Price Setting and Volatility: Evidence from Oil Price Volatility Shocks

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Abstract

How do changes in aggregate volatility alter the impulse response of output to monetary policy? To analyze this question, I study whether individual prices in Producer Price Index micro data are more likely to move in the same direction when aggregate volatility is high, which would increase aggregate price flexibility and reduce the effectiveness of monetary policy. Taking advantage of plausibly exogenous oil price volatility shocks and heterogeneity in oil usage across industries, I find that price changes are more dispersed, implying that prices are *less* likely to move in the same direction when aggregate volatility is high. This contrasts with findings in the literature about *idiosyncratic* volatility. I use a state-dependent pricing model to interpret my findings. Random menu costs are necessary for the model to match the positive empirical relationship between oil price volatility and price change dispersion. This is the case because random menu costs reduce the extent to which firms with prices far from their optimum all act in a coordinated fashion when volatility increases. The model implies that increases in aggregate volatility do not substantially reduce the ability of monetary policy to stimulate output.

JEL: E30, E31, E50

Keywords: Volatility, Ss model, menu cost, monetary policy, oil

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1 Introduction

Do changes in aggregate volatility alter the ability of monetary policy to stimulate the economy? During periods of high volatility, the economy is buffeted by large macroeconomic shocks that are likely to impact price changes. Policy makers are concerned that policy effectiveness may decrease during these periods. This paper examines the role of time varying aggregate volatility in price setting and its implications for monetary policy.

Monetary policy effectiveness is dependent on the flexibility of the aggregate price level, which is determined by the extent to which firms change their price in the same direction after monetary stimulus. A key measure of the extent to which price changes move together is price change dispersion. I analyze whether price change dispersion is affected by heightened volatility and find that price change dispersion increases during periods of greater volatility.

I use well-measured and plausibly exogenous oil price volatility shocks to study how price setting behavior responds to changes in the volatility of a common shock. While many commodity prices exhibit time varying volatility, as figure 1 shows, oil price shocks are advantageous in studying how prices react to changes in a common source of volatility for three reasons. First, oil price volatility has large variation over time. Secondly, heterogeneity in oil usage across sectors allows me to construct industry-specific exposure to oil shocks in the spirit of Bartick (1991). Industries that rely on oil more intensively as an input would be expected to have stronger responses to oil price volatility shocks. Lastly, the industry-specific oil demand variables are plausibly exogenous common volatility shocks. Oil prices are also a specific source of volatility that the FOMC is concerned about, as the following quote shows.

> What will happen with the price of oil? The uncertainties are sizable, and progress toward our goals and, by implication, the appropriate stance of monetary policy will depend on how these uncertainties evolve.

Janet Yellen, June 6, 2016

My main finding is that increased oil price volatility leads to increased price change dispersion and no associated change in price change frequency, which implies that monetary policy is not less effective. I show this by using heterogeneity in long run oil usage, and find that industries more exposed to oil exhibit greater price change dispersion in response to increases in volatility than industries with low oil exposure. My main results imply that the doubling of oil price volatility from December 2007 to September 2008 explains 46% of the average increase in price change dispersion. The results are robust to various measures of volatility, additional control variables, and hold both within and outside of the 2008 crisis period.

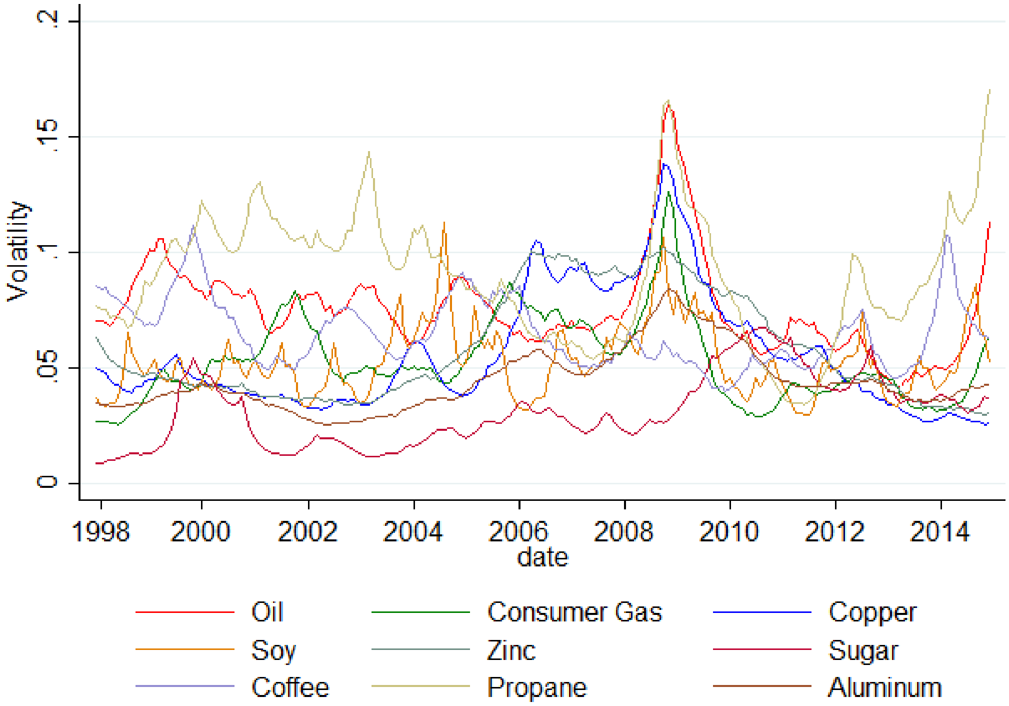
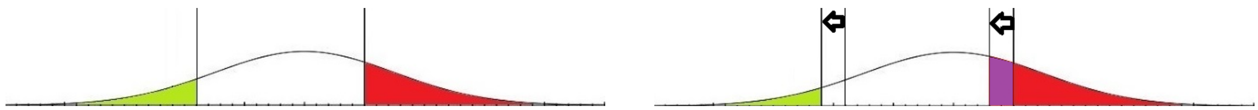


FIGURE 1: Commodity Volatility Shocks

NOTE: Each line represents the stochastic volatility, e^{σ_t}, of it's respective price series.

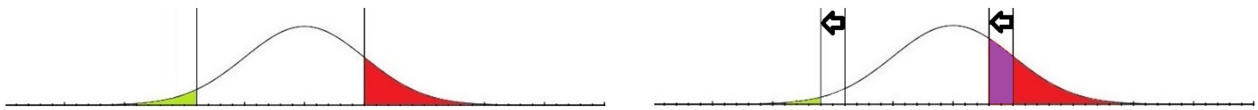
Monetary policy has the ability to stimulate output by changing the supply of money in a basic monetary framework. However, if prices are completely flexible, then monetary policy has no effect on output. Micro-price data shows that prices change approximately twice a year for both consumer and producer goods. Yet the selection of prices that do change is also important for monetary non-neutrality. Greater dispersion of price changes lowers the fraction of price changes that are affected by a change in money, and is therefore a key measure of the degree of monetary non-neutrality. This is illustrated in Figures 2 and 3. The left panels show a disperse and less disperse desired price change distribution prior to a monetary shock. Both distributions feature positive and negative price changes but have on average positive price changes.

The right panels show the distribution after a positive monetary shock. An increase in the supply of money shifts the desired price change distribution to the right, with more positive price changes than prior to the shock. The purple area shows the increase in positive price changes. The figures show that the monetary shock has greater inflationary consequences in the less disperse distribution, as more desired prices are close to the adjustment threshold. Heightened aggregate volatility causes the price change distribution to be more disperse, which leads to decreased inflationary effects and increased real effects of monetary policy.



No Shock Positive Monetary Shock

FIGURE 2: Disperse Desired Price Change Distribution



No Shock Positive Monetary Shock

FIGURE 3: Less Disperse Desired Price Change Distribution

A general equilibrium price setting model with fixed costs of price adjustment that matches the micro-pricing facts is used to quantify the effects of monetary policy during periods of increased aggregate volatility. Changes in volatility have two mechanisms through which they affect firm price setting in a model with fixed costs of adjustment, a real options effect and a volatility effect. The real options effect increases the region of inactivity in the model, by pushing the action and inaction bands outward, thereby decreasing frequency of price adjustment. The volatility effect increases the variance of the common aggregate shock that affects firms. Increases in volatility to a common shock imply that larger shocks will affect firms, but the resultant price changes will be synchronized in the direction of the common cost shock which decreases price change dispersion. This stands in contrast to changes in idiosyncratic volatility, where the volatility effect pushes more price changes in both directions and increases price change dispersion.

I first show that the empirical relationship between price change dispersion and oil price volatility is particularly surprising in the context of a modern menu cost model similar to Golosov and Lucas (2007) and Midrigan (2011). This type of model with a fixed menu cost predicts decreased price change dispersion in response to an oil price volatility shock, and the dispersion falls more for sectors with greater oil usage. An increase in oil price volatility is a common shock, and this causes more prices to change and move in the direction of the cost shock which decreases price change dispersion.

I then introduce heterogeneous and random menu costs to the model as in Dotsey et al. (1999) or Luo and Villar (2015) and show that it is able to match the empirical findings. Firms draw menu costs from a non-degenerate distribution, which increases the randomness of which prices will change. Firms have a substantial probability of a large menu cost such that the price will almost never change, which attenuates the price response to a more volatile common shock. During a period of increased oil price volatility some price changes will be more extreme, but due to the firm specific random menu cost a substantial portion of price changes will be reacting to their idiosyncratic productivity shock which decreases the synchronization of price change direction in response the common shock. This feature also limits the increase in price change frequency, by having some fixed costs be large enough such that a firm would never choose to change the price that period[1].

The model is then used to quantify the effectiveness of monetary policy to stimulate consumption during a period of increased oil price volatility. I find that in the general equilibrium model the graphical intuition about the empirical results holds, and that monetary policy is only slightly less effective. The model shows that monetary policy's ability to stimulate consumption on impact of the shock falls by 0.1% during a one standard deviation increase in oil price volatility. The small decrease in ability to generate real effects is due to an increase in price change frequency, which balances out the increase in effectiveness due to the increase in price change dispersion. The slight decrease is in comparison to the counterfactual fixed menu cost model, which would suggest that monetary policy effectiveness falls by nearly 8%. More prices are changing because of the large oil price shocks, which enables them to simultaneously incorporate the increase in money.

Aggregate and idiosyncratic volatility can both increase price change dispersion, but they have different implications for the effectiveness of monetary policy. My results suggest that policy makers need to consider the source of volatility, aggregate or idiosyncratic, in order to effectively manage the tradeoff between inflation and output stabilization.

The paper is organized as follows. Section 2 describes the micro-price data and oil volatility processes. Section 3 analyzes the micro-price data and shows that price changes are more dispersed during periods of high oil volatility for industries with greater sensitivity to oil. Section 4 presents and calibrates a quantitative price setting model with first and second moment oil price shocks. Section 5 discusses model implications for monetary policy effectiveness during periods of heightened oil price volatility. Section 6 discusses other models of price setting. Section 7 concludes.

1.1 Related Literature

This paper contributes to our understanding of the effects of volatility on the economy. The literature includes the seminal paper on volatility of Bloom (2009) and the introduction of volatility into a general equilibrium framework of Bloom et al. (2012). Fernandez-

[1] I focus on price change dispersion in the analysis because I find no evidence of a positive relationship between frequency of price change and oil price volatility. This further supports a model that limits the reaction of frequency to aggregate volatility shocks.

Villaverde et al. (2015) study the effects of changes in fiscal policy volatility in a New Keynesian model with quadratic adjustment costs for pricing. This paper differs by studying the effects of oil price volatility in a model with fixed costs of adjustment for pricing while matching micro-pricing facts.

Within the literature on the association between volatility and price setting behavior, Vavra (2014) and Bachmann et al. (2013) are most closely related to this paper. Vavra (2014) studies the impact of idiosyncratic volatility shocks on price setting moments over time. He uses CPI data to document the distribution of final goods prices over the business cycle and shows that the cross sectional variance of price changes as well as frequency of price adjustment are countercyclical. The paper then shows that these two facts are matched by a standard menu cost model with second moment shocks to idiosyncratic productivity, while a model with only first moment shocks makes the counterfactual prediction that price change dispersion and frequency of adjustment are negatively correlated. Bachmann et al. (2013) asks how business forecast uncertainty affects the frequency of price change. They find that increased uncertainty about production increases price flexibility. My paper differs by examining the effects of a common source of volatility on price setting behavior.

More broadly in the price setting literature, papers have investigated how various sources of volatility affect prices. Baley and Blanco (2016) construct a model with menu costs and imperfect information about idiosyncratic productivity, and find that this mechanism strengthens the volatility effect and increases price flexibility due to uncertainty. Drenik and Perez (2016) use the manipulation of inflation statistics in Argentina to understand the role of informational frictions on price level dispersion. They find that the manipulation of statistics is associated with greater price level dispersion, and construct a price setting model with noisy information about inflation and find monetary policy is more effective when there is less precise information. Berger and Vavra (2015) document a positive relationship between exchange rate pass through and item level price change dispersion.

This paper contributes to the literature on state dependent models of price setting consistent with micro-data facts by introducing a new empirical fact on the relationship between price change dispersion and oil price volatility. The model of Golosov and Lucas (2007) features a very strong selection effect, where only large price changes occur. Many papers such as Midrigan (2011), Nakamura and Steinsson (2010), and Karadi and Reiff (2016) have since argued that the selection effect is weaker than in the Golosov and Lucas model. In particular, Midrigan (2011) introduces leptokurtic productivity shocks, which increases the dispersion of price changes. This reduces the mass of prices that would change for a small monetary shock, increasing monetary non-neutrality. Nakamura and Steinsson (2010) introduce real rigidities into the menu cost model through a multi-sector model. Heterogeneity amongst sectors in frequency and average size of price change increases monetary non-neutrality by a factor of three. Karadi and Reiff (2016) show that idiosyncratic productivity shocks that feature stochastic volatility better matches the response to large VAT changes, and argue that this model would feature a degree of non-neutrality between that of the Midrigan model and Golosov and Lucas model. Luo and Villar (2015) document that the price change distribution skewness increases as the rate of inflation increases and argue that the previous set of models are unable to match this empirical fact. They augment the model with random menu costs to increase the randomness of price changes in order to fit this fact.

Lastly, this paper also discusses the effects of first and second moment oil price shocks on the economy. Bloom (2009) and Stein and Stone (2013) also use oil shocks as a plausibly exogenous source of volatility on investment decisions. Studying the effects of oil shocks themselves, Blanchard and Gali (2007) construct a model with nominal rigidities in price and wage setting, where firms and consumers use oil to study the declining role of oil in the US economy over time. They find that a combination of a decrease in wage rigidities, increase in monetary policy credibility, and a decrease in oil consumption for both firms and consumers have contributed to the decrease in importance of oil price shocks. Clark and Terry (2010) use a Bayesian vector autoregression framework and show that energy price pass through has declined over time starting from the 1970's. Chen (2009) also studies oil price pass through into inflation across countries using a time varying pass through coefficient. She finds a long run pass through of 16 percent for the US over the period of 1970 to 2006, and a short run pass through of slightly less than 1 percent over one quarter. Jo (2012) uses a VAR with stochastic volatility to study the effects of oil price volatility on real economic activity and finds that an increase in oil price volatility decreases industrial production.

2 Data Sources and Methods

2.1 Micro-Price Data

This paper constructs industry level measures of relevant price statistics using confidential item level micro-data underlying the producer price index from the Bureau of Labor Statistics[2]. The micro-level data starts in 1998 and extends through 2014[3]. Each month around 100,000 prices are collected from about 25,000 reporters. Prices are collected for the

[2]The data set has been studied before in Gilchrist et al. (2015), Goldberg and Hellerstein (2009), Gorodnichenko and Weber (2016), and Nakamura and Steinsson (2008) along with several other papers.

[3]The BLS collects this price data from the view of the firm rather than the consumer, thus price collected is the revenue received by a producer and does not include sales or excise taxes. This is in contrast to the CPI which is the out of pocket expenditure for a consumer for a given item.

entire U.S. production sector.

Prices are collected from a survey that asks producers for the price of an item each month. Items are sampled in a three stage procedure. The BLS first creates a list of establishments within an industry. The second stage is selecting price forming units within each industry, which are created by clustering establishments. The third and final stage is selecting specific items within a price forming unit to sample. The BLS uses a probabilistic technique to select items within a price setting unit, where items are weighted proportional to the value of the category within the unit[4].

I restrict the pricing data to a subset of items within the PPI. Only manufacturing industries are included which enables the study of price setting in markets where goods are not homogeneous and firms have some price setting power[5]. Gopinath and Itskhoki (2010) make the same restriction in their study of international producer pricing data. Manufacturing industries are also a setting where oil is used as an input for production. This leaves 81 four digit industries in the micro-level data sample. While the PPI collects data on finished goods, intermediate goods, and crude materials, only finished goods products are used in the construction of these statistics. Aggregate price statistics are calculated by first constructing an item level unweighted statistic within each four digit NAICS industry. Industry price statistics are then aggregated using value added weights to construct the weighted mean of each price setting moment[6].

The main focus of the empirical section of the paper is to study the effect of oil price volatility on producer price change dispersion. Dispersion is measured as either the standard deviation of price changes or the interquartile range of price changes. Producer price change dispersion is measured at the industry-month level as $PriceDisp_{j,t} = \sqrt{\frac{1}{I}\sum_{i=1}^{I}(dp_{i,j,t} - \overline{d_{i,j,t}})^2}$, where i indexes items within industry j during month t. Price change dispersion is calculated using only non-zero price changes[7]. The interquartile range is calculated for the same set of item level price changes within an industry at time t.

Figure 4 shows aggregate price change standard deviation during the 1998 to 2014 data sample. It shows there is a large amount of variation over time ranging from 0.09 during 1999 up to 0.15 during 2003. During the Great Recession the dispersion measure increased from

[4]Further details about the BLS sampling process is in appendix B.3.

[5]This includes goods that have a two digit NAICS code of 31, 32, or 33. However it excludes all items in NAICS 324, Petroleum and Coal manufacturing industry, as these industries view oil price volatility as both profit and cost volatility.

[6]This is the similar to the method Nakamura and Steinsson (2008) use to construct PPI price statistics. They first took the average price statistic within an item group, then took a median across item groups.

[7]Price change dispersion is typically constructed using only non-zero price changes such as in Vavra (2014), Berger and Vavra (2015), Luo and Villar (2015). Similar results are obtained however when including zeros in the standard deviation of price changes measure and results are in appendix B.8.

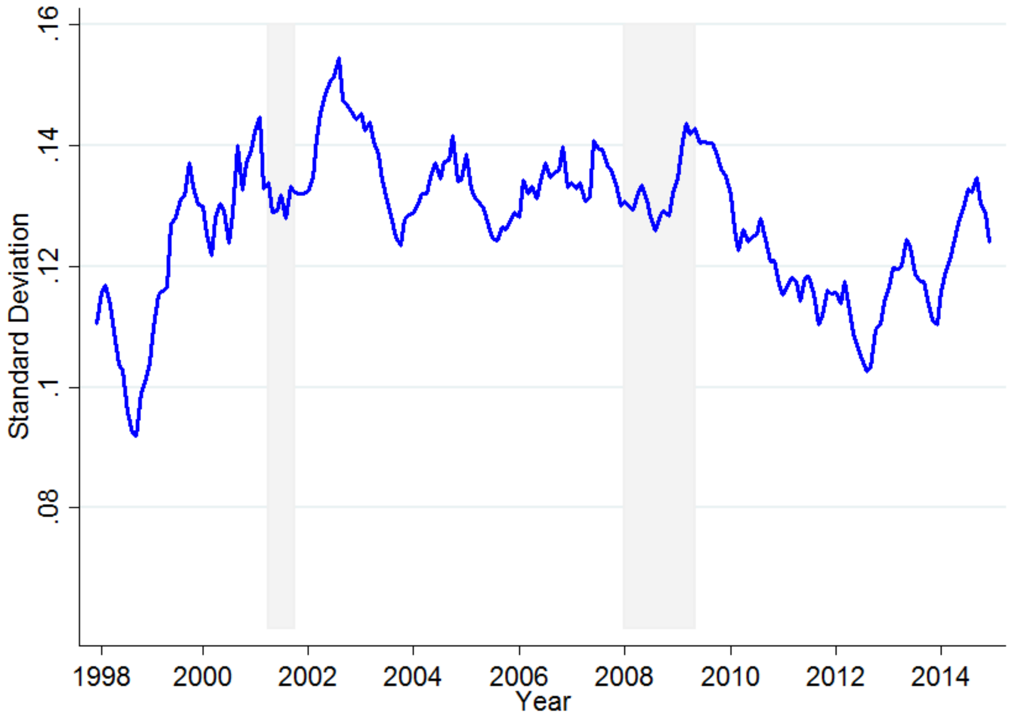


FIGURE 4: Monthly Standard Deviation of Price Changes

NOTE: Data is seasonally adjusted with X-12 seasonal filter and presented as 6 month moving average.

0.13 to 0.14, an increase of 7%. This stands in contrast with Berger and Vavra (2015) who find the IQR of price change dispersion nearly doubles from 0.09 to 0.17 in the international producer price data set[8].

To further substantiate the similarities between consumer and producer prices, table 1 shows price statistics for both the CPI and the PPI. The most notable difference between the two data sets is that there are more small price changes in the PPI than the CPI, which increases the kurtosis of the price change distribution in the PPI[9]. The correlation between the monthly inflation measures of consumer prices and producer prices is 0.8 over the 1998 to 2014 time period[10]. Temporary sales are not common in the PPI, so sales filtering techniques are not applied.

[8] I find that the IQR of price change dispersion increases from 0.07 to 0.09 during the Great Recession.

[9] Nakamura and Steinsson (2008) show that there is a high correlation between the frequency of price change within narrow item groups between the CPI and PPI data.

[10] A comparison of the CPI and PPI inflation rates are shown in appendix B.9.

Moment	Freq	Avg Size	Frac Up	Frac Small	SD	Skew	Kurt
CPI	0.15	0.08	0.65	0.12	0.08	0.12	6.4
PPI	0.15	0.07	0.60	0.22	0.13	0.10	15.0

Table 1: Consumer and Producer Price Index Moments

Note: All CPI moments calculated for 1988-2012 from Vavra (2014) except for fraction of small price changes which is calculated for 1977-2014 from Luo and Villar (2015). PPI moments calculated for 1998-2014 are author's calculation. Small price changes are defined as $|dp_{i,t}| < 0.01$.

2.2 Oil Prices

I measure oil prices using the average monthly West Texas Intermediate (WTI) spot price of oil, a particular grade of light and sweet crude oil traded in Cushing, Oklahoma. The WTI oil price is beneficial to use because it is available at daily frequency, and allows construction of within month volatility of oil prices. I argue that oil price and volatility movements are plausibly exogenous to disaggregated US industries. Evidence in favor of this is that many large price movements can be traced to events that are unrelated to the US. Rather they can be explained by events in large oil producing regions such as the Middle East or South America, or changes in demand elsewhere in the world.

This section will briefly summarize the evolution of oil price changes over time[11]. There was a spike in the price and volatility of oil during late 2002 and 2003 related to the Venezuelan oil strike from December 2002 to February 2003 and the Iraq war in 2003. The nominal price of oil then increased over 350 percent from 2003 until the middle of 2008, and Hamilton (2009) and Kilian (2008) attribute this to an increase in demand from Asia. Oil prices plummeted from \$134 in June 2008 to \$34 in February 2009 due to anticipation of a global recession while oil volatility more than doubled during the associated period. Another spike in oil prices and volatility occurred in 2011 and is associated with 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, as well as an increase in the supply of oil likely due to US shale production.

2.3 Oil Price Volatility

This section estimates the latent oil price volatility process using three different measures. The preferred method of measuring oil price volatility is with a stochastic volatility model that estimates independent first and second moment shocks from the single process for oil prices. This process will also be consistent with the modeling section.

[11] Additional discussion about the potential causes of oil price changes are in appendix B.5.

Parameter	Prior	Posterior		
		Mean	Median	95% PI
ρ_o	Uniform(0,1)	0.999	0.999	(0.992,0.999)
ρ_σ	Uniform(0,1)	0.887	0.9429	(0.574,0.999)
ϕ	Uniform(0,6)	0.140	0.127	(0.053,0.276)
$\overline{\sigma}$	Uniform(-20,20)	-2.607	-2.602	(-3.000,-2.234)

TABLE 2: Priors and Posteriors of Stochastic Volatility Oil Process

NOTE: Stochastic Volatility priors for real oil price process with time varying volatility. Process estimated using monthly WTI data from 1986 to 2014.

I assume real oil prices follow an AR(1) process with time varying volatility, where volatility follows a mean reverting AR(1) process[12]. Specifically,

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

$$\sigma_t = (1-\rho_\sigma)\overline{\sigma} + \rho_\sigma\sigma_{t-1} + \phi\nu_{\sigma,t} \tag{2}$$

where $\{\nu_t, \nu_{\sigma,t}\} \sim$ N(0,1), and $\overline{\sigma}$ is the unconditional mean of σ_t. The shock to oil price volatility $\nu_{\sigma,t}$ is assumed to be independent of the level shock ν_t. The postulated oil price process is the same as in Plante and Traum (2012) or Blanchard and Gali (2007) with time varying volatility.

The parameters are estimated using Bayesian Markov Chain Monte Carlo methods. Due to the nonlinear interaction between the innovations to oil price shocks and volatility, the Kalman filter cannot be used but a particle filter can evaluate the likelihood, as proposed by Fernandez-Villaverde et al. (2015). Markov Chain Monte Carlo is used to sample from the posterior distribution. Following Born and Pfeifer (2014), a backward smoothing routine is then used to extract the historical distribution of shocks from the model[13].

However other measures of oil price volatility are also constructed for robustness. A GARCH model of volatility is estimated, and the extracted volatility series shows that the two methods measure the same underlying process. Realized volatility is constructed from within month daily oil price returns. While this is a noisier volatility process it has a significant correlation with the other volatility series. The high correlation between the three measures of oil price volatility shows that they are extracting a common volatility factor that underlies oil price movements.

The conditional heteroskedasticity of oil prices in the estimated GARCH(1,1) model of oil prices has both significant autoregressive and moving average components. Complete

[12]Nominal oil prices are deflated by the PPI finished goods index.

[13]Further estimation details for the stochastic volatility process are in Appendix B.1.

Variable	Mean	Median	Standard Dev	Max	Min
Stochastic Vol	0.0763	0.0724	0.0222	0.1730	0.0416
GARCH Vol	0.0785	0.0736	0.0191	0.1980	0.0582
Realized Vol	0.0580	0.0510	0.0332	0.2566	0.0170
$\Delta log(P_t^o)$	0.0042	0.0119	0.0820	0.2130	-0.3132

TABLE 3: Oil Price Summary Statistics

NOTE: Summary statistics for monthly WTI real oil prices over 1998:M1-2014:M12. Volatility measures are the standard deviation of each oil price volatility measure.

description of the results is in the appendix. The GARCH volatility series is noisier than the stochastic volatility series, but they have a correlation of 0.74 between 1998 and 2014. GARCH volatility shows a large increase in volatility during 2009 that is also present in the stochastic volatility measure.

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

$$RV_t = \sqrt{\frac{\sum_{n=1}^{N}(dp_n - \overline{dp_t})^2}{N-1}} \tag{3}$$

where dp_n is the log difference in daily 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. However, there is still a significant correlation between realized volatility and the other two volatility series, implying that all three are extracting a similar latent volatility process for oil prices[14].

Figure 5 compares the three oil volatility measures over time, while table 3 shows oil price summary statistics during the 1998 to 2014 period. 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.

[14]Over the period 1998 to 2014, the correlation between stochastic volatility and GARCH volatility is 0.74, while the correlation between stochastic volatility and realized volatility is 0.66. GARCH volatility and realized volatility of oil prices have a correlation of 0.42.

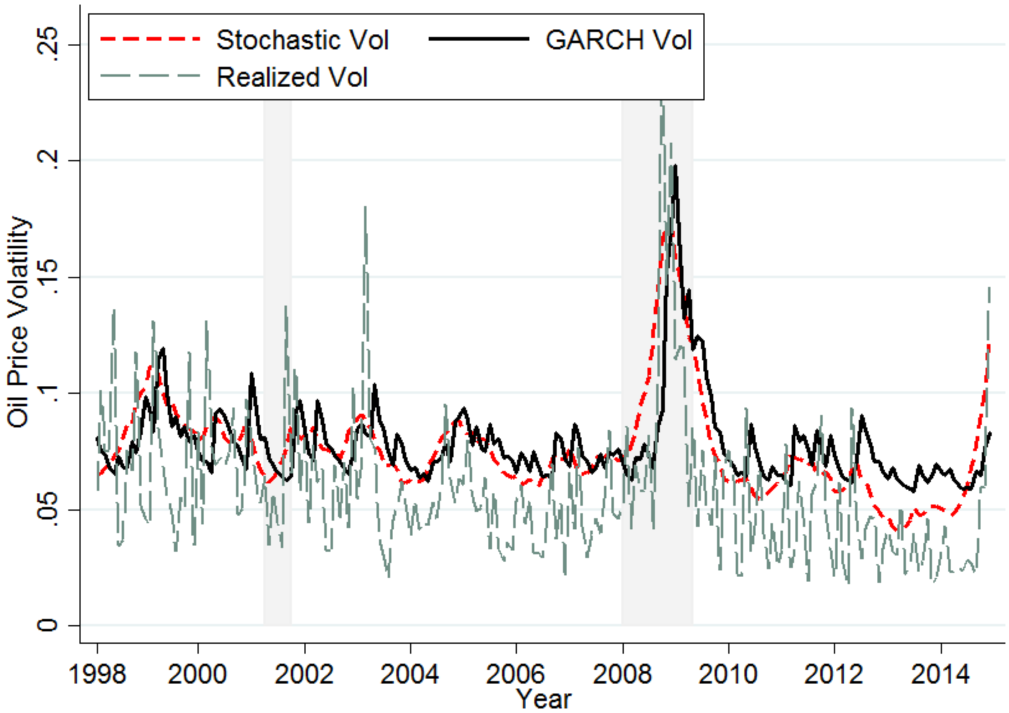


FIGURE 5: Oil Volatility

NOTE: The thick dotted red line shows the extracted stochastic volatility of oil prices, e^{σ_t}, while the solid black line shows the GARCH volatility, σ_t. The thin dotted gray line shows within month realized volatility of daily oil prices.

3 Empirical Analysis

3.1 Oil Price Pass Through

Before moving to the main analysis, I examine the pass through of oil prices to producer prices to show that oil price inflation affects producer price setting behavior. I estimate the pass through equation:

$$\pi_{j,t} = \alpha_j + \sum_{i=0}^{12} b_i \left(\Delta log P^o_{t-i}\right) + \epsilon_{j,t} \tag{4}$$

where $\pi_{j,t}$ is monthly producer price inflation for a NAICS 4 industry j. α_j are industry fixed effects and $\Delta log P^o_t$ are monthly changes in the spot price of oil. The regression includes 12 months of lagged oil price changes[15]. The results are in table 4.

The short run pass through is the coefficient b_0, the impact of a change of oil prices

[15] Additional oil price lags do not substantially change the results.

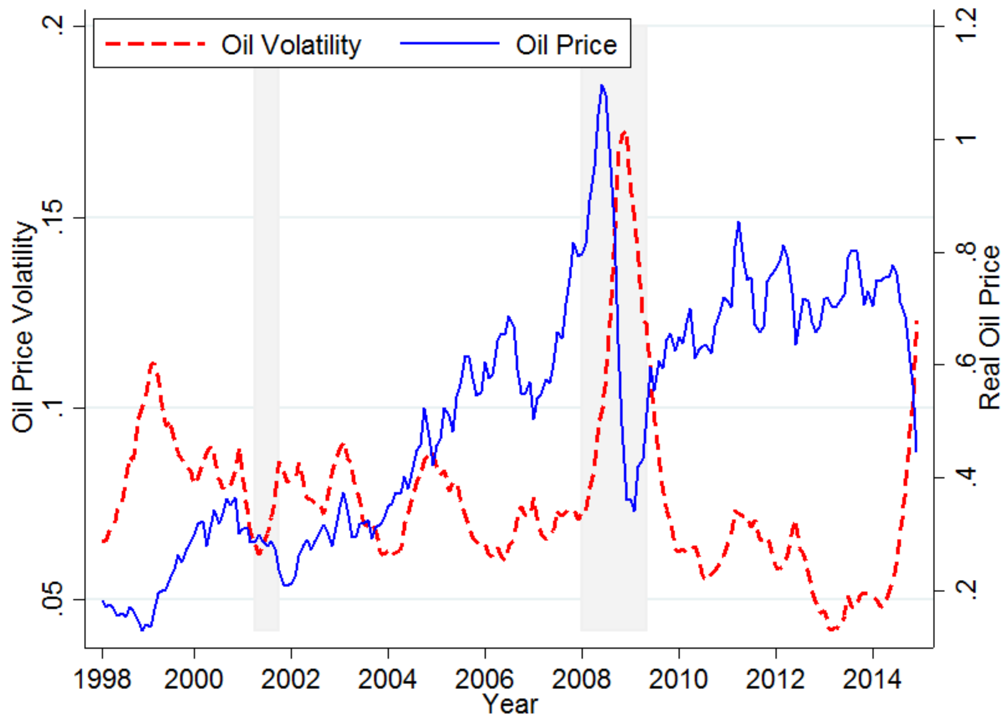


FIGURE 6: Stochastic Oil Volatility and Real Oil Price

NOTE: WTI nominal monthly oil price deflated by PPI finished goods index on right vertical axis and stochastic volatility, e^{σ_t}, on the left vertical axis.

Short Run Pass Through	Long Run Pass Through
0.010***	0.086***
(0.003)	(0.017)

TABLE 4: Pass Through Regression

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Number of observation=10,106. Number of industries=66. $R^2 = 0.06$. Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

on producer prices during the same month[16]. The coefficient is positive and statistically significant. Given that the average industry in the sample has an oil share of 1.6%, the size of the pass through is large. It can be interpreted as 1.0% of a change in oil price inflation is passed through to producer prices.

The long run coefficient is $\sum_{i=0}^{12} b_i$, and implies that 8.6% of a change in oil prices is passed through over a year[17]. Oil prices can pass through not only through a direct cost channel, but also through changes in other material costs due to input output linkages.

[16]Restricting oil prices to pass through with at least a one month lag does not change the results. The short run pass through coefficient is $b_1 = 0.012^{***}$ and the long run pass through coefficient is $\sum_{i=1}^{12} b_i = 0.076^{***}$.

[17]Exchange rate pass through regressions generally find long run coefficients close to 0.3.

Another reason pass through can be large is due to capital-energy complementarities which can generate oil price effects above their cost share as argued by Atkeson and Kehoe (1999).

These pass through estimates imply short run and long run pass through of oil prices to industry inflation for manufacturing industries[18]. This is important because the pass through estimates imply industries price setting behavior reacts to changes in the price of oil, and could be impacted by the volatility of oil prices. In the next section I will show that volatility of oil prices affects dispersion of industry price changes.

3.2 Price Change Dispersion and Oil Price Volatility

As motivating evidence before exploiting heterogeneity in industry oil share, I first estimate the time series relationship between price change dispersion and oil price volatility. Oil price volatility is a common cost volatility shock to firms. The time series relationship does not control for all common shocks and is not causal. Variation in industry price change dispersion over time allows me to run the following regression:

$$Y_{j,t} = \eta * \Delta log(P^o_{t-1}) + \lambda * \sigma_{t-1} + \gamma' X_{j,t} + \alpha_j + \epsilon_{jt} \tag{5}$$

where t indexes time and j indexes industry. This specification maps a change in oil price inflation and oil volatility into the average change in price change standard deviation after controlling for industry heterogeneity with the use of fixed effects and movements in aggregate financial conditions and volatility. The results for the three measures of oil price volatility are in table 5.

The regression controls for macroeconomic fluctuations in financial constraints and idiosyncratic volatility. Economy wide financial conditions are controlled for with the excess bond premium measure of Gilchrist and Zakrajsek (2012), while a broad measure of volatility is controlled for with the VIX index. Industry fixed effects control for time invariant differences between industries and average industry item level inflation rate and industrial production changes are included to control for movements in industry price and production. The unit of observation is monthly price change dispersion at the 4-digit NAICS level. This level of industry aggregation includes on average nearly 500 items at the industry month level, allowing me to construct reasonably precise price change dispersion numbers while limiting the amount of heterogeneity within an industry. The dependent variable is the standard deviation of price change conditional on adjustment. Similar results are obtained using the interquartile range of price changes and are in appendix B.8.

Column 1 shows results for the stochastic volatility of oil prices. Oil price inflation

[18] Adding additional lags to the pass through regression does not substantively change the results.

Dependent Variable: Standard Deviation of Price Change

Volatility Measure	Stochastic Vol	Realized Vol	GARCH Vol
	(1)	(2)	(3)
$\Delta log(P^o_{t-1})$	0.010	0.019	0.011
	(0.009)	(0.090)	(0.009)
σ_{t-1}	0.210***	0.081***	0.123***
	(0.057)	(0.031)	(0.048)
$\pi_{j,t-1}$	0.111	0.114	0.122
	(0.115)	(0.115)	(0.115)
$\Delta IP_{j,t}$	0.002	-0.004	-0.005
	(0.016)	(0.017)	(0.016)
EBP$_{t-1}$	0.003	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
VIX$_{t-1}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Industry FE	Yes	Yes	Yes
Number of Industries	63	63	63
N	10,946	10,946	10,946

Table 5: Producer Price Change Dispersion and Macroeconomic Shocks

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Robust asymptotic standard errors reported in parentheses are double clustered at the industry-month level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

and volatility are included with a one month lag which reduces the potential endogeneity. The second row shows the coefficient of interest for oil price volatility. The results show that increases in oil price volatility increase the average producer price change dispersion. A one standard deviation increase in oil price volatility is 0.022, which implies that the average industry price change dispersion will increase by 0.005. The unweighted average price change standard deviation is 0.109; the estimate implies a 4% increase in price change dispersion for the average industry. Excess bond premium and the VIX measure of volatility do not affect price change dispersion in this regression. The fact that the VIX index does not predict producer price change dispersion shows that oil price volatility is not simply correlated over time with other measures of volatility but rather has further explanatory power in producer pricing. Oil price inflation and lagged industry inflation are positive but insignificant. Bachmann et al. (2013) argue that changes in unforecasted production can affect the frequency of price change, however changes in industrial production are negative and insignificant in predicting price change dispersion.

Column 2 shows the regression results with the realized volatility of oil prices, and it shows that within month volatility of oil prices is also correlated with increased producer price change standard deviation. Realized volatility of oil prices is on a different scale than stochastic volatility, and a one standard deviation increase in realized volatility implies an increase of 0.003 in average price change dispersion. The excess bond premium is positive and significant which implies an increase in price change dispersion in the producer price data. This result could be explained by the model of Gilchrist et al. (2015), who argue that more financially constrained firms are likely to increase prices while financially unconstrained firms will lower them during periods of financial crisis in order to increase market share.

GARCH volatility results are in column 3, and it shows the same pattern that exists with stochastic and realized volatility. Periods of high GARCH oil price volatility are related to increased price change dispersion for producer prices. These regression results show that all measures of oil price volatility increase producer price change dispersion, and price change dispersion is related to changes in the underlying volatility of oil prices.

The previous regressions shows that producer price change dispersion is correlated with oil price volatility over time. However it does not identify how changes in oil price volatility impact price change dispersion due to potential omitted variables. In order to identify this relationship I will exploit heterogeneity in oil usage across industries to construct industry specific oil demand variables.

3.3 Industry Specific Oil Volatility

I now construct industry specific oil demand variables in order to identify the effects of oil volatility on industry level producer price setting behavior. The empirical strategy uses variation in oil price and volatility interacted with a preexisting share of oil that represents the importance of oil in each industry's cost function. The idea behind the demand variables is to exploit the heterogeneity in industry oil usage, which is a measure of the importance of oil prices from the cost channel. Industries that use more oil should respond more strongly to oil price shocks than industries that are not as reliant on oil. The industry specific oil demand variables allow me to control for any common shocks over time and any time invariant differences between industries, which enables identification of oil price volatility shocks on price setting behavior.

The oil demand variables are constructed similar to those used in Shea (1993), Perotti (2007), or Nekarda and Ramey (2011) who study the effects of fiscal policy on industries. The Input-Output tables contain information on the dollar amount of oil used as well as industry production. A preexisting oil usage sensitivity is constructed to remove dependence on the current year's oil price. There is substantial variation in experiences after an oil volatility shock due to the heterogeneity in oil usage across industries. An industry that does not use oil would be unlikely to experience any immediate changes in costs due to oil price volatility changes, while an industry with a large share of oil will need to adjust prices by a larger amount to reset their optimal price. Constructing industry specific oil price variables allows use of industry and time fixed effects, thereby studying the partial equilibrium effects of an aggregate volatility shock. This partial equilibrium effect allows me to study the mechanism through which volatility shocks affect price setting behavior.

The Benchmark IO use table with detailed 6-digit NAICS industry from 1997 is used to construct the oil sensitivity measure. An industry's oil sensitivity is given by:

$$s_{o,j} = \frac{\text{Nominal Dollars Spent on Oil Input Industry j in 1997}}{\text{Nominal Dollars Value Added Industry j in 1997}} \tag{6}$$

where j indexes an industry[19]. This sensitivity to oil usage is motivated by an industry's oil share of production. The oil usage measure is constructed using data from before the sample, reducing concerns about reverse causality between oil usage and oil price[20].

Oil demand variables for oil price change and volatility are then constructed by interacting the preexisting oil share, $s_{o,j}$, with oil price volatility or oil price inflation[21]. These oil demand variables are in the spirit of 'Bartik' style measures, an interaction between a predefined share of oil usage within a narrowly defined manufacturing industry and aggregate changes in oil price or volatility. The idea behind this measure is that global changes in oil price and volatility differentially impacted industries because of preexisting oil usage technology. The sensitivity, $s_{o,j}$, is a directional measure of the degree to which oil price and volatility movements will affect price setting behavior.

Figure 7 illustrates the identification and previews the main result by comparing the price change dispersion time series for high and low oil share industries with the stochastic volatility of oil prices. I define the high and low oil share sectors as the 10% of industries with the highest or lowest oil share each period. The correlation between the high oil share sector average price change dispersion and stochastic oil price volatility is 0.423, while the correlation between the low oil share sector average price change dispersion and oil price volatility is only 0.073. This figure suggests that industries that are more oil intensive have greater price change dispersion during periods of high oil price volatility.

[19] The oil producing sector is defined as NAICS 324111, Petroleum Refining.

[20] An alternative long run measure of oil usage is constructed by averaging over 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, $s_{o,j} = \sum_{t=1}^{T} \frac{s_{o,j,t}}{T}$, is defined as the long run usage and it is in the spirit of Nekarda and Ramey (2011).

[21] Using the time averaged oil usage from the sample period does not change the results. Full results using this measure are in appendix B.8.

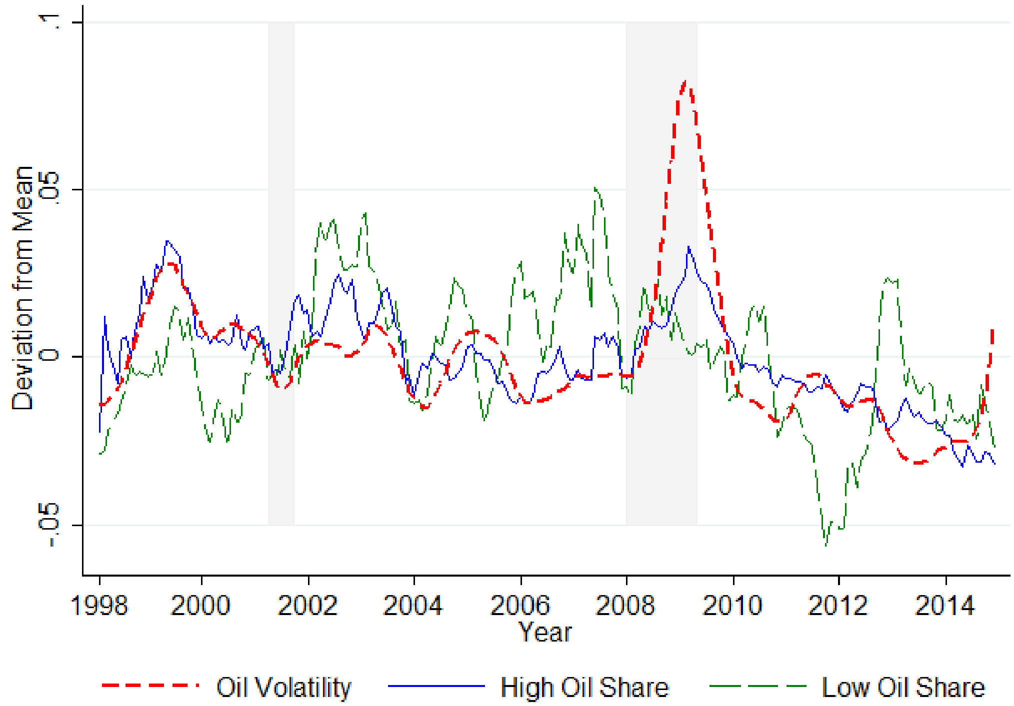


FIGURE 7: Average price change dispersion for high and low oil share industries.
NOTE: Average price change dispersion for top and bottom 10% of industries in each month. Oil volatility is the extracted stochastic volatility of oil prices, e^{σ_t}. Data is demeaned, seasonally adjusted with the X-12 filter, and then presented as a 6 month moving average. The shaded areas represent NBER-dated recessions.

However the correlation between price change dispersion and oil price volatility for high and low oil share industries does not control for aggregate shocks or cyclical changes in production by industry. Using the oil demand variables I control for both industry differences and time variation in common shocks such as aggregate volatility or financial constraints through the use of time fixed effects. The main regression of interest is the specification:

$$Y_{j,t} = \eta * (s_{o,j} * \Delta log(P^o_{t-1})) + \lambda * (s_{o,j} * \sigma_{t-1}) + \gamma' X_{j,t} + \alpha_j + \alpha_t + \epsilon_{jt} \tag{7}$$

where $Y_{j,t}$ is the price change dispersion measure. The coefficient of interest is λ, which is the marginal effect of an increase in oil price volatility for an industry with oil share $s_{o,j}$. $X_{j,t}$ are a vector of control variables that can influence inflation dispersion. Controls include industrial production growth and industry inflation. Identification of volatility comes from variation across time within an industry for a given $s_{o,j}$. The main results using the stochastic volatility measure are in table 6. GARCH volatility and realized volatility oil price measure results are in appendix B.8. They have similar implications.

The identifying assumption is that the interaction of oil price volatility and oil share is not correlated with unobserved shocks to an individual industry. Separate identification of oil price and oil volatility comes from the fact that oil prices and volatility do not move together. The exogeneity of the variable hinges on each industry being a price taker in the global oil market, as well as the degree to which oil usage is irreversible in the short run. However oil is likely to be characterized by large amounts of specific capital or irreversible investment as a material input or energy source which make it difficult to quickly substitute away from.

The regression results show that after controlling for differences across time and between industries, an increase in oil price volatility increases price change dispersion for industries that are more oil dependent. Changes in industrial production are negatively correlated with price change dispersion in aggregate data, but at the industry level I find no relationship between the two measures. Industry specific oil price inflation has no estimated effect on price change dispersion.

Oil price volatility more than doubled from 0.071 to 0.144 between December 2007 and September 2008. The associated change in the average price change standard deviation was from 0.125 to 0.133. The estimate from column 2 implies that oil price volatility could explain 46% of the average observed price change dispersion increase after controlling for oil price inflation and other observables.

Frequency of price change is also an important component of aggregate price flexibility and therefore monetary policy effectiveness. I find no evidence of a positive relationship between price change frequency and oil price volatility. The full results are available in appendix B.8.

It has been argued by Gilchrist et al. (2015) that financial frictions impacted prices differentially during the financial crisis in 2008. Given that this is the same period when the largest movements in oil price volatility occurred, an indicator variable is included to examine if the large changes in oil prices and volatility had differential effects during the financial crisis period of 2008. Column 1 of Table 7 shows that even with the doubling of oil volatility during 2008, oil price volatility has the same effect on price change dispersion within and outside of the crisis period.

As an additional robustness exercise, column 2 shows the results using a 3-digit NAICS classification of industry and the stochastic volatility measure of oil price volatility. The results show that increased oil price volatility increases price change dispersion. The specification in column 3 uses GARCH volatility of oil prices, and implies a statistically significant increase in the standard deviation of price changes. Column 4 shows the baseline specification using stochastic volatility of oil prices but restricts the sample to the 1998 through

Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.196	0.190	0.140	0.162
	(0.149)	(0.147)	(0.115)	(0.117)
$s_{o,j} * \sigma_{t-1}$	3.181***	3.199***	2.976***	2.813***
	(0.696)	(0.706)	(0.566)	(0.535)
$\pi_{j,t}$		0.073	0.070	0.072
		(0.118)	(0.116)	(0.113)
$\Delta IP_{j,t}$			0.003	-0.001
			(0.014)	(0.015)
$\text{PriceDisp}_{j,t-1}$				0.067***
				(0.016)
$\overline{s_o} * \sigma_{t-1}$	0.050***	0.050***	0.047***	0.044***
	(0.011)	(0.011)	(0.009)	(0.008)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

Table 6: Industry Specific Oil Demand Variables Regression

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. 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. $\text{PriceDisp}_{j,t-1}$ is the lagged industry price change dispersion. $\overline{s_o} * \sigma_{t-1}$ is the transformed coefficient for a marginal change in oil price volatility for an average industry with oil share of 0.016. Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

2007 period, before the financial crisis and the zero lower bound on interest rates. Column 5 uses the Brent Crude oil price and it's stochastic volatility rather than the WTI oil price. These results show that greater oil price volatility implies higher price change dispersion both during the restricted sample, and using an alternative oil price.

Column 6 controls for the median industry realized stock volatility in the baseline stochastic volatility of oil price regression. It shows that after controlling for an additional measure of industry level volatility, oil price volatility still increases the dispersion of price changes.

3.4 Within Firm Price Change Dispersion

A possible identification concern with the main industry regression is that there is differential oil usage across firms within an industry. As a robustness exercise to address this concern, I include firm level fixed effects and identify the effect of oil price volatility within a firm across industries. Item level price change dispersion is constructed at the firm level

Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)	(5)	(6)
$s_{o,j} * \Delta log(P^o_{t-1}) * [Crisis = 0]$	0.258**					
	(0.126)					
$s_{o,j} * \Delta log(P^o_{t-1}) * [Crisis = 1]$	0.005					
	(0.391)					
$s_{o,j} * \sigma_{t-1} * [Crisis = 0]$	2.737***					
	(0.837)					
$s_{o,j} * \sigma_{t-1} * [Crisis = 1]$	3.342***					
	(0.831)					
$s_{o,j} * \Delta log(P^o_{t-1})$		-0.124	0.065	0.279*	0.091	0.196
		(0.267)	(0.131)	(0.142)	(0.140)	(0.151)
$s_{o,j} * \sigma_{t-1}$		3.696***	2.877***	5.722***	1.817**	3.151***
		(1.238)	(0.716)	(1.752)	(0.713)	(0.666)
$\pi_{j,t}$	0.071	-0.211	0.075	0.147	0.070	0.064
	(0.118)	(0.124)	(0.116)	(0.196)	(0.118)	(0.122)
Realized Stock $\text{Vol}_{j,t-1}$						0.050
						(0.037)
Time & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	81	20	81	80	81	80
N	13,606	3,176	13,606	7,543	13,606	13,161

Table 7: Robustness Analysis

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Columns (1) and (2) use the stochastic volatility measure of oil price volatility. Crisis year indicator is defined as 1 during 2008 and 0 otherwise. This is the same crisis definition timing as Gilchrist et al. (2015). Column (2) defines an industry at the 3-digit NAICS level. Column (3) uses the GARCH measure of oil price volatility with 4-digit NAICS industries. Column (4) uses the stochastic volatility measure of oil price volatility with the 4-digit NAICS industries but restricts the sample from 1998:M1 to 2007:M12. Column (5) uses Brent Crude oil prices and stochastic volatility with 4-digit NAICS industries. Column (6) uses the stochastic volatility measure of oil price volatility with 4-digit NAICS industries and includes the median industry realized stock volatility. No stock data is available from NAICS 3161, "Leather and Hide Tanning and Finishing", reducing the number of industries. Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

over 2005-2014; that is the standard deviation of price changes within a month for a firm indexed by i[22]. This allows me to control for time invariant firm specific differences using firm fixed effects, such as differences in oil share within an industry. Specifically I estimate the following regression:

$$Y_{i,j,t} = \eta * (s_{o,j} * \Delta log(P^o_{t-1})) + \lambda * (s_{o,j} * \sigma_{t-1}) + \gamma' X_{j,t} + \alpha_i + \alpha_t + \epsilon_{ijt} \tag{8}$$

[22]Firm level analysis is conducted only over 2005-2014 due to a change in firm level identification in 2005.

Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.020	0.018	0.008	0.005
	(0.074)	(0.074)	(0.092)	(0.091)
$s_{o,j} * \sigma_{t-1}$	1.301***	1.304***	1.657***	1.663***
	(0.334)	(0.334)	(0.431)	(0.430)
$\pi_{j,t-1}$		-0.107***		-0.099***
		(0.017)		(0.018)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Number of Firms	20,162	20,162	11,764	11,764
N	202,938	202,938	100,841	100,841

Table 8: Producer Price Change Dispersion and Macroeconomic Shocks

Note: Sample period: 2005:M1 to 2014:M12 at a monthly frequency. Columns (1) and (2) include all firm-month observations with at least two price changes, while columns (3) and (4) restrict the sample to be firm-month observations with at least four price changes. Robust asymptotic standard errors reported in parentheses are clustered at the firm level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

The regression is linking item level price change dispersion within an firm to industry specific changes in oil prices and oil volatility while controlling for industry inflation. Firm and time fixed effects control for differences between firms and common aggregate shocks over time. The coefficient λ is the average firm level response to oil price volatility for an industry with an oil share of $s_{o,j}$. Results are in table 8.

The results show that using only within firm variation, price change dispersion increases more within oil intensive industries during periods of high oil price volatility[23]. These regressions show that the relationship between oil price volatility and price change dispersion is robust to controlling for time invariant firm level heterogeneity.

The empirical analysis provides evidence that oil price volatility, a common cost volatility shock, is positively related to price change dispersion at the industry and firm level. Industries that use more oil exhibit greater price change dispersion in response to high oil volatility. Additionally, the average price change dispersion of a firm within an industry with high oil usage is greater than the average firm within a low oil usage industry. This suggests that it is not due to heterogeneity within industries, but rather, is due to a common response to the aggregate shock.

Price change dispersion is a measure of aggregate price level flexibility, with greater price change dispersion implying less flexibility. The next section will examine the relationship be-

[23] Average industry level price change dispersion is greater than average firm level price change dispersion, causing the decrease in coefficient magnitude. The average firm level non-zero price change standard deviation in the sample is 0.046 while the average industry level non-zero price change standard deviation is 0.112.

tween oil price volatility and price change dispersion in a state dependent general equilibrium model of price setting.

4 Menu Cost Model

This section presents a generalized menu cost model of price setting in order to quantify the effects of volatility on monetary non-neutrality. The baseline quantitative menu cost model follows Golosov and Lucas (2007) with a fixed menu cost. It includes the leptokurtic productivity shocks as in Midrigan (2011) and a small probability of a free price change such as in Nakamura and Steinsson (2010). Oil is modeled as a non-produced input in the firm production function with an exogenous real price as in Blanchard and Gali (2007), and a time varying second moment to represent volatility shocks.

In the fixed menu cost model an oil price volatility shock predicts lower price change dispersion on impact of an oil price volatility shock, due to the selection effect of the firms which choose to change prices. The selection effect states that the prices that are most likely to change are those that are furthest from their optimal price. The common oil price shock pushes more price changes in one direction, which decreases price change dispersion.

The generalized price setting model nests a random menu cost model, which reduces the selection effect by issuing firms a random heterogeneous menu cost each period. The random menu costs imply firms have a differential likelihood of changing prices based on the menu cost they receive. This mechanism alters the mix of price changes and enables the model to match the positive relationship between the common cost volatility shock and price change dispersion.

Monetary policy effectiveness is then examined during periods of high and low oil price volatility. In the counterfactual fixed menu cost model there is a greater tradeoff between output and inflation when oil price volatility is high, due to increased price flexibility. The random menu cost model, which matches the positive empirical relationship between oil price volatility and price change dispersion, implies near constant monetary non-neutrality in response to changes in aggregate cost shock volatility.

4.1 Households

A model of price setting with first and second moment shocks to oil prices is now presented. Households maximize current expected utility, given by

$$E_t \sum_{\tau=0}^{\infty} \beta^t \left[log(C_{t+\tau}) - \omega L_{t+\tau} \right] \tag{9}$$

They consume a continuum of differentiated products indexed by z. The composite consumption good C_t is the Dixit-Stiglitz aggregate of these differentiated goods,

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz \right]^{\frac{\theta}{\theta-1}} \tag{10}$$

where θ is the elasticity of substitution between the differentiated goods.

Households decide each period how much to consume of each differentiated good. For any given level of spending in time t, households choose the consumption bundle that yields the highest level of the consumption index C_t. This implies that household demand for differentiated good z is

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta} \tag{11}$$

where $p_t(z)$ is the price of good z at time t and P_t is the price level in period t, calculated as

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz \right]^{\frac{1}{1-\theta}} \tag{12}$$

A complete set of Arrow-Debreu securities is traded, which implies that the budget constraint of the household is written as

$$P_t C_t + E_t[D_{t,t+1} B_{t+1}] \leq B_t + W_t L_t + \int_0^1 \pi_t(z) dz + T_t \tag{13}$$

where B_{t+1} is a random variable that denotes state contingent payoffs of the portfolio of financial assets purchased by the household in period t and sold in period t+1. D_{t+1} is the unique stochastic discount factor that prices the payoffs, W_t is the wage rate of the economy at time t, $\pi_t(z)$ is the profit of firm z in period t. T_t are lump sum government transfers. A no ponzi game condition is assumed so that household financial wealth is always large enough and future income is high enough to avoid default.

The first order conditions of the household maximization problem are

$$D_{t,t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)\frac{P_t}{P_{t+1}} \tag{14}$$

$$\frac{W_t}{P_t} = \omega L_t C_t \tag{15}$$

where equation (14) describes the relationship between asset prices and consumption, and (15) describes labor supply.

4.2 Firms

In the model there are a continuum of firms indexed by z. The production function of firm z is Leontief in labor and oil to describe the lack of substitutability between them in the short run.

$$y_t(z) = A_t(z)\min\{L_t(z), \frac{1}{s_o}O_t(z)\} \tag{16}$$

where $L_t(z)$ is labor rented from households and $O_t(z)$ is the quantity of oil used to produce output. Oil usage is likely to be have large amounts of specific capital or irreversible investment in the short run, which motivates the Leontief structure.

Firm z maximizes the present discounted value of future profits

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau}\pi_{t+\tau}(z) \tag{17}$$

where profits are given by:

$$\pi_t(z) = p_t(z)y_t(z) - W_tL_t(z) - Q_tO_t(z) - \chi_t(z)W_tI_t(z), \chi_t(z) \overset{iid}{\sim} F(\chi) \tag{18}$$

and Q_t is the nominal price of oil. $I_t(z)$ is an indicator function equal to one if the firm changes its price and equal to zero otherwise. $\chi_t(z)$ is a menu cost drawn from the distribution $F(\chi)$. In the fixed menu cost model, $F(\chi)$ is a degenerate distribution which implies a single menu cost χ as in the model of Golosov and Lucas (2007). The random menu cost model uses a continuous distribution where menu costs are drawn independently each period. The next section will further explain this feature. The final term indicates that firms must hire an extra $\chi_t(z)$ units of labor if they decide to change prices with probability $1 - \alpha$, or may change their price for free with probability α[24]. A small probability of receiving a free price change enables the model to generate small price changes.

Total demand for good z is given by:

$$y_t(z) = Y_t\left(\frac{p_t(z)}{P_t}\right)^{-\theta} \tag{19}$$

The firm problem is to maximize profits in (18) subject to its production function (16), demand for its final good product (19), and the behavior of aggregate variables.

Firms supply all goods demanded at a given price. Cost minimization at a given price implies that firms keep a constant proportion of oil input to labor input:

[24]This is a reduced form mechanism representing multiproduct firms in Midrigan (2011).

$$\frac{1}{s_o}O_t(z) = L_t(z) \tag{20}$$

The log of firm productivity follows a mean reverting process with leptokurtic shocks as in Gertler and Leahy (2008) and Midrigan (2011):

$$logA_t(z) = \begin{cases} \rho_a logA_{t-1}(z) + \sigma_a \epsilon_t(z) & \text{with probability } p_a \\ logA_{t-1}(z) & \text{with probability } 1 - p_a, \end{cases} \tag{21}$$

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

Nominal aggregate spending follows a random walk with drift:

$$log(S_t) = \mu + log(S_{t-1}) + \sigma_s \eta_t \tag{22}$$

where $S_t = P_t C_t$ and $\eta_t \sim$ N(0,1). This is a standard way to model nominal aggregate spending in a menu cost model.

The oil price process follows Blanchard and Gali (2007), by assuming that oil is a non-produced input purchased in a world market at real price P_t^o. The log of P_t^o follows an AR(1) process with time varying standard deviation:

$$logP_t^o = \rho_p logP_{t-1}^o + e^{\sigma_t}\nu_t \tag{23}$$

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

To model time varying volatility of oil prices, it is assumed that the standard deviation of oil prices follows a mean reverting AR(1) process as estimated in section 2.3:

$$\sigma_t = (1 - \rho_\sigma)\overline{\sigma} + \rho_\sigma \sigma_{t-1} + \phi \nu_{\sigma,t} \tag{24}$$

where $\nu_{\sigma,t}(z) \sim$ N(0,1) and $\overline{\sigma}$ is the unconditional mean of σ_t.

The state space of the firms problem is an infinite dimensional object because the evolution of the aggregate price level depends on the joint distribution of all firms' prices, productivity levels, and menu costs. It is assumed that firms only perceive the evolution of the price level as a function of a small number of moments of the distribution as in Krusell and Smith (1998). In particular, I assume that firms use a forecasting rule of the form:

$$log(\frac{P_t}{S_t}) = \gamma_0 + \gamma_1 logP_t^o + \gamma_2\sigma_t + \gamma_3 log(\frac{P_{t-1}}{S_t}) + \gamma_4(log(\frac{P_{t-1}}{S_t}) * logP_t^o) + \gamma_5(log(\frac{P_{t-1}}{S_t}) * \sigma_t) \tag{25}$$

The accuracy of the rule is checked using the maximum Den Haan (2010) statistic in a dynamic forecast[25].

Using equations (14), (15), (16), (18), (19), (20), (25) and market clearing I am able to write the firm problem recursively as:

$$\begin{aligned} V\big(A_t(z), \frac{p_{t-1}(z)}{S_t}, P_t^o, \sigma_t, \chi_t(z), \psi_t\big) = \max_{p_t(z)} \Big\{ & V^N\big(A_t(z), \frac{p_{t-1}(z)}{S_t}, P_t^o, \sigma_t, \psi_t\big), \\ & V^A\big(A_t(z), P_t^o, \sigma_t, \chi_t(z), \psi_t\big) \Big\} \end{aligned} \tag{26}$$

where ψ_t is the Krusell-Smith aggregate state describing the joint distribution of prices, productivities, and menu costs. $\pi_t^R(z)$ is firm z's real profits in period t, and $D_{t,t+1}^R$ is the real stochastic discount factor between periods t and t+1. Nominal variables have been normalized by current aggregate nominal spending in the economy to bound the state space. V^N and V^A are the values of not adjusting and adjusting the current period's relative price. The value of not adjusting is given by:

$$\begin{aligned} V^N\big(A_t(z), \frac{p_{t-1}(z)}{S_t}, P_t^o, \sigma_t, \psi_t\big) = & \pi_t^R(\frac{p_{t-1}(z)}{S_t}, A_t(z), P_t^o, \sigma_t, \psi_t) \\ & + E_t\big[D_{t,t+1}^R V\big(A_{t+1}(z), \frac{p_{t-1}(z)}{S_{t+1}}, P_{t+1}^o, \sigma_{t+1}, \chi_t(z), \psi_{t+1}\big)\big] \end{aligned} \tag{27}$$

while the value of adjusting the current price is given by:

$$\begin{aligned} V^A\big(A_t(z), P_t^o, \sigma_t, \chi_t(z), \psi_t\big) = & -\chi_t(z)\frac{W_t}{P_t} + \pi_t^R(\frac{p_t(z)}{S_t}, A_t(z), P_t^o, \sigma_t, \psi_t) \\ & + E_t\big[D_{t,t+1}^R V\big(A_{t+1}(z), \frac{p_t(z)}{S_{t+1}}, P_{t+1}^o, \sigma_{t+1}, \chi_t(z), \psi_{t+1}\big)\big] \end{aligned} \tag{28}$$

The model is solved by discretization and simulated using the non-stochastic simulation method of Young (2010). Full details on the solution method are available in the appendix section A.2.

4.3 Calibration

There are three sets of parameters that need to be calibrated in the model. The first set are household parameters and aggregate shocks that are common to both the fixed menu cost and random menu cost versions of the model. These parameters are standard menu cost models. It is a monthly model so the discount rate is set to $\beta = (0.96)^{\frac{1}{12}}$. Household utility is assumed to be log utility in consumption and linear disutility of labor. The elasticity of

[25] Adding price change dispersion to the forecasting rule does not qualitatively affect the model predictions.

Parameter		Value
θ	Elasticity of Substitution	4.0
β	Discount Factor	$(0.96)^{\frac{1}{12}}$
μ	Growth of Nominal Spending	0.002
σ_s	Standard Deviation of Nominal Spending	0.0037
ρ_a	Idiosyncratic TFP Persistence	0.70
s_o	Oil Share of Production	0.016
ρ_o	Oil Price Persistence	0.99
$\overline{\sigma}$	Oil Price Standard Deviation	0.07
ρ_σ	Oil Volatility Persistence	0.88
ϕ	Oil Volatility Standard Deviation	0.14

TABLE 9: Common Calibration Parameters

substitution is set to $\theta = 4$ following Nakamura and Steinsson (2010)[26]. The average oil share of production is set to $s_o = 0.016$, and matches the time averaged share of production from the IO tables from 1997, 2002, and 2007. The nominal shock process calibrates $\mu = 0.002$ to match the difference between the mean growth rate of nominal GDP and the mean growth rate of real GDP over 1998 to 2012, and $\sigma_s = .0037$ to match the standard deviation of nominal GDP growth over the same period. They are given in table 9.

The second set of parameters are for the oil price and oil price volatility processes estimated in section 2.3. The oil price persistence parameter is $\rho_o = 0.99$, oil price standard deviation $\overline{\sigma} = 0.07$, oil price volatility persistence $\rho_\sigma = 0.88$, and oil price volatility standard deviation is $\phi = 0.14$. These numbers imply a high persistence for oil price and relatively low persistence for oil price volatility.

The final set of parameters are related to the specific price setting model. These are the persistence and standard deviation of idiosyncratic productivity shocks ρ_a and σ_a, the probability of an idiosyncratic productivity shock p_a, the cost of changing a price $\chi_t(z)$, and the probability of a free price change α. These five parameters will change depending on the particular menu cost distribution assumption. Both the fixed and random menu cost models calibrate these parameters to match some salient price setting statistics in the total PPI data.

I will now discuss the calibration for the fixed menu cost model. 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

[26]Other papers set higher values such as 6.8 in Vavra (2014) or 7 in Golosov and Lucas (2007), which imply lower values of the mark up.

deviation of price changes, and the fraction of small price changes[27]. This model has a single point mass in the menu cost distribution that determine the value of the fixed menu cost and 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[28]. 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 a large absolute average size of price changes and a large dispersion of price changes.

The distribution from which random menu costs are drawn is now explained. The random menu costs are drawn from a transformation of an exponential distribution. This particular model specification is taken from Luo and Villar (2015). Specifically, random menu costs are drawn that are independent over time and across firms from the process:

$$\chi_t(z) = \begin{cases} 0 & \text{with probability } \alpha \\ \tilde{\chi}_t & \text{with probability } 1-\alpha, \end{cases} \quad \text{where } F(k) = P(\tilde{\chi} \leq k) = 1 - e^{-\lambda k^{\xi}} \tag{29}$$

The parameter λ determines the average value of the menu cost that is drawn, while ξ determines the curvature of the distribution. Higher values of ξ imply that a firm is less likely to draw very small or very large menu costs. These two parameters are calibrated along with the other four parameters to match the same price setting statistics and also price change skewness. In particular, $\lambda = 1.49$ and $\xi = 0.25$, where ξ is identified by the skewness of the distribution. This implies a relatively high average menu cost, and a distribution that has fat tails. There is substantial probability that firms draw very low or very high menu costs. The persistence of idiosyncratic productivity shocks remains set to 0.7, and the probability of a productivity shock is 0.4. The volatility of idiosyncratic productivity shocks is set to 0.146 while the probability of a free price change is set to 0.01.

4.4 Model Results

The model moments are listed in table 10. Both models match the frequency of price change as well as the dispersion of price changes. The fraction of price changes that are small is under predicted in both models, this is due to the large idiosyncratic shocks that are needed to match the dispersion of price changes. The average size of price changes is slightly too high, but it allows the models to match the standard deviation of price changes. The low

[27] A small price changes is defined as $|dp_{i,t}| < 0.01$.

[28] 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%.

Price Setting Statistic	Data	MC	Random MC
Frequency	0.154	0.153	0.153
Average Size of Price Change	0.071	0.096	0.091
Fraction Small Price Changes	0.215	0.143	0.152
Standard Deviation Price Changes	0.125	0.125	0.125
Skewness Price Changes	0.095	-0.205	0.097
Fraction Price Increases	0.602	0.651	0.660

Table 10: Model Moments

probability of receiving a productivity shock helps the models increase the dispersion of price changes relative to a Golosov and Lucas menu cost model. Due to the large oil price shocks in the model, if the probability of a productivity shock is set too low then all price changes will be dominated by changes in the oil price. In the random menu cost model the average size of price changes is closer to the data, due to more small price changes. Both models have a fraction of price increases that is close to the data. The random menu cost model also matches the skewness of the distribution with the additional menu cost parameter.

In order to test the predictions from the model against the empirical results, I compute the price response on impact of an oil price volatility shock. This is a one period impulse response to an increase in oil price volatility. For the fixed menu cost model calibration, a one standard deviation increase in oil price volatility decreases price change dispersion by 6.7%. The volatility effect dominates the real options effect, increasing the frequency of price adjustment. 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 shock pushes more price changes in one direction, decreasing price change dispersion. The strong selection effect is illustrated in an example in figure 8[29]. 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.

The selection effect of price changes becomes more apparent during a comparative static exercise. Table 11 shows the response of price change dispersion on impact to an oil price volatility shock. The oil share of production changes while holding all other parameters fixed from the original calibration. As the oil share of production increases, the drop in price change dispersion becomes larger. This is due to both an extensive and intensive change in item level inflation. Oil price changes become more important for firms, making firms more likely to change prices as well as by a larger amount. All price changes move

[29]The price change distribution is generated using the fixed menu cost model with a lower value of α in order to illustrate the selection effect mechanism.

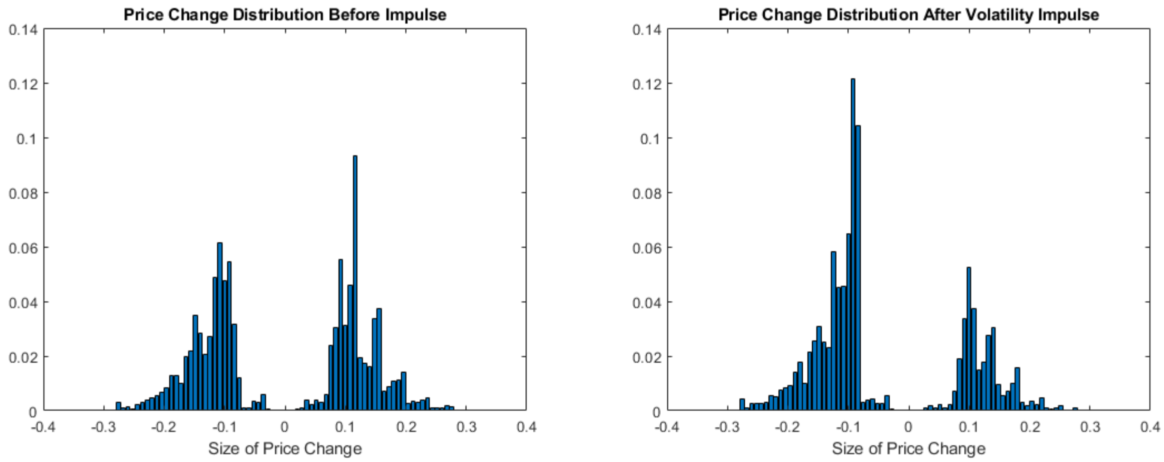


FIGURE 8: Oil Price Volatility Shock: Fixed Menu Cost Model Price Change Distribution

s_o	Δ Price Dispersion	Δ Frequency
0.010	-3.84%	10.34%
0.016	-6.66%	19.40%
0.025	-9.54%	36.76%
0.050	-9.65%	85.63%

TABLE 11: Menu Cost Comparative Static Exercise

in the direction of the oil price change, increasing the synchronization of price changes and decreasing inflation dispersion.

The random menu cost model is able to reduce the selection effect of price changes, and match the empirical relationship between price change dispersion and oil price volatility. In this model, the menu costs are drawn independently across firms and over time. This mechanism implies that prices are now a function of the random menu cost draw as well as the state of the economy. Random menu costs attenuate the price change reaction to a common shock and change the mix of price changes.

The evolution of the price change distribution due to an oil price volatility shock is illustrated in figure 9[30]. Due to the random menu costs that firms draw, the selection of prices that will change depends less on the common shock than in the fixed menu cost model, but also on the random menu cost that is drawn by each firm. During an increase in oil price volatility, the firms are buffeted by larger realized oil price shocks. This pushes some price changes that are primarily responding to the oil price to be more extreme. But

[30]The price change distribution is constructed using the random menu cost model with a lower value of ξ in order to cleanly illustrate the mechanism generating increased dispersion.

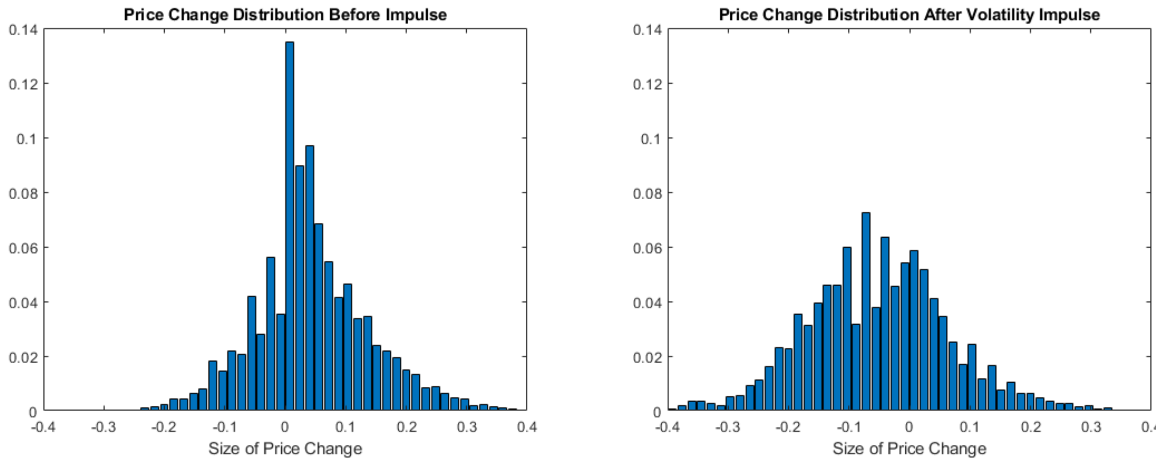


Figure 9: Oil Price Volatility Shock: Random Menu Cost Price Change Distribution

some price changes will occur simply due to a low menu cost draw, and will be relatively small in reaction to idiosyncratic shocks. The overall effect is to create a more disperse price change distribution during periods of high oil price volatility, with a fraction of price changes responding to the oil price volatility shock but substantial mass remaining in the middle of the price change distribution. This implies that the random menu cost model matches the empirical relationship between price change dispersion and oil price volatility[31].

A comparative static exercise is performed in table 12 for the random menu cost model. Only the share of oil is varied from the original random menu cost calibration. The table reports the increase in price change dispersion on impact of an oil price volatility shock as the oil share of production increases. For low levels of oil usage, an oil price volatility shock gives small increases in price change dispersion. At the oil share of production of 1.6%, an oil price volatility shock increases price change dispersion by 0.83%. As oil share of production increases to 2.5%, a one standard deviation increase in oil price volatility increases price change dispersion by 1.36%. This comparative static exercise shows that the random menu cost model can replicate the empirical finding that industries that use more oil have greater price change dispersion during a period of high oil price volatility.

The model results show that a standard state dependent pricing model with a fixed menu cost implies decreased price change dispersion on impact of an aggregate volatility shock. Larger shocks cause prices to respond in the same direction, decreasing the dispersion of the price change distribution. Introducing random menu costs enables the model to match the effects of aggregate volatility on price setting behavior, by attenuating the reaction to a

[31] Further evidence in favor of random menu costs is that it dampens the response of frequency to oil price volatility. I found no evidence that price change frequency responds positively to oil price volatility shocks.

s_o	Δ Price Dispersion	Δ Frequency
0.010	0.57%	2.32%
0.016	0.83%	3.46%
0.025	1.36%	5.21%
0.050	7.18%	10.18%

Table 12: Random Menu Cost Model Comparative Static Exercise

common cost shock and changing the mix of prices that adjust.

5 Implications for Monetary Policy Effectiveness

The modeling section has shown that a random menu cost model is able to match the empirical relationship between oil price volatility and price change dispersion. I will now study how changes in oil price volatility affect the ability of monetary policy to stimulate output.

I shock the model with a permanent increase of 0.002 to log nominal output in order to assess if the tradeoff between output and inflation is a function of the aggregate volatility in the economy. This size shock amounts to a one month doubling of the nominal output growth rate. The response of consumption and inflation on impact examined for periods of high and steady state oil price volatility[32]. In the random menu cost model, which is able to generate the increase in price change dispersion due to an increase in oil price volatility, 52.7% of the doubling of log nominal output translates into an increase in output. The other 47.3% of the increase goes into inflation. When the model is shocked with a one standard deviation increase in oil price volatility and a 0.002 permanent increase in log nominal output, 52.6% of the increase in nominal output goes into output while 47.4% goes into the increase in price level. These results show that there is not an increasing tradeoff between output stabilization and inflation during periods of high oil price volatility.

I conduct the same numerical exercise in the counterfactual fixed menu cost model. In this model, only 48.1% of the increase in log nominal output goes into consumption on impact in the ergodic state of the economy while 51.9% goes into inflation. During a period of increased oil price volatility, the percentage of the log nominal output that goes into consumption drops to 44.4% and 55.6% goes into inflation.

These results show that increases in the volatility of an aggregate cost shock do not substantially increase the trade off between output stabilization and inflation. During periods

[32]High oil price volatility is defined as a period with a one standard deviation positive shock to oil price volatility.

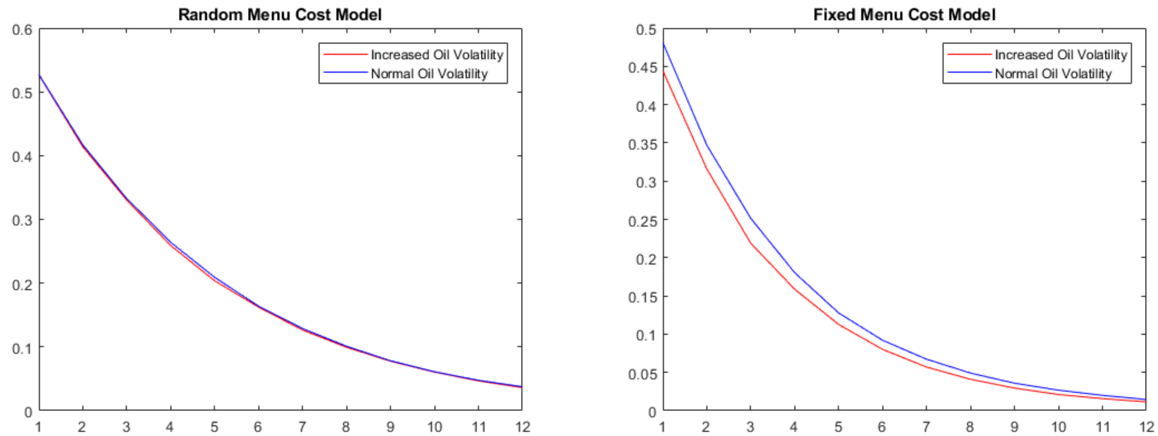


FIGURE 10: Real Output Response to Nominal Shock

NOTE: The output impulse response is represented as a percent of the nominal shock. Both models have a 0.002 shock to log nominal output.

of high oil price volatility, there is a decrease of 0.1% in the efficacy of nominal stimulus to increase consumption. Contrasting with this result are the implications of the fixed menu cost model, where 7.6% less of the increase in nominal output goes into consumption. The large decrease in monetary policy effectiveness is primarily due to the increase in the extensive margin of price adjustment. All prices that adjust move to their optimal price, but more prices are adjusting due to the larger oil price shocks. The increased price adjustment causes more of the nominal output change to be incorporated into the aggregate price level.

Figure 10 traces out the full impact of the monetary shock during a period of high oil price volatility and steady state volatility. The decrease in monetary policy effectiveness due to the oil price volatility shock grows larger over time in the counterfactual fixed menu cost model. The share of the monetary shock entering consumption is reduced by over 11% during the course of a year in the fixed menu cost model, while it is reduced by only 1% in the random menu cost model.

Price change dispersion is a key moment of the price change distribution for measuring monetary non-neutrality. Midrigan (2011) shows that increased price change dispersion increases monetary policy effectiveness. In testing how monetary policy effectiveness responds to changes in volatility, price change dispersion is therefore a key moment to examine. Matching the relationship between oil price volatility and price change dispersion in a state dependent model implies that monetary policy effectiveness is nearly time invariant in response to changes in volatility.

6 Discussion

Another strand of the price setting literature asks how informational rigidities affect price setting behavior. A noisy information processing model, such as that used by Drenik and Perez (2016), would suggest that as the volatility of the common oil price shock increases, firms would put more weight on their idiosyncratic shocks. This mechanism would increase price change dispersion during periods of high oil price volatility by decreasing the importance of the common cost shock. However, oil prices are easily and accurately observable suggesting this is not an important channel for the impact of oil price volatility on price setting behavior.

Rational inattention type models would in general generate the counterfactual results for price change dispersion like the fixed menu cost model. If volatility of an aggregate variable increases, firms optimally allocate more attention to the aggregate shock. This makes the shock more important, and causes firms to put more weight more on the common shock. This is argued in a general context by Menkulasi (2009) and a price setting context by Zhang (2016). In a context without changes in volatility, Mackowiak and Wiederhold (2009) argue that price setters pay more attention to sectoral shocks than aggregate shocks because they are more volatile on average.

7 Conclusion

This paper argues that changes in aggregate volatility do not substantially reduce monetary policy effectiveness. I do this by showing that the average industry price change dispersion is greater during periods of high oil price volatility. Then by exploiting the heterogeneity across industries in oil usage, I show that the increase in price change dispersion is larger for sectors with more oil usage. In order to match this key empirical relationship, I introduce random and heterogeneous menu costs. This mechanism attenuates the price reaction to a common volatility shock and increases price change dispersion during periods of high volatility.

My analysis of the effects of common volatility shocks on price setting behavior can be applied beyond oil price volatility. Policy uncertainty, such as changes in the volatility of fiscal or taxation plans, is another source of time varying volatility to a common shock that can affect prices. Exchange rate volatility and global demand volatility are other examples of common volatility shocks that affect price setting behavior. Does increased monetary policy volatility cause price changes to be more disperse and alter the monetary authority's ability to be effective? In particular, did the effects of nominal stimulus change during 1979 to 1982? During this period the FOMC targeted the quantity of money rather than a federal funds rate, which increased the observed volatility of the federal funds rate.

The tradeoff between output stabilization and inflation is nearly time invariant in response to changes in aggregate volatility, suggesting that policy makers need to take into account the source of volatility. If policy makers increase nominal stimulus more strongly because they believe effectiveness is dampened during periods of increased aggregate volatility, it would be an overreaction and induce unnecessary inflation.

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A Model Appendix

A.1 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.

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big) y_t(z) - \frac{W_t}{P_t} L_t(z) - \frac{P_t^o}{P_t} O_t(z) - \chi_t(z) \frac{W_t}{P_t} I_t(z) \tag{30}$$

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

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big) y_t(z) - \frac{W_t + s_o P_t^o}{P_t} L_t(z) - \chi_t(z) \frac{W_t}{P_t} I_t(z) \tag{31}$$

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 $L_t(z)$.

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big) y_t(z) - \Big(\frac{W_t + s_o P_t^o}{P_t}\Big) \frac{y_t(z)}{A_t(z)} - \chi_t(z) \frac{W_t}{P_t} I_t(z) \tag{32}$$

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

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big)^{1-\theta} Y_t - \frac{1}{A_t(z)} Y_t \Big(\frac{p_t(z)}{P_t}\Big)^{-\theta} \Big(\omega C_t + s_o \frac{P_t^o}{P_t}\Big) - \chi_t(z)(\omega C_t) I_t(z) \tag{33}$$

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

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big)^{1-\theta} C_t - \frac{1}{A_t(z)} C_t \Big(\frac{p_t(z)}{P_t}\Big)^{-\theta} \Big(\omega C_t + s_o \frac{P_t^o}{P_t}\Big) - \chi_t(z)(\omega C_t) I_t(z) \tag{34}$$

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

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t} - \frac{1}{A_t(z)} \frac{W_t + s_o P_t^o}{P_t}\Big) \Big(\frac{p_t(z)}{P_t}\Big)^{-\theta} C_t - \chi_t(z)(\omega C_t) I_t(z) \tag{35}$$

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

$$\frac{P_t}{S_t} = e^{\gamma_0 + \gamma_1 log P_t^o + \gamma_2 \sigma_t + \gamma_3 log(\frac{P_{t-1}}{S_t}) + \gamma_4 (log(\frac{P_{t-1}}{S_t}) * log P_t^o) + \gamma_5 (log(\frac{P_{t-1}}{S_t}) * \sigma_t)} \tag{36}$$

and I can write C_t as

$$C_t = e^{-\big(\gamma_0 + \gamma_1 log P_t^o + \gamma_2 \sigma_t + \gamma_3 log(\frac{P_{t-1}}{S_t}) + \gamma_4 (log(\frac{P_{t-1}}{S_t}) * log P_t^o) + \gamma_5 (log(\frac{P_{t-1}}{S_t}) * \sigma_t)\big)} \tag{37}$$

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

$$\pi_t^R(z) = \Big(\frac{\frac{p_t(z)}{S_t}}{\frac{P_t}{S_t}} - \frac{1}{A_t(z)}\frac{W_t + s_o P_t^o}{P_t}\Big)\Big(\frac{\frac{p_t(z)}{S_t}}{\frac{P_t}{S_t}}\Big)^{-\theta}\frac{S_t}{P_t} - \chi_t(z)(\omega\frac{S_t}{P_t})I_t(z) \tag{38}$$

then use (15) to replace the real wage in terms of consumption.

$$\pi_t^R(z) = \Big(\frac{\frac{p_t(z)}{S_t}}{\frac{P_t}{S_t}} - \frac{1}{A_t(z)}(\omega C_t + s_o P_t^o)\Big)\Big(\frac{\frac{p_t(z)}{S_t}}{\frac{P_t}{S_t}}\Big)^{-\theta}\frac{S_t}{P_t} - \chi_t(z)(\omega\frac{S_t}{P_t})I_t(z) \tag{39}$$

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

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{S_t}e^{-(\Theta)} - \frac{1}{A_t(z)}(\omega e^{-(\Theta)} + s_o P_t^o)\Big)\Big(\frac{p_t(z)}{S_t}e^{-(\Theta)}\Big)^{-\theta}(e^{-(\Theta)}) - \chi_t(z)(\omega e^{-(\Theta)})I_t(z) \tag{40}$$

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

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{S_t}e^{-(\Theta)} - \frac{1}{A_t(z)}(\omega e^{-(\Theta)} + s_o P_t^o\Big)\Big(\frac{p_t(z)}{S_t}\Big)^{-\theta}(e^{(\Theta)})^{\theta-1} - \chi_t(z)(\omega e^{-(\Theta)})I_t(z) \tag{41}$$

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

$$D_{t,t+1}^R = \beta\frac{C_t}{C_{t+1}} = \beta\frac{e^{-\big(\gamma_0+\gamma_1 logP_t^o+\gamma_2\sigma_t+\gamma_3 log(\frac{P_{t-1}}{S_t})+\gamma_4(log(\frac{P_{t-1}}{S_t})*logP_t^o)+\gamma_5(log(\frac{P_{t-1}}{S_t})*\sigma_t)\big)}}{e^{-\big(\gamma_0+\gamma_1 logP_{t+1}^o+\gamma_2\sigma_{t+1}+\gamma_3 log(\frac{P_t}{S_{t+1}})+\gamma_4(log(\frac{P_t}{S_{t+1}})*logP_{t+1}^o)+\gamma_5(log(\frac{P_t}{S_{t+1}})*\sigma_{t+1})\big)}} \tag{42}$$

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

A.2 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.

B Data Appendix

B.1 Stochastic Volatility Model

The stochastic volatility model is given by

$$logP^o_t = \rho_p logP^o_{t-1} + e^{\sigma_t}\nu_t \tag{43}$$

$$\sigma_t = (1-\rho_\sigma)\overline{\sigma} + \rho_\sigma \sigma_{t-1} + \phi\nu_{\sigma,t} \tag{44}$$

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 et al. (1996). In order to obtain the volatility series of the data, the backwards-smoothing routine of Godsill et al. (2004) is used.

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

$(e^{\phi}$-1) $\times$ 100%= 15%. [33]

The prior and posterior distributions are in table 2.

B.1.1 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:

$$p(P_o^T;\Theta) = \prod_{t=1}^{T} p(P_o^t|P_o^{t-1};\Theta)$$
$$= \int \frac{1}{e^{\sigma_0}\sqrt{2\pi}} exp\Bigg[-\frac{1}{2}(\frac{P_o^1-\rho_p P_o^0}{e^{\sigma_0}})^2\Bigg] d\sigma_0$$
$$\times \prod_{t=2}^{T} \frac{1}{e^{\sigma_t}\sqrt{2\pi}} exp\Bigg[-\frac{1}{2}(\frac{P_o^t-\rho_p P_o^{t-1}}{e^{\sigma_0}})^2\Bigg] p(\sigma^t|P_o^{t-1};\Theta)d\sigma_t \tag{45}$$

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:

$$p(\sigma_t|P_o^t;\Theta) \cong \sum_{i=0}^{N} \omega_t^i \delta_{\sigma_t^i}(\sigma_t) \tag{46}$$

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 (44) 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 (44) 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 $\omega_t^i = p(\sigma_t|P_o^{t-1},\sigma_{t-1};\Theta) = \frac{1}{e^{\sigma_t}\sqrt{2\pi}} exp\Bigg[-\frac{1}{2}(\frac{P_o^1-\rho_p P_o^0}{e^{\sigma_t}})^2\Bigg]$. The weights are then normalized to

$$\tilde{\omega}_t^i = \frac{\omega_t^i}{\sum_{i=1}^{N}\omega_t^i} \tag{47}$$

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

[33] 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 $e^{-2.607+0.14} = 0.085$.

$$p(P_o^T;\Theta) \cong \frac{1}{N}\sum_{i=1}^{N}\frac{1}{e^{\sigma_0^i}\sqrt{2\pi}}exp\Big[-\frac{1}{2}(\frac{P_o^1-\rho_p P_o^0}{e^{\sigma_0^i}})^2\Big]$$
$$\times\prod_{t=2}^{T}\frac{1}{N}\sum_{i=1}^{N}\frac{1}{e^{\sigma_{t|t-1}^i}\sqrt{2\pi}}exp\Big[-\frac{1}{2}(\frac{P_o^t-\rho_p P_o^{t-1}}{e^{\sigma_{t|t-1}^i}})^2\Big] \tag{48}$$

B.1.2 Particle Smoother

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

$$p(\sigma^T|P_o^t;\Theta) = p(\sigma_T|P_o^t;\Theta)\prod_{t=1}^{T-1}p(\sigma_t|\sigma_{t+1:T},P_o^T;\Theta) \tag{49}$$

The second factor is then simplified to

$$\begin{aligned} p(\sigma_t|\sigma_{t+1:T},P_o^T;\Theta) &= p(\sigma_t|\sigma_{t+1},P_o^t;\Theta) \\ &= \frac{p(\sigma_t|P_o^t;\Theta)f(\sigma_{t+1}|\sigma_t)}{p(\sigma_{t+1}|P_o^t)} \\ &\propto p(\sigma_t|P_o^t;\Theta)f(\sigma_{t+1}|\sigma_t) \end{aligned} \tag{50}$$

The first equality comes from the Markovian properties of the model, f is the state transition density from 44. Equation 46 allows us to construct $p(\sigma_t|P_o^t;\Theta)$ by forward filtering, therefore I can approximate the above equation RHS by

$$p(\sigma_t|\sigma_{t+1},P_o^t;\Theta) \cong \sum_{i=0}^{N}\omega_{t|t+1}^i\delta_{\sigma_t^i}(\sigma_t) \tag{51}$$

The weights are given by

$$\omega_{t|t+1}^i = \frac{\omega_t^i f(\sigma_{t+1}|\sigma_t^i)}{\sum_{i=1}^N\omega_t^i f(\sigma_{t+1}|\sigma_t^i)} \tag{52}$$

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 52.

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.

B.1.3 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 et al. (1996).

2) The Metropolis-Hasting step. Compute the acceptance ratio $\psi = min\big(\frac{p(\Theta_{j+1}^{prop}|p^T}{p(\Theta_j^{prop}|p^T}, 1\big)$. A random number m is drawn from a uniform distribution over the unit interval. Then $\Theta_{j+1} = \Theta_{j+1}^{prop}$ if m ¡ ψ 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.

B.2 GARCH Model

The estimated GARCH Model is

$$logP_t^o = \rho_p logP_{t-1}^o + \epsilon_t \tag{53}$$

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

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{54}$$

The estimated GARCH parameters are $\rho_p = 0.997$ (0.003), $\omega = 0.001$ (0.001), $\alpha = 0.199$ (0.050), β= 0.615 (0.102).

B.3 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.

B.4 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.

B.5 Oil Prices

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 1986-2015 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. During the stochastic volatility model and GARCH model estimation, data from 1986 to 2014 is used.

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. This data is available monthly.

All three data series are available from the U.S. Energy Information Administration.

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) argue 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) argue that when it became clear the financial system would not collapse in 2009, oil prices stabilized at \$100 per barrel. Kilian and Lee (2014) argue 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, as well as an increase in the supply of oil likely due to US shale production.

B.6 Industry Specific Oil Pass Through

I run an industry specific oil pass with industry and time fixed effects to control for the macroeconomic cycle. Specifically I run a pass through regression of the form:

$$\pi_{j,t} = \alpha_j + \alpha_t + \sum_{i=0}^{12} b_i \big(s_{o,j} * \Delta log P^o_{t-i}\big) + \epsilon_{j,t} \tag{55}$$

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 13.

Short Run Pass Through	Long Run Pass Through
0.135***	1.649***
(0.003)	(0.017)

Table 13: Pass Through Regression

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Number of observation=7,984. Number of industries=51. $R^2 = 0.15$. Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

These results show that after conditioning on common aggregate shocks, that industries

Table 14: NAICS 4 Industry Oil Share

Rank	Industry	Name	θ
1	3251	Basic Chemical Manufacturing	0.243
2	3252	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	0.143
3	3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	0.124
4	3259	Other Chemical Product and Preparation Manufacturing	0.108
5	3255	Paint, Coating, and Adhesive Manufacturing	0.093
6	3333	Commercial and Service Industry Machinery Manufacturing	0.043
7	3274	Lime and Gypsum Product Manufacturing	0.041
8	3221	Pulp, Paper, and Paperboard Mills	0.035
9	3212	Veneer, Plywood, and Engineered Wood Product Manufacturing	0.034
10	3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing	0.033
	Average		0.016

with greater oil usage have greater pass through of oil prices.

B.7 Input Output Tables

Detailed Input Output "Use" tables from the Bureau of Economic are constructed every 5 years. I use them 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 dollar share of oil to value added is listed in table 14 along with the four digit industries with the largest oil share.

B.8 Regression Robustness Checks

As an additional robustness check I use the interquartile range of price changes rather than the standard deviation. The results for the industry invariant regression are shown in table 15. The regressions for the three different measures of oil price volatility show that oil price volatility is positive and statistically significantly related to price change dispersion.

Panel A of Table 16 shows the main industry specific oil price volatility results using the interquartile range of non-zero price changes as the dependent variable. Panel B of Table 16 shows the results using the standard deviation of price changes, including non-zero price changes. The table shows that oil price volatility still has a positive correspondence with robust measures of price change dispersion.

The main industry results with GARCH oil price volatility is listed in Panel A of 17. Realized oil price volatility results are listed in Panel B of 17.

Table 18 shows the main results are robust to using the time averaged oil usage, as in Nekarda and Ramey (2011).

Dependent Variable: IQR of Price Change

	Stochastic Vol	Realized Vol	GARCH Vol
$\Delta log(P^o_{t-1})$	0.012	0.010	0.000
	(0.007)	(0.007)	(0.007)
σ_{t-1}	0.397***	0.092***	0.239***
	(0.054)	(0.023)	(0.037)
$\pi_{j,t-1}$	-0.099	0.038	0.053
	(0.083)	(0.111)	(0.112)
$\Delta IP_{j,t}$	-0.007	-0.010	-0.010
	(0.012)	(0.011)	(0.010)
EBP_t	-0.001	0.003**	0.002
	(0.002)	(0.002)	(0.001)
VIX_{t-1}	0.000	0.000	0.0002*
	(0.000)	(0.000)	(0.0001)
Industry FE	Yes	Yes	Yes
Number of Industries	63	63	63
N	10,946	10,946	10,946

Table 15: Producer Price Change Dispersion and Macroeconomic Shocks

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Robust asymptotic standard errors reported in parentheses are double clustered at the industry-month level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Robustness results with 2008 dummy and additional covariates in Table 19. These results use the stochastic volatility measure of oil prices, and show that adding additional covariates to the regression do not affect the impact that oil price volatility has on price change dispersion inside or outside of the 2008 crisis period.

Table 20 includes controls for lags of all variables and reports the sum. The reported total effect is similar to the regression with one lagged observation for oil price volatility.

I estimate the same regression for price change frequency as I have for price change dispersion at the industry level. That is,

$$Y_{j,t} = \eta * (so, j * \Delta log(P^o_{t-1})) + \lambda * (so, j * \sigma_{t-1}) + \gamma' X_{j,t} + \alpha_j + \alpha_t + \epsilon_{jt} \qquad (56)$$

where $Y_{j,t}$ is industry level price change frequency. The results are in table 21. I find no evidence that oil price volatility affects price change frequency.

Using a higher level of aggregation does not impact the baseline results. Table 22 shows the baseline results for a NAICS 3 level of industry aggregation for different volatility measures. They show that all three measures of oil price volatility increase industry price change dispersion even when there is greater heterogeneity within an industry due to aggregation.

B.9 Price Data Comparison

Figure 11 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

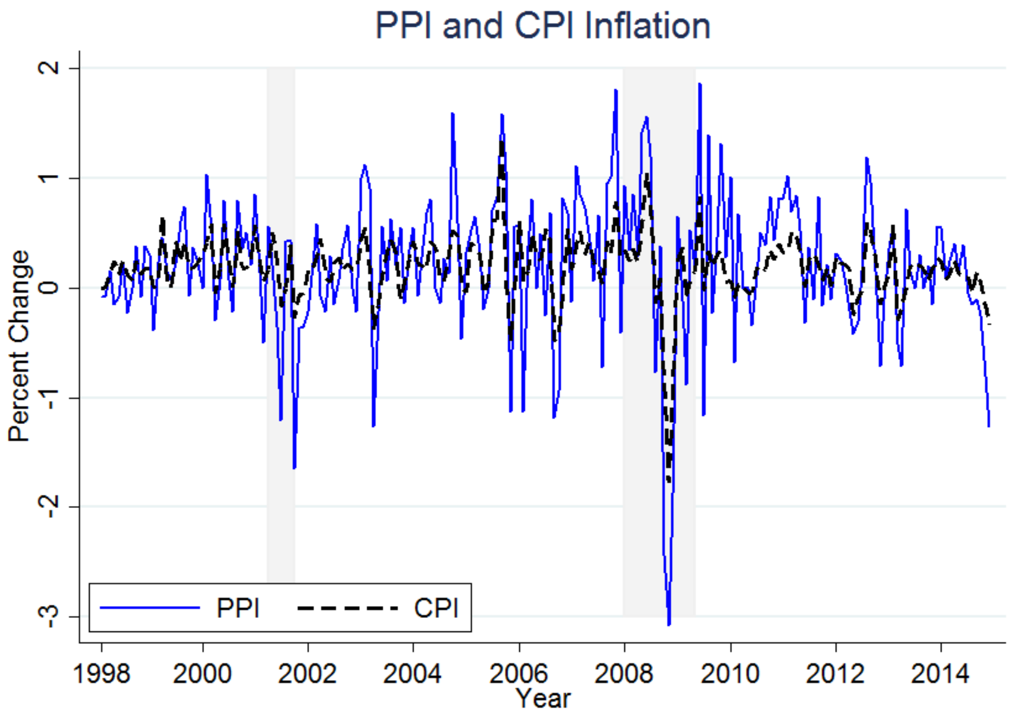

Figure 11: Monthly PPI Inflation and CPI Inflation
Note: Consumer Price index for all Urban Consumers and Producer Price Index by Commodity for Finished Goods. Both indices are seasonally adjusted.

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. The low fraction of small price changes removes mass from the middle of the price change distribution, which increases the kurtosis of the distribution.

B.10 Central Bank Quote

The full text of Janet Yellen's quote from the "Current Conditions and the Outlook for the Economy" on June 6, 2016 is below.

> In particular, an important theme of my remarks today will be the inevitable uncertainty surrounding the outlook for the economy. Unfortunately, all economic projections are certain to turn out to be inaccurate in some respects, and possibly significantly so. Will the economic situation in Europe or China take a turn for the worse or exceed expectations? Will U.S. productivity growth pick up and allow stronger growth of gross domestic product (GDP) and incomes or instead continue to stagnate? What will happen with the price of oil? The uncertainties are sizable, and progress toward our goals and, by implication, the appropriate stance of monetary policy will depend on how these uncertainties evolve. Indeed, the policy path that my colleagues and I judge most likely to achieve and

maintain maximum employment and price stability has evolved and will continue to evolve in response to developments that alter our economic outlook and the associated risks to that outlook.

Panel A
Dependent Variable: IQR of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	-0.158**	-0.159**	-0.135**	-0.122**
	(0.064)	(0.064)	(0.054)	(0.053)
$s_{o,j} * \sigma_{t-1}$	2.014***	2.018***	1.909***	1.809***
	(0.706)	(0.709)	(0.630)	(0.615)
$\pi_{j,t}$		0.018	0.002	0.006
		(0.110)	(0.092)	(0.090)
$\Delta IP_{j,t}$			0.003	0.002
			(0.008)	(0.008)
$\text{PriceDisp}_{j,t-1}$				0.040***
				(0.008)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

Panel B
Dependent Variable: Standard Dev of Price Change with Zeros

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.049	0.034	0.020	0.027
	(0.049)	(0.046)	(0.038)	(0.039)
$s_{o,j} * \sigma_{t-1}$	1.956***	2.003***	1.823***	1.778***
	(0.469)	(0.503)	(0.379)	(0.370)
$\pi_{j,t}$		0.189**	0.183**	0.183**
		(0.071)	(0.072)	(0.071)
$\Delta IP_{j,t}$			0.005	0.004
			(0.007)	(0.007)
$\text{PriceDisp}_{j,t-1}$				0.019***
				(0.005)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

Table 16: Industry Specific Coefficient: Robust Price Change Dispersion Measures

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Panel A shows main regression specifications with the interquartile range of price changes as the dependent variable. Panel B shows the main regression specifications with the standard deviation of price changes including zeros as the dependent variable. Robust asymptotic standard errors reported in parentheses are double clustered at the industry-month level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Panel A
Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.071	0.065	0.026	0.054
	(0.133)	(0.131)	(0.109)	(0.111)
$s_{o,j} * \sigma_{t-1}$	2.842***	2.877***	2.797***	2.590***
	(0.701)	(0.716)	(0.610)	(0.573)
$\pi_{j,t}$		0.075	0.072	0.075
		(0.116)	(0.115)	(0.112)
$\Delta IP_{j,t}$			0.002	-0.002
			(0.014)	(0.015)
$\text{PriceDisp}_{j,t-1}$				0.067***
				(0.016)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

Panel B
Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.234	0.229	0.014	0.164
	(0.194)	(0.192)	(0.129)	(0.131)
$s_{o,j} * \sigma_{t-1}$	1.700**	1.714**	1.299***	1.234***
	(0.700)	(0.708)	(0.415)	(0.399)
$\pi_{j,t}$		0.072	0.069	0.071
		(0.118)	(0.117)	(0.114)
$\Delta IP_{j,t}$			0.003	-0.001
			(0.015)	(0.015)
$\text{PriceDisp}_{j,t-1}$				0.068***
				(0.016)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

Table 17: Industry Specific Coefficient: Alternative Oil Volatility Measures

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Panel A shows main regression specifications with GARCH oil price volatility and the standard deviation of non-zero price changes as the dependent variable. Panel B shows main regression specifications with realized oil price volatility and the standard deviation of non-zero price changes as the dependent variable. Robust asymptotic standard errors reported in parentheses are double clustered at the industry-month level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.086	0.078	-0.002	0.022
	(0.096)	(0.097)	(0.086)	(0.082)
$s_{o,j} * \sigma_{t-1}$	3.033***	3.059***	3.088***	2.928***
	(0.839)	(0.851)	(0.946)	(0.891)
$\pi_{j,t}$		0.081	0.085	0.086
		(0.116)	(0.112)	(0.110)
$\Delta IP_{j,t}$			0.001	-0.002
			(0.014)	(0.015)
$\text{PriceDisp}_{j,t-1}$				0.066***
				(0.016)
$\overline{s_o} * \sigma_{t-1}$	0.048***	0.048***	0.048***	0.046***
	(0.013)	(0.013)	(0.015)	(0.014)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

TABLE 18: Time Invariant Theta- Industry Specific Oil Demand Variables Regression

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. 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. $\text{PriceDisp}_{j,t-1}$ is the lagged industry price change dispersion. $\overline{s_o} * \sigma_{t-1}$ is the transformed coefficient for a marginal change in oil price volatility for an average industry with oil share of 0.016. Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1}) * [Crisis = 0]$	0.263**	0.258**	0.228**	0.250**
	(0.128)	(0.126)	(0.110)	(0.112)
$s_{o,j} * \Delta log(P^o_{t-1}) * [Crisis = 1]$	0.029	0.005	-0.275	-0.258
	(0.403)	(0.391)	(0.242)	(0.226)
$s_{o,j} * \sigma_{t-1} * [Crisis = 0]$	2.709***	2.737***	2.502***	2.338***
	(0.825)	(0.837)	(0.679)	(0.638)
$s_{o,j} * \sigma_{t-1} * [Crisis = 1]$	3.352***	3.342***	2.873***	2.705***
	(0.834)	(0.831)	(0.596)	(0.557)
$\pi_{j,t}$		0.071	0.069	0.071
		(0.117)	(0.117)	(0.114)
$\Delta IP_{j,t}$			0.003	-0.000
			(0.015)	(0.015)
$\text{PriceDisp}_{j,t-1}$				0.067***
				(0.016)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

TABLE 19: 2008 Crisis Year Regression

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. σ_t is the stochastic volatility measure of oil price volatility. Crisis year indicator is defined as 1 during 2008 and 0 otherwise. This is the same crisis definition timing as Gilchrist et al. (2015). Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Dependent Variable: Standard Deviation of Price Change

	SV		RV		GARCH	
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=0}^{3} \theta_j \Delta log(P^o_{t-i})$	-0.305		-0.283		-0.289	
	(0.197)		(0.221)		(0.191)	
$\sum_{i=0}^{3} \theta_j \sigma_{t-i}$	2.488***		1.752**		3.063***	
	(0.619)		(0.725)		(0.670)	
$\sum_{i=0}^{3} \pi_{j,t-i}$	0.018		0.012		0.022	
	(0.136)		(0.137)		(0.135)	
$\sum_{i=0}^{3} \Delta IP_{j,t-i}$	-0.007		-0.007		-0.009	
	(0.055)		(0.055)		(0.055)	
$\sum_{i=1}^{3} \theta_j \Delta log(P^o_{t-i})$		-0.027		-0.172		-0.198
		(0.146)		(0.170)		(0.145)
$\sum_{i=1}^{3} \theta_j \sigma_{t-i}$		2.590***		1.336**		2.270***
		(0.579)		(0.641)		(0.619)
$\sum_{i=1}^{3} \pi_{j,t-i}$		0.019		0.015		0.024
		(0.136)		(0.136)		(0.134)
$\sum_{i=1}^{3} \Delta IP_{j,t-i}$		-0.008		-0.009		-0.010
		(0.055)		(0.055)		(0.055)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	48	48	48	48	48	48
N	10,835	10,835	10,835	10,835	10,835	10,835

Table 20: Industry Specific Coefficient: Lagged Volatility Structure

Note: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. The dependent variable is non-zero price change dispersion. All specifications use the stochastic volatility of oil prices. The reported coefficients are the sum of the listed lagged variables. Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

Panel A

Dependent Variable: Frequency of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	-0.281***	-0.346***	-0.301***	-0.304***
	(0.065)	(0.078)	(0.079)	(0.079)
$s_{o,j} * \sigma_{t-1}$	-1.446**	-1.234*	-1.307*	-1.267*
	(0.587)	(0.696)	(0.691)	(0.685)
$\pi_{j,t}$		0.851***	0.901***	0.896***
		(0.201)	(0.223)	(0.222)
$\Delta IP_{j,t}$			-0.046	-0.045
			(0.029)	(0.029)
$\text{Freq}_{j,t-1}$				-0.021*
				(0.011)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,941

Panel B

Dependent Variable: Frequency of Price Change - Time Invariant

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	-0.183**	-0.271***	-0.262***	-0.181**
	(0.087)	(0.085)	(0.093)	(0.076)
$s_{o,j} * \sigma_{t-1}$	0.470	0.739	0.897	0.537
	(1.451)	(1.610)	(1.845)	(0.906)
$\pi_{j,t}$		0.859***	0.913***	0.839***
		(0.203)	(0.227)	(0.190)
$\Delta IP_{j,t}$			-0.046	-0.052
			(0.029)	(0.035)
$\text{Freq}_{j,t-1}$				0.547***
				(0.040)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,941

TABLE 21: Industry Specific Coefficient: Frequency of Price Change

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Panel A shows the main specification with frequency of price change as the dependent variable and stochastic volatility of oil prices. Panel B shows the main specification with frequency of price change as the dependent variable while measuring the oil sensitivity using the time-invariant oil usage from the input output tables with the stochastic volatility of oil prices. Robust asymptotic standard errors reported in parentheses are double clustered at the industry-month level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

TABLE 22: Oil Volatility and Price Setting Behavior-NAICS 3

Dependent Variable: Standard Deviation of Price Change

	SV			RV			GARCH		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\theta_j \Delta log(P^o_{t-1})$	-0.122	-0.124	-0.123	-0.016	0.072	0.071	-0.261	-0.274	-0.270
	(0.213)	(0.267)	(0.268)	(0.236)	(0.287)	(0.287)	(0.199)	(0.254)	(0.255)
$\theta_j \sigma_{t-1}$	3.741***	3.696***	3.621***	2.462**	3.185***	3.130***	4.199***	3.632***	3.528***
	(1.222)	(1.238)	(1.223)	(0.857)	(0.639)	(0.620)	(0.872)	(1.007)	(0.982)
$\pi_{j,t-1}$		-0.211	-0.220		-0.214	-0.223		-0.203	-0.213
		(0.124)	(0.122)		(0.125)	(0.123)		(0.118)	(0.120)
$\Delta IP_{j,t}$			0.056			0.055			0.056
			(0.044)			(0.044)			(0.044)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Industries	20	20	20	20	20	20	20	20	20
N	3,994	3,176	3,176	3,994	3,176	3,176	3,994	3,176	3,176

NOTE: Sample period: 1998:M1 to 2014:M12 at a monthly frequency. Dependent variable is the standard deviation of non-zero price changes. Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.