Online Appendix to "Price Setting and Volatility: Evidence from Oil Price Volatility Shocks"

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Model Appendix

This section has further details about the menu cost model. In section A.A1 is shows how the profit function can be written in terms of $A_t(z)$, $\frac{P_{t-1}}{S_t}$, P_t^o, and σ_t that enables the model to be solved recursively. It then discusses the model solution in section A.A2. Section A.A3 has additional details about the multisector model and presents the price response to an expansionary monetary shock. Section A.A4 presents the menu cost model that features a fixed menu cost and shows that it counterfactually predicts decreased price dispersion during periods of high oil price volatility. Lastly, section A.A5 displays the parameters, moments, and impulse responses to the alternative calibration.

A1. Profit Function

This section shows how to write the profit function in terms of $A_t(z)$, $\frac{P_{t-1}}{S_t}$, P_t^o, and σ_t.

To write the firm flow profits in real terms, I divide by P_t.

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big)y_t(z) - \frac{W_t}{P_t}L_t(z) - \frac{Q_t}{P_t}O_t(z) - \chi_t(z)\frac{W_t}{P_t}I_t(z) \tag{A1}$$

Then using equation (20) I substitute out for $O_t(z)$ which gives after simplification

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big)y_t(z) - \frac{W_t}{P_t}\frac{s_o}{1-s_o}L_t(z) - \chi_t(z)\frac{W_t}{P_t}I_t(z) \tag{A2}$$

After using firm cost minimization to write the production function as $y_t(z) = A_t(z)L_t(z)$, I substitute out for labor $L_t(z)$.

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big)y_t(z) - (1-s_o)^{s_o-1}s_o^{-s_o}\frac{W_t}{P_t}(\frac{W_t}{P_t}\frac{P_t}{Q_t})^{s_o}\frac{y_t(z)}{A_t(z)} - \chi_t(z)\frac{W_t}{P_t}I_t(z) \tag{A3}$$

Now I substitute in the firm's demand curve (19) and labor supply (15) to give

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big)^{1-\theta}Y_t - (1-s_o)^{s_o-1}s_o^{-s_o}(\omega C_t)^{1-s_o}(\frac{Q_t}{P_t})^{s_o}\frac{1}{A_t(z)}Y_t\Big(\frac{p_t(z)}{P_t}\Big)^{-\theta} - \chi_t(z)(\omega C_t)I_t(z) \tag{A4}$$

Lastly, the aggregate resource constraint implies that $Y_t = C_t$. This gives the equation

(A5) $$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big)^{1-\theta} C_t - \frac{1}{A_t(z)} C_t \Big(\frac{p_t(z)}{P_t}\Big)^{-\theta} (1-s_o)^{s_o-1} s_o^{-s_o} (\omega C_t)^{1-s_o} (\frac{Q_t}{P_t})^{s_o} - \chi_t(z)(\omega C_t) I_t(z)$$

Thus I am able to rewrite flow profits as a function of $\big(A_t(z), \frac{p_{t-1}(z)}{P_t}, P_t^o, \sigma_t\big)$.

To simplify notation, I can write

(A6) $$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t} - \frac{1}{A_t(z)} \frac{Q_t}{P_t} (\omega C_t)^{1-s_o}\Big) \Big(\frac{p_t(z)}{P_t}\Big)^{-\theta} C_t - \chi_t(z)(\omega C_t) I_t(z)$$

I need to write firm profits as a function of $\frac{p_t}{S_t}$ in order to bound the state space. To do this, first note that from equation (25) I can write $\frac{P_t}{S_t}$ as

(A7) $$\frac{P_t}{S_t} = e^{\gamma_0 + \gamma_1 log P_t^o + \gamma_2 \sigma_t + \gamma_3 log(\frac{P_{t-1}}{S_t}) + \gamma_4 (log(\frac{P_{t-1}}{S_t}) * log P_t^o) + \gamma_5 (log(\frac{P_{t-1}}{S_t}) * \sigma_t)}$$

and I can write C_t as

(A8) $$C_t = e^{-\Big(\gamma_0 + \gamma_1 log P_t^o + \gamma_2 \sigma_t + \gamma_3 log(\frac{P_{t-1}}{S_t}) + \gamma_4 (log(\frac{P_{t-1}}{S_t}) * log P_t^o) + \gamma_5 (log(\frac{P_{t-1}}{S_t}) * \sigma_t)\Big)}$$

Then I take firm profits, multiply and divide by S_t, and replace $C_t = \frac{S_t}{P_t}$.

(A9) $$\pi_t^R(z) = \Bigg(\frac{\frac{p_t(z)}{S_t}}{\frac{P_t}{S_t}} - \frac{1}{A_t(z)} (\frac{Q_t}{P_t})^{s_o} (\omega C_t)^{1-s_o}\Bigg) \Bigg(\frac{\frac{p_t(z)}{S_t}}{\frac{P_t}{S_t}}\Bigg)^{-\theta} \frac{S_t}{P_t} - \chi_t(z)(\omega \frac{S_t}{P_t}) I_t(z)$$

Finally I replace $\frac{P_t}{S_t}$ and C_t with the expressions from the law of motion.

(A10)
$$\pi_t^R(z) = \Big(\frac{p_t(z)}{S_t} e^{-(\Theta_t)} - \frac{1}{A_t(z)} (P_t^o)^{s_o} (\omega e^{-\Theta_t})^{1-s_o}\Big) \Big(\frac{p_t(z)}{S_t} e^{-(\Theta_t)}\Big)^{-\theta} (e^{-(\Theta_t)}) - \chi_t(z)(\omega e^{-(\Theta_t)}) I_t(z)$$

where Θ_t is the expression for the law of motion of $\frac{P_t}{S_t}$. Rearranging gives

(A11) $$\pi_t^R(z) = \Big(\frac{p_t(z)}{S_t} - \frac{1}{A_t(z)} (P_t^o)^{s_o} (\omega)^{1-s_o} e^{\Theta_t s_o}\Big) \Big(\frac{p_t(z)}{S_t}\Big)^{-\theta} (e^{(\Theta_t)})^{\theta-2} - \chi_t(z)(\omega e^{-(\Theta_t)}) I_t(z)$$

which is the value function written in terms of $\big(A_t(z), \frac{p_{t-1}(z)}{S_t}, P_t^o, \sigma_t\big)$. I also need to rewrite the stochastic discount factor as

$$D^R_{t,t+1} = \beta\frac{C_t}{C_{t+1}} = \beta\frac{e^{-\left(\gamma_0+\gamma_1 logP^o_t+\gamma_2\sigma_t+\gamma_3 log(\frac{P_{t-1}}{S_t})+\gamma_4(log(\frac{P_{t-1}}{S_t})*logP^o_t)+\gamma_5(log(\frac{P_{t-1}}{S_t})*\sigma_t)\right)}}{e^{-\left(\gamma_0+\gamma_1 logP^o_{t+1}+\gamma_2\sigma_{t+1}+\gamma_3 log(\frac{P_t}{S_{t+1}})+\gamma_4(log(\frac{P_t}{S_{t+1}})*logP^o_{t+1})+\gamma_5(log(\frac{P_t}{S_{t+1}})*\sigma_{t+1})\right)}} \tag{A12}$$

where expectations can be formed by using the law of motions for P^o_t, σ_t, S_t.

A2. Model Solution

The recursive problem is solved on a discretized grid using value function iteration. Knotek and Terry (2008) argue in favor of discretization over colocation in state dependent pricing models due to robustness. The productivity grid is discretized using 21 points, the real price grid has 171 points, oil price has 15 grid points, and oil price volatility has 5 points. Expectations must be taken over the monetary growth rate and are discretized using 7 points, while the Krusell-Smith aggregate state is discretized with 8 points.

The model is simulated using the non-stochastic simulation method of Young (2010). Non-stochastic simulation tracks a histogram of firm states rather than a large number of firms which removes Monte Carlo sampling error, and increases the speed of the simulation compared to large firm panels. The overall numerical solution is outlined below.

1) Guess a set of γ_i for i $\in \{0, 1, 2, 3, 4, 5\}$ in the aggregate law of motion.

2) Firms choose relative price to solve profit maximization given the conjectured forecast for the aggregate state. They are maximizing equation (26).

3) Given the policy function from step 2, the model is simulated using non-stochastic simulation. This implies that the aggregate variables P^o_t, σ_t, and S_t are simulated from their discretized transition matrices. A histogram of weights is tracked over the idiosyncratic variables $\frac{p_t(z)}{P_t}$, $A_t(z)$, and $\chi_t(z)$. The density of prices at each individual state is updated each period using the transition matrix for each variable.

4) Using the simulated data, the aggregate law of motion is re-estimated using the data.

5) γ_i^{iter+1} are updated using the new values.

6) Check if the equilibrium has converged. The maximum Den Haan (2010) statistic is computed over the full simulation of 2000 periods (166.66 years). The maximum Den Haan

statistic is the maximum difference between the simulated value of $log(\frac{P_t}{S_t})$ from the model, and a dynamic forecast of $log(\frac{P_t}{S_t})^{DH}$. The dynamic forecast of $log(\frac{P_t}{S_t})$ is constructed by repeated application of the Krusell and Smith forecasting equation, using the resulting predicted dependent variable in the construction of the following periods forecast. This method allows for accumulation of prediction error within the forecasting system. The specific equilibrium convergence criterion is $\mid DH^{max}_{iter+1} - DH^{max}_{iter} \mid < .0001$. After this criterion is met the aggregate law of motion has converged and model equilibrium is reached.

A3. Multisector model details

This section provides additional details about the multisector model. For computational purposes, I assume the Krusell and Smith forecasting rule is the same as the one solved in the one sector model. This is similar to assuming that the eight sectors are part of a competitive fringe, and do not affect aggregate dynamics. However, fully iterating the model until the Krusell and Smith forecasting equation has converged does not affect the model implications, or imply large changes in pricing moments relative to the chosen solution method.

The model price response is shown in Figure A1.

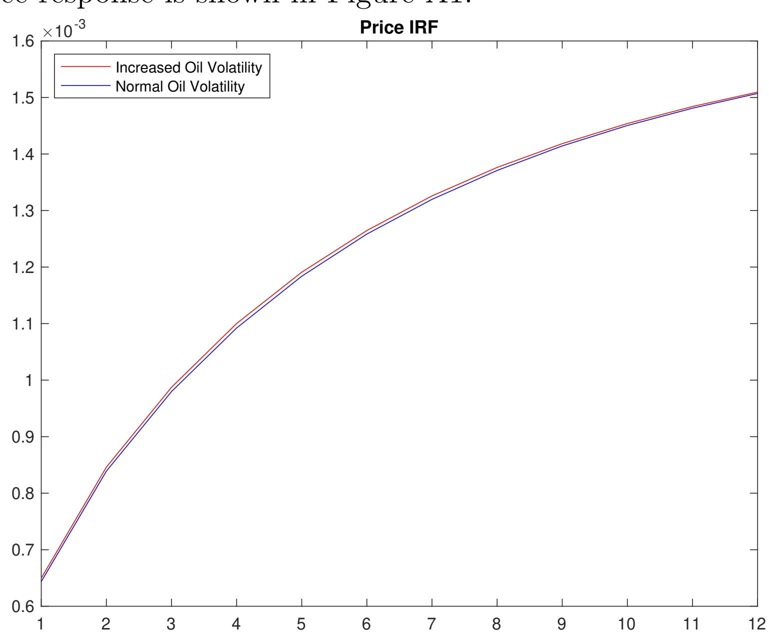


Figure A1. Price Response to Nominal Shock

NOTE: Impulse response of the price level in the baseline multisector model to a one time permanent increase in log nominal output of size 0.002 under different levels of oil price volatility.

A4. Fixed Menu Cost Model: Volatility Implications

This section discusses the calibration of a fixed menu cost model like in Golosov and Lucas (2007), and shows that it is not capable of matching the new empirical facts. This model features a strong selection effect that implies prices react strongly to a common oil price volatility change, decreasing dispersion and increasing frequency.

The model is the same as in Section III, except for the nature of menu costs. The menu cost distribution is reduced to a single point mass at χ, implying that a firm can change their price at any point if they pay the fixed menu cost. The model is calibrated to match the same moments of the data, but skewness of price change is not targeted. The persistence of idiosyncratic productivity is set to $\rho_a = 0.7$, which matches Nakamura and Steinsson (2008). Then the remaining four parameters χ, σ_a, p_a, and α are set to target four moments of the PPI data. The moments are frequency of price change, average size of price change, standard deviation of price changes, and the fraction of small price changes. The value of the fixed menu cost is set to $\chi = 0.20$. However a fraction $\alpha = 0.125$ of firms receive a free opportunity to change prices. This parameter is identified by the fraction of small price changes.[41] The volatility and probability of receiving an idiosyncratic productivity shock determines the average size and dispersion of price changes. The standard deviation of shocks is set to 0.105 and the probability of receiving a shock is set to 0.4. This enables the model to match the large absolute average size of price change and the large dispersion of price change. Moments of the model are in Table A1.

The model matches frequency and dispersion exactly. Fraction of small price changes is slightly too low, and this causes the average size to be too large. Fraction of positive price changes is also too high like in the random menu cost model, but this is primarily determined by the nominal GDP process. While not targeted, the model is not capable of matching the positive skewness in the data.

In order to test the predictions of the model against the empirical results, I compute the price response on impact of a one standard deviation increase in oil price volatility. In this fixed menu cost model calibration, a one standard deviation increase in oil price volatility

[41] The pricing parameters imply that total adjustment costs in the economy are $\chi * (Freq - \alpha) * \frac{\theta - 1}{\theta} = 0.42\%$ of revenues per month. Estimates from Levy et al. (1997) suggest that menu costs are 0.7% of revenues, while Stella (2014) estimates menu costs to be bounded between 0.22% and 0.59%.

Table A1—Fixed Menu Cost Model Moments

Price Setting Statistic	Data	Model
Frequency	0.154	0.152
Average Size of Price Change	0.071	0.097
Fraction Small Price Changes	0.215	0.142
Standard Deviation Price Changes	0.125	0.124
Skewness Price Changes	0.095	- 0.195
Fraction Price Increases	0.602	0.648

decreases price change dispersion by 2.7%. The volatility effect dominates the real options effect, increasing the frequency of price adjustment as frequency of price change increases by 8.1%. The increase in oil price volatility creates a larger realized oil price, which increases the gap between a firm's current price and optimal price. The common volatility increase pushes more price changes in one direction, decreasing price change dispersion. There is an increase in the directional synchronization of price changes that does not occur during an increase in idiosyncratic volatility. During periods of increased oil price volatility, more price changes move in the direction of the larger oil price shock, causing a decrease in price change dispersion.

This section has showed that a menu cost model with a fixed menu cost does not match the positive relationship between oil price volatility and price change dispersion that is seen in the data. Rather, a strong selection effect generates a counterfactual decrease in price change dispersion and an increase in price change frequency when oil price volatility is increased.

A5. Alternative Calibration

This section displays model parameters and moments from the alternative calibration targeting the regression coefficients. Model moments are in Table A2 while model parameters are in Table A3. The corresponding consumption and price impulse response functions to an expansionary monetary shock are displayed in Figures A2.

Data Appendix

In B.B1, estimation and details of the stochastic volatility process are discussed. Next in Section B.B2, I discuss data sets that are used in the paper including the BLS micro-price data and show robustness to the oil price series used. Section B.B3 presents additional robustness exercises such as robustness to oil volatility series used, generated regressor standard errors, and robustness to

Table A2—Alternative Sectoral Characteristics of Multisector Model

Sector	Oil Share	Frequency	Avg. Size	Fraction Small	S.D.	Skewness
			Data			
1	0.00041	0.10	0.08	0.20	0.15	0.12
2	0.00102	0.08	0.08	0.19	0.13	0.00
3	0.00158	0.17	0.07	0.23	0.12	-0.02
4	0.00208	0.23	0.06	0.20	0.10	0.14
5	0.00308	0.11	0.06	0.27	0.12	0.13
6	0.00579	0.15	0.07	0.28	0.13	0.37
7	0.01056	0.19	0.06	0.17	0.11	0.05
8	0.05547	0.27	0.06	0.21	0.10	0.13
			Model			
1	0.00041	0.06	0.13	0.08	0.16	-0.11
2	0.00102	0.08	0.12	0.10	0.16	-0.08
3	0.00158	0.11	0.10	0.15	0.13	-0.01
4	0.00208	0.14	0.08	0.18	0.11	0.02
5	0.00308	0.09	0.10	0.14	0.14	-0.07
6	0.00579	0.19	0.09	0.26	0.13	-0.01
7	0.01056	0.20	0.08	0.24	0.11	0.11
8	0.05547	0.34	0.06	0.38	0.10	0.01

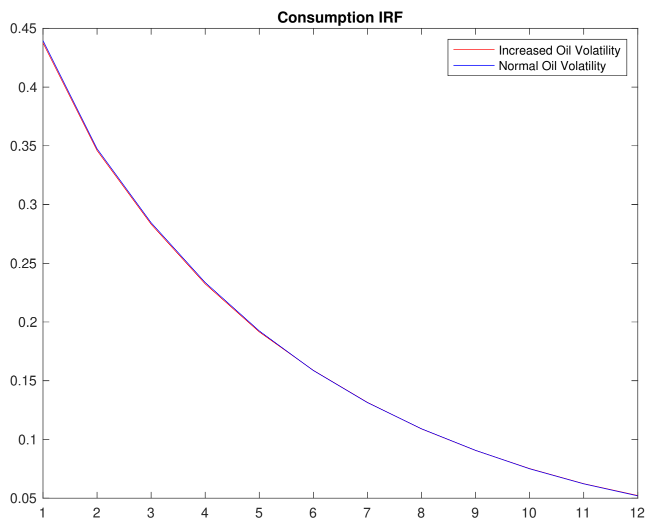
NOTE: The top panel presents the weighted average price setting moments from the PPI data from 1998-2014 at monthly frequency. PPI industries are grouped into octiles according to oil share in column one. S.D. is the standard deviation of price changes, while fraction of small price changes is defined as the percent of prices changes less than 1% in absolute value.

Table A3—Alternative Sectoral Parameters

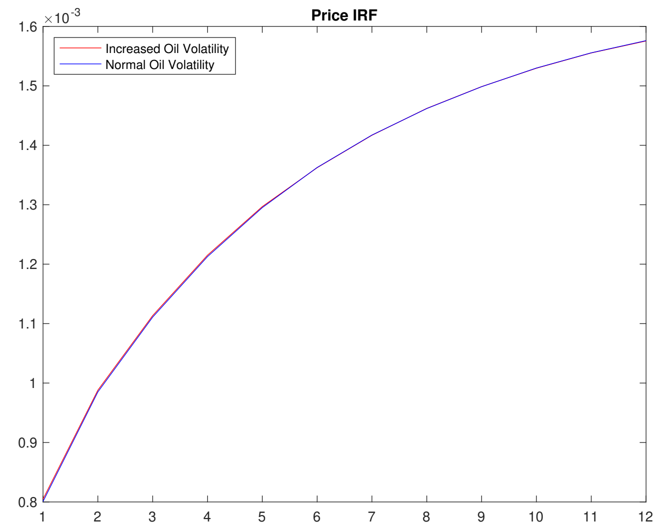
Parameter:	$\sigma_{a,j}$	$p_{a,j}$	λ_j	ξ_j	α_j
Sector					
1	0.250	0.30	0.165	0.060	0.01
2	0.220	0.45	0.162	0.055	0.03
3	0.160	0.44	0.160	0.050	0.08
4	0.120	0.50	0.158	0.045	0.13
5	0.190	0.44	0.145	0.040	0.09
6	0.220	0.44	0.190	0.035	0.12
7	0.160	0.44	0.120	0.030	0.20
8	0.220	0.50	0.110	0.025	0.35

NOTE: This table presents the multisector model parameters that are calibrated to match the unconditional pricing moments for each sector j. $p_{a,j}$ is the probability that log firm productivity follows an AR(1) process with standard deviation $\sigma_{a,j}$, λ_j determines the average value of the menu cost that is drawn, ξ_j determines the curvature of the menu cost distribution, and α_j is the probability of a free price change.

price change dispersion. Lastly, Section B.B4 presents additional results on aggregate pricing moment regressions, industry dependent oil price pass-through, empirical price distributions, and a balance check of observables across high and low oil usage industries.



(a) Output Response



(b) Price Response

Figure A2. Output and Price Response to Nominal Shock in Alternative Calibration Model

NOTE: Panel (a) shows the impulse response of output in the alternative calibration multisector model to a one time permanent increase in log nominal output of size 0.002 under different levels of oil price volatility. Panel (b) shows the accompanying impulse response of the price level.

B1. Stochastic Volatility Model

The stochastic volatility model for real oil prices P_t^o is given by

$$logP_t^o = \rho_p logP_{t-1}^o + e^{\sigma_t}\nu_t \tag{B1}$$

$$\sigma_t = (1-\rho_\sigma)\overline{\sigma} + \rho_\sigma\sigma_{t-1} + \phi\nu_{\sigma,t} \tag{B2}$$

The process for σ_t is latent, and following Plante and Traum (2012), Fernandez-Villaverde et al. (2015), and Born and Pfeifer (2014), a sequential importance resampling particle filter is used to evaluate the likelihood function due to the nonlinearity in the SV model. Once the likelihood function of the data is constructed, a random walk Metropolis-Hastings algorithm is used to compute the posterior distribution of the four parameters. Uniform priors are used for each parameter. The particle filter uses 40,000 particles to construct the likelihood, while 150,000 draws are used in the RWMH algorithm with the first 50,000 discarded. The final acceptance ratio of proposals is 0.32, within the recommended window of 15% to 40% in Roberts, Gelman and Gilks (1996). In order to obtain the volatility series of the data, the backwards-smoothing routine of Godsill, Doucet and West (2004) is used.

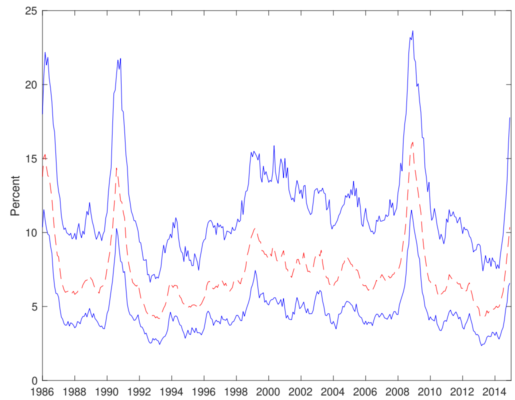


Figure B1. Stochastic Oil Price Volatility

NOTE: Red dashed line is the smoothed estimate of stochastic volatility in percent, $100{*}e^{\sigma_t}$. The top and bottom solid blue lines represent the 95 percent probability interval.

The mean estimates of the volatility process imply that a positive one standard deviation increase in the oil volatility increases the standard deviation of the oil price level shock by (e^{ϕ}-1) $\times$ 100%= 15%.[42]

The prior and posterior distributions are in Table 3. In Figure B1, I plot the estimated historical smoothed time varying volatility with 95 percent posterior probability interval. Estimates show that there is a large amount of variability in oil price volatility, such as the increase during the Great Recession.

Particle Filter Algorithm

A Sequential Importance Resampling particle filter is used to obtain the filtering density $p(\sigma_t|P_t^o;\Theta)$, the probability of σ_t given the oil price observations and process parameters. The likelihood of observing a series of oil prices P_T^o , given an initial value P_0^o, can be written as:

(B3)

$$p(P_o^T;\Theta) = \prod_{t=1}^{T} p(P_o^t|P_o^{t-1};\Theta)$$
$$= \int \frac{1}{e^{\sigma_0}\sqrt{2\pi}} exp\Big[-\frac{1}{2}(\frac{P_o^1-\rho_p P_o^0}{e^{\sigma_0}})^2\Big] d\sigma_0$$
$$\times \prod_{t=2}^{T} \frac{1}{e^{\sigma_t}\sqrt{2\pi}} exp\Big[-\frac{1}{2}(\frac{P_o^t-\rho_p P_o^{t-1}}{e^{\sigma_0}})^2\Big] p(\sigma^t|P_o^{t-1};\Theta) d\sigma_t$$

[42]A one standard deviation increase in the oil volatility shock increases the standard deviation of the oil price shock from $e^{-2.607} = 0.074$ to $e^{-2.607+0.14} = 0.085$.

The particle filter approximates the filtering density $p(\sigma_t|P_o^{t-1};\Theta)$ with a simulated distribution. The distribution is formed with particles:

$$p(\sigma_t|P_o^t;\Theta) \cong \sum_{i=0}^{N} \omega_t^i \delta_{\sigma_t^i}(\sigma_t) \tag{B4}$$

where $\sum_{i=0}^{N} \omega_t^i = 1$ and $\omega_t^i \geq 0$. The SIR is a two step prediction and filtering procedure that starts with an initial condition $p(\sigma_0|P_o^t;\Theta) = p(\sigma_0;\Theta)$.

Using equation (B2) I construct the conditional density $p(\sigma_1|P_o^0;\Theta) = p(\nu_{\sigma,1})p(\sigma_0;\Theta)$. To do this given N draws $\left(\sigma_{t|t}^i\right)_i^N$ from $p(\sigma_t|P_o^t;\Theta)$ and a draw of exogenous shocks $\nu_{\sigma,t}^i \sim N(0,1)$, equation (B2) is used to compute $\left(\sigma_{t+1|t}^i\right)_i^N$.

The filtering step uses importance sampling to update the conditional probability from $p(\sigma_t|P_o^{t-1};\Theta)$ to $p(\sigma_t|P_o^t;\Theta)$. Assign to each draw a weight defined by $\omega_t^i = p(\sigma_t|P_o^{t-1},\sigma_{t-1};\Theta) = \frac{1}{e^{\sigma_t}\sqrt{2\pi}} exp\Big[-\frac{1}{2}(\frac{P_o^1-\rho_p P_o^0}{e^{\sigma_t}})^2\Big]$. The weights are then normalized to

$$\tilde{\omega}_t^i = \frac{\omega_t^i}{\sum_{i=1}^{N} \omega_t^i} \tag{B5}$$

The prediction step is then repeated for time period t+1 up to time period T. The likelihood function is then approximated by

$$\begin{aligned} p(P_o^T;\Theta) &\cong \frac{1}{N}\sum_{i=1}^{N} \frac{1}{e^{\sigma_0^i}\sqrt{2\pi}} exp\Big[-\frac{1}{2}(\frac{P_o^1-\rho_p P_o^0}{e^{\sigma_0^i}})^2\Big] \\ &\times \prod_{t=2}^{T} \frac{1}{N}\sum_{i=1}^{N} \frac{1}{e^{\sigma_{t|t-1}^i}\sqrt{2\pi}} exp\Big[-\frac{1}{2}(\frac{P_o^t-\rho_p P_o^{t-1}}{e^{\sigma_{t|t-1}^i}})^2\Big] \end{aligned} \tag{B6}$$

Particle Smoother

I use the backward-smoothing routine of Godsill, Doucet and West (2004) to extract the historical distribution of the volatilities. The factorization of the joint likelihood is given by

$$p(\sigma^T|P_o^t;\Theta) = p(\sigma_T|P_o^t;\Theta) \prod_{t=1}^{T-1} p(\sigma_t|\sigma_{t+1:T}, P_o^T;\Theta) \tag{B7}$$

The second factor is then simplified to

$$p(\sigma_t|\sigma_{t+1:T}, P_o^T; \Theta) = p(\sigma_t|\sigma_{t+1}, P_o^t; \Theta) \tag{B8}$$
$$= \frac{p(\sigma_t|P_o^t; \Theta) f(\sigma_{t+1}|\sigma_t)}{p(\sigma_{t+1}|P_o^t)}$$
$$\propto p(\sigma_t|P_o^t; \Theta) f(\sigma_{t+1}|\sigma_t)$$

The first equality comes from the Markovian properties of the model, f is the state transition density from B2. Equation B4 allows us to construct $p(\sigma_t|P_o^t; \Theta)$ by forward filtering, therefore I can approximate the above equation RHS by

$$p(\sigma_t|\sigma_{t+1}, P_o^t; \Theta) \cong \sum_{i=0}^{N} \omega_{t|t+1}^i \delta_{\sigma_t^i}(\sigma_t) \tag{B9}$$

The weights are given by

$$\omega_{t|t+1}^i = \frac{\omega_t^i f(\sigma_{t+1}|\sigma_t^i)}{\sum_{i=1}^N \omega_t^i f(\sigma_{t+1}|\sigma_t^i)} \tag{B10}$$

where the ω_t^i are the weights from the filtering step. Denote $\tilde{\sigma}_t^i$ the i^{th} draw from the smoothing density at time t. At time T, draws $\tilde{\sigma}_T^i$ are obtained from $p(\sigma_T|P_o^T)$ with the weights ω_T^i. Progressing backwards in time, the recursions iteratively obtain draws $\tilde{\sigma}_t^i$ by resampling with the weights B10.

This process is repeated many times using different independent smoothing trajectories to construct the smoothing distribution. Given the sequence of smoothed states the smoothed residuals for both the level and volatility equations can also be extracted. The smoothed volatilities were constructed using the mean of the posterior distribution using 10,000 trajectories with 40,000 particles each.

RWMC Algorithm

The random walk Metropolis-Hastings algorithm estimates the oil process parameters ρ_o, ρ_σ, $\overline{\sigma}$, and ϕ. The algorithm works as follows:

1) Starting from an initial guess Θ^*, the parameter vector, generate the random walk proposal density $\Theta_{j+1}^{prop} = \Theta_j^{prop} + cN(0,1)$, j=1,...,150,000

where j is the number of draws and c is a scaling parameter set to induce an acceptance ratio suggested in Roberts, Gelman and Gilks (1996).

2) The Metropolis-Hasting step. Compute the acceptance ratio $\psi = min\left(\frac{p(\Theta_{j+1}^{prop}|p^T}{p(\Theta_j^{prop}|p^T}, 1\right)$. A random number m is drawn from a uniform distribution over the unit interval. Then $\Theta_{j+1} = \Theta_{j+1}^{prop}$ if m $< \psi$ and $\Theta_{j+1} = \Theta_{j+1}$ otherwise. This procedure is repeated for all draws.

The first 50,000 draws are used as a burn-in period, and the remaining 100,000 draws are used as the invariant distribution of the resulting Markov Chain.

B2. Data

This section gives details about data sets used in the analysis and shows robustness to the oil price series used.

Price Data

The BLS sampling process is now described in more detail. Prices are collected from a survey that asks producers for the price as of Tuesday of the week containing the 13th of the month. The BLS uses a a three stage procedure to select individual items to include in the PPI. An industry is considered the starting point of sampling by the BLS. The first sampling stage is selecting establishments within an industry. An industry's frame of establishments are drawn from all firms listed in Unemployment Insurance as well as supplementary public lists used to refine the sampling population.

A price forming unit is created by clustering establishments within an industry in the second step. Within a price forming unit, all members must belong to the same industry. Within an industry, strata may then be established before sampling units due to differences in price determining behavior due to firm characteristics such as production technology or geographic location. In each strata a price forming unit is selected to be in the sample in proportion to its shipment value or number of employees.

In the third step, after an establishment is selected and chooses to participate the BLS uses disaggregation to select specific items to sample. This technique selects a category of items to be included in the PPI by assigning a probability of selection proportional to the value of the category within the reporting unit. The categories are broken into smaller units until individual goods and services are identified. If an individual item selected is sold at more than one price due to some characteristic such as customer, size of order, or color, then the particular transaction is selected also by probabilistic sampling.

Resampling of an industry accounts for changing market conditions every five to seven years. In practice, many reporters and items are included before and after the resampling. Nakamura and Steinsson (2008) exploit a two month period in 2001 when the BLS collected all data via by phone survey, rather than in the paper survey, and show that the data collection method does not change price behavior.

The BLS item level data is used to construct all dispersion and frequency variables. The monthly industry level data is trimmed in the panel regressions if there are less than 50 items within the industry in month t, and less than 15 observed price changes during month t. Having a reasonable number of price changes for industry j during month t is important to create an accurate measure of price change dispersion. Increasing the number of observed price changes does not change the results. Industry level inflation used as an independent variable comes from the official published Bureau of Labor Statistics numbers. Constructing average item level inflation within a month does not affect the coefficient on oil price volatility, but does remove significance for the lagged inflation coefficient.

Table B1 replicates the main regression results in Table 6, but does not trim the pricing data if there are only few price changes or less than 50 items within a industry in a month. The table shows this trimming methodology does not affect the results.

Table B1—Industry Specific Oil Demand Variables Regression - Robustness to Trimming

Dependent Variable:	S.D.				Frequency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.098	0.073	0.082	0.140	-0.194	-0.325	-0.208	-0.218
	(0.217)	(0.215)	(0.228)	(0.222)	(0.168)	(0.154)	(0.198)	(0.123)
$s_{o,j} * \sigma_{t-1}$	3.266	3.330	2.999	2.921	-2.156	-1.789	-1.938	-0.796
	(1.461)	(1.465)	(1.587)	(1.453)	(1.181)	(1.378)	(1.366)	(0.744)
$\pi_{j,t}$		0.159	0.073	-0.024		0.886	1.139	1.063
		(0.115)	(0.121)	(0.109)		(0.326)	(0.361)	(0.323)
$\Delta IP_{j,t}$			0.006	0.006			-0.060	-0.051
			(0.021)	(0.019)			(0.024)	(0.027)
S.D.$_{\cdot j,t-1}$				0.060				
				(0.016)				
Frequency$_{j,t-1}$								0.509
								(0.057)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,808	15,808	12,321	12,215	16,122	16,122	12,542	12,529

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(4) and price change frequency in column (5)-(8). This table shows results when no observations are trimmed due to small numbers of price changes. All industries within the oil producing NAICS 324 sector are excluded. $s_{o,j} * \Delta log(P^o_{t-1})$ and $s_{o,j} * \sigma_{t-1}$ are the industry specific oil demand variables using monthly WTI real price of oil. $\pi_{j,t}$ is the average item level inflation rate for industry j. σ_t is the extracted stochastic volatility measure of oil price volatility. S.D.$_{\cdot j,t-1}$ is lagged industry price change standard deviation. Frequency$_{j,t-1}$ is lagged industry price change frequency. Robust asymptotic standard errors reported in parentheses are clustered at the industry level.

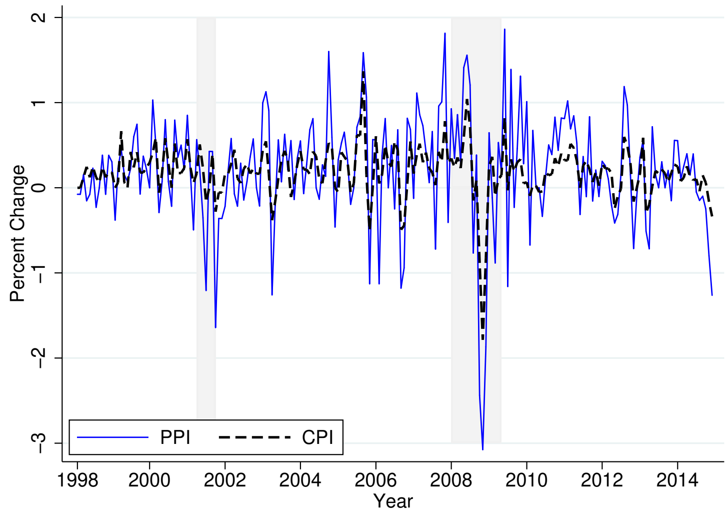


Figure B2. Monthly PPI Inflation and CPI Inflation

Note: Consumer Price Index for all Urban Consumers and Producer Price Index by Commodity for Finished Goods. Both indices are seasonally adjusted.

Price Data Comparison

Figure B2 shows producer price inflation plotted against consumer price inflation for the sample period. The month over month producer inflation rate is more volatile than the consumer inflation rate. The correlation between the two series is 0.82. The price setting statistics are broadly similar except for a lower fraction of small price changes in the PPI.

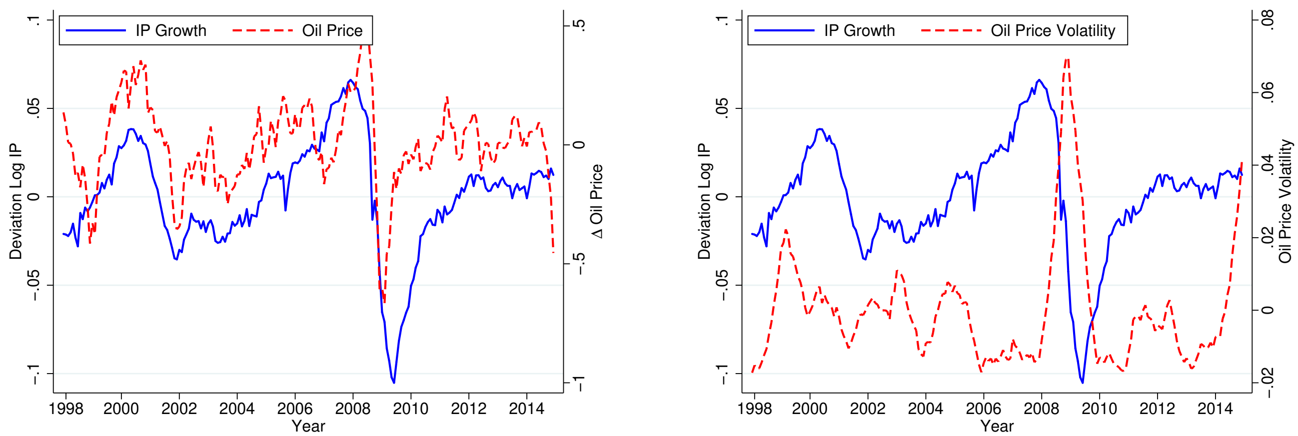
Industrial Production

Industrial production is taken from the Federal Reserve Board website. It covers manufacturing, mining, and electric and gas utilities and is intended to measure variation in national output over the course of the business cycle.

Oil Prices

This section describes the oil price series used and shows robustness to alternatives.

Daily oil prices are taken from the Department of Energy website. It is measured as the spot price of West Texas Intermediate (WTI) crude oil in Cushing, OK. This data is available daily from 1986-2014 to construct realized volatility. Monthly measures are the average monthly spot price. All nominal amounts are transformed into real prices by deflating with the PPI Finished goods index. For the stochastic volatility model and GARCH model estimation, data from 1986 to 2014 is used.



(a) Oil Price

(b) Oil Price Volatility

Figure B3. Cyclicality of Oil Prices and Oil Price Volatility

Composite Refiners Acquisition Cost and Brent Crude oil prices are used for robustness. RAC is a weighted average of domestic and imported oil. Brent Crude is extracted from the North Sea and is a leading price benchmark for Atlantic basin crude oils. All three data series are available from the U.S. Energy Information Administration.

One potential concern is that movements in oil prices or oil price volatility are simply measuring a spurious correlation with the business cycle. The left panel of Figure B3 shows the cyclical component of overall U.S. industrial production growth and the cyclical component of monthly changes in WTI oil prices from 1998 through 2014. The correlation of the two series is 0.63. However, the right panel of Figure B3 shows the cyclical component of overall U.S. industrial production growth and the cyclical component of oil price volatility, as measured with the stochastic volatility model. The correlation of the two series is only -0.26, suggesting that oil price volatility is not capturing spurious correlations of the business cycle.

A large literature attempts to explain movements in the price of oil. This section will summarize some of the main findings, which show that most movements in the price of oil that have been identified come from outside of the United States.

US oil prices were regulated by government agencies prior to 1973, leading to long periods of constant price followed by infrequent adjustments. Due to the oil price increase in 1973 and 1974, it became too difficult to provide a ceiling on the price of oil and prices have since been allowed to fluctuate in response to supply and demand. In the early 1980's there was an increase in oil production in non-OPEC countries, which decreased the market share of OPEC from 43 percent in 1980 to 28 percent in 1985 as documented by Baumeister and Kilian (2016). During this time, OPEC's efforts to influence the price of oil were unsuccessful.

There was a drop in the price of oil in the late 1990's due to a decrease in the demand for the price of oil that was partially caused by the Asian financial crisis of 1997. Kilian and Murphy (2014) show the increase in the price of oil following in 1999 reflected a combination of factors including higher demand for oil from a global demand recovery, and increased inventory demand due to coordinated supply cuts. A brief increase in the price of oil in late 2002 and early 2003 were related to two global oil supply disruptions. The first disruption was the Venezuelan oil strike from December 2002 to February 2003. The second oil supply disruption was due to the Iraq War in 2003

The large, long price increase in the nominal price of oil from $28 in 2003 to $134 in mid 2008, an increase of over 350 percent, or 250 percent in real terms is generally considered to be due to increases in demand. Hamilton (2009), Kilian (2008), and Kilian and Hicks (2013) argue that the demand shifts are associated to the expansion of the global economy and in particular additional demand from Asia. Oil producers were unable to supply the increase in demand during this time, leading to the increase in price.

Oil prices plummeted from $134 in June 2008 to $34 in February 2009 due to anticipation of a global recession. Baumeister and Kilian (2015) provided evidence that when it became clear the financial system would not collapse in 2009, oil prices stabilized at $100 per barrel. Kilian and Lee (2014) establish that a brief spike in prices in 2011 is related to the Libyan uprising. Between June 2014 and January 2015 the price of oil fell nearly fifty percent. This decline is attributed by Baumeister and Kilian (2015) to a decline in global activity. Kilian (2017) estimates that oil prices were about $10 lower due the increase in the supply of oil from to U.S. fracking.

I now present the main regressions when using alternative oil prices. First, I replicate regression specifications (4) and (5) in Table B2. The column title denotes the oil price series used. Columns (1) through (3) show that all three oil price series predict increased price change dispersion, measured using standard deviation of price change, during periods of high oil price volatility. Columns (7) through (9) confirm this finding using the interquartile range of price changes. Price change frequency is used as the dependent variable in columns (4) through (6). Results show that there is not a positive relationship between price change frequency and oil price volatility. Brent oil price volatility is negatively related to price change frequency.

The main regression specifications (7) and (8) using RAC and Brent oil prices are in Table B3.

Table B2—Price Setting Behavior and Macroeconomic Shocks - Robustness to Oil Price

Dependent Variable:	S.D.			Frequency			IQR		
Oil Price:	WTI (1)	RAC (2)	Brent (3)	WTI (4)	RAC (5)	Brent (6)	WTI (7)	RAC (8)	Brent (9)
$\Delta log(P^o_{t-1})$	0.008	0.022	0.005	-0.038	-0.053	-0.030	0.003	0.016	0.002
	(0.010)	(0.010)	(0.008)	(0.024)	(0.028)	(0.022)	(0.006)	(0.007)	(0.006)
σ_{t-1}	0.255	0.203	0.254	0.067	-0.086	-0.358	0.392	0.274	0.283
	(0.070)	(0.049)	(0.064)	(0.151)	(0.118)	(0.145)	(0.049)	(0.035)	(0.041)
EBP_{t-1}	0.002	0.003	0.003	0.007	0.009	0.011	-0.001	0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Realized Stock $\text{Vol}_{j,t}$	0.009	0.012	0.005	0.146	0.151	0.168	0.014	0.020	0.015
	(0.011)	(0.013)	(0.012)	(0.018)	(0.020)	(0.026)	(0.006)	(0.012)	(0.009)
$\pi_{j,t}$	0.085	0.092	0.082	1.287	1.289	1.291	0.022	0.035	0.019
	(0.118)	(0.118)	(0.118)	(0.337)	(0.340)	(0.341)	(0.113)	(0.112)	(0.115)
$\Delta IP_{j,t}$	0.004	0.006	0.007	-0.051	-0.057	-0.071	0.000	0.002	-0.000
	(0.016)	(0.015)	(0.016)	(0.032)	(0.031)	(0.031)	(0.009)	(0.009)	(0.010)
VIX_{t-1}	0.000	0.000	-0.000	-0.001	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	63	63	63	63	63	63	63	63	63
N	10,586	10,586	10,586	10,586	10,586	10,586	10,586	10,586	10,586

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(3), frequency of price change in columns (4)-(6), and the interquartile range of price change sin columns (7)-(9). All industries within the oil producing NAICS 324 sector are excluded. $\Delta log(P^o_{t-1})$ and σ_{t-1} are real oil price inflation and oil price volatility using the extracted stochastic volatility measure for each oil price series. $\pi_{j,t}$ is the average item level inflation rate for industry j,Realized Stock $\text{Vol}_{j,t}$ is the median industry realized stock volatility of industry j at time t, EBP is the excess bond premium, $\Delta IP_{j,t}$ is the change in the industrial production index of industry j at time t, and VIX is a measure of equity market volatility. The column title denotes the oil price series Robust asymptotic standard errors reported in parentheses are double clustered at the industry-month level.

Columns (1) through (4) show that both RAC and Brent oil price volatility cause increased price change dispersion. Columns (5) through (8) show that price change frequency is negatively related to oil price volatility using either price series. These results are consistent with the main results in Table 6.

Table B3—Industry Specific Oil Regression: Alternative Oil Prices

Dependent Variable:	S.D.				Frequency			
Oil Price:	RAC (1)	RAC (2)	Brent (3)	Brent (4)	RAC (5)	RAC (6)	Brent (7)	Brent (8)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.278	0.266	0.139	0.128	-0.471	-0.614	-0.470	-0.604
	(0.190)	(0.187)	(0.174)	(0.169)	(0.133)	(0.158)	(0.132)	(0.188)
$s_{o,j} * \sigma_{t-1}$	3.500	3.532	2.066	2.081	-4.004	-3.638	-7.895	-7.718
	(0.765)	(0.779)	(1.063)	(1.072)	(0.822)	(0.854)	(1.489)	(1.394)
$\pi_{j,t}$		0.075		0.069		0.847		0.848
		(0.118)		(0.119)		(0.201)		(0.201)
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	81	81	81	81	81	81	81	81
N	13,606	13,606	13,606	13,606	13,606	13,606	13,606	13,606

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(4) and price change frequency in column (5)-(8). All industries within the oil producing NAICS 324 sector are excluded. $s_{o,j} * \Delta log(P^o_{t-1})$ and $s_{o,j} * \sigma_{t-1}$ are the industry specific oil demand variables using either RAC or Brent real price of oil indicated in the column title. $\pi_{j,t}$ is the average item level inflation rate for industry j. σ_t is volatility measure of oil price volatility indicated in the column title. Robust asymptotic standard errors reported in parentheses are clustered at the industry level.

Table B4—NAICS 4 Industry Oil Share

Rank	Industry	Name	θ
1	3251	Basic Chemical Manufacturing	0.161
2	3365	Railroad Rolling Stock Manufacturing	0.051
3	3259	Other Chemical Product and Preparation Manufacturing	0.043
4	3255	Paint, Coating, and Adhesive Manufacturing	0.032
5	3252	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	0.026
6	3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing	0.024
7	3221	Pulp, Paper, and Paperboard Mills	0.020
8	3311	Iron and Steel Mills and Ferroalloy Manufacturing	0.023
9	3362	Motor Vehicle Body and Trailer Manufacturing	0.022
10	3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	0.021
	P10		0.001
	Average		0.008
	P90		0.022

Input Output Tables

Detailed Input Output "Use" tables from the Bureau of Economic are constructed every 5 years. I use the 1997 table to construct value added weights to aggregate industries for price statistics. The oil share of value added is also constructed using the Input Output tables. The oil producing sector is defined as NAICS 324110, Petroleum Refineries. The NAICS definition of this category is:

> This industry comprises establishments primarily engaged in refining crude petroleum into refined petroleum. Petroleum refining involves one or more of the following activities: (1) fractionation; (2) straight distillation of crude oil; and (3) cracking.

The overall average, 10th percentile, and 90th percentile of dollar share of oil to value added is listed in Table B4 along with the four digit industries with the largest oil share in 1997.

An alternative long run measure of oil usage is constructed by averaging over the oil usage from the detailed IO tables from 1997, 2002, and 2007 in order to reduce the sensitivity of the measure to short run effects of oil price changes. An industry's oil share of production could change over time due to technological change or substitution towards or away from oil due to changes in oil price. Specifically, $\overline{s_{o,j}} = \sum_{t=1}^{T} \frac{s_{o,j,t}}{T}$, is defined as the long run usage and is in the spirit of Nekarda and Ramey (2011). Results using this measure are in Table B5. Columns (1) through (4) show that price change dispersion is associated with increased oil price volatility using the long run oil usage. Columns (5) through (8) show no relationship between price change frequency and oil price volatility.

Table B5—Industry Specific Oil Demand Variables Regression- Long Run Oil Sensitivity

Dependent Variable:	S.D.				Frequency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{s_{o,j}} * \Delta log(P^o_{t-1})$	0.076	0.066	-0.030	0.021	-0.217	-0.323	-0.315	-0.150
	(0.110)	(0.111)	(0.097)	(0.094)	(0.094)	(0.100)	(0.109)	(0.091)
$\overline{s_{o,j}} * \sigma_{t-1}$	3.448	3.471	3.456	3.290	0.307	0.553	0.743	0.577
	(0.969)	(0.976)	(1.094)	(1.022)	(1.792)	(1.937)	(2.239)	(0.988)
$\pi_{j,t}$		0.077	0.079	0.103		0.858	0.911	0.787
		(0.117)	(0.113)	(0.112)		(0.203)	(0.226)	(0.187)
$\Delta IP_{j,t}$			0.002	0.013			-0.046	-0.042
			(0.014)	(0.016)			(0.029)	(0.036)
S.D.$_{\cdot j,t-1}$				0.075				
				(0.016)				
Frequency$_{j,t-1}$								0.572
								(0.038)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63	81	81	63	63
N	13,606	13,606	10,946	10,939	13,606	13,606	10,946	10,946

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(4) and price change frequency in column (5)-(8). All industries within the oil producing NAICS 324 sector are excluded. $\overline{s_{o,j}} * \Delta log(P^o_{t-1})$ and $\overline{s_{o,j}} * \sigma_{t-1}$ are the industry specific oil demand variables using the time averaged oil usage from the 1997, 2002, and 2007 Input Output tables and monthly WTI real price of oil. $\pi_{j,t}$ is the average item level inflation rate for industry j. σ_t is the extracted stochastic volatility measure of oil price volatility. S.D.$_{\cdot j,t-1}$ is lagged industry price change standard deviation. Frequency$_{j,t-1}$ is lagged industry price change frequency. Robust asymptotic standard errors reported in parentheses are clustered at the industry level.

B3. Additional Robustness Exercises

This section presents additional robustness exercises. It first describes alternative oil price volatility series, then presents robustness exercises on the relationship between pricing behavior and oil price volatility.

Alternative Oil Price Volatility Measures

The main text of the paper uses stochastic volatility of real oil prices, however alternative oil price volatility measures can be constructed. In this section I construct two alternative measures, GARCH and realized volatility of real oil prices, and show the results on price setting behavior are robust to measurement of volatility.

First, a GARCH model of volatility is estimated, and the extracted volatility series shows that GARCH volatility and stochastic volatility measure the same underlying process. The estimated

Table B6—Oil Price and Volatility Correlation Matrix

	SV	GV	RV	$\Delta log(P_t^o)$
SV	1.00			
GV	0.74	1.00		
RV	0.68	0.57	1.00	
$\Delta log(P_t^o)$	-0.16	-0.05	-0.39	1.00

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Number of observation=203. SV is stochastic volatility of real oil price, GV is GARCH volatility of real oil price, RV is realized volatility of real oil price, and $\Delta log(P_t^o)$ is monthly real oil price inflation.

GARCH model is

(B11) $$logP_t^o = \rho_p logP_{t-1}^o + \epsilon_t$$

where $\epsilon_t = \sigma_t z_t$, and $z_t \sim$ N(0,1)

(B12) $$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

The estimated GARCH parameters are $\rho_p = 0.997$ (0.003), $\omega = 0.001$ (0.001), $\alpha = 0.190$ (0.048), β= 0.622 (0.104). The conditional heteroskedasticity of oil prices in the estimated GARCH(1,1) model of oil prices has both significant autoregressive and moving average components.

The final measure of volatility for robustness is the realized volatility of daily real oil price returns. The monthly realized volatility value is constructed as:

(B13) $$RV_t = \sqrt{\frac{\sum_{n=1}^{N}(dp_n - \overline{dp_t})^2}{N-1}}$$

where dp_n is the log difference in daily real oil prices between days and n indexes number of trading days in month t. This volatility measure differs significantly from the extracted stochastic volatility and GARCH processes. The realized volatility series is more volatile than the other two because it only relies on within month variation in oil prices without any between month smoothing mechanism due to autocorrelation in the oil price volatility process.

The three series are highly correlated, as shown in Table B6, suggesting they are picking up a common volatility component. The volatility series are plotted in Figure B4 and their summary statistics are in Table B7. It shows that the GARCH volatility series is noisier than the stochastic

Table B7—Oil Price Summary Statistics

Variable	Mean	Median	Standard Dev	Max	Min
Stochastic Vol	0.0759	0.0718	0.0198	0.1579	0.0433
GARCH Vol	0.0783	0.0736	0.0183	0.1939	0.0587
Realized Vol	0.0225	0.0198	0.0106	0.0741	0.0072
$\Delta\ \log(P_t^o)$	0.0042	0.0119	0.0820	0.2130	-0.3132

NOTE: Summary statistics for monthly WTI real oil prices over 1998:M1-2014:M12.

volatility series, but they are following the same latent volatility process with a correlation of 0.74 between the two series. GARCH volatility shows a large increase in volatility during 2009 that is also present in the stochastic volatility measure. Additionally, realized volatility is noisier than the other two series but is still highly correlated. Realized volatility also shows the large increase in 2009. All three series are negatively correlated with real oil price inflation.

Large movements in the volatility of oil price are correlated across all three series. There is a spike in volatility in all three measures during the last months of 2002 and early 2003 that occurs during the Venezuelan oil strike and beginning of the Iraq War. Between March 2008 and December 2008, stochastic volatility more than doubles from 0.078 to 0.172. GARCH and realized volatility have similar large increases during the same time period. GARCH volatility rises from 0.06 to 0.15, and realized volatility nearly quadruples from 0.04 to 0.15. All three series also have large increases during the second half of 2014.

I now show that the main results are robust to alternative oil price volatility measures. First, Table B8 shows results from regression specifications (4) and (5). Columns (1) through (3) show that price change dispersion is associated with increased oil price volatility using all of the three measures. Columns (4) through (6) show no relationship between price change frequency and oil price volatility.

Next, I replicate regression specifications (7) and (8) using GARCH and realized volatility of oil prices. Results are in Table B9. The table shows that both GARCH and realized volatility cause increased relative price change dispersion. Price change frequency is negatively related to both measures of volatility, but significantly so for realized volatility. These result are consistent with the stochastic volatility measure.

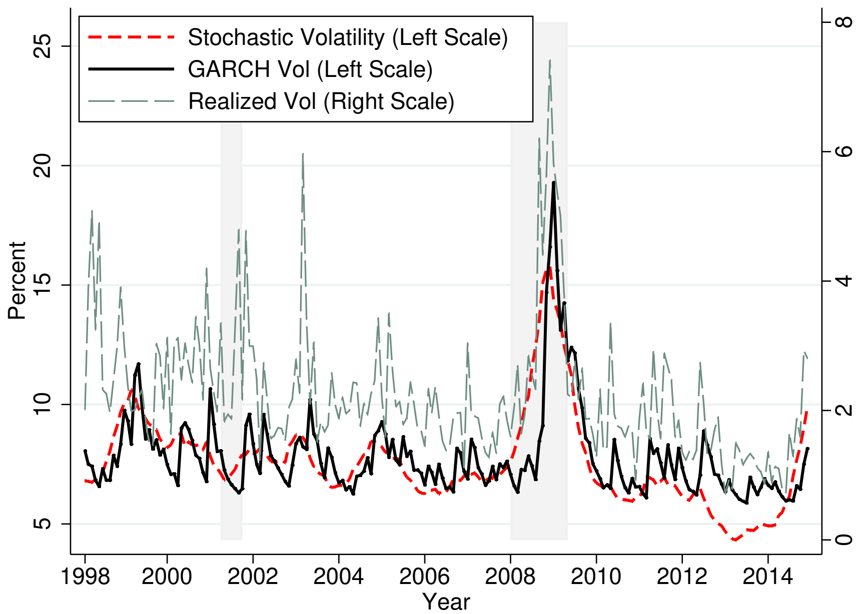


Figure B4. Oil Price Volatility

Note: The thick dotted red line shows the extracted stochastic volatility of oil prices, $100{*}e^{\sigma_t}$, while the solid black line shows the GARCH volatility, $100{*}\sigma_t$. The thin dotted gray line shows within month realized volatility of daily oil prices in percentage.

Table B8—Price Setting Behavior and Macroeconomic Shocks - Robustness to Volatility

Dependent Variable:	S.D.			Frequency		
Volatility Measure:	Stochastic (1)	GARCH (2)	Realized (3)	Stochastic (4)	GARCH (5)	Realized (6)
$\Delta log(P^o_{t-1})$	0.008	0.004	0.014	-0.038	-0.040	-0.034
	(0.010)	(0.009)	(0.011)	(0.024)	(0.025)	(0.023)
σ_{t-1}	0.255	0.174	0.223	0.067	0.076	0.130
	(0.070)	(0.054)	(0.115)	(0.151)	(0.131)	(0.276)
EBP_{t-1}	0.002	0.004	0.004	0.007	0.007	0.007
	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Realized Stock $\text{Vol}_{j,t}$	0.009	0.015	0.017	0.146	0.147	0.148
	(0.011)	(0.013)	(0.013)	(0.018)	(0.019)	(0.018)
$\pi_{j,t}$	0.085	0.103	0.089	1.287	1.295	1.289
	(0.118)	(0.118)	(0.119)	(0.337)	(0.340)	(0.338)
$\Delta IP_{j,t}$	0.004	-0.003	-0.002	-0.051	-0.053	-0.052
	(0.016)	(0.016)	(0.016)	(0.032)	(0.034)	(0.033)
VIX_{t-1}	0.000	0.000	0.000	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	63	63	63	63	63	63
N	10,586	10,586	10,586	10,586	10,586	10,586

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1) through (3), and the frequency of price change in columns (3) through (6). All industries within the oil producing NAICS 324 sector are excluded. $\Delta log(P^o_{t-1})$ and σ_{t-1} are real oil price inflation and oil price volatility using the extracted stochastic volatility measure. $\pi_{j,t}$ is the average item level inflation rate for industry j,ealized Stock $\text{Vol}_{j,t}$ is the median industry realized stock volatility of industry j at time t, EBP is the excess bond premium, $\Delta IP_{j,t}$ is the change in the industrial production index of industry j at time t, and VIX is a measure of equity market volatility. Column title denotes the measure of real oil price volatility used. Robust asymptotic standard errors reported in parentheses are double clustered at the industry-month level.

Table B9—Industry Specific Oil Regression: Alternative Oil Volatility Measures

Dependent Variable:	S.D.				Frequency			
Volatility Measure:	GARCH	GARCH	Realized	Realized	GARCH	GARCH	Realized	Realized
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.127	0.116	0.466	0.458	-0.269	-0.393	-0.624	-0.714
	(0.212)	(0.209)	(0.302)	(0.297)	(0.106)	(0.137)	(0.140)	(0.164)
$s_{o,j} * \sigma_{t-1}$	3.805	3.870	7.612	7.686	-0.284	0.450	-7.003	-6.154
	(0.999)	(1.018)	(2.811)	(2.855)	(0.959)	(1.285)	(1.689)	(1.641)
$\pi_{j,t}$		0.076		0.073		0.854		0.849
		(0.118)		(0.118)		(0.201)		(0.201)
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	81	81	81	81	81	81	81	81
N	13,606	13,606	13,606	13,606	13,606	13,606	13,606	13,606

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(4) and price change frequency in column (5)-(8). All industries within the oil producing NAICS 324 sector are excluded. $s_{o,j} * \Delta log(P^o_{t-1})$ and $s_{o,j} * \sigma_{t-1}$ are the industry specific oil demand variables using monthly WTI real price of oil. $\pi_{j,t}$ is the average item level inflation rate for industry j. σ_t is volatility measure of oil price volatility indicated in the column title. Robust asymptotic standard errors reported in parentheses are clustered at the industry level.

Generated Regressor

Both stochastic volatility and GARCH volatility are latent processes and must be generated in an estimation procedure. Therefore, I incorporate estimation uncertainty for the volatility process from the stochastic volatility and GARCH volatility processes by employing a two stage bootstrap procedure to adjust the standard errors. This two step procedure then incorporates estimation uncertainty from the oil price volatility process as well as within-industry correlation and arbitrary residual correlation across industries in proximate time periods.

The bootstrap procedure to address the generated regressor standard errors is a two step procedure. First estimation uncertainty for the volatility process is constructed and second the estimation uncertainty is included in the baseline regressions of interest. I first follow Lee and Fan (2006) to bootstrap the stochastic volatility process, then include the estimation uncertainty in the regression by using the panel moving blocks bootstrap of Goncalves (2011) in the second step.

The first step to construct estimation uncertainty in the stochastic volatility process is summarized as follows. First, the stochastic volatility model is estimated:

(B14) $$logP^o_t = \rho_p logP^o_{t-1} + e^{\sigma_t}\nu_t$$

where $\nu_t(z) \sim$ N(0,1).

(B15) $$\sigma_t = (1-\rho_\sigma)\overline{\sigma} + \rho_\sigma\sigma_{t-1} + \phi\nu_{\sigma,t}$$

where $\nu_{\sigma,t}(z) \sim$ N(0,1).

The parameters of the model, $\theta = \{\rho_p, \, \rho_\sigma, \, \overline{\sigma}, \, \phi\}$, are estimated by $\hat{\theta} = \{\hat{\rho}_p, \, \hat{\rho}_\sigma, \, \hat{\overline{\sigma}}, \, \hat{\phi}\}$, using the full sample of data. The residuals, $\hat{\nu}_t$ and $\hat{\nu_{\sigma,t}}$ are then computed, $t = 1, ...T$.

The second step is to generate K bootstrap replicates of oil prices and volatilities using the following recursions:

(B16) $$\sigma^*_t = (1-\hat{\rho}_\sigma)\hat{\overline{\sigma}} + \hat{\rho}_\sigma\sigma^*_{t-1} + \hat{\phi}\nu^*_{\sigma,t}$$

(B17) $$logP^{*o}_t = \hat{\rho}_p logP^{*o}_{t-1} + e^{\sigma^*_t}\nu^*_t$$

Table B10—Industry Specific Oil Demand Robustness: Stochastic Volatility Standard Errors

Dependent Variable:	S.D.				Frequency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.263	0.249	0.201	0.230	-0.256	-0.295	-0.347	-0.298
	[-0.235, 0.942]	[-0.251, 0.938]	[-0.281, 0.849]	[-0.259,0.854]	[-1.241, 0.545]	[-1.298, 0.489]	[-1.267, 0.435]	[-0.866,0.242]
$s_{o,j} * \sigma_{t-1}$	7.485	7.486	7.094	6.726	-4.131	-3.955	-4.119	-1.786
	[1.603, 20.403]	[1.603, 20.263]	[1.446, 21.095]	[1.255,20.096]	[-15.129, 6.526]	[-14.759, 8.410]	[-12.530, 4.295]	[-5.902,2.178]
$\pi_{j,t}$		0.075	0.086	0.088		0.393	0.930	0.855
		[-0.128, 0.284]	[-0.110, 0.293]	[-0.103, 0.285]		[-0.067, 0.791]	[0.451, 1.424]	[0.539, 1.163]
$\Delta IP_{j,t}$			0.002	-0.001			-0.048	-0.051
			[-0.040, 0.041]	[-0.043, 0.035]			[-0.088, -0.009]	[-0.092, -0.010]
S.D.$_{\cdot j,t-1}$				0.065				
				[0.037, 0.092]				
Frequency$_{j,t-1}$								0.065
								[0.037, 0.092]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63	81	81	63	63
N	13,606	13,606	10,946	10,939	13,606	13,606	10,946	10,946

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(4) and price change frequency in column (5)-(8). All industries within the oil producing NAICS 324 sector are excluded. $s_{o,j} * \Delta log(P^o_{t-1})$ and $s_{o,j} * \sigma_{t-1}$ are the industry specific oil demand variables using monthly WTI real price of oil. $\pi_{j,t}$ is the average item level inflation rate for industry j. σ_t is the extracted stochastic volatility measure of oil price volatility. S.D.$_{\cdot j,t-1}$ is lagged industry price change standard deviation. Frequency$_{j,t-1}$ is lagged industry price change frequency. Point estimates are the mean from the two-step panel moving blocks bootstrap and the 95% bootstrap confidence intervals are reported in brackets below the parameter estimates.

where ν^*_t and $\nu^*_{\sigma,t}$ are jointly generated using a moving block bootstrap resampling with replacement from the empirical distribution function of centered residuals, while $\hat{\sigma}^{*2}_1 = \hat{\sigma}^2_1$ and $logP^{*o}_1 = logP^o_1$. I use a block length of 12 and set $K = 200$.

The final step to construct estimation uncertainty is using the K bootstrapped replicates of oil prices to then re-estimate the stochastic volatility model to generate the bootstrapped estimates $\hat{\theta}^*$ $= \{\hat{\rho}^*_p, \hat{\rho_\sigma}^*, \hat{\bar{\sigma}}^*, \hat{\phi}^*\}$. The K bootstrap parameter estimates are then used to construct forecasts of oil price volatility. Specifically, using the bootstrap estimated parameters the following recursion generates volatility forecasts:

$$logP^o_t = \hat{\rho}^*_p logP^o_{t-1} + e^{\sigma_{t,k}}\nu_{t,k} \tag{B18}$$

$$\sigma_{t,k} = (1 - \hat{\rho}^*_\sigma)\hat{\bar{\sigma}}^* + \hat{\rho_\sigma}^*\sigma_{t-1,k} + \hat{\phi}^*\nu_{\sigma,t,k} \tag{B19}$$

where $\sigma^2_{t,k}$, $t = 1, ...T$, for bootstrap iteration $k = 1, ..., K$, are the bootstrapped values of volatility.

The second step of the procedure is to incorporate the estimation uncertainty from the stochastic volatility model into the regressions of interest. Specifically, for the main regression of interest I use the panel moving blocks bootstrap of Gonçalves (2011) while incorporating the uncertainty

Table B11—Industry Specific Oil Demand Robustness: GARCH Volatility Standard Errors

Dependent Variable:	S.D.				Frequency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.137	0.121	0.087	0.122	-0.204	-0.340	-0.285	-0.268
	[-0.401, 0.879]	[-0.386, 0.876]	[-0.427, 0.745]	[-0.366, 0.763]	[-1.121, 0.542]	[-1.319, 0.388]	[-1.076, 0.415]	[-0.790, 0.222]
$s_{o,j} * \sigma_{t-1}$	4.118	4.195	4.065	3.789	-1.536	-0.745	-0.844	-0.222
	[0.411, 8.873]	[0.500, 8.969]	[0.549, 8.508]	[0.334, 8.056]	[-8.390, 2.881]	[-7.503, 3.650]	[-6.696, 2.844]	[-3.156, 1.902]
$\pi_{j,t}$		0.101	0.089	0.091		0.879	0.931	0.855
		[-0.105, 0.357]	[-0.106, 0.300]	[-0.102, 0.293]		[0.300, 1.404]	[0.447, 1.422]	[0.538, 1.167]
$\Delta IP_{j,t}$			0.001	-0.002			-0.048	-0.051
			[-0.040, 0.041]	[-0.043, 0.035]			[-0.087, -0.009]	[-0.091, -0.010]
S.D.$_{\cdot j,t-1}$				0.065				
				[0.037, 0.092]				
Frequency$_{j,t-1}$								0.544
								[0.505, 0.581]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63	81	81	63	63
N	13,606	13,606	10,946	10,939	13,606	13,606	10,946	10,946

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(4) and price change frequency in column (5)-(8). All industries within the oil producing NAICS 324 sector are excluded. $s_{o,j} * \Delta log(P^o_{t-1})$ and $s_{o,j} * \sigma_{t-1}$ are the industry specific oil demand variables using monthly WTI real price of oil. $\pi_{j,t}$ is the average item level inflation rate for industry j. σ_t is the extracted GARCH volatility measure of oil price volatility. S.D.$_{\cdot j,t-1}$ is lagged industry price change standard deviation. Frequency$_{j,t-1}$ is lagged industry price change frequency. Point estimates are the mean from the two-step panel moving blocks bootstrap and the 95% bootstrap confidence intervals are reported in brackets below the parameter estimates.

from the first stage estimation. For each of the k bootstrapped volatility series, I estimate:

$$Y_{j,t} = \eta_k * (s_{o,j} * \Delta log(P^o_{t-1})) + \lambda_k * (s_{o,j} * \sigma_{t-1,k}) + \gamma'_k X_{j,t} + \alpha_{j,k} + \alpha_{t,k} + \epsilon_{j,t,k} \quad \text{(B20)}$$

where $Y_{j,t}$ is price change dispersion or frequency, and the bootstrap procedure resamples the data with replacement using a moving block bootstrap on the vector containing all industries in a given time period. The bootstrap length is 3. The panel bootstrap is estimated for each of the k volatility series. This two step procedure then incorporates estimation uncertainty from the oil price volatility process as well as within-industry correlation and arbitrary residual correlation across industries in proximate time periods. Table B10 presents the results. The point estimate is the mean and the 95% bootstrapped confidence intervals are below. The table shows that estimation uncertainty does not diminish the statistical significance of the relationship between oil price volatility and price change dispersion. It does show that price change frequency has a more tenuous negative relationship than in the main regression table. Results from a two-step estimation procedure using GARCH volatility are constructed in an analogous manner and yield similar results. GARCH volatility results are in Table B11. Finally, I can employ the moving block bootstrap standard errors using realized volatility without needing to construct the generated regressor in a first stage. Results for this method using realized volatility are in Table B12.

Table B12—Industry Specific Oil Demand Robustness: Realized Volatility Standard Errors

Dependent Variable:	S.D.				Frequency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.445	0.431	0.361	0.390	-0.604	-0.714	-0.589	-0.345
	[-0.123, 1.261]	[-0.125, 1.258]	[-0.175, 1.080]	[-0.137, 1.092]	[-1.645, 0.188]	[-1.876, 0.135]	[-1.588, 0.138]	[-1.012, 0.171]
$s_{o,j} * \sigma_{t-1}$	7.118	7.162	6.349	6.178	-8.396	-7.729	-6.319	-1.595
	[3.131, 10.889]	[3.259, 10.834]	[1.699, 10.203]	[1.801, 9.770]	[-20.315, -0.580]	[-19.992, 0.570]	[-14.842, 0.157]	[-6.607, 2.597]
$\pi_{j,t}$		0.098	0.086	0.087		0.875	0.929	0.854
		[-0.108, 0.355]	[-0.111, 0.300]	[-0.104, 0.288]		[0.293, 1.407]	[0.447, 1.421]	[0.539, 1.164]
$\Delta IP_{j,t}$			0.001	-0.003			-0.046	-0.051
			[-0.041, 0.040]	[-0.044, 0.034]			[-0.087, -0.004]	[-0.091, -0.009]
S.D.$_{\cdot j,t-1}$				0.065				
				[0.037, 0.092]				
Frequency$_{j,t-1}$								0.544
								[0.505, 0.581]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63	81	81	63	63
N	13,606	13,606	10,946	10,939	13,606	13,606	10,946	10,946

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(4) and price change frequency in column (5)-(8). All industries within the oil producing NAICS 324 sector are excluded. $s_{o,j} * \Delta log(P^o_{t-1})$ and $s_{o,j} * \sigma_{t-1}$ are the industry specific oil demand variables using monthly WTI real price of oil. $\pi_{j,t}$ is the average item level inflation rate for industry j. σ_t is the realized volatility measure of oil price volatility. S.D.$_{\cdot j,t-1}$ is lagged industry price change standard deviation. Frequency$_{j,t-1}$ is lagged industry price change frequency. Point estimates are the mean from the panel moving blocks bootstrap and the 95% bootstrap confidence intervals are reported in brackets below the parameter estimates.

Table B13—Industry Specific Coefficient: Robust Price Change Dispersion Measures

Dependent Variable:	I.Q.R.				S.D.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$s_{o,j} * \Delta log(P^o_{t-1})$	-0.284	-0.287	-0.222	-0.174	0.048	0.021	0.009	0.024
	(0.118)	(0.119)	(0.094)	(0.084)	(0.076)	(0.072)	(0.066)	(0.052)
$s_{o,j} * \sigma_{t-1}$	2.718	2.726	2.561	2.315	2.958	3.034	2.584	2.377
	(1.024)	(1.028)	(0.940)	(0.842)	(0.796)	(0.852)	(0.619)	(0.562)
$\pi_{j,t}$		0.019	0.002	0.004		0.190	0.183	0.173
		(0.110)	(0.092)	(0.087)		(0.072)	(0.072)	(0.067)
$\Delta IP_{j,t}$			0.004	0.002			0.005	0.010
			(0.009)	(0.008)			(0.007)	(0.007)
S.D.$_{\cdot j,t-1}$								0.123
								(0.021)
I.Q.R.$_{\cdot j,t-1}$				0.136				
				(0.043)				
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries								
N	13,606	13,606	10,946	10,944	13,606	13,606	10,946	10,944

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is the standard deviation of price change including zeros of a 4-digit NAICS industry in the manufacturing sector in columns (1)-(4) and interquartile range of price changes in columns (5)-(8). All industries within the oil producing NAICS 324 sector are excluded. $s_{o,j} * \Delta log(P^o_{t-1})$ and $s_{o,j} * \sigma_{t-1}$ are the industry specific oil demand variables using monthly WTI real price of oil. $\pi_{j,t}$ is the average item level inflation rate for industry j. σ_t is the extracted stochastic volatility measure of oil price volatility. S.D.$_{\cdot j,t-1}$ is lagged industry price change standard deviation including zeros. I.Q.R.$_{\cdot j,t-1}$ is lagged industry price change frequency. Robust asymptotic standard errors reported in parentheses are clustered at the industry level.

Alternative Price Dispersion Measures

Table B13 shows the main regression specification when the dependent variable is standard deviation of price change including zeros in columns (1) through (4) and the interquartile range in columns (5) through (8). The table shows that the results are robust to the measure of dispersion used.

Table B14—Aggregate Pricing Moment Regression

Dependent Variable:	S.D.	Frequency
	(1)	(2)
σ_{t-1}	0.203	-0.093
	(0.091)	(0.204)
Sum of coefficients on:		
$\sum_{k=1}^{3}(\Delta log(P^o_{t-k}))$	0.073	-0.065
	(0.032)	(0.036)
$\sum_{k=1}^{3}(\Delta IP_{t-k})$	-0.206	-1.115
	(0.347)	(0.683)
$\sum_{k=1}^{3}(\pi_{t-k})$	-0.370	1.199
	(0.449)	(0.648)
N	200	200

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Number of observation=200. Newey-West standard errors with lag length of 12 reported in parentheses.

B4. Additional Results

This section presents additional empirical results. It first presents additional aggregate evidence on the relationship between oil price volatility and pricing behavior in Section B.B4. It then presents additional pass-through results in Section B.B4. It shows the aggregate empirical price change distribution during high and low oil price volatility in Section B.B4, presents average moments by high and low oil share in Section B.B4.

Additional Aggregate Evidence

In this subsection I provide additional aggregate time series evidence that oil price volatility affects pricing behavior. To do this I run the following regressions:

$$Y_t = \alpha + \sum_{k=1}^{3} \beta_k(\Delta log(P^o_{t-k})) + \eta\sigma_{t-1} + \sum_{k=1}^{3} \gamma_k(\Delta IP_{t-k}) + \sum_{k=1}^{3} \nu_k(\pi_{t-k}) + \epsilon_t$$

where Y_t is aggregate price change frequency or standard deviation, $\Delta log(P^o_{t-k})$ is real oil price inflation, σ_{t-1} is lagged real oil price volatility, ΔIP_{t-k} is industrial production growth to control for the state of the business cycle, and π_{t-k} is PPI inflation. Results are in Table B14. Column (1) shows that increased oil price volatility is associated with greater price change dispersion. Column (2) shows that price change frequency is not associated with oil price volatility. These aggregate results are consistent with the industry-level results.

Table B15—Industry Specific Pass-Through Regression

Short Run Pass-Through	12 Month Cumulative Response
0.224	2.080
(0.034)	(0.504)

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Number of observation=7,786. Number of industries=51. $R^2 = 0.15$. Robust asymptotic standard errors reported in parentheses are clustered at the industry level.

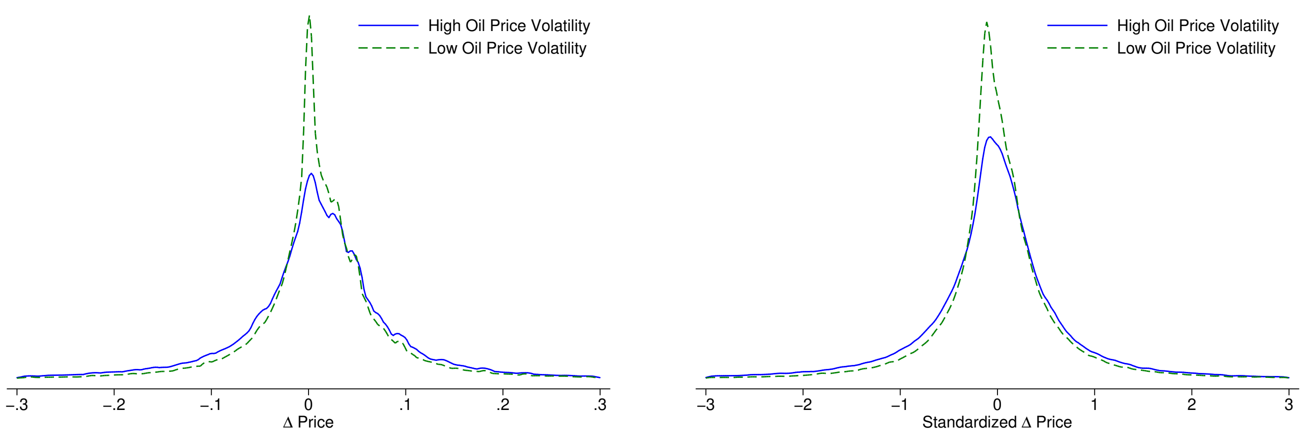
Industry Specific Oil Pass-Through

I examine if sectors that use more oil have greater pass-through, by running an industry specific oil pass-through regression with industry and time fixed effects to control for the macroeconomic cycle. Specifically I run a pass-through regression of the form:

$$\pi_{j,t} = \alpha_j + \alpha_t + \sum_{i=0}^{12} b_i \big(s_{o,j} * \Delta log P^o_{t-i}\big) + \epsilon_{j,t} \tag{B21}$$

If there is greater oil price pass-through for industries with more oil usage then b_0 and $\sum_{i=0}^{12} b_i$ should be positive. The results are in Table B15.

These results show that after conditioning on common aggregate shocks, that industries with greater oil usage have greater pass-through of oil prices. These results are consistent with the main regression results showing that pricing moments depend on oil usage.



(a) Raw Distribution

(b) Standardized Distribution

Figure B5. Empirical Price Distributions under Volatility Regimes

Empirical Price Change Distributions

Figure B5a shows the price change distribution during periods of high and low oil price volatility, where high oil price volatility is defined as a month when oil price volatility is above the median value over the 1998 to 2014 period. Measurement error when aggregating sectors can be problematic, so I standardize price changes at sectoral level then aggregate in Figure B5b. Both distributions show that price change dispersion is greater during periods of high oil price volatility.

Observable Characteristics by Oil Share

Table B16 presents selected average moments by above and below median oil share over the sample period of 1998 to 2014. The top panel shows the average pricing moments and summary statistics at industry level for 41 industries at or below the median oil share. The bottom panel shows the same variables for the 40 industries above median oil share. The results show that pricing moments and inflation are relatively balanced across the two groups. The high oil share industries have had higher average industrial growth rates over the sample. In the final row in each panel, statistics on the annual real export growth rate are presented. It shows that the export trade characteristics are the same between high and low oil usage industries.[43]

[43]Trade data is downloaded from the United States International Trade Commission.

Table B16—Summary Statistics by Oil Share

Low Oil Share					
Variable	Mean	STD	Min	P50	Max
Frequency	0.15	0.11	0.05	0.11	0.54
Frequency Up	0.08	0.06	0.03	0.06	0.30
Standard Deviation	0.12	0.04	0.04	0.11	0.22
$\overline{\pi_{j,t}}$	0.00	0.00	-0.00	0.00	0.00
Average Size Up	0.07	0.02	0.02	0.07	0.13
Average Size Down	-0.08	0.02	-0.12	-0.07	-0.02
Δ log(IP)	-0.01	0.22	-0.48	-0.01	0.60
Δ Annual Exports	0.02	0.04	-0.11	0.02	0.10
High Oil Share					
Variable	Mean	STD	Min	P50	Max
Frequency	0.21	0.15	0.07	0.13	0.51
Frequency Up	0.12	0.08	0.04	0.08	0.28
Standard Deviation	0.11	0.03	0.05	0.10	0.16
$\overline{\pi_{j,t}}$	0.00	0.00	0.00	0.00	0.00
Average Size Up	0.06	0.01	0.04	0.06	0.10
Average Size Down	-0.06	0.02	-0.12	-0.06	-0.03
Δ log(IP)	0.01	0.17	-0.43	0.01	0.40
Δ Annual Exports	0.02	0.03	-0.10	0.02	0.08

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. This table presents average pricing moments and other observable characteristics by high and low oil share. Low oil share is defined as the 41 industries at or below the median oil share, and high oil share is defined as the 40 industries above median oil share. Δ annual exports defined at an annual frequency. Total exports are deflated by the PPI finished goods index.