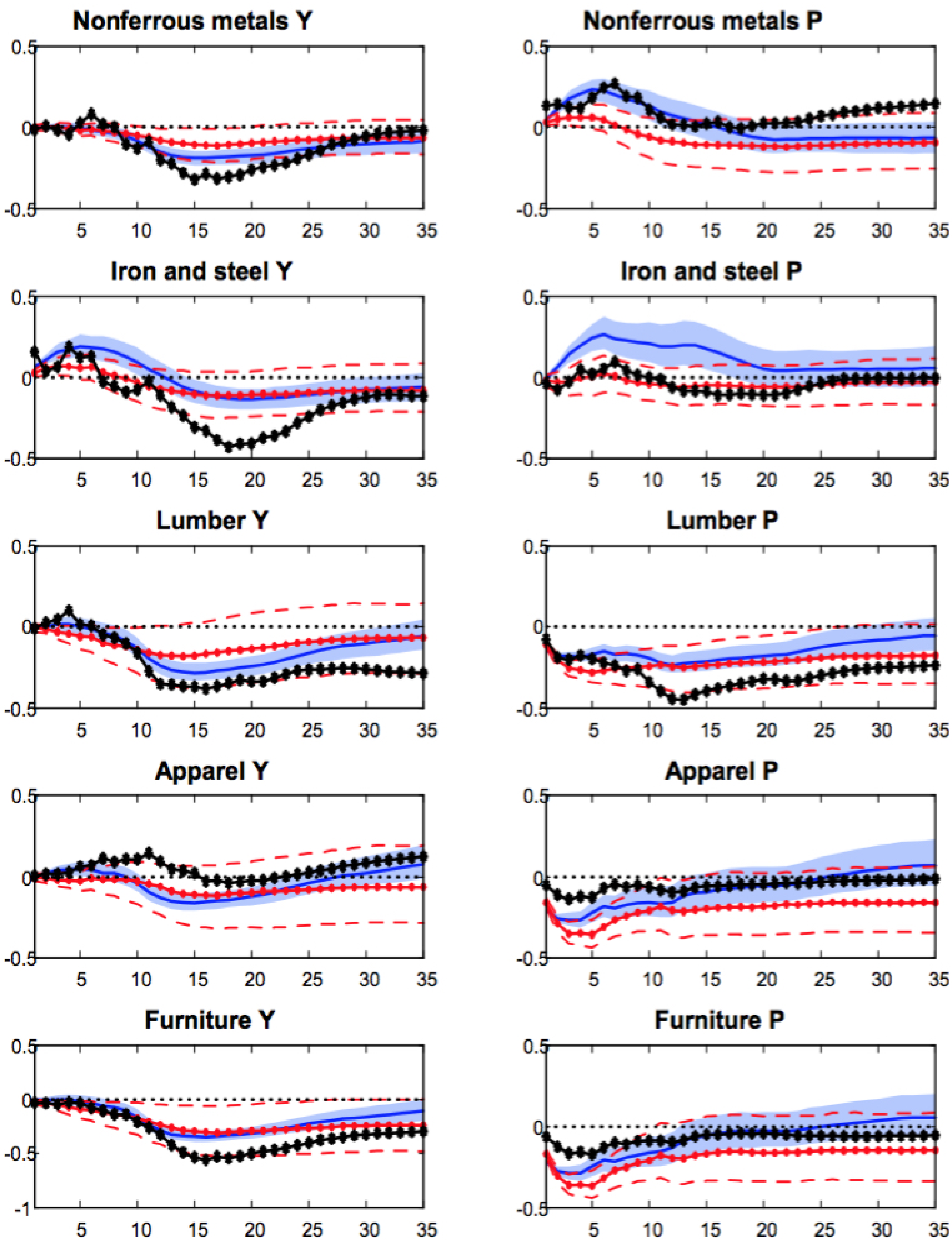
Notes: Industry equations (9) and (10) are classified as demand or supply, depending of the signs of the estimated output and price coefficients, as explained in Lee and Ni (2002). For each industry, the first two rows are from Table 6 of Lee and Ni (2002). The subscripts [A] and [B] denote the electronic machinery and office and computing machines industries in LN (2002).

B Impulse responses of industry-level output and price in the FAVAR models

Figure B plots the impulse responses of industry output Y and price P to a 1% increase in Hamilton's net oil price increase measure that are obtained from the IND-FAVAR and the FULL-FAVAR models. The models are estimated for the full sample period, from 1972:1 to 2017:2. The blue solid lines are the median point estimates from the IND-FAVAR model with four industry factors. The blue shaded areas are the 16 and 84 percentile bootstrap confidence bands. The red lines with circles and dashed red lines are the impulse responses and the bootstrap confidence bands for the FULL-FAVAR model with eight factors. The black solid lines with stars are the impulse responses estimated using the non-block-recursive model of Lee and Ni (2002).

Figure A.2: Impulse responses of industry-level output and price to a one percent oil price shock (FAVARs; 1972:1-2017:2)





Nonferrous metals Y
Nonferrous metals P
Iron and steel Y
Iron and steel P
Lumber Y
Lumber P
Apparel Y
Apparel P
Furniture Y
Furniture P
0.5
0
-0.5
-1
5
10
15
20
25
30
35

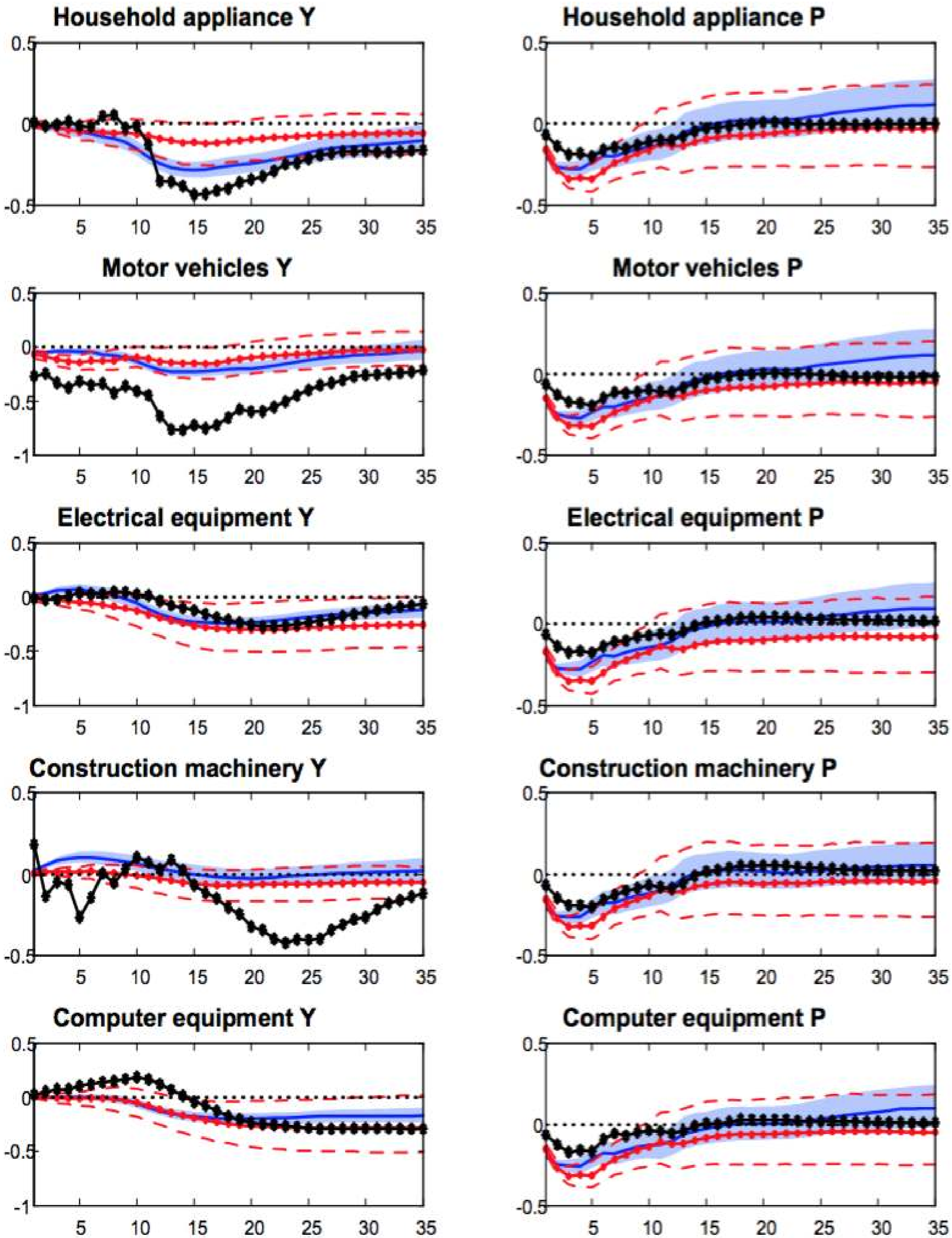
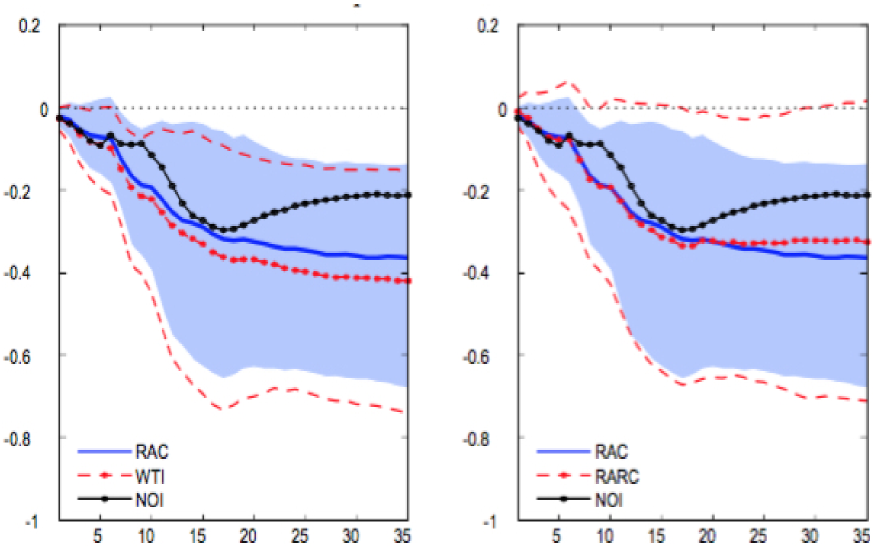

Household appliance Y
0.5
0
-0.5
5 10 15 20 25 30 35
Household appliance P
0.5
0
-0.5
5 10 15 20 25 30 35
Motor vehicles Y
0.5
0
-0.5
-1
5 10 15 20 25 30 35
Motor vehicles P
0.5
0
-0.5
5 10 15 20 25 30 35
Electrical equipment Y
0.5
0
-0.5
-1
5 10 15 20 25 30 35
Electrical equipment P
0.5
0
-0.5
5 10 15 20 25 30 35
Construction machinery Y
0.5
0
-0.5
5 10 15 20 25 30 35
Construction machinery P
0.5
0
-0.5
5 10 15 20 25 30 35
Computer equipment Y
0.5
0
-0.5
-1
5 10 15 20 25 30 35
Computer equipment P
0.5
0
-0.5
5 10 15 20 25 30 35

Figure A.3: Impulse responses of industrial production to a one percent increase in alternative oil price measures



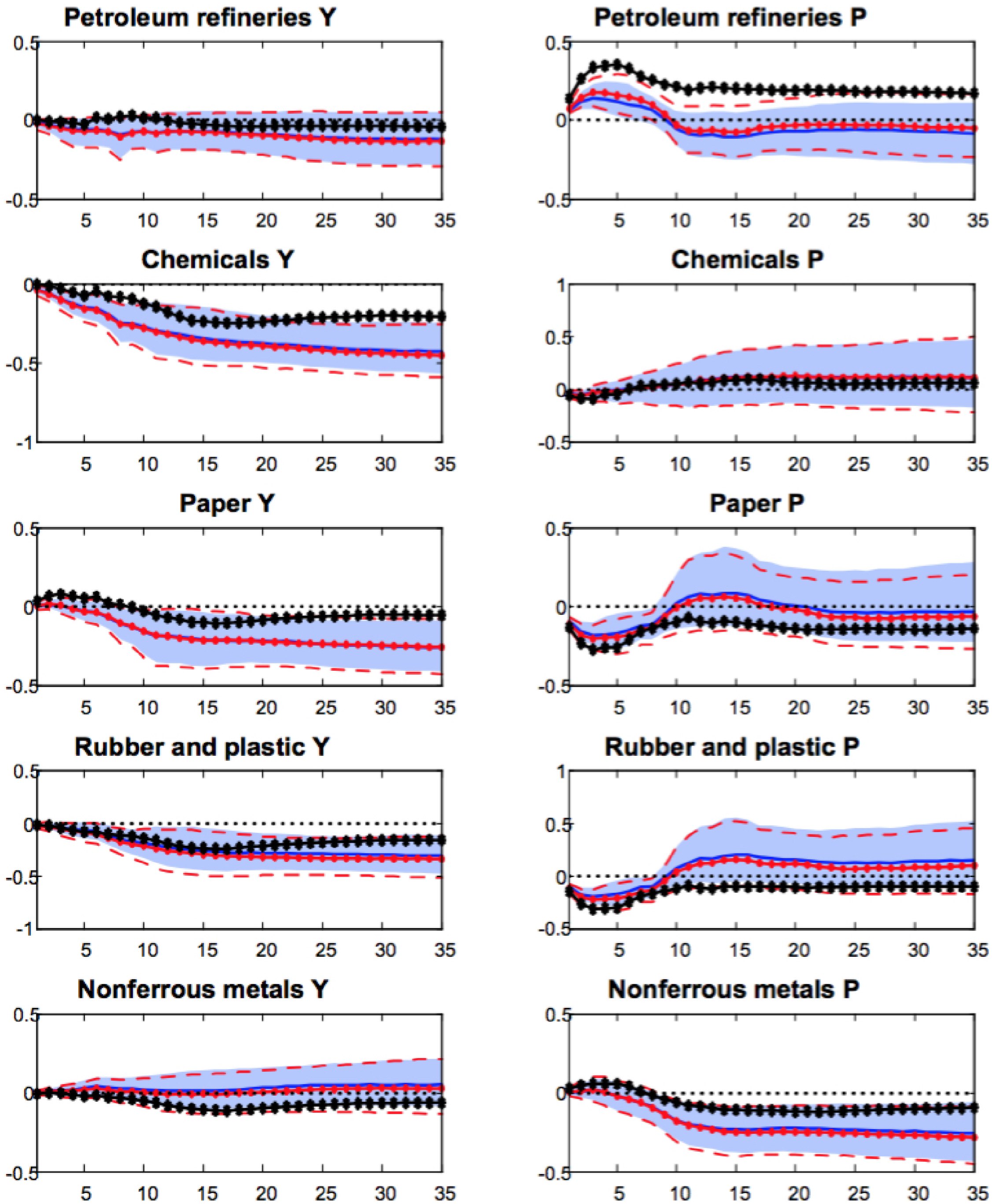
C Impact of the alternative oil price measures

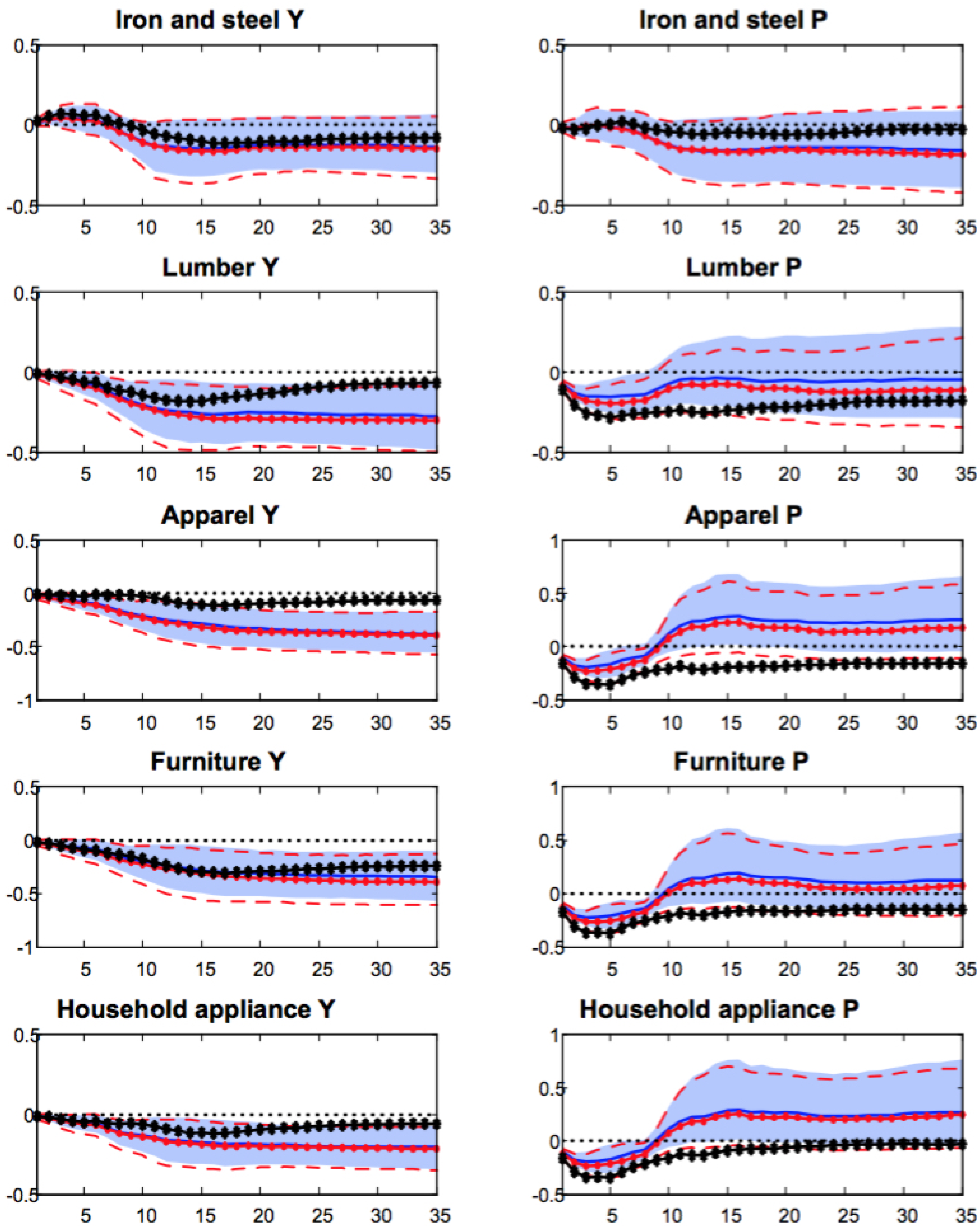
All impulse responses reported in this section are estimated using modified FULL-FAVAR models, in which Hamilton's net oil price increase measure is replaced by alternative oil price series. All specifications are estimated with eight factors and the full sample period, from 1972:1 to 2017:2. The RAC price is equal to refiners' acquisition cost of crude oil (composite) after 1974:1 and to the producer price index (PPI) for crude petroleum, adjusted for the effects of the price controls in the 1970s, as in Mork (1989). The RACR measure is the RAC series adjusted by the PPI for all commodities. The WTI series, equal to the West Texas Intermediate spot oil price until 2013:7 and Cushing WTI spot price after.

Figure C focuses on the total industrial production. The blue solid lines are the median point estimates from the model that uses the RAC oil price measure. The blue shaded areas are the 16 and 84 percentile bootstrap confidence bands. The red lines with circles and dashed red lines are the impulse responses and the bootstrap confidence bands for the model with the WTI measure on the left panel and the RARC measure on the right panel. The black solid lines with stars are the impulse responses estimated using the non-block-recursive model of Lee and Ni (2002).

C.1 RAC versus WTI

Figure A.4: Impact of alternative oil price measures (RAC versus WTI)




Iron and steel Y
Iron and steel P
Lumber Y
Lumber P
Apparel Y
Apparel P
Furniture Y
Furniture P
Household appliance Y
Household appliance P
0.5
0
-0.5
-1
1
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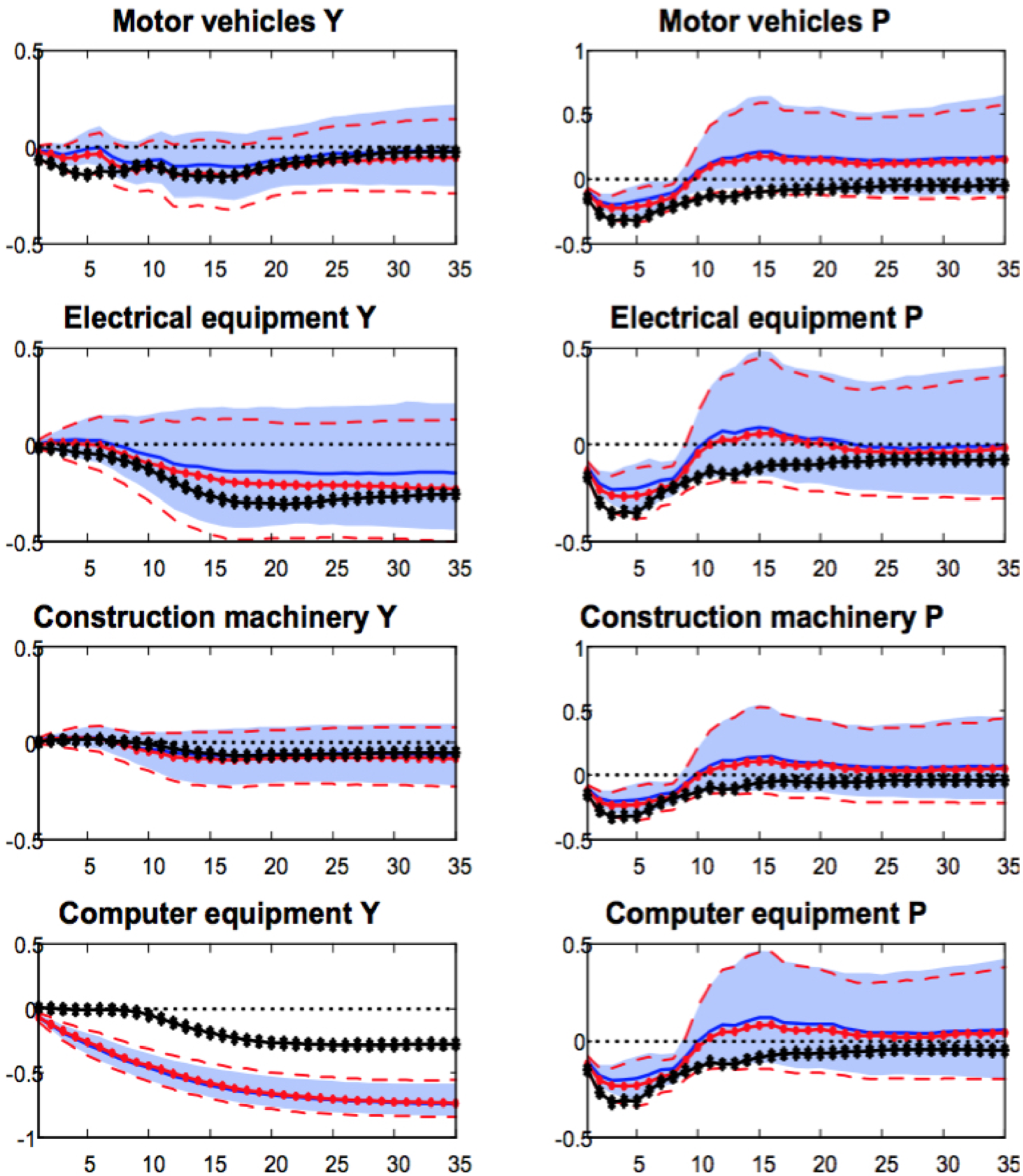
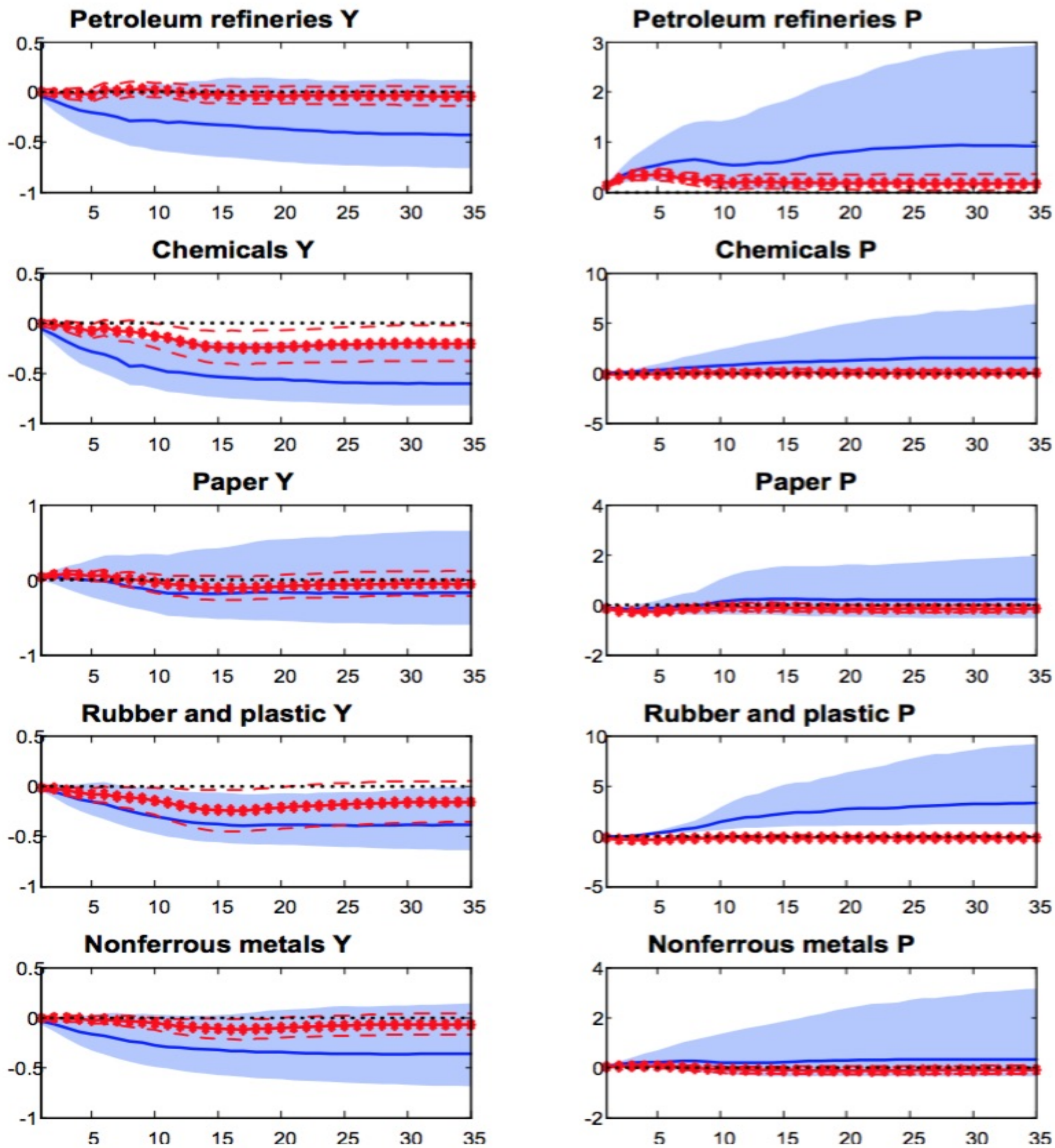
10
15
20
25
30
35

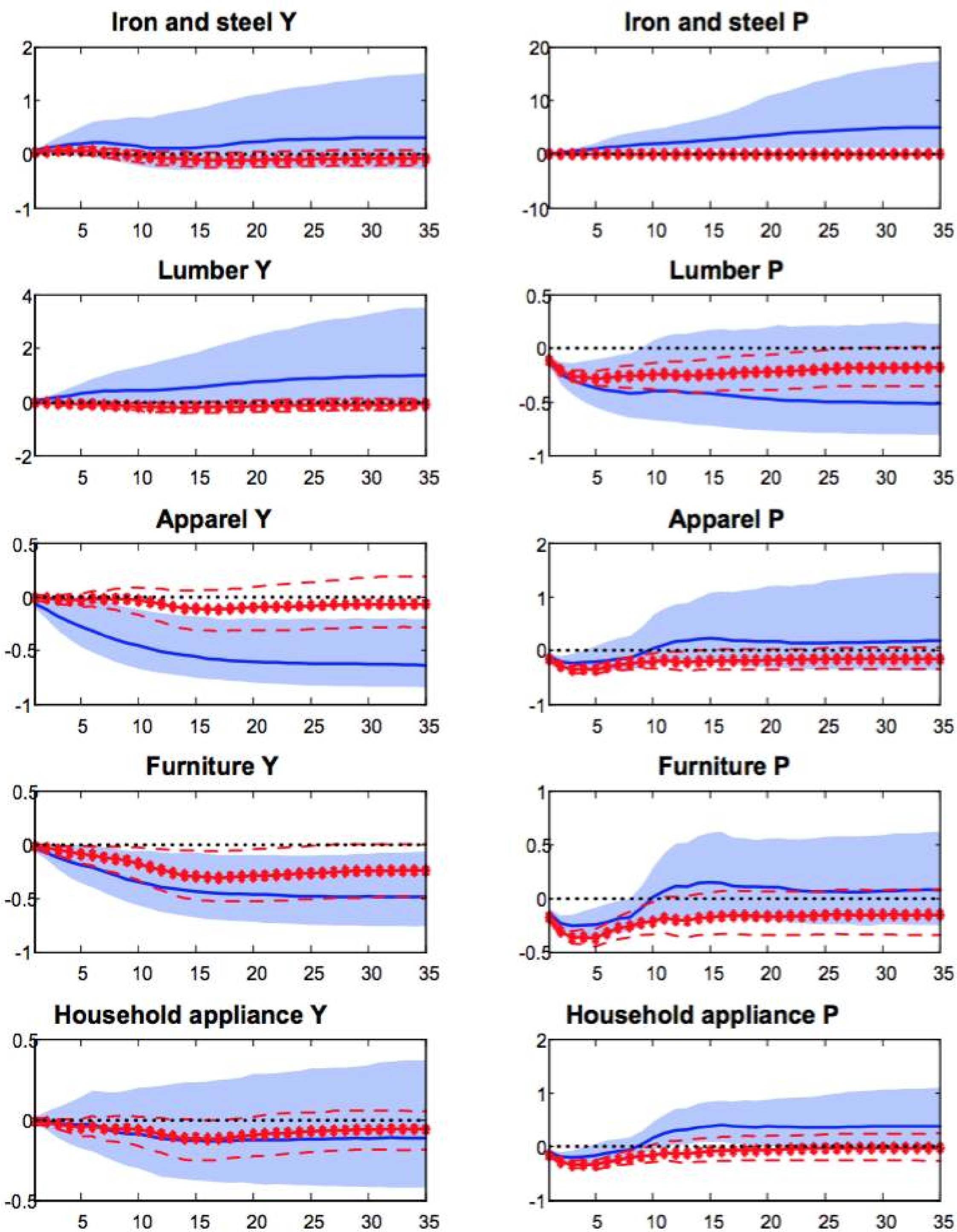


Notes: The figure plots the impulse reponses of industry output Y and price P to a 1% increase in the oil price measure. The blue solid lines with the shaded area are the median point estimates with the one standard error confidence bands for the FULL-FAVAR model with the RAC oil price measure. The red lines with circles and dashed red lines are the impulse responses and the one standard error confidence bands for the FULL-FAVAR model with the WTI oil price. The black solid lines with stars are the impulse responses from the benchmark FULL-FAVAR model.

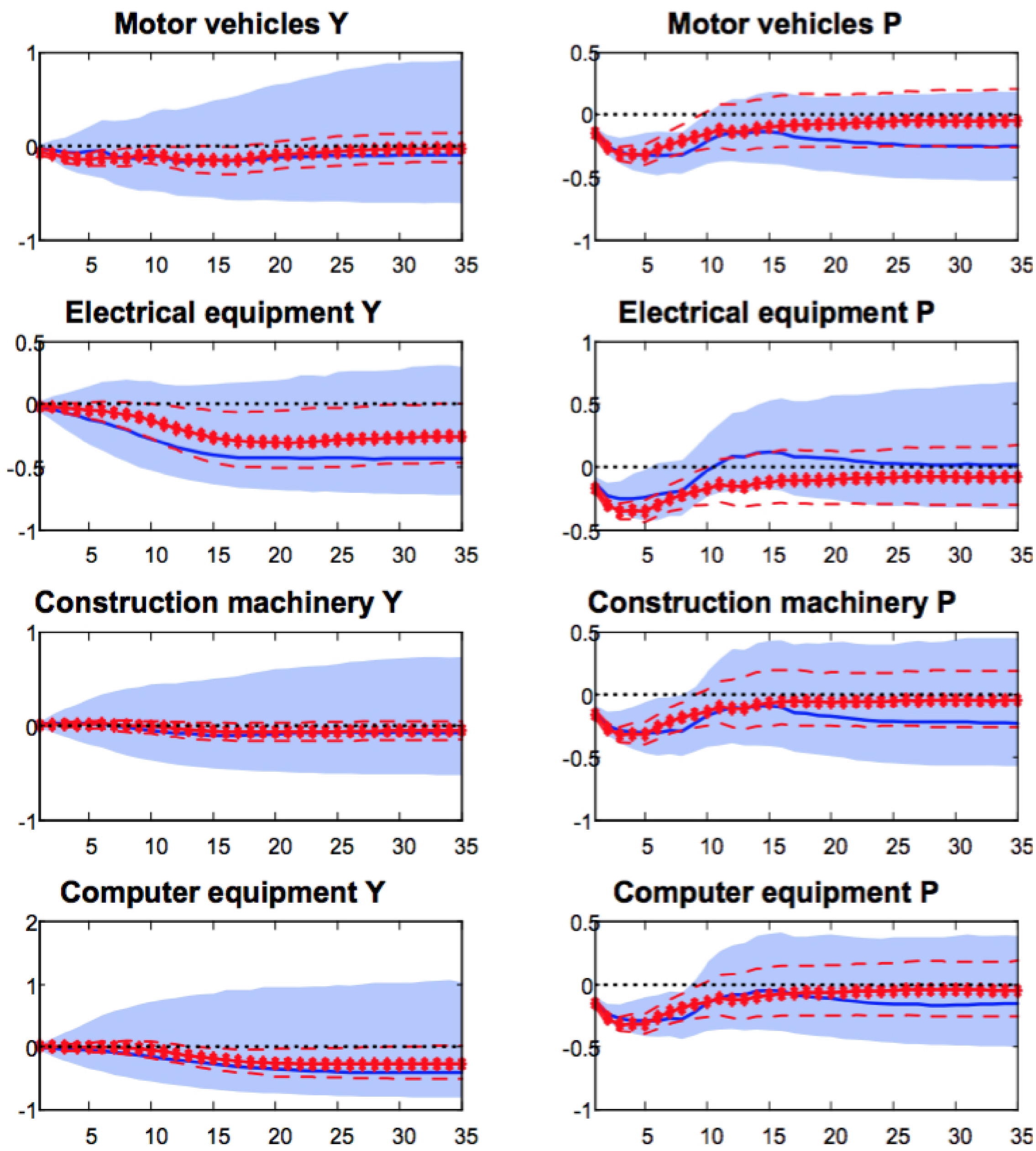
C.2 RAC versus RACR

Figure A.5: Impact of alternative oil price measures (RAC versus RACR)





Iron and steel Y
Iron and steel P
Lumber Y
Lumber P
Apparel Y
Apparel P
Furniture Y
Furniture P
Household appliance Y
Household appliance P



Notes: The figure plots the impulse reponses of industry output Y and price P to a 1% increase in the oil price measure. The blue solid lines with the shaded area are the median point estimates with the one standard error confidence bands for the FULL-FAVAR model with the RAC oil price measure. The red lines with circles and dashed red lines are the impulse responses and the one standard error confidence bands for the FULL-FAVAR model with the RACR oil price.