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Abstract

This paper evaluates the degree of pass-through from oil price shocks to disaggregate U.S. consumer prices. We find significantly positive effects of the oil price shock only on energy-intensive CPIs, which imply that significantly positive, though quantitatively small, response of the total CPI is mainly driven by substantial increases in prices of energy-related commodities. Unexpected changes in the oil price may result in decreases in the budget for non-energy commodities, if the demand for energy is inelastic (Edelstein and Kilian, 2009). Decreases in the demand for non-energy commodities will then result in limited influences on prices of those goods, which is consistent with our empirical findings.

Key Words**:** Oil Price Shocks; Pass-Through; Disaggregated Consumer Price Indices; Vector Autoregression

JEL Classification**:** E21; E31; Q43

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1 Introduction

The extent to which oil price shocks are passed through to domestic inflation has a long tradition in macroeconomics (see, e.g., Barsky and Kilian 2002, Hooker 2002, van den Noord and Andre 2007, Chen 2009, Kilian and Lewis 2011). As discussed in Kilian (2014), from a theoretical point of view, the effect of exogenous oil price shocks on consumer prices is ambiguous. On the one hand, oil price shocks may raise the price level, to the extent that they reduce the domestic supply of real output. On the other hand, they may lower the price level to the extent that they depress domestic demand.

This paper provides disaggregate evidence on the effect of oil price shocks on the components of the U.S. consumer price index (CPI), complementing existing evidence on the pass-through at the aggregate level. The importance of studying the effects of oil price shocks using disaggregate data has been illustrated in number of related contexts including stock returns (Kilian and Park, 2009), consumer expenditures (Edelstein and Kilian, 2009), and industrial production (Herrera, Lagalo, and Wada, 2011).

In what follows, we report very strong and statistically significant inflationary effects only in the expenditure categories of highly energy-intensive commodities, while very limited degree of pass-through to goods and services are found from less energy-intensive expenditures.

We interpret these findings as follows. When the oil price shock occurs, consumers may experience a decrease in real consumption expenditures for non-energy-related goods and services, if the demand for energy-related goods and services is inelastic (Edelstein and Kilian, 2009). This may shift the demand for less energy-intensive goods and services more than those of highly energy-intensive expenditures, resulting in heterogeneous responses to the oil price shock.

The rest of our manuscript is organized as follows. Section 2 provides a data description and the empirical model to study the degree of pass-through to U.S. CPIs. In Section 3, we provide our main findings using highly disaggregated CPI components as well as aggregate level indices. Section 4 concludes.

2 Data Descriptions and the Empirical Model

All data are seasonally adjusted and obtained from the Federal Reserve Economic Data (FRED). The oil price is the spot western Texas intermediate (WTI) and deflated by the US Consumer Price Index (CPI). We study pass-through from the oil price shock to 5 categories of CPI sub-indices that include: Food and Beverages; Housing; Apparel; Medical Care; Transportations. We also implement similar analysis for 24 components in two additional categories: Commodity and Services Groups; Special Indexes. Observations are monthly and span from 1974 M1 to 2014 M7 for most indices.[1,2,3]

To measure the dynamic effects of an oil price shock on each CPI component, we employ structural impulse response analysis. We postulate a recursively identified bivariate vector autoregressive (VAR) model for the change in the real spot oil price (Δr_t) and the j^{th} component of CPI inflation (π_t^j).

$$\boldsymbol{x}_t = v + \sum_{i=1}^{6} \boldsymbol{A}_i \, \boldsymbol{x}_{t-i} + \boldsymbol{u}_{t}, \tag{1}$$

[1] We follow Alquist, Kilian, and Vigfusson (2013) in restricting the sample to start in 1974 in recognition of the structural change taking place in late 1973 in the relationship between oil prices and the U.S. economy.

[2] We don't report empirical results for Recreation, and Education and Communication due to lack of observations.

[3] Detailed information is available upon request.

Where v is the intercept, $\boldsymbol{A}_i$ denotes the slope parameter matrices, $\boldsymbol{u}_t$ is a vector of independent white noise processes, and $\boldsymbol{x}_t = [\Delta r_t, \pi_t^j]'$. We use six lags to be consistent with Edelstein and Kilian (2009).[4] The identifying assumption is that the real price of oil is predetermined with respect to the U.S. CPI (see Kilian and Vega 2011). 95% percentile confidence bands are constructed based on the recursive design wild bootstrap of Goncalves and Kilian (2004).

3 Estimated Effects of the Oil Price Shock

We first report impulse-response function estimates for 7 CPI sub-indices as well as the total (all items) CPI to a 1% oil price shock in Figure 1. We find qualitatively different responses across indices to the positive oil price shock. That is, we observe a statistically significant positive response of the total CPI and the Energy, the Housing, and the Transportation CPI sub-indices, while very weak evidence of pass-through was found from the rest of other CPI sub-indices.

Based on point estimates, the Energy CPI increases by about 0.4% in 6 months then stabilizes in about 1 year with a 0.34% permanent increase. The Transportation CPI exhibits an about 0.16% permanent increase. The Housing CPI increases by about 0.05% in two years. The total CPI responds weaker than these sub-indices, increasing by about 0.07% in two years, but its responses are statistically significant at the 5% level. Responses of Other sub-indices are not only negligibly small but also insignificant.

It should be noted that the response function estimates for the Energy CPI are quite strong and significant at the 5% level, whereas the CPI sub-index of All Items *Less* Energy exhibits negligible and statistically insignificant responses at any conventional significance levels. This implies that the significant, though small,

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[4] Results with 3 lags yielded similar results. These results are available upon request.

responses of the total CPI are mainly obtained from the substantial rises in the Energy CPI sub-index to the oil price shock. We note that the responses of the total CPI are relatively weaker than those of the Energy CPI, which makes sense because the Energy CPI has a relatively small weight in the total CPI.

Figure 1 around here

Also, we report the forecast error variance decomposition (FEVDC) analysis for the CPI component inflation in Table 1. Being consistent with the impulse-response function analysis, the oil price shock explains almost 50% of variations in the forecast error for the Energy CPI in most forecast horizons. Similar evidence is found for the Transportation CPI. On the contrary, the oil price shock explains about 6% variations for the Housing CPI. It explains 11% to 30% variations for the total CPI, which are substantial but not as large as in the cases of the Energy and the Transportation CPIs. The FEVDC analysis demonstrates negligible contributions of the oil price shock in explaining variations in the forecast error for other CPI sub-indices.

In a nutshell, we found that the statistically significant, though quantitatively small, degree of pass-through from the oil price shock to the overall CPI might have been driven by substantial increases in prices of energy-intensive goods and services. In what follows, we extend our investigation of the effects of oil price shocks to highly disaggregated CPI components to study how the oil price shock may affect the consumers through heterogeneous responses of CPI sub-indices.

Table 1 around here

Figure 2 reports estimated effects of the oil price shock on the Food and Beverages category CPIs. Overall, we fail to find statistically significant effects of the oil price shock on most prices in this category. For example, the Food and Beverage CPI responded positively by 0.02%, though insignificant, in the long-run. Other prices show similarly negligible and insignificant responses. The Alcoholic Beverage CPI is an exception as it responds significantly at the 5% level after 7 months since the impact. However, the degree of pass-through is very small, around 0.03%.

We also report the FEVDC analysis for these category prices in Table 2. The results are consistent with the IRF evidence as we find very small contributions of the oil price shock in explaining variations of these inflation expectations even in the long-run.

Figure 2 and Table 2 around here

We note that the Housing CPI exhibits statistically significant and positive, but small responses that reaches about 0.05% in two years (see Figure 3). However, some energy-related component CPIs in this category such as the Fuel Oil, Fuels and Utilities, and Household Energy CPIs show quantitatively larger and significant responses. In particular, the Fuel Oil CPI increases by about 0.6% in about a half year then stabilizes around 0.5% after about 1 and half year. Note that these responses seem to be attributable to the energy-related components. Other component CPIs such as the Shelter and the Household Furnishings CPIs exhibit neither large nor significant responses.[5] The FEVDC analysis is reported in Table 3. All results are again consistent with the IRF results. The oil price shock explains substantial portions of forecast errors for π_t^j only for the price of energy intensive expenditures.

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[5] We also obtained response function estimates for other component CPI in this category that have shorter sample periods. Most of those prices responded insignificantly. All results are available upon requests.

Figure 3 and Table 3 around here

We do not find any meaningful degrees of pass-through to component prices in categories of Apparel and Medical Care, thus we do not report the results.[6] All responses were statistically insignificant at the 5% level and the responses are quantitatively small.

As can be seen in Figure 4, Transportation expenditures shows statistically significant pass-through in many sub-components. The Transportation CPI increases about 0.16% after about 1 year. The Gasoline CPI shows a maximum 0.68% in a half-year, then stabilizes around 0.56%. The Motor Fuel CPI (not reported) also shows similar responses. The Private Transportation CPI responds by about 0.15%.

The Public Transportation CPI shows a lot weaker responses (not reported) than those of the Private Transportation CPI. However, the Public Transportation CPI has a shorter sample period (January 1989 to July 2014), which may be responsible for weaker responses. To see if this is the case, we re-estimated the IRFs of the Private Transportation using the same sample period as that of the Public Transportation CPI. We find very similar results. Therefore, these IRFs jointly imply higher level price stickiness in the Public Transportation CPI than its unregulated counterpart.

The FEVDC analysis is reported in Table 4. For the Transportation, Gasoline, and the Private Transportation CPIs, the oil price shock explains over 40%, while it explains less than 10% for the rest CPI inflation rates in this category.

Figure 4 and Table 4 around here

[6] All results are available upon requests.

We find statistically significant evidence of pass-through only from 2 major expenditure categories, the Transportation and Housing CPIs. We also note that significant responses are often quantitatively small with exceptions of highly energy-related components CPIs such as the Gasoline and the Fuel Oil CPIs. These findings imply that observed significant degree of pass-through to the (total) All Items CPI might be driven by a few energy-related expenditures, even though their influence as to the quantitative measure may be weak. Does this mean that the oil price shock may not matter to consumers because it shows insignificant degree of pass-through in majority expenditure categories?

We do not think so. When the oil price shock occurs, consumers experience a decrease in real income for non-energy expenditures if the demand for energy is inelastic. As decreases in real spending for non-energy expenditures shift the demand curve to the left, prices in those expenditure categories will increase less than those of energy-intensive expenditures, because both the supply and the demand curve shift back in those markets. Our findings are consistent with this interpretation.

We also investigate the effect of the oil price shock on expenditures for Commodities, Nondurables, Services, Durables, and All Items Less Food/Medical Care. As shown in Figure 5, we observed significant pass-through to all of these CPIs. Compared with the Commodities and the Nondurable CPIs, evidence of pass-through to the Service and Durables CPI is relatively less significant both quantitatively and qualitatively. Interestingly, we find significant effects of the oil price shock on component CPIs when Food and Medical Care expenditures are excluded, which is consistent with our findings because those components responded to the oil price shock insignificantly. The FEVDC analysis reported in Table 5 is again consistent with the IRFs since we find the oil price shock explains about 40% of innovations in the Commodities and the Nondurables inflation, while it explains a lot less in the Service and the Durables inflation.

Figure 5 and Table 5 around here

5 Concluding Remarks

This paper empirically evaluates the degree of pass-through from the oil price shock to disaggregated component CPIs in the US. We find very limited effects of the oil price shock on majority CPIs including the Food and Beverage, the Apparel, the Housing, and the Medical Care CPIs, while more energy-intensive expenditures such as the Energy and Transportation CPIs show statistically significant evidence pass-through. Therefore, a significant response of the total CPI to the oil price shock seems to be mainly driven by substantial increases in the prices of energy-related expenditures. However, we also note that the response of the total CPI is quantitatively small, though highly significant at the 5%, reflecting relatively small shares of those energy-related expenditure CPIs in the determination of the total CPI.

These heterogeneous responses may not be explained if one views the oil price shock as primarily the supply shock, because a negative shift of the supply curve will result in increases in the equilibrium price. We attempt to solve this puzzle using the spending adjustment effect based on the work of Edelstein and Kilian (2009), who propose the possibility of a negative income effect caused by unexpected changes in the oil price. When the oil price increases unexpectedly, consumers will face substantial decreases in their expenditures of non-energy related commodities if the demand for energy is inelastic. Put it differently, they must reduce consumption for non-energy commodities since they are not able to adjust the budget for energy products.

Decreases in the demand for those non-energy commodities then increase the price a lot less compared with more energy-intensive goods and services, because not only the supply but also the demand curve shift to the left, resulting in weak and limited pass-through from the oil price shock to those CPI sub-indices. That is, even though the oil price shock has limited effects, quantitatively and qualitatively, on majority expenditures, its influence on consumers may not be negligible because overall consumption is likely to fall, which may provide useful information from the perspective of policymakers.

References

Alquist, R., Kilian, L., Vigfusson, R.J., 2013. Forecasting the Price of Oil, in: Elliott, G., Timmermann, A. (Eds.), Handbook of Economic Forecasting, 2, Amsterdam: North-Holland, pp. 427-507.

Barsky, R., Kilian, L., 2002. Do we really know that oil caused the great stagflation? A monetary alternative. NBER Macroeconomics Annual 2001. 16, 137 –183.

Chen, S.S. 2009. Oil price pass-through into inflation. Energy Economics, 31(1), 126-133.

Edelstein, P., Kilian, L., 2009. How sensitive are consumer expenditures to retail energy prices? J. Monetary Econ. 56, 766–779.

Goncalves, S., Kilian, L., 2004. "Bootstrapping autoregressions with conditional heteroskedasticity of unknown form," J. Econometrics. 123(1), 89-120.

Herrera, A.M., Lagalo, L.G., Wada, T. 2011. Oil price shocks and industrial production: is the relationship linear? Macroecon. Dynam. 15, 472-497.

Hooker, M.A. 2002. Are oil shocks inflationary? Asymmetric and nonlinear specifications versus changes in regime. J. Money Credit Bank. 34 (2), 540–561.

Kilian, L., Lewis, L.T., 2011. Does the fed respond to oil price shocks? Econ. J. 121, 1047–1072.

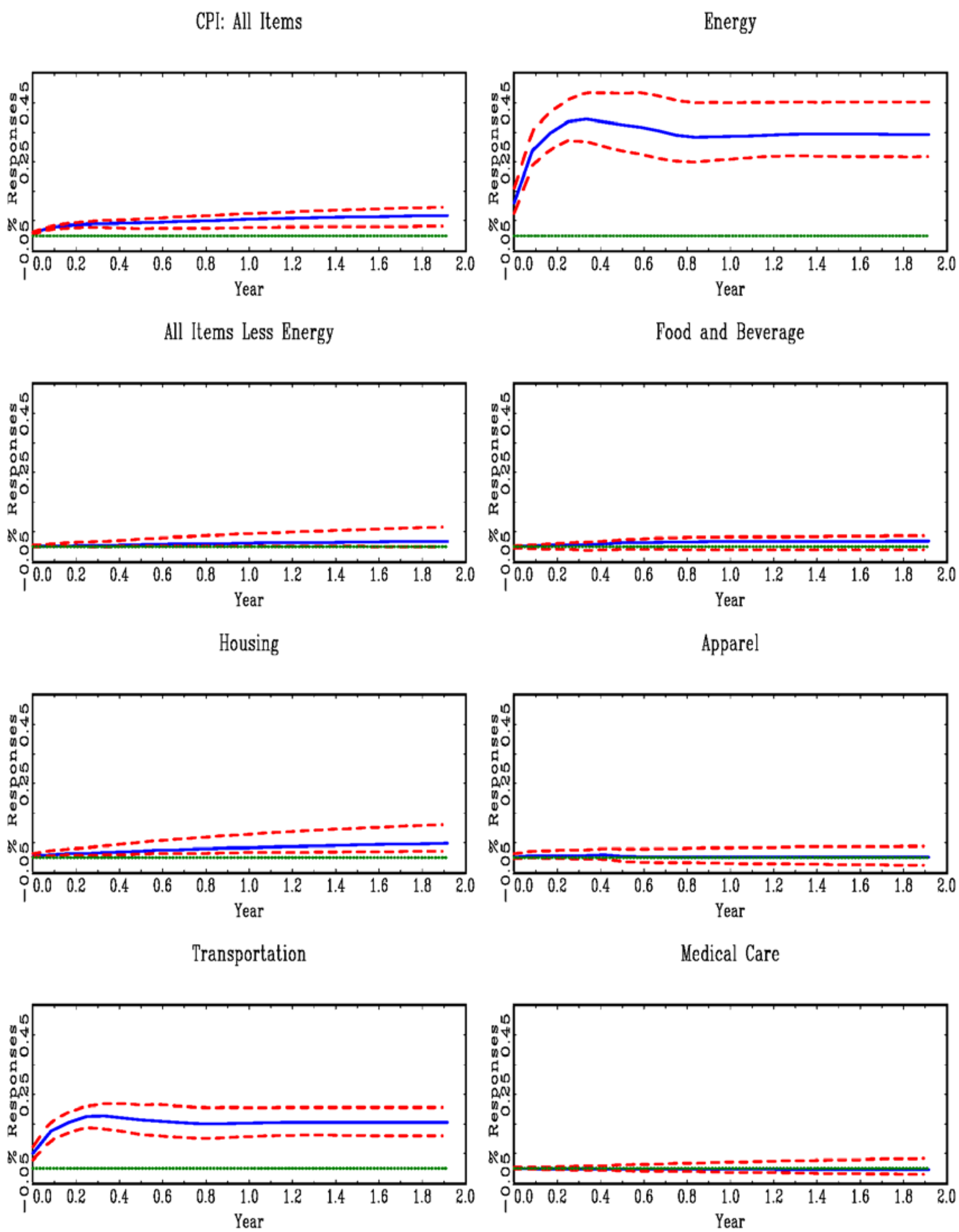
Kilian, L., Park, C., 2009. The impact of oil price shocks on the U.S. stock market. Int. Econ. Rev. 50(4), 1267-1287.

Kilian, L., Vega, C., 2011. Do energy prices respond to U.S. macroeconomic news? A test of the hypothesis of predetermined energy prices. Rev. Econ. Stat. 93(2), 660-671.

Kilian, L. 2014. Oil Price Shocks: Causes and Consequences. Forthcoming: Annual Review of Resource Economics. Annu. Rev. Resour. Econ.

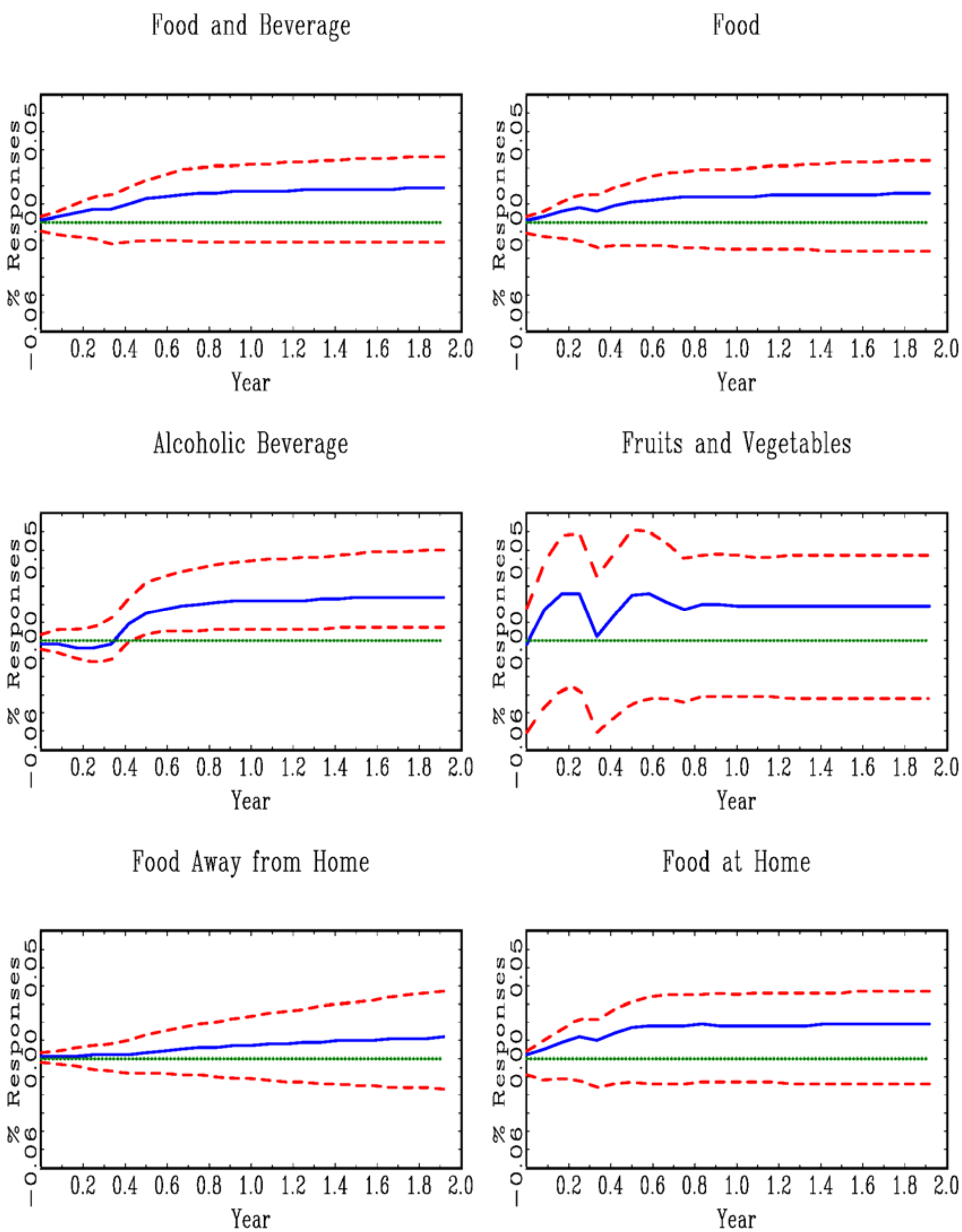
van den Noord, P., Andre, C. 2007. Why has core inflation remained so muted in the face of the oil shock? Working Paper, Economics Department, OECD.

Figure 1. Consumer Price Index Responses to a 1% Oil Price Shock



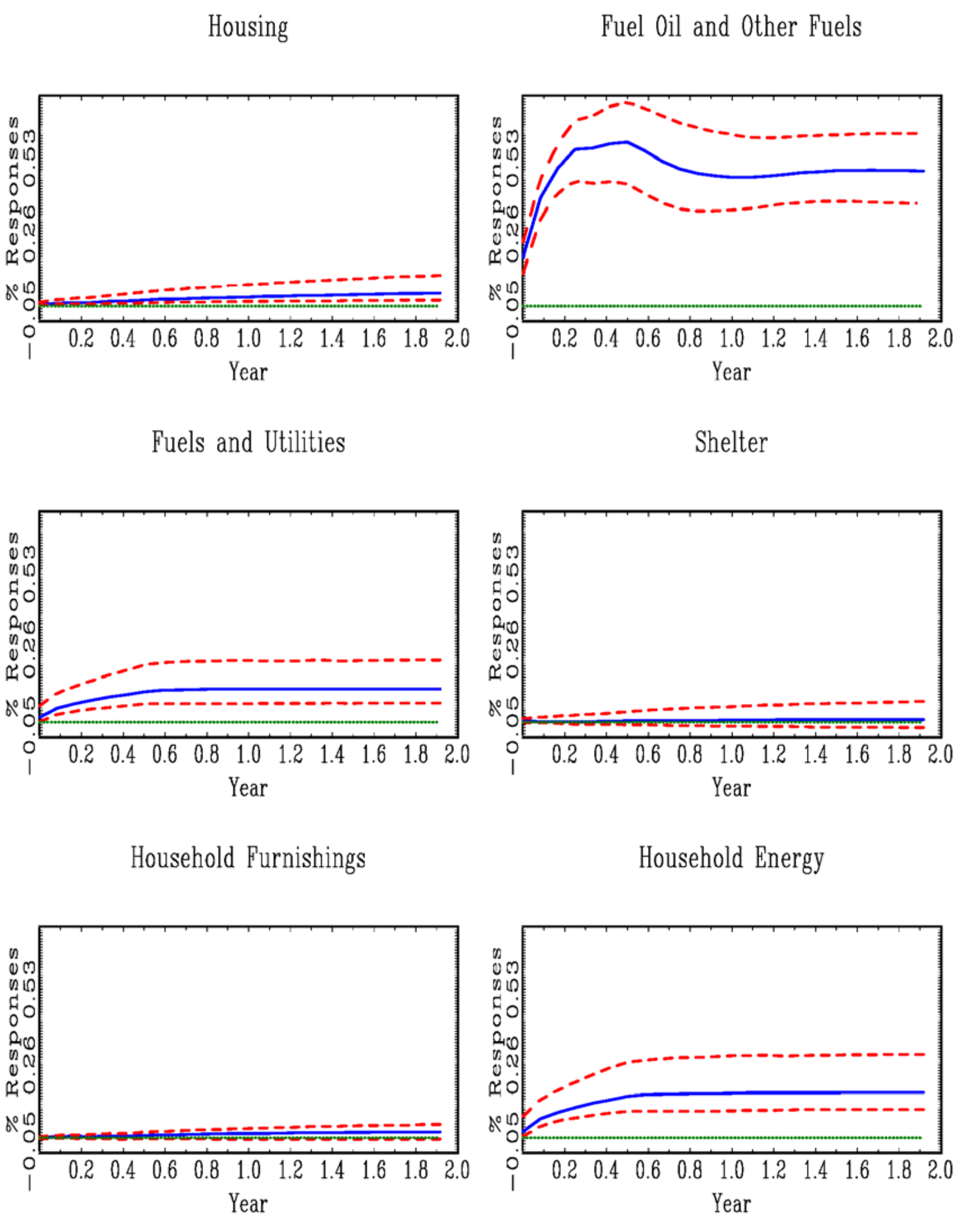
Note: Accumulated response functions are obtained from a bivariate vector autoregressive model with the real oil price inflation ordered first. The 95% confidence bands (dashed lines) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Figure 2. Food and Beverage Price Responses to a 1% Oil Price Shock



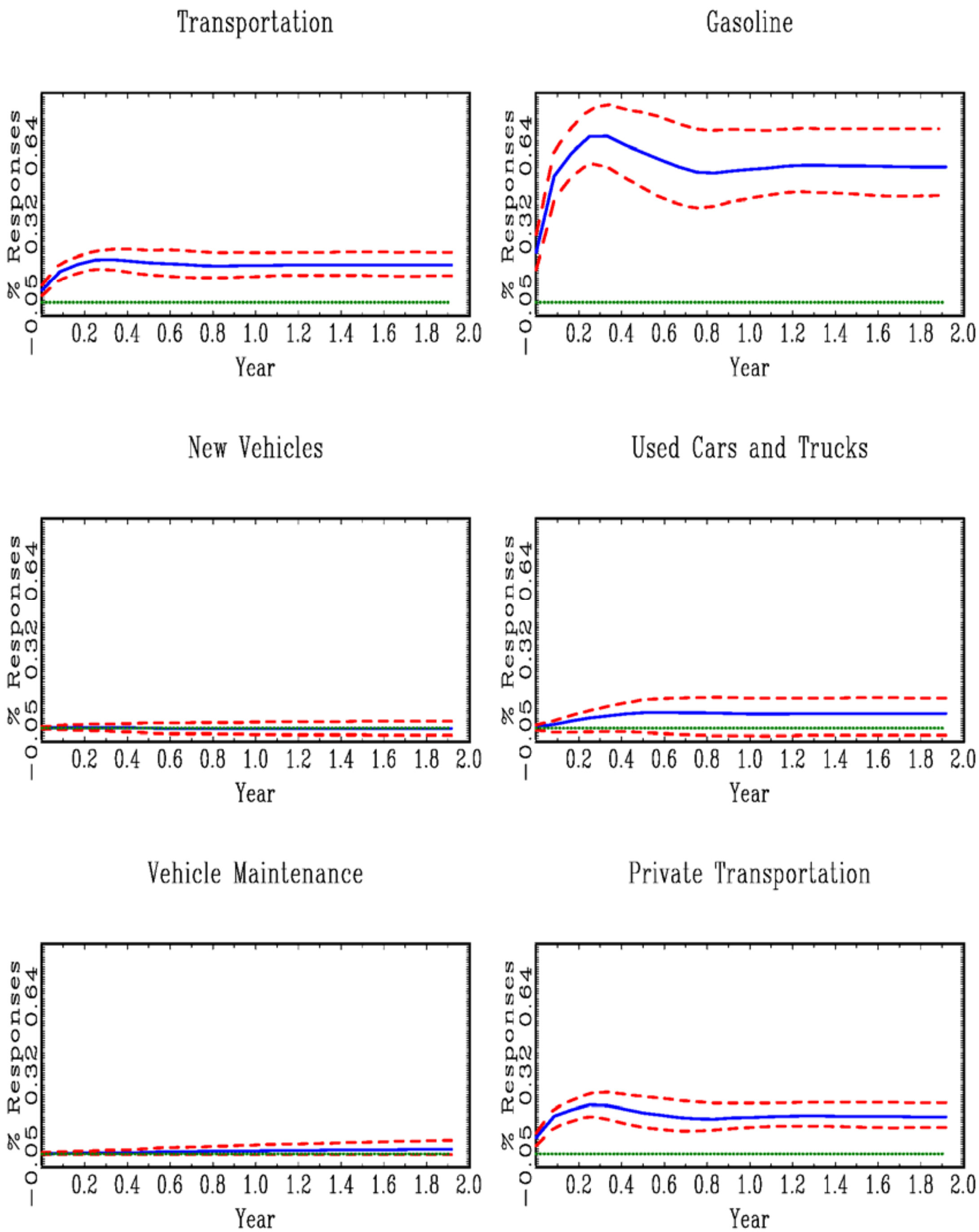
Note: Accumulated response functions are obtained from a bivariate vector autoregressive model with the real oil price inflation ordered first. The 95% confidence bands (dashed lines) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Figure 3. Housing Price Responses to a 1% Oil Price Shock



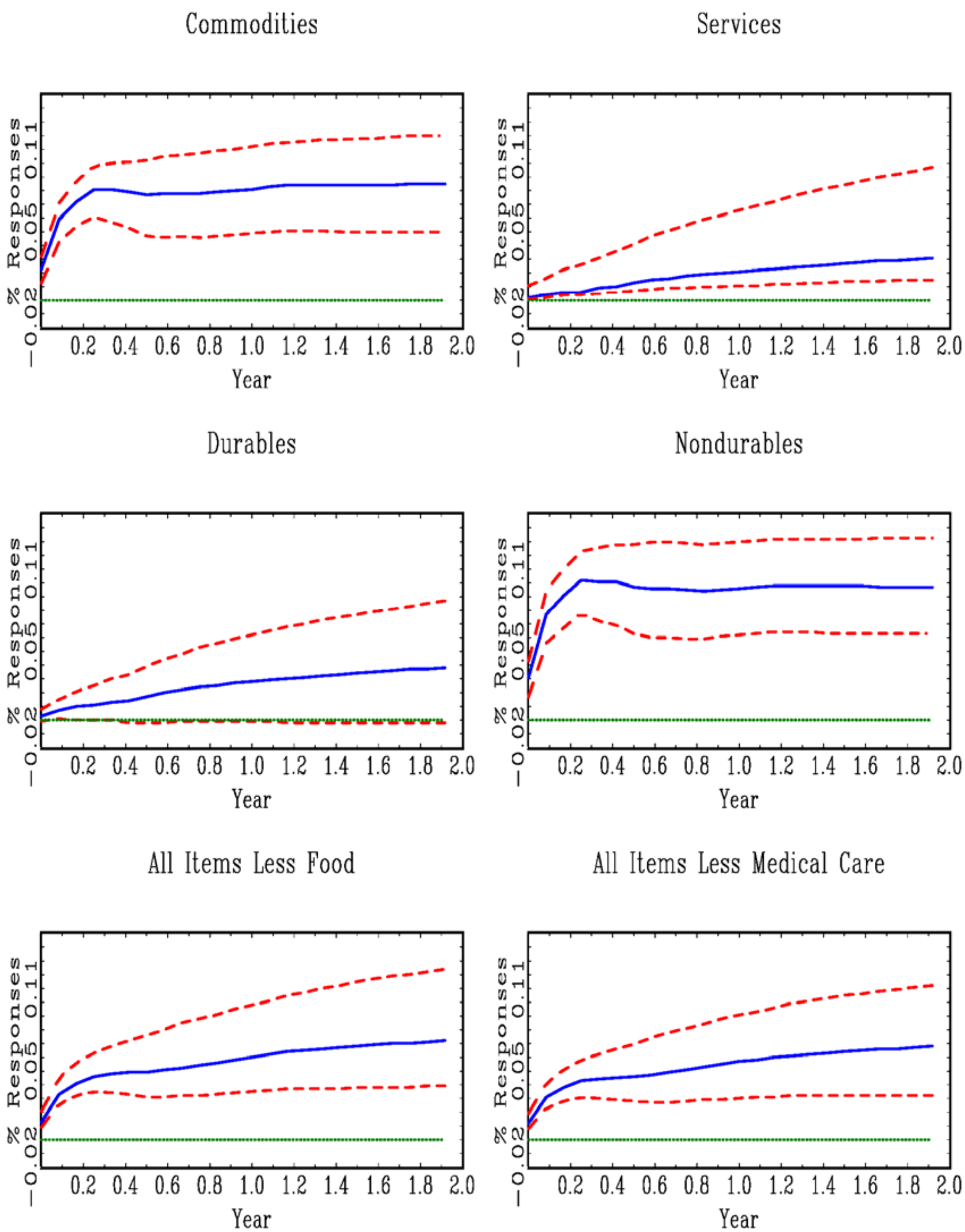
Note: Accumulated response functions are obtained from a bivariate vector autoregressive model with the real oil price inflation ordered first. The 95% confidence bands (dashed lines) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Figure 4. Transportation Price Responses to a 1% Oil Price Shock



Note: Accumulated response functions are obtained from a bivariate vector autoregressive model with the real oil price inflation ordered first. The 95% confidence bands (dashed lines) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Figure 5. Other Price Responses to a 1% Oil Price Shock



Note: Accumulated response functions are obtained from a bivariate vector autoregressive model with the real oil price inflation ordered first. The 95% confidence bands (dashed lines) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Table 1. Forecast Error Variance Decomposition Analysis

	CPI: All Items				*Energy*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.112	0.888	0.036	1	0.235	0.765	0.050
2	0.278	0.722	0.048	2	0.504	0.496	0.050
3	0.306	0.694	0.051	3	0.499	0.501	0.051
6	0.300	0.700	0.051	6	0.488	0.512	0.051
12	0.277	0.723	0.052	12	0.489	0.511	0.050
24	0.271	0.729	0.054	24	0.489	0.511	0.050

	All Items Less Energy				*Food and Beverage*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.001	0.999	0.007	1	0.000	1.000	0.008
2	0.004	0.996	0.007	2	0.008	0.992	0.008
3	0.007	0.993	0.008	3	0.012	0.988	0.009
6	0.021	0.979	0.011	6	0.031	0.969	0.013
12	0.022	0.978	0.015	12	0.052	0.948	0.017
24	0.023	0.977	0.017	24	0.052	0.948	0.017

	Housing				*Apparel*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.028	0.972	0.016	1	0.000	1.000	0.006
2	0.057	0.943	0.025	2	0.018	0.982	0.011
3	0.052	0.948	0.027	3	0.018	0.982	0.011
6	0.067	0.933	0.029	6	0.021	0.979	0.012
12	0.063	0.937	0.035	12	0.025	0.975	0.015
24	0.062	0.938	0.038	24	0.025	0.975	0.015

	Transportation				*Medical Care*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	se
1	0.171	0.829	0.047	1	0.000	1.000	0.010
2	0.404	0.596	0.053	2	0.000	1.000	0.011
3	0.429	0.571	0.054	3	0.001	0.999	0.012
6	0.424	0.576	0.053	6	0.003	0.997	0.014
12	0.426	0.574	0.053	12	0.006	0.994	0.015
24	0.426	0.574	0.053	24	0.005	0.995	0.016

Note: The Forecast Error Variance Decomposition analysis is implemented from a bivariate vector autoregressive model with the real oil price inflation ordered first. We report the variance decomposition for the k-period (month) ahead forecast of the variable x (each component CPI) at time t. Standard errors (s.e.) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Table 2. FEVDC Analysis: Food and Beverage

	Food and Beverage				*Food*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.000	1.000	0.008	1	0.000	1.000	0.007
2	0.008	0.992	0.008	2	0.009	0.991	0.008
3	0.012	0.988	0.009	3	0.014	0.986	0.009
6	0.031	0.969	0.013	6	0.030	0.970	0.012
12	0.052	0.948	0.017	12	0.047	0.953	0.014
24	0.052	0.948	0.017	24	0.047	0.953	0.015

	Alcoholic Beverage				*Fruits and Vegetables*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.007	0.993	0.024	1	0.000	1.000	0.009
2	0.007	0.993	0.024	2	0.010	0.990	0.013
3	0.007	0.993	0.024	3	0.010	0.990	0.014
6	0.063	0.937	0.035	6	0.019	0.981	0.018
12	0.082	0.918	0.042	12	0.037	0.963	0.020
24	0.082	0.918	0.042	24	0.038	0.962	0.020

	Food Away from Home				*Food at Home*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.000	1.000	0.008	1	0.000	1.000	0.009
2	0.001	0.999	0.008	2	0.008	0.992	0.009
3	0.001	0.999	0.009	3	0.014	0.986	0.010
6	0.008	0.992	0.012	6	0.029	0.971	0.014
12	0.011	0.989	0.018	12	0.047	0.953	0.015
24	0.011	0.989	0.020	24	0.047	0.953	0.016

Note: The Forecast Error Variance Decomposition analysis is implemented from a bivariate vector autoregressive model with the real oil price inflation ordered first. We report the variance decomposition for the k-period (month) ahead forecast of the variable x (each component CPI) at time t. Standard errors (s.e.) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Table 3. FEVDC Analysis: Housing

	Housing				*Fuel Oil and Other Fuels*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.028	0.972	0.016	1	0.137	0.863	0.040
2	0.057	0.943	0.025	2	0.290	0.710	0.070
3	0.052	0.948	0.027	3	0.306	0.694	0.076
6	0.067	0.933	0.029	6	0.319	0.681	0.077
12	0.063	0.937	0.035	12	0.323	0.677	0.079
24	0.062	0.938	0.038	24	0.323	0.677	0.079

	Fuels and Utilities				*Shelter*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.078	0.922	0.028	1	0.000	1.000	0.009
2	0.215	0.785	0.041	2	0.005	0.995	0.010
3	0.221	0.779	0.045	3	0.009	0.991	0.012
6	0.266	0.734	0.050	6	0.025	0.975	0.015
12	0.279	0.721	0.053	12	0.024	0.976	0.016
24	0.279	0.721	0.053	24	0.022	0.978	0.016

	Household Furnishings				*Household Energy*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.015	0.985	0.013	1	0.055	0.945	0.027
2	0.019	0.981	0.013	2	0.192	0.808	0.041
3	0.019	0.981	0.013	3	0.202	0.798	0.045
6	0.064	0.936	0.016	6	0.256	0.744	0.051
12	0.057	0.943	0.017	12	0.266	0.734	0.053
24	0.051	0.949	0.017	24	0.266	0.734	0.053

Note: The Forecast Error Variance Decomposition analysis is implemented from a bivariate vector autoregressive model with the real oil price inflation ordered first. We report the variance decomposition for the k-period (month) ahead forecast of the variable x (each component CPI) at time t. Standard errors (s.e.) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Table 4. FEVDC Analysis: Transportation

	Transportation				*Gasoline*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.171	0.829	0.047	1	0.263	0.737	0.054
2	0.404	0.596	0.053	2	0.518	0.482	0.054
3	0.429	0.571	0.054	3	0.500	0.500	0.054
6	0.424	0.576	0.053	6	0.480	0.520	0.053
12	0.426	0.574	0.053	12	0.481	0.519	0.053
24	0.426	0.574	0.053	24	0.482	0.518	0.053
	New Vehicles				*Used Cars and Trucks*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.001	0.999	0.021	1	0.008	0.992	0.028
2	0.001	0.999	0.022	2	0.013	0.987	0.031
3	0.002	0.998	0.023	3	0.035	0.965	0.038
6	0.007	0.993	0.022	6	0.087	0.913	0.048
12	0.028	0.972	0.022	12	0.098	0.902	0.049
24	0.028	0.972	0.022	24	0.098	0.902	0.049
	Vehicle Maintenance				*Private Transportation*		
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.030	0.970	0.015	1	0.163	0.837	0.049
2	0.034	0.966	0.015	2	0.398	0.602	0.054
3	0.039	0.961	0.015	3	0.420	0.580	0.055
6	0.041	0.959	0.017	6	0.415	0.585	0.054
12	0.036	0.964	0.018	12	0.417	0.583	0.054
24	0.030	0.970	0.019	24	0.417	0.583	0.054

Note: The Forecast Error Variance Decomposition analysis is implemented from a bivariate vector autoregressive model with the real oil price inflation ordered first. We report the variance decomposition for the k-period (month) ahead forecast of the variable x (each component CPI) at time t. Standard errors (s.e.) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Table 5. FEVDC Analysis: Other CPIs

Commodities				*Services*			
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.117	0.883	0.038	1	0.002	0.998	0.007
2	0.349	0.651	0.050	2	0.002	0.998	0.009
3	0.394	0.606	0.052	3	0.002	0.998	0.011
6	0.401	0.599	0.052	6	0.032	0.968	0.016
12	0.396	0.604	0.051	12	0.031	0.969	0.023
24	0.396	0.604	0.051	24	0.032	0.968	0.026

Durables				*Nondurables*			
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.009	0.991	0.030	1	0.151	0.849	0.041
2	0.016	0.984	0.035	2	0.380	0.620	0.053
3	0.021	0.979	0.037	3	0.399	0.601	0.054
6	0.020	0.980	0.039	6	0.401	0.599	0.054
12	0.024	0.976	0.047	12	0.401	0.599	0.053
24	0.024	0.976	0.049	24	0.402	0.598	0.053

All Items Less Food				*All Items Less Medical Care*			
k	Δr_t	π_t^j	s.e.	k	Δr_t	π_t^j	s.e.
1	0.135	0.865	0.040	1	0.084	0.916	0.038
2	0.312	0.688	0.050	2	0.249	0.751	0.048
3	0.344	0.656	0.053	3	0.278	0.722	0.051
6	0.333	0.667	0.053	6	0.269	0.731	0.052
12	0.304	0.696	0.053	12	0.241	0.759	0.052
24	0.294	0.706	0.055	24	0.229	0.771	0.053

Note: The Forecast Error Variance Decomposition analysis is implemented from a bivariate vector autoregressive model with the real oil price inflation ordered first. We report the variance decomposition for the k-period (month) ahead forecast of the variable x (each component CPI) at time t. Standard errors (s.e.) are obtained from 2,000 recursive design wild bootstrap draws (Goncalves and Kilian, 2004).

Not-For-Publication Appendix

Consumer Price Index Data: January 1974 to July 2014

Category	FRED Code
Food and Beverages	Food and Beverages
	Food
	Food away from home
	Alcoholic beverages
	Meats, poultry, fish, and eggs
	Food at home
	Fruits and vegetables
Housing	Housing
	Fuel oil and other fuels
	Fuels and utilities
	Shelter
	Household furnishings and operations
	Household energy
Apparel	Apparel
	Footwear
	Men's and boys' apparel
	Women's and girls' apparel
	Apparel less footwear
Transportation	Transportation
	New vehicles
	Gasoline (all types)
	Used cars and trucks
	Motor fuel
	Motor vehicle maintenance and repair
	Private transportation
Medical Care	Medical Care
	Medical care services
	Medical care commodities
Commodity and services groups	Commodities
	Services
	Durables
	Transportation services
	Commodities less food and beverages
	Other services
Special indexes	All Items Less Food & Energy
	Energy
	Commodities less food and energy commodities

All Items Less Energy
All items less shelter
All Items Less Food
Nondurables
All items less medical care
Services less energy services
Energy commodities
Commodities less food

Note: All data are obtained from the FRED website.