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Food and Energy Prices in Core Inflation

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Abstract

Many central bankers have made monetary policy decisions by focusing on core inflation data that exclude food and energy prices from overall inflation. In this paper, estimation results from multivariate GARCH models show that food prices not only help forecast future core inflation, but their conditional variance also affects the conditional variance of core inflation. Energy prices, on the other hand, affect core inflation primarily through the GARCH-in-mean effect. To the extent that food and energy prices affect the underlying trend and volatility of overall inflation, policymakers should not ignore these components in their assessment of future inflation risk.

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1. Introduction

Many central bankers, including officials at the Federal Reserve and the Bank of England, pay attention to measures of core inflation instead of overall or headline inflation in when they make monetary policy decisions. The central idea is that the conventional inflation measures, like the consumer price index (CPI), contain noise or transitory changes that are not useful for monetary policy conduct. By contrast, the concept of core inflation captures persistent price movements that help delineate the underlying inflation trend (Clark, 2001).

While there is no consensus on the best measure of core inflation, the most popular measure is the CPI less food and energy.[1] As Gordon (1975) asserts, food and energy periodically face volatile price movements that may diverge from changes of the overall price level in the long run, which is caused primarily by excessive money growth. However, Gavin and Mandal (2002) show that food prices indeed help forecast future inflation, although energy prices do not. Rich and Steindel (2007) also report that the CPI less food and energy measure is no better than a moving average of the overall CPI as a predictor of future inflation.

This paper seeks to reexamine the role that food and energy prices play in overall inflation and, in particular, core inflation. Most existing studies evaluate the role of alternative price indices by their performance in inflation forecasts. We follow a different approach in this paper. To the extent that many central bank officials ignore food and energy prices because of their "excessive" volatility, we focus on their conditional volatility in determining future inflation risk. By applying CPI inflation data to a multivariate GARCH-in-mean model, we show that food and energy prices not only help forecast the conventional measure of core inflation, but they also affect the degree of inflation uncertainty.

The rest of the paper is organized as follows. The next section presents the estimation methodology and data. The third section reports our empirical findings. The fourth section concludes the paper.

2. Methodology and Data

To explore possible interactions between core inflation and changes in food and energy prices, we consider a multivariate GARCH model. For n price series that are included in the model, their conditional means are assumed to follow a VAR(12) process with GARCH-in-mean effects:

$$\boldsymbol{p}_t = \Theta + \sum_{s=1}^{12} \Phi_s \boldsymbol{p}_{t-s} + \Psi \boldsymbol{H}_{t-1} + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t \sim (\mathbf{0}, \boldsymbol{H}_t) \tag{1}$$

where

[1] Other measures include trimmed mean and median price series, as reported by the Federal Reserve Bank of Cleveland. See Wynne (1999) and Clark (2001) for detailed discussions of alternative concepts and measures of core inflation

$$
\boldsymbol{p}_t = \begin{bmatrix} p_{1t} \\ \vdots \\ p_{nt} \end{bmatrix}, \boldsymbol{\Theta} = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}, \boldsymbol{\Phi}_s = \begin{bmatrix} \phi_{11}^s & \cdots & \phi_{1n}^s \\ \vdots & \ddots & \vdots \\ \phi_{n1}^s & \cdots & \phi_{nn}^s \end{bmatrix}, \boldsymbol{\Psi} = \begin{bmatrix} \psi_{11} & \cdots & \psi_{1n} \\ \vdots & \ddots & \vdots \\ \psi_{n1} & \cdots & \psi_{nn} \end{bmatrix}, \boldsymbol{H}_t = \begin{bmatrix} h_{11} & \cdots & h_{1n} \\ \vdots & \ddots & \vdots \\ h_{n1} & \cdots & h_{nn} \end{bmatrix},
$$

$$
\boldsymbol{\varepsilon}_t = \begin{bmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix}.
$$

The lag order in equation (1) is selected in light of the Bayesian Information Criterion. The variance/covariance matrix $\boldsymbol{H}_t$ is assumed to follow a GARCH(1,1) process:

$$
\boldsymbol{H}_t = \boldsymbol{C}'\boldsymbol{C} + \boldsymbol{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}'\boldsymbol{A} + \boldsymbol{B}'\boldsymbol{H}_{t-1}\boldsymbol{B} \tag{2}
$$

where

$$
\boldsymbol{C} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}.
$$

The particular BEKK parameterization of equation (2) imposes positive definiteness on $\boldsymbol{H}_t$. The conditional mean and conditional variance/covariance equations are estimated simultaneously by Bollerslev and Wooldridge's (1992) quasi-maximum likelihood method, which generates consistent standard errors that are robust to possible non-normality.

Following common practice, core inflation is measured by changes in the CPI excluding both food and energy items. We also consider the separate categories of "food and energy," i.e., the CPI less food and CPI less energy. As such, the alternative vectors of price series for $\boldsymbol{p}_t$ are $[p_t^{xfe}, p_t^{fe}]'$, $[p_t^{xf}, p_t^{f}]'$, $[p_t^{xe}, p_t^{e}]'$ and $[p_t^{xfe}, p_t^{f}, p_t^{e}]'$, where a price series with a superscript "xfe" denotes the CPI less both food and energy as the core price measure, "xf" denotes the exclusion of only food, "xe" denotes the exclusion of only energy, "fe" denotes the CPI of only food and energy items, "f" denotes the CPI of food items, and "e" denotes the CPI of energy items. All CPI data are seasonally adjusted and observed monthly over the period between 1960:1 and 2007:12. The data are obtained from the U.S. Bureau of Economic Analysis. For estimation, all price series are expressed as 100 times the first difference of its log value, i.e., $100 \times \ln(p_{it} / p_{i,t-1})$.

3. Empirical Results

In this section, we discuss estimation results of the GARCH-in-mean model outlined previously in Section 2.[2] Table 1 reports results for a bivariate model that includes the CPI less both food

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[2] Instead of the whole observation period, we took into account possible structural change and ran estimations for two separate periods: 1960:1-1983:12 and 1984:1-2007:12. In addition, rather than monthly CPI data, we ran

and energy (p_t^{xfe}) and the aggregate index of food and energy (p_t^{fe}). The first two rows display some diagnostic statistics for the estimated model. The first row contains Lagrange multiplier statistics for testing remaining ARCH effects up to the 12th lag order. The results reveal little evidence of ARCH effects in the residuals. The second row shows the Ljung-Box Q statistics for testing autocorrelation in the residuals also up to the 12th order. Similarly, there is scant evidence of serial correlation. These test results together support that the empirical model accounts for most of the conditional heteroskedasticity and autocorrelation in the two price series. Similar results are found for other price series examined in this paper.

Table 1 also contains estimation results for the conditional mean and conditional variance equations. In the conditional mean equation, more than half of the lag coefficient estimates are statistically significant at the 10 percent level or higher. The four *F* statistics test for the predictive power of all lags of an explanatory variable. They are all statistically significant, indicating that past movements of the food and energy price series help predict the current movement of the core price series, and vice versa.

In the conditional variance equation, the statistically significant estimate of b_{12} indicates a volatility spillover from the food and energy price series to the core price series. All estimates in the ***A*** matrix are also statistically meaningful, indicating that a shock to either price series also affects the conditional variance of another price series. In addition, there is some evidence of the GARCH-in-mean effect. More specifically, the positive estimate of ψ_{12} in the conditional mean equation is statistically significant at the 10 percent level. This suggests that core inflation is positively related to the conditional variance of food and energy prices.

In addition to examining the CPI that excludes food and energy items as a whole, we explore the interactions between the core CPI and the two separate price series of the food and energy categories. Corresponding to Table 1, Table 2 reports estimation results for the bivariate model containing the CPI less only food (p_t^{xf}) and the CPI of only food items (p_t^{f}). The *F*-statistics for testing the lag coefficients in the conditional mean equation indicate that past movements of the food price series help explain the current movement of the non-food core price series, while the non-food price series fails to explain food price movements.

The estimates for all elements in Ψ, which capture the GARCH-in-mean effect, are not statistically meaningful. The insignificant estimate of ψ_{12} suggests that food price volatility does not affect core price movements even though the volatility of food and energy prices together does (as shown in Table 1). Despite the absence of any GARCH-in-mean effect, the estimates in the conditional variance equation indicate that the conditional variance of the non-food price series is associated with the past conditional variance of the food price series as well as the past shock to food prices.

Instead of focusing on the food category, we now investigate the energy component of the CPI. Table 3 reports estimation results for the bivariate model containing CPI less energy

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estimations using quarterly Personal Consumption Expenditures (PCE) price indices. The general conclusions are not sensitive to these changes

(p_t^{xe}) and the energy price index (p_t^e). In contrast to the corresponding statistics in Tables 1 and 2, the *F*-statistics for testing the lag coefficients in the conditional mean equation indicate that each of the two price series contains no statistically meaningful information about future movements of the other price series. However, the estimates for elements in Ψ suggest that the non-energy core inflation series is positively related to the conditional variances of both energy prices and (non-energy) core prices. In the conditional variance equation, the estimates for all off-diagonal elements of the coefficient matrices are not significantly different from zero, indicating an absence of any relationship between the conditional variances of the two price series.

Table 4 further reports estimation results for a model containing three price series: the core CPI less food and energy, the food CPI, and the energy CPI. In this trivariate case, the *F*-statistics for testing the lag coefficients in the conditional mean equation indicate that past food price movements significantly explain the current movement of the core price series, while energy price movements do not. These findings are consistent with those from the bivariate cases above. The finding of no predictive power from energy prices is also in line with the results reported by Gavin and Mandal (2002). Nevertheless, the estimate of ψ_{13} is significant at the 10 percent level. This supports that energy price volatility affects core inflation.

Similar to those in Table 2, the statistically significant estimates of a_{21} and b_{21} in the conditional variance equation suggest that the lagged value of a food price shock as well as the conditional variance of food prices affect the conditional variance of core inflation. There is, however, little evidence to support a corresponding effect from the energy price series. The estimates in the conditional variance equation also offer no meaningful evidence of interactions between food price volatility and energy price volatility.

The overall estimation results of the trivariate model are line with those in the separate cases of bivariate models. Together, the findings highlight the varying roles of food and energy prices in overall inflation dynamics. Food and energy prices affect not only the level of core inflation but also its conditional volatility. In particular, food prices affect the conditional variance of inflation—a common proxy for inflation uncertainty. For this reason, policymakers should not ignore food prices when assessing inflation risk. In addition, energy price volatility helps forecast the underlying trend of inflation so that policymakers should not exclude energy prices simply because of their relatively high volatility.

4. Conclusion

In this paper, estimation results with a multivariate GARCH-in-mean model support that food price movements not only help predict future core inflation, but their conditional variance also affects the conditional variance of core inflation—a measure of inflation uncertainty. Energy price movements, on the other hand, affect core inflation primarily through the GARCH-in-mean effect. These findings imply that policymakers who choose to look past price movements of food and energy due to their excessive volatility might leave out meaningful information about the risk of future inflation.

Given the findings against the exclusion-based approach in assessing inflation trends, monetary policymakers should consider other measures of core inflation. For example, officials at the Federal Reserve Bank of Cleveland advocate a "trimmed mean" inflation measure that accounts for all volatility in consumer prices. Similarly, Bryan and Cecchetti (1994), and Wynne (1999) suggest a concept capturing the price change that is common to all goods in the long run, while Woodford (2003, Chapter 6) focuses on the cost of inflation. These concepts have been incorporated by Anderson *et al.* (2007) in a signal extraction problem for forecasting inflation. In light of our empirical results, a core inflation measure should also take GARCH effects—a measure of inflation costs—into consideration.

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Table 1: GARCH Model Estimation with CPI Excluding Food & Energy.

Dependent variable: p_t^{xfe}			Dependent variable: p_t^{fe}		
ARCH(12)	3.055		ARCH(12)	13.487	
Ljung-Box Q(12)	11.472		Ljung-Box Q(12)	12.989	
Conditional Mean:	Estimate	*t*-value		Estimate	*t*-value
θ_1	0.015	(3.444) ***	θ_2	0.027	(4.560) ***
ϕ_{11}^1	0.095	(3.933) ***	ϕ_{21}^1	0.209	(4.109) ***
ϕ_{11}^2	0.170	(8.975) ***	ϕ_{21}^2	-0.070	(-2.592) ***
ϕ_{11}^3	0.085	(7.950) ***	ϕ_{21}^3	0.008	(0.340)
ϕ_{11}^4	0.063	(5.067) ***	ϕ_{21}^4	-0.054	(-2.676) ***
ϕ_{11}^5	0.189	(4.913) ***	ϕ_{21}^5	-0.033	(-1.139)
ϕ_{11}^6	0.138	(6.845) ***	ϕ_{21}^6	-0.043	(-1.545)
ϕ_{11}^7	0.023	(1.920) *	ϕ_{21}^7	-0.068	(-2.847) ***
ϕ_{11}^8	0.097	(4.241) ***	ϕ_{21}^8	-0.097	(-6.840) ***
ϕ_{11}^9	0.056	(1.558)	ϕ_{21}^9	0.063	(1.789) *
ϕ_{11}^{10}	0.060	(8.472) ***	ϕ_{21}^{10}	0.078	(4.000) ***
ϕ_{11}^{11}	-0.038	(-1.937) *	ϕ_{21}^{11}	0.070	(3.004) ***
ϕ_{11}^{12}	-0.013	(-1.092)	ϕ_{21}^{12}	-0.073	(-2.878) ***
ϕ_{12}^1	0.090	(5.115) ***	ϕ_{22}^1	0.195	(3.864) ***
ϕ_{12}^2	0.046	(1.692) *	ϕ_{22}^2	-0.093	(-2.019) **
ϕ_{12}^3	0.002	(0.082)	ϕ_{22}^3	0.057	(1.536)
ϕ_{12}^4	0.015	(0.666)	ϕ_{22}^4	0.026	(0.813)
ϕ_{12}^5	0.026	(1.105)	ϕ_{22}^5	0.063	(1.920) *
ϕ_{12}^6	0.022	(1.015)	ϕ_{22}^6	0.060	(1.918) *
ϕ_{12}^7	0.021	(1.092)	ϕ_{22}^7	0.042	(1.069)
ϕ_{12}^8	0.002	(0.090)	ϕ_{22}^8	0.056	(1.811) *
ϕ_{12}^9	0.035	(1.431)	ϕ_{22}^9	0.088	(2.338) **
ϕ_{12}^{10}	-0.045	(-2.275) **	ϕ_{22}^{10}	0.128	(3.620) ***
ϕ_{12}^{11}	0.020	(0.871)	ϕ_{22}^{11}	0.123	(4.167) ***
ϕ_{12}^{12}	-0.031	(-1.853) *	ϕ_{22}^{12}	-0.142	(-4.648) ***
ψ_{11}	-0.076	(-0.345)	ψ_{21}	-0.302	(-0.743)
ψ_{12}	0.793	(1.920) *	ψ_{22}	-0.001	(-0.007)
F-Tests:					
$\phi_{11}^1 = \ldots = \phi_{11}^{12} = 0$	63.451 ***		$\phi_{21}^1 = \ldots = \phi_{21}^{12} = 0$	2.354 ***	
$\phi_{12}^1 = \ldots = \phi_{12}^{12} = 0$	4.168 ***		$\phi_{22}^1 = \ldots = \phi_{22}^{12} = 0$	5.149 ***	

Table 1 (Continued).

Conditional Variance:	Estimate	*t*-value
c_{11}	0.010	(1.982) **
c_{21}	0.052	(1.401)
c_{22}	0.091	(3.670) ***
a_{11}	0.290	(8.768) ***
a_{12}	0.088	(1.823) *
a_{21}	0.045	(1.928) *
a_{22}	0.702	(3.724) ***
b_{11}	0.956	(5.103) ***
b_{12}	0.195	(9.626) ***
b_{21}	0.015	(1.024)
b_{22}	0.499	(8.568) ***
Log-likelihood	509.460	

Notes: *, **, and *** denote statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 2: GARCH Model Estimation with CPI Excluding Food.

Dependent variable: p_t^{xf}			Dependent variable: p_t^{f}		
ARCH(12)	14.098		ARCH(12)	0.983	
Ljung-Box Q(12)	1.838		Ljung-Box Q(12)	0.925	
Conditional Mean:	Estimate	*t*-value		Estimate	*t*-value
θ_1	0.026	(2.128) **	θ_2	0.065	(6.092) ***
ϕ_{11}^1	0.206	(6.652) ***	ϕ_{21}^1	0.063	(2.132) **
ϕ_{11}^2	0.049	(1.685) *	ϕ_{21}^2	-0.021	(-0.681)
ϕ_{11}^3	0.091	(5.024) ***	ϕ_{21}^3	-0.007	(-0.254)
ϕ_{11}^4	0.023	(2.326) **	ϕ_{21}^4	-0.022	(-0.622)
ϕ_{11}^5	-0.021	(-0.904)	ϕ_{21}^5	0.091	(2.467) **
ϕ_{11}^6	0.080	(3.972) ***	ϕ_{21}^6	0.038	(1.217)
ϕ_{11}^7	0.063	(2.166) **	ϕ_{21}^7	-0.039	(-0.955)
ϕ_{11}^8	0.024	(1.267)	ϕ_{21}^8	0.063	(1.954) *
ϕ_{11}^9	0.040	(1.965) **	ϕ_{21}^9	0.120	(4.529) ***
ϕ_{11}^{10}	0.062	(2.844) ***	ϕ_{21}^{10}	0.125	(3.593) ***
ϕ_{11}^{11}	0.077	(4.584) ***	ϕ_{21}^{11}	-0.043	(-1.170)
ϕ_{11}^{12}	-0.073	(-2.550) **	ϕ_{21}^{12}	-0.031	(-0.957)
ϕ_{12}^1	0.012	(1.103)	ϕ_{22}^1	0.121	(5.247) ***
ϕ_{12}^2	0.060	(5.340) ***	ϕ_{22}^2	0.025	(0.778)
ϕ_{12}^3	0.016	(1.252)	ϕ_{22}^3	-0.016	(-0.553)
ϕ_{12}^4	-0.003	(-0.176)	ϕ_{22}^4	-0.052	(-1.987) **
ϕ_{12}^5	0.025	(2.032) **	ϕ_{22}^5	0.097	(2.958) ***
ϕ_{12}^6	0.031	(3.008) ***	ϕ_{22}^6	0.083	(3.470) ***
ϕ_{12}^7	0.024	(1.463)	ϕ_{22}^7	0.006	(0.238)
ϕ_{12}^8	0.023	(1.563)	ϕ_{22}^8	0.027	(0.824)
ϕ_{12}^9	0.013	(1.100)	ϕ_{22}^9	0.047	(1.467)
ϕ_{12}^{10}	0.037	(2.542) **	ϕ_{22}^{10}	0.076	(2.615) ***
ϕ_{12}^{11}	0.035	(2.347) **	ϕ_{22}^{11}	0.040	(1.241)
ϕ_{12}^{12}	0.003	(0.199)	ϕ_{22}^{12}	-0.115	(-3.476) ***
ψ_{11}	0.087	(0.340)	ψ_{21}	0.555	(0.627)
ψ_{12}	-0.403	(-1.345)	ψ_{22}	0.116	(1.177)
F-Tests:					
$\phi_{11}^1 = \ldots = \phi_{11}^{12} = 0$		15.005 ***	$\phi_{21}^1 = \ldots = \phi_{21}^{12} = 0$		1.046
$\phi_{12}^1 = \ldots = \phi_{12}^{12} = 0$		4.043 ***	$\phi_{22}^1 = \ldots = \phi_{22}^{12} = 0$		8.008 ***

Table 2 (Continued).

Conditional Variance:	Estimate	*t*-value
c_{11}	0.048	(3.969) ***
c_{21}	-0.025	(-1.419)
c_{22}	-0.020	(-0.662)
a_{11}	0.340	(5.146) ***
a_{12}	0.083	(2.133) **
a_{21}	0.003	(0.386)
a_{22}	0.293	(5.627) ***
b_{11}	0.918	(8.602) ***
b_{12}	0.051	(2.370) **
b_{21}	0.003	(0.807)
b_{22}	0.952	(7.452) ***
Log-likelihood	479.620	

Notes: *, **, and *** denote statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 3: GARCH Model Estimation with CPI Excluding Energy.

Dependent variable: p_t^{xe}			Dependent variable: p_t^{e}		
ARCH(12)	6.585		ARCH(12)	7.766	
Ljung-Box Q(12)	1.088		Ljung-Box Q(12)	1.913	
Conditional Mean:	Estimate	*t*-value		Estimate	*t*-value
θ_1	0.019	(2.856) ***	θ_2	-0.008	(-0.696)
ϕ_{11}^1	0.109	(5.949) ***	ϕ_{21}^1	0.050	(1.571)
ϕ_{11}^2	0.125	(6.023) ***	ϕ_{21}^2	0.019	(0.656)
ϕ_{11}^3	0.078	(2.402) **	ϕ_{21}^3	0.006	(0.251)
ϕ_{11}^4	0.003	(0.119)	ϕ_{21}^4	-0.073	(-4.128) ***
ϕ_{11}^5	0.162	(9.719) ***	ϕ_{21}^5	0.018	(0.619)
ϕ_{11}^6	0.160	(4.017) ***	ϕ_{21}^6	0.009	(0.358)
ϕ_{11}^7	-0.016	(-0.448)	ϕ_{21}^7	-0.107	(-3.410) ***
ϕ_{11}^8	0.064	(2.755) ***	ϕ_{21}^8	0.002	(0.103)
ϕ_{11}^9	0.105	(4.790) ***	ϕ_{21}^9	0.056	(2.479) **
ϕ_{11}^{10}	0.117	(3.662) ***	ϕ_{21}^{10}	0.100	(6.733) ***
ϕ_{11}^{11}	-0.012	(-0.610)	ϕ_{21}^{11}	-0.051	(-3.229) ***
ϕ_{11}^{12}	-0.013	(-0.762)	ϕ_{21}^{12}	-0.085	(-4.563) ***
ϕ_{12}^1	0.004	(1.754) *	ϕ_{22}^1	0.036	(7.530) ***
ϕ_{12}^2	0.004	(1.303)	ϕ_{22}^2	-0.007	(-1.324)
ϕ_{12}^3	-0.001	(-0.459)	ϕ_{22}^3	-0.002	(-0.377)
ϕ_{12}^4	-0.001	(-0.439)	ϕ_{22}^4	0.002	(0.273)
ϕ_{12}^5	0.004	(1.392)	ϕ_{22}^5	-0.005	(-0.757)
ϕ_{12}^6	0.001	(0.441)	ϕ_{22}^6	0.013	(2.672) ***
ϕ_{12}^7	0.002	(0.925)	ϕ_{22}^7	-0.006	(-1.234)
ϕ_{12}^8	-0.001	(-0.430)	ϕ_{22}^8	0.001	(0.306)
ϕ_{12}^9	0.005	(2.671) ***	ϕ_{22}^9	0.007	(1.664) *
ϕ_{12}^{10}	-0.002	(-1.092)	ϕ_{22}^{10}	0.004	(0.821)
ϕ_{12}^{11}	0.000	(0.159)	ϕ_{22}^{11}	0.022	(4.908) ***
ϕ_{12}^{12}	-0.002	(-1.270)	ϕ_{22}^{12}	-0.025	(-5.417) ***
ψ_{11}	0.360	(2.145) **	ψ_{21}	0.222	(0.579)
ψ_{12}	1.190	(2.652) ***	ψ_{22}	0.216	(1.156)
F-Tests:					
$\phi_{11}^1 = \ldots = \phi_{11}^{12} = 0$		37.934 ***	$\phi_{21}^1 = \ldots = \phi_{21}^{12} = 0$		6.349 ***
$\phi_{12}^1 = \ldots = \phi_{12}^{12} = 0$		1.391	$\phi_{22}^1 = \ldots = \phi_{22}^{12} = 0$		1.075

Table 3 (Continued).

Conditional Variance:	Estimate	*t*-value
c_{11}	0.005	(0.985)
c_{21}	0.028	(0.672)
c_{22}	0.043	(2.273) **
a_{11}	0.236	(3.561) ***
a_{12}	0.008	(0.103)
a_{21}	0.010	(0.351)
a_{22}	0.436	(7.973) ***
b_{11}	0.970	(9.755) ***
b_{12}	0.005	(0.249)
b_{21}	0.002	(0.147)
b_{22}	0.867	(6.683) ***
Log-likelihood	480.780	

Notes: *, **, and *** denote statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table 4: Trivariate GARCH Model Estimation with CPI Excluding Food & Energy.

Dependent variable:	p_t^{xfe}			p_t^{f}			p_t^{e}	
ARCH(12)	13.128			0.517			0.558	
Ljung-Box Q(12)	3.537			1.088			4.71	
Conditional Mean:								
F-Tests:								
$\phi_{11}^{1}=\ldots=\phi_{11}^{12}=0$	20.271 ***		$\phi_{21}^{1}=\ldots=\phi_{21}^{12}=0$	1.021		$\phi_{31}^{1}=\ldots=\phi_{31}^{12}=0$	0.698	
$\phi_{12}^{1}=\ldots=\phi_{12}^{12}=0$	4.642 ***		$\phi_{22}^{1}=\ldots=\phi_{22}^{12}=0$	7.665 ***		$\phi_{32}^{1}=\ldots=\phi_{32}^{12}=0$	1.665 *	
$\phi_{13}^{1}=\ldots=\phi_{13}^{12}=0$	1.075		$\phi_{23}^{1}=\ldots=\phi_{23}^{12}=0$	1.127		$\phi_{33}^{1}=\ldots=\phi_{33}^{12}=0$	15.064 ***	
	Estimate	*t*-value		Estimate	*t*-value		Estimate	*t*-value
ψ_{11}	1.249	(1.707) *	ψ_{21}	0.594	(0.903)	ψ_{31}	1.720	(1.573)
ψ_{12}	1.925	(0.854)	ψ_{22}	0.111	(0.880)	ψ_{32}	0.060	(0.313)
ψ_{13}	6.476	(1.784) *	ψ_{23}	5.868	(1.309)	ψ_{33}	0.006	(0.092)
Conditional Variance:								
c_{11}	0.008	(1.419)						
c_{21}	-0.033	(-1.536)						
c_{22}	0.012	(1.744) *						
c_{31}	0.026	(0.266)						
c_{32}	0.428	(5.816) ***						
c_{33}	0.000	(0.000)						
a_{11}	0.004	(0.177)						
a_{12}	0.196	(1.681) *						
a_{13}	0.092	(0.285)						
a_{21}	0.024	(3.263) ***						
a_{22}	0.247	(3.461) ***						
a_{23}	0.114	(1.846) *						
a_{31}	0.000	(0.382)						
a_{32}	0.003	(0.523)						
a_{33}	0.557	(6.897) ***						
b_{11}	0.995	(4.055) ***						
b_{12}	0.027	(1.518)						
b_{13}	0.006	(0.294)						
b_{21}	0.012	(2.676) ***						
b_{22}	0.963	(9.700) ***						
b_{23}	0.002	(0.238)						
b_{31}	0.000	(0.896)						
b_{32}	0.003	(0.948)						
b_{33}	0.793	(6.526) ***						
Log-likelihood	847.070							

Notes: *, **, and *** denote statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.