Price Setting and Volatility: Evidence from Oil Price Volatility Shocks

Matthew Klepacz*
Boston University

Job Market Paper

October 31, 2016

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 which implies 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

*I would like to thank Simon Gilchrist, Adam Guren, Raphael Schoenle, and Stephen Terry for their valuable guidance and support on this project. I am also grateful to my BLS project coordinator Ryan Ogden for his assistance with the project.
Contact: mklepacz@bu.edu

1 Introduction

How do changes in aggregate volatility affect monetary policy's ability to stimulate the economy during recessions? Monetary policy effectiveness is dependent on the flexibility of the price level, which is given by the frequency of price change as well as the dispersion of price changes. When price changes are more disperse they are less likely to move in the same direction as a monetary policy shock, increasing monetary non-neutrality. 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.

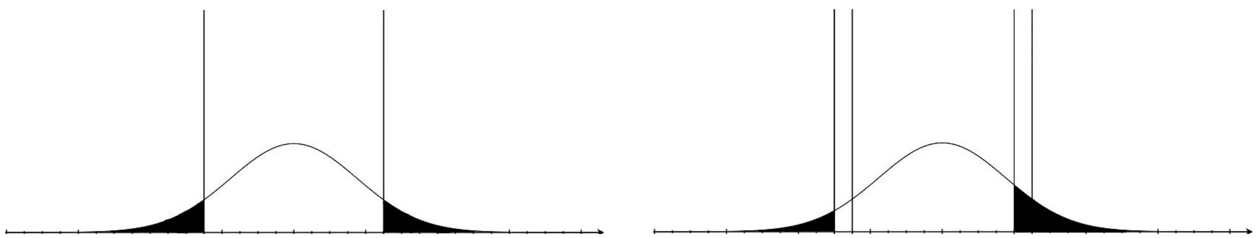
Monetary policy has the ability to stimulate output by changing the supply of money in a basic monetary framework. However, if prices are completely flexible, then monetary policy has no effect on output. Micro-price data shows that prices change approximately twice a year for both consumer and producer 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 as shown in Figures 1 and 2. These figures show a highly dispersed price change distribution and a distribution with lower dispersion. A small change in the supply of money causes more prices to change in response to the monetary shock in the less dispersed distribution, leading to increased inflationary effects and reduced real effects of monetary policy.

This paper uses well-measured and plausibly exogenous oil price volatility shocks to test the role of common cost volatility shocks on price setting behavior. Oil price shocks are advantageous in studying how prices react to changes in 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 Bartik (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 usage is likely to be characterized by large amounts of specific capital or irreversible investment, which make it difficult to substitute away from this input and ensure relevance.

The main results show that increased oil price volatility leads to increased price change dispersion. Increases in oil price volatility implies greater price change dispersion, which would increase the effectiveness of monetary policy holding other price setting behavior constant. Furthermore, I find that industries that are more exposed to oil as an input

((A)) No Shock ((B)) Positive Monetary Shock

Figure 1: Disperse Price Change Distribution



((A)) No Shock ((B)) Positive Monetary Shock

Figure 2: Synchronized Price Change Distribution

increase price change dispersion in response more than those with low oil usage. My main results imply that during the period of December 2007 to September 2008 when oil price volatility more than doubled, holding all else constant, the increase in oil price volatility can explain 44% of the average increase in price change dispersion. These results can be shown when measuring oil price volatility using stochastic volatility, GARCH volatility, or realized volatility.

The empirical results are then used to test between price setting models and quantify the strength of the selection effect. It is shown that the increase in price change dispersion on impact of an aggregate volatility shock is particularly surprising in the context of a modern menu cost model similar to Midrigan (2011) or Nakamura and Steinsson (2010). This type of model predicts decreased price change dispersion in response to an oil price volatility shock, and the dispersion falls more for sectors with greater oil usage. 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, decreasing frequency of price adjustment. The volatility effect increases the spread 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.

I then show that a random menu cost model with random menu costs is able to match the empirical findings. The baseline menu cost model is altered by introducing heterogeneous and random menu costs as in Luo and Villar (2015) or Dotsey et al. (1999). 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 decreases the synchronization of prices changes in response to a more volatile common shock.

Does the effectiveness of monetary policy, that is the tradeoff between output stabilization and inflation, change during periods of increased oil price volatility? This is a question that is on the mind of central banks, 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

The model is able to provide an answer to Chair Yellen's remarks about the effects of uncertainty on monetary policy. I show that the random menu cost model which matches this key empirical fact that relates changes in aggregate volatility to price change dispersion, predicts monetary policy effectiveness is reduced by less than 1% during a high volatility episode. In the baseline menu cost model which predicts counterfactual decreased price change dispersion during high volatility, monetary policy effectiveness is reduced by nearly 12% during a one standard deviation increase in oil price volatility. More prices are changing because of the large oil price shocks, which enables them to simultaneously incorporate the increase in money. This suggests 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 the strength of the selection effect, and its 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. (2014). Fernandez-Villaverde et al. (2014) 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.

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. This paper differs from both of these papers in both its' empirical and modeling framework by looking at the effects of a common aggregate 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 (2015) 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 (2014) 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 our understanding of the selection effect of price changes. 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 on non-neutrality between 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 (2014) also use oil shocks as a plausibly exogenous source of volatility on investment decisions. Studying the effects of oil shocks themselves, Blanchard and Gali (2008) 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 from the 1970's. Chen (2008) also studies oil price pass through into inflation across countries using a time varying pass through coefficient. She finds that long run pass through of 16 percent for the US over the period 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 uncertainty 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 microdata underlying the producer price index from the Bureau of Labor

Statistics[1]. The micro level data starts in 1998 and extends through 2014[2]. Each month around 100,000 prices are collected from about 25,000 reporters. Prices are collected for the 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. Price forming units 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 that are weighted proportional to the value of the category within the unit[3].

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[4]. 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[5].

The main focus of the empirical section of the paper is 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. Price change dispersion is calculated using only non-zero price changes[6]. The interquartile range is calculated for the same set of item level price

[1]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.

[2]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.

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

[4]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.

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

[6]Price change dispersion is typically constructed using only non-zero price changes such as in Vavra (2014),

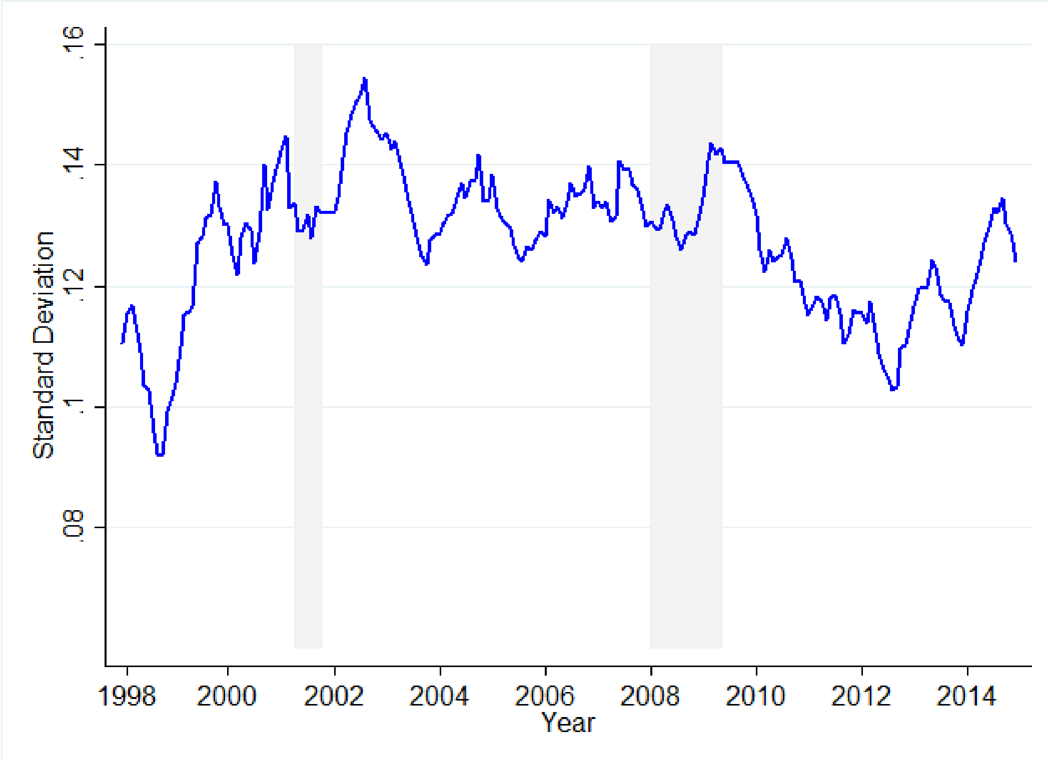


Figure 3: Monthly Standard Deviation of Price Changes

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

changes within an industry at time t.

Figure 3 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 a 0.15 during 2003. During the Great Recession the dispersion measure increased from 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[7].

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 CPI than the PPI, which decreases the kurtosis of the price change distribution in the CPI. [8]. The correlation between the monthly inflation measures of consumer prices and producer prices is 0.8 over the 1998 to

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.

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

[8]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.

Moment	Freq	Avg Size	Frac Up	Frac Small	SD	Kurt
CPI	0.11	0.08	0.65	0.33	0.08	6.4
PPI	0.15	0.07	0.60	0.07	0.13	15.0

Table 1: Consumer and Producer Price Index Moments

Note: CPI moments calculated for 1988-2012 from Vavra (2014). PPI moments calculated for 1998-2014 are author's calculation. Small price changes are defined as $|dp_{i,t}| < \frac{1}{2}|\overline{d_{i,t}}|$.

2014 time period[9]. Temporary sales are not common in the PPI, so sales filtering techniques are not applied.

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 daily, 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[10]. There is a spike in the price and volatility of oil during late 2002 and 2003 related due 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 mid 2008, and Hamilton (2009) and Kilian (2008b) attribute it 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.

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

[10] 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

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 a stochastic volatility model that estimates independent first and second moment shocks from the single process for oil prices. The process will also be consistent with the modeling section.

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

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

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

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) and Blanchard and Gali (2008) 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 and Rubio-Ramirez (2007). 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[11].

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

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

significant correlation with the other volatility series as well. The high correlation between the three measures of oil price volatility show 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 description of the results is in the appendix. The volatility process is noisier than the stochastic volatility process, but has a correlation of 0.74 over the time period. It 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 relies on within month variation in oil prices without any 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[12].

Figure 4 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.

[12]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.

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 measure of oil price volatility.

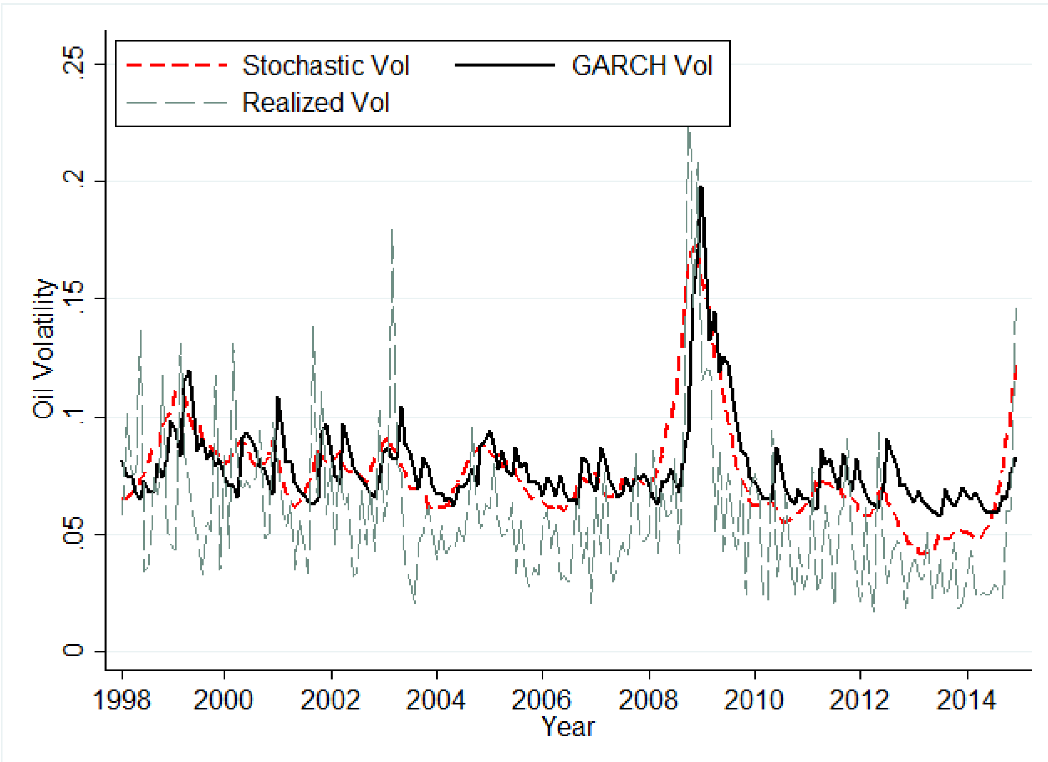


FIGURE 4: Oil Volatility

NOTE: The thick dotted red line shows the extracted stochastic volatility of oil prices, while the solid black line shows the GARCH volatility. 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 analyze 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:

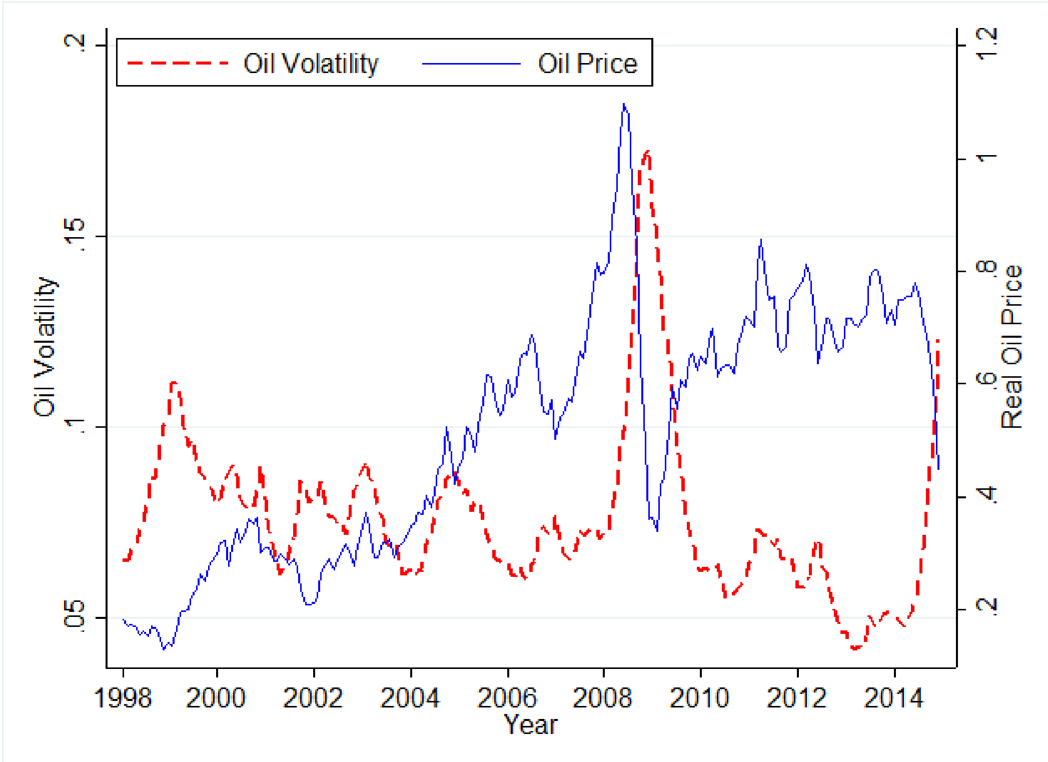


FIGURE 5: Stochastic Oil Volatility and Real Oil Price

NOTE: WTI nominal monthly oil price deflated by PPI finished goods index on right vertical axis and stochastic volatility 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 *** $p < .01$.

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

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[13]. The results are in table 4.

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

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

on producer prices during the same month[14]. 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 fairly large. It can be interpreted as 0.01% of a 1% change in oil prices is passed through to producer prices.

The long run coefficient is $\sum_{i=0}^{12} b_i$, and implies that 0.086% of a 1% change in oil prices is passed through over a year[15]. 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. 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. This is important because it implies that industries react 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 the heterogeneity in oil share, I now estimate the time series relationship between price change dispersion and oil price volatility. Oil price volatility measures changes in the volatility of a common cost 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 us 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 are in table 5 for the three measures of oil price volatility.

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 idiosyncratic volatility is controlled for with the VIX index. Industry fixed effects control for time invariant differences

[14] 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 $\sum_{i=0}^{12} b_i = 0.076^{***}$.

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

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 *** $p < .01$.

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 and volatility are included as a one month lag which reduces the potential endogeneity. The second row shows the coefficient of interest for oil price volatility. It shows 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 an increase of 4% in price change dispersion for the average industry. Excess bond premium and the VIX measure of volatility do not effect 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.

Realized volatility results are in column 2, and it shows that within month volatility of oil prices are also correlated with increased price change standard deviation. The scale of the realized volatility of oil prices is different 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 increases 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. All three measures of oil price volatility are related to changes in the underlying volatility of oil prices.

This previous regression 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 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 long run 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 long run 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 similar to those used in Shea (1993), Perotti (2008), 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 long run oil usage sensitivity is constructed by averaging over the time dimension of the data 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 prices 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 us to study the mechanism through which volatility shocks affect price setting behavior.

Benchmark IO use tables are published every five years at a detailed 6-digit NAICS industry. The tables from 1997, 2002, and 2007 are used for this study. An industry's oil sensitivity in year t is given by

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

where j indexes an industry[16]. This sensitivity to oil usage is motivated by an industry's oil share of production. However this measure could be correlated with industry technological change, due to substitution towards or away from oil due to changes in oil price. Therefore in order to reduce the short run effects of oil price changes from this sensitivity measure, the share of oil is averaged over the time dimension of the IO tables:

$$s_{o,j} = \sum_{t=1}^{T} \frac{s_{o,j,t}}{T} \tag{7}$$

Oil demand variables for oil price change and volatility are then constructed by interacting the long run oil share, $s_{o,j}$, with oil price volatility or oil price inflation. These oil demand variables are in the spirit of 'Bartik' style measures, an interaction between a predefined share of oil usage and aggregate changes in oil price or volatility within narrowly defined manufacturing industries. The idea behind this measure is that global changes in oil price

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

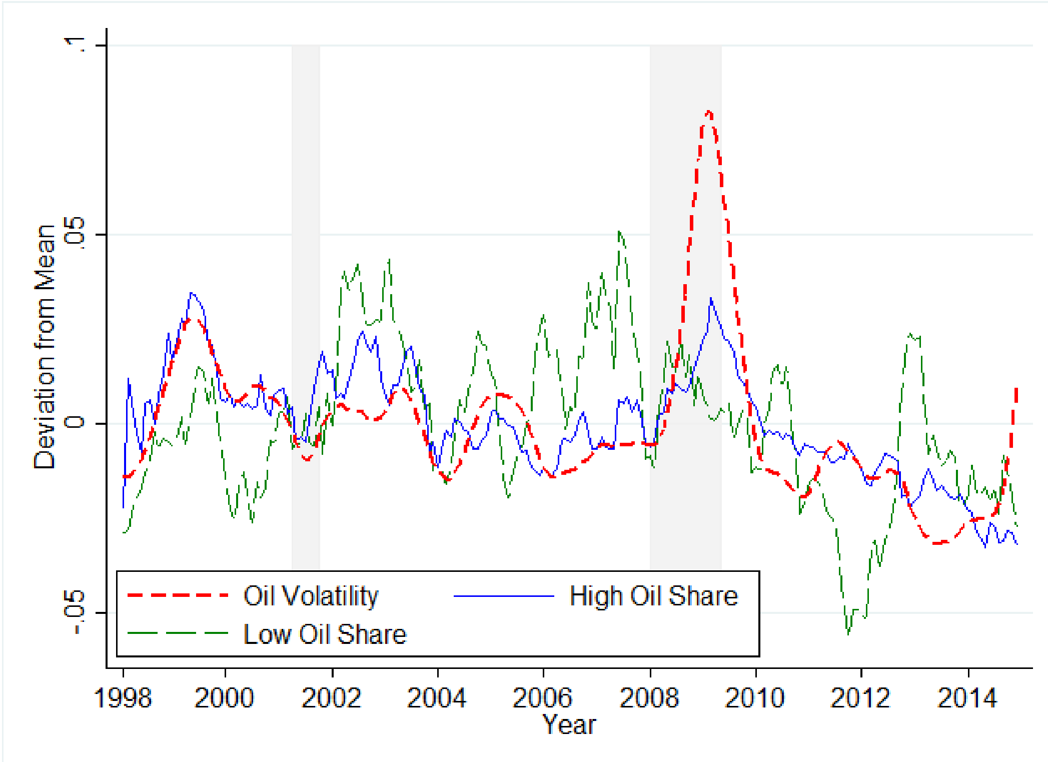


FIGURE 6: Average price change dispersion for high and low oil share industries.

NOTE: Average price change dispersion for top and bottom 10% of industries in each month. 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.

and volatility differentially impacted industries because of long run oil usage technology. The sensitivity, $s_{o,j}$, is a directional measure of the degree to which oil price and volatility movements will effect price setting mechanisms.

Figure 6 illustrates the identification and previews the main result by comparing the price dispersion time series for high and low oil share industries with the volatility of oil prices. The correlation between the high oil share sector average price change dispersion and stochastic oil volatility is 0.423, while the correlation is for the lowest oil share average price change dispersion is only 0.073.

However the correlation between high oil share and oil price volatility does not control for things like differential cyclical sensitivity 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:

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

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 including industry inflation and industrial production. 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 and realized volatility oil price measure results are in appendix B.8, but 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.

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 there is little 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 0.0144 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 on average oil volatility could explain 44% of the observed price change dispersion increase after controlling for oil price inflation and other observables.

Frequency of price change is also an important price setting behavior for monetary policy effectiveness. I find no evidence that price change frequency reacts to changes in oil price volatility with full results in appendix B.8.

However 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. Oil volatility doubled during this period, but the estimates imply that oil volatility has the same size and sign within and outside the financial crisis. This shows that the relationship between oil price volatility and price change dispersion does not rely on the large change occurring in the economy during the Great Recession.

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)
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 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. PriceDisp$_{j,t-1}$ is the lagged industry price change dispersion. $\overline{s_o} * \sigma_t$ 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 *** $p < .01$.

3.4 Within Firm Price Change Dispersion

A possible identification issue 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 over 2005-2014; that is the standard deviation of price changes within a month for a firm indexed by i[17]. 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:

$$Y_{i,j,t} = \eta * (s_{o,j} * \Delta log(P^o_{t-1})) + \lambda * (s_{o,j} * \sigma_{t-1}) + \gamma' X_{j,t} + \alpha_i + \alpha_t + \epsilon_{ijt} \quad (9)$$

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

[17] 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)
$s_{o,j} * \Delta log(P^o_{t-1}) * [Crisis = 0]$	0.138	0.131	0.088	0.112
	(0.084)	(0.085)	(0.087)	(0.083)
$s_{o,j} * \Delta log(P^o_{t-1}) * [Crisis = 1]$	-0.130	-0.171	-0.591*	-0.553
	(0.352)	(0.360)	(0.311)	(0.298)
$s_{o,j} * \sigma_{t-1} * [Crisis = 0]$	2.727***	2.763***	2.727***	2.561***
	(0.852)	(0.866)	(0.948)	(0.888)
$s_{o,j} * \sigma_{t-1} * [Crisis = 1]$	3.018***	3.000***	2.704**	2.563**
	(0.966)	(0.963)	(1.035)	(0.972)
$\pi_{j,t}$		0.081	0.088	0.089
		(0.117)	(0.113)	(0.111)
$\Delta IP_{j,t}$			0.003	-0.001
			(0.014)	(0.015)
PriceDisp$_{j,t-1}$				0.066***
				(0.015)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

TABLE 7: 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 *** $p < .01$.

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 industries that use more oil during periods of high oil price volatility. Industry level price change dispersion is greater than average firm level price change dispersion, so the decrease in coefficient magnitude is reasonable. This shows 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

Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.016	0.017	0.056	0.056
	(0.058)	(0.058)	(0.088)	(0.088)
$s_{o,j} * \sigma_{t-1}$	1.317***	1.304***	1.567***	1.563***
	(0.270)	(0.269)	(0.491)	(0.489)
$\pi_{j,t-1}$		-0.104***		-0.106***
		(0.017)		(0.023)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Number of Firms	20,162	20,162	4,721	4,721
N	202,938	202,938	50,930	50,930

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 five price changes. Robust asymptotic standard errors reported in parentheses are clustered at the firm level: * $p < .10$; ** $p < .05$; and *** $p < .01$.

response to the aggregate shock. The next section will try to understand the mechanism through which common cost volatility shocks are able to increase price change dispersion in a price setting model.

4 Menu Cost Model

This section presents a generalized menu cost model of price setting in order to study the effects of volatility on monetary non-neutrality. The baseline quantitative menu cost model follows Golosov and Lucas (2007) with the addition of leptokurtic shocks of Midrigan (2010) and a "Calvo-plus" mechanism of Nakamura and Steinsson (2010), but incorporates oil into the production function. Oil is modeled as a non-produced input with an exogenous real price shock as in Blanchard and Gali (2008), with a time varying second moment to represent volatility shocks.

In the baseline 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 who 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 i firms have a differential likelihood of changing prices based on the menu cost they receive. This mechanism 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 baseline menu cost model there is a greater tradeoff between output and inflation when oil price volatility is high, primarily due to increased price flexibility. The random menu cost model which is able to match the positive 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 multi-sector model of price setting with first and second moment shocks to oil prices is now presented. Households maximize current expected utility, given by

$$E_t \sum_{\tau=0}^{\infty} \beta^t \big[log(C_{t+\tau}) - \omega L_{t+\tau}\big] \tag{10}$$

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,

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz\right]^{\frac{\theta}{\theta-1}} \tag{11}$$

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

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t}\right)^{-\theta} \tag{12}$$

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

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz\right]^{\frac{1}{1-\theta}} \tag{13}$$

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

$$P_tC_t + E_t[D_{t,t+1}B_{t+1}] \leq B_t + W_tL_t + \int_0^1 \pi_t(z)dz + T_t \tag{14}$$

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 so that future income is high enough to avoid default.

The first order conditions of the household maximization problem are

$$D_{t,t+1} = \beta(\frac{C_{t+1}}{C_t})\frac{P_t}{P_{t+1}} \tag{15}$$

$$\frac{W_t}{P_t} = \omega L_t C_t \tag{16}$$

where equation (15) describes the relationship between asset prices and consumption, and (16) describes labor supply.

4.2 Firms

In the model there are a continuum of firms indexed by z[18]. The production function of firm z is Leontief in labor and oil to describe the lack of substitutability of oil and labor in the short run.

$$y_t(z) = A_t(z)\min\{L_t(z), \frac{1}{s_o}O_t(z)\} \tag{17}$$

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

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau}\pi_{t+\tau}(z) \tag{18}$$

where profits are given by:

[18] The model abstracts from multi-product firms, however the aggregate dynamics will be similar because some firms receive a free opportunity to change prices which creates a fraction of small price changes.

$$\pi_t(z) = p_t(z)y_t(z) - W_t L_t(z) - Q_t O_t(z) - \chi(z) W_t I_t(z), \chi(z) \overset{iid}{\sim} F(\chi) \tag{19}$$

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. $\chi(z)$ is a menu cost drawn from the distribution $F(\chi)$. In the baseline model, $F(\chi)$ is a degenerate distribution which implies a single menu cost as in the model of Golosov and Lucas (2007). The random menu cost model uses a continuous distribution where menu costs are drawn from independently each period. The next section will further explain this feature. The final term indicates that firms must hire an extra $\chi(z)$ units of labor if they decide to change prices with probability $1-\alpha$, or may change their price for free with probability α[19]. A small probability of receiving a free price change enables the model to have small price changes.

Total demand for good z is given by:

$$y_t(z) = Y_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta} \tag{20}$$

The firm problem is to maximize profits in (19) subject to its production function (17), demand for its final good product (20), 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:

$$\frac{1}{s_o} O_t(z) = L_t(z) \tag{21}$$

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

$$logA_t(z) = \begin{cases} \rho_a logA_{t-1}(z) + \sigma_a \epsilon_t(z) & \text{with probability } p_a \\ logA_{t-1}(z) & \text{with probability } 1 - p_a, \end{cases} \tag{22}$$

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

Nominal aggregate spending follows a random walk with drift:

$$log(S_t) = \mu + log(S_{t-1}) + \sigma_s \eta_t \tag{23}$$

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 (2008), by assuming that oil is a non-

[19] This is the "Calvo-plus" parameter of Nakamura and Steinsson (2010).

produced input purchased in a world market at real price P^o_t. The log of P^o_t follows an AR(1) process with time varying standard deviation:

$$logP^o_t = \rho_p logP^o_{t-1} + e^{\sigma_t}\nu_t \tag{24}$$

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:

$$\sigma_t = (1-\rho_\sigma)\overline{\sigma} + \rho_\sigma \sigma_{t-1} + \phi\nu_{\sigma,t} \tag{25}$$

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:

$$log(\frac{P_t}{S_t}) = \gamma_0 + \gamma_1 logP^o_t + \gamma_2\sigma_t + \gamma_3 log(\frac{P_{t-1}}{S_t}) + \gamma_4(log(\frac{P_{t-1}}{S_t}) * logP^o_t) + \gamma_5(log(\frac{P_{t-1}}{S_t}) * \sigma_t) \tag{26}$$

The accuracy of the rule is checked using the maximum Den Haan statistic in a dynamic forecast.

Using equations (15), (16), (17), (19), (20), (21), (26) and market clearing I am able to write the firm problem recursively as:[20].

$$V\big(A_t(z), \frac{p_{t-1}(z)}{S_t}, P^o_t, \sigma_t, \chi(z), \psi_t\big) = \max_{p_t(z)}\Big\{V^N\big(A_t(z), \frac{p_{t-1}(z)}{S_t}, P^o_t, \sigma_t, \psi_t\big), V^A\big(A_t(z), P^o_t, \sigma_t, \chi(z), \psi_t\big)\Big\} \tag{27}$$

where ψ_t is the Krusell-Smith aggregate state describing the joint distribution of prices, productivities, and menu costs. $\pi^R_t(z)$ is firm z's real profits in period t, and $D^R_{t,t+1}$ 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:

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

$$V^N\big(A_t(z), \frac{p_{t-1}(z)}{S_t}, P^o_t, \sigma_t, \psi_t\big) = \pi^R_t\big(\frac{p_{t-1}(z)}{S_t}, A_t(z), P^o_t, \sigma_t, \psi_t\big) \\ +E_t\big[D^R_{t,t+1} V\big(A_{t+1}(z), \frac{p_{t-1}(z)}{S_{t+1}}, P^o_{t+1}, \sigma_{t+1}, \chi(z), \psi_{t+1}\big)\big] \tag{28}$$

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

$$V^A\big(A_t(z), P^o_t, \sigma_t, \chi(z), \psi_t\big) = -\chi(z)\frac{W_t}{P_t} + \pi^R_t\big(\frac{p_t(z)}{S_t}, A_t(z), P^o_t, \sigma_t, \psi_t\big) \\ +E_t\big[D^R_{t,t+1} V\big(A_{t+1}(z), \frac{p_t(z)}{S_{t+1}}, P^o_{t+1}, \sigma_{t+1}, \chi(z), \psi_{t+1}\big)\big] \tag{29}$$

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 baseline menu cost and random menu cost versions of the model. The first set are standard parameters in menu costs 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 substitution is set to $\theta = 4$ following Nakamura and Steinsson (2010)[21]. 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 minus 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 $\rho_v = 0.99$, 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 and σ_a, the

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

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

probability of an idiosyncratic productivity shock p_a, the cost of changing a price $\chi(z)$, and the probability of a free price change α directly affect the price setting statistics. These five parameters will change depending on the particular menu cost distribution assumption. Both 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 baseline menu cost model. The persistence of idiosyncratic productivity is set to $\rho = 0.7$, which matches Nakamura and Steinsson (2008). Then the remaining four parameters $\chi(z)$, σ_a, p_a, and α are set to target four moments of the PPI data. The moments are frequency of price change, average size of price change, standard deviation of price changes, and the fraction of small price changes[22]. This model has a single point mass in the menu cost distribution that determines the value of the high menu cost and is set to $\chi(z) = 0.037$, which implies that firms must pay 3.7% of their monthly revenues to change a price. However a fraction $\alpha = 0.01$ of firms receive a free opportunity to change prices. This parameter is identified by the fraction of small price changes[23]. 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 0.085 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 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:

[22] A small price changes is defined as $|dp_{i,t}| < \frac{1}{2}|\overline{dp}|$.

[23] The pricing parameters imply that total adjustment costs in the economy are $\chi * (Freq - \alpha) * \frac{\theta-1}{\theta} = 0.4\%$ of revenues per month. Estimates from Levy et al. (1997) suggest that menu costs are 0.7% of revenues, while Stella (2013) estimates menu costs to be bounded between 0.22% and 0.59%.

Price Setting Statistic	Data	MC	Random MC
Frequency	0.154	0.152	0.153
Average Size of Price Change	0.071	0.118	0.098
Fraction Small Price Changes	0.074	0.076	0.368
Standard Deviation Price Changes	0.125	0.125	0.125
Fraction Price Increases	0.602	0.612	0.648

TABLE 10: One Sector Model Moments

$$\chi(z) = \begin{cases} 0 & \text{with probability } \alpha \\ \tilde{\chi} & \text{with probability } 1-\alpha, \end{cases} \quad \text{where } F(k) = P(\tilde{\chi} \leq k) = 1 - e^{-\lambda k^{\xi}} \tag{30}$$

The parameter λ determines the average value of the menu cost that is drawn, while ξ determines the curvature of distribution. Higher values of ξ imply that it 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. In particular, $\lambda = 5$ and $\xi = 2$. This implies a relatively high menu cost and a low likelihood of receiving an extreme menu cost. The persistence of idiosyncratic productivity shocks remains set to 0.7, and the probability of a shock is 0.4. The volatility of idiosyncratic productivity shocks is increased to 0.105 while the probability of a free price change is set to 0.12, which enables the model to match the dispersion of price changes.

4.4 One Sector 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. In the baseline menu cost model the fraction of small price changes is also matched exactly, due to the Calvo plus parameter. The average size of price changes is slightly too high, but it enables the model to match the standard deviation of price changes. The probability of receiving a productivity shock helps the model increase the dispersion of price changes relative to a Golosov and Lucas menu cost model, but due to the large oil price shocks if the probability of productivity shock is too low then all price changes will be dominated by the oil price shocks. The random menu cost model is average size of price changes is closer to the data, but this is at the cost of too many small price changes. Both models have a fraction of price increases that is close to the data.

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 baseline menu cost model calibration, a

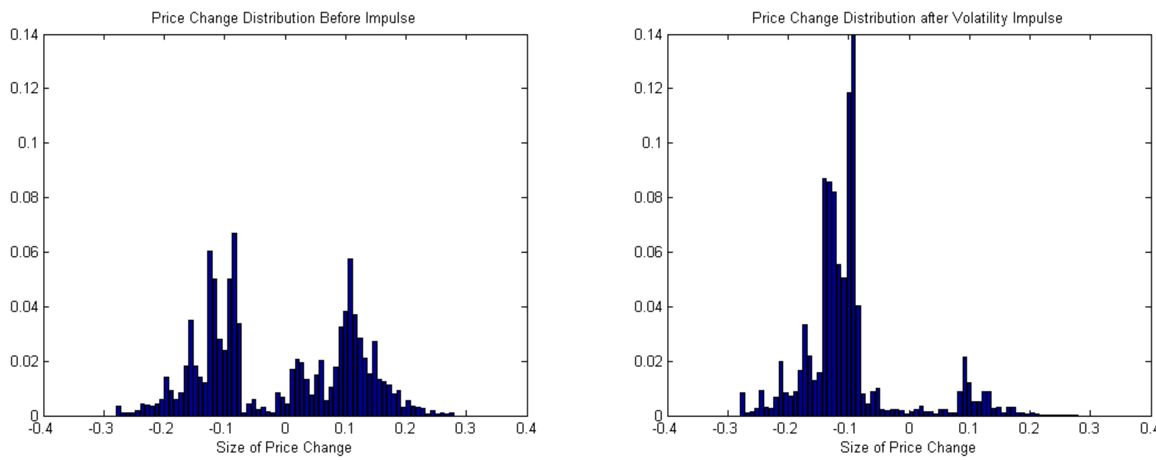


Figure 7: Oil Price Volatility Shock: Menu Cost Model Price Change Distribution

one standard deviation increase in oil price volatility decreases the price change dispersion by 11.4%. The reasoning behind this is shown in figure 7. The selection effect of price changes dominates the real options effect, which would decrease the fraction of price changes, that occurs from the increase in volatility. 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 shock pushes more price changes in one direction, decreasing price change dispersion. There is an increase in the directional synchronization of price changes that does not occur during an increase in idiosyncratic volatility shocks. In the ergodic distribution of the model, nearly 40% of price changes are negative. During periods of increased oil price volatility, more prices move in the direction of the larger oil price shock which decreases price change dispersion.

The pricing selection effect 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 baseline calibration. As the oil share of production increases, the fall in price change dispersion becomes larger. This is due to both an intensive and extensive change in item level inflation. Oil price changes become more important for producers, making them more likely to change prices as well as by a larger amount. All price changes move 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

s_o	Price Dispersion	Frequency
0.010	-6.79%	13.71%
0.016	-11.41%	27.84%
0.025	-17.08%	50.12%
0.050	-25.88%	108.24%

TABLE 11: Menu Cost Comparative Static Exercise

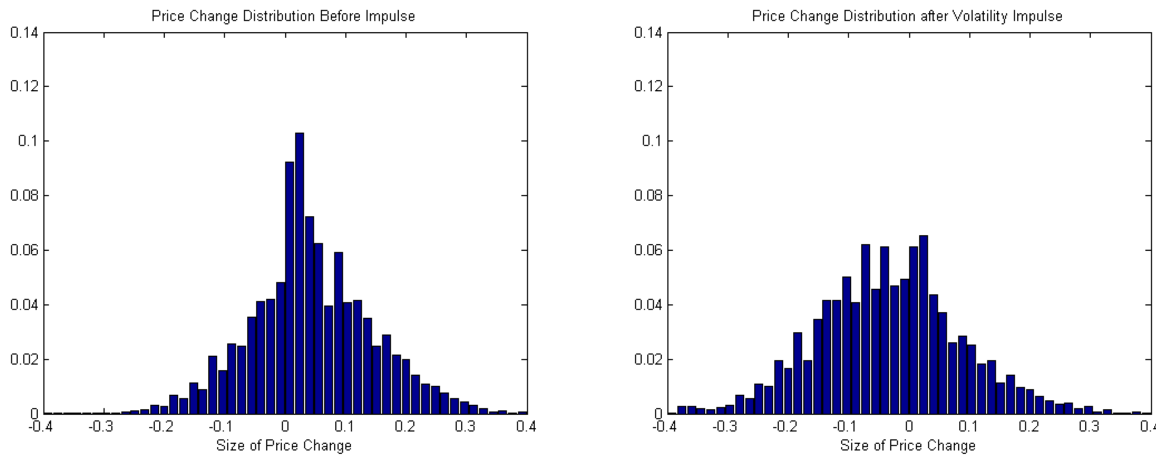


FIGURE 8: Oil Price Volatility Shock: Random Menu Cost Price Change Distribution

mechanism implies that prices are now a function of the random menu cost draw as well as the state of the economy. The change in price change distribution due to an oil price volatility shock is pictured in figure 8. Due to the random menu costs that firms draw, the selection of prices that are will change depends less on the common shock. During an increase in oil price volatility, the model is 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 some price changes will occur simply due to a low menu cost draw, and will be relatively small[24]. The overall effect is to create a more disperse price change distribution during periods of high oil price volatility, with larger skewness but substantial mass 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[25].

A comparative static exercise is performed in table 12 for the random menu cost model.

[24]While the fraction of small price changes is larger than in the data, this is not the critical element of the model that enables it to match the positive empirical relationship between oil price volatility and price change dispersion. I show in appendix A.3 that a standard menu cost that instead matches a large fraction of small price changes still implies a counterfactual negative relationship.

[25]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 to oil price volatility shocks.

s_o	Price Dispersion	Frequency
0.010	0.58%	2.62%
0.016	1.33%	6.46%
0.025	3.57%	12.87%
0.050	17.73%	32.58%

TABLE 12: Random Menu Cost Model Comparative Static Exercise

Only the share of oil is varied from the baseline calibration. The table reports the increases in price change dispersion on impact of an oil price volatility shock. For low levels of oil usage, an oil price volatility shock gives small increases in price change dispersion. For an average oil share of production of 1.6%, an oil price volatility shock increases price change dispersion by 1.33%. As oil share of production increases to 2.5%, a one standard deviation increase in oil price volatility increases price change dispersion by 3.57%.

The model results show that a standard state dependent pricing model implies decreased price change dispersion on impact of an aggregate volatility shock. Larger shocks cause prices to respond in the same direction, decreases the dispersion of the price change distribution. Introducing random menu costs enables the model to match this key volatility relationship, by reducing the reaction to a common cost shock.

5 Implications for Monetary Policy Effectiveness

This section has shown that a model that decreases the price change selection effect is able to match the empirical relationship between oil price volatility and price change dispersion. This enables me to ask the question of how monetary policy effectiveness varies during periods of high and low oil price volatility.

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 is shown in Table 13 for periods of high and baseline oil price volatility. In the first row is the impact on consumption in the ergodic state of the economy, while the second row is during a period of high volatility[26]. In the random menu cost model, which is able to match the change in the price change dispersion during increases in oil price volatility, 46.3% of the doubling of log nominal output translates into an increase in output. The other 53.7% of the increase goes into inflation. When the

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

Random Menu Cost Model	Output IRF on Impact	Price IRF on Impact
Baseline Volatility	46.3%	53.7%
High Volatility	45.9%	54.1%
Menu Cost Model		
Baseline Volatility	38.1%	61.9%
High Volatility	34.2%	65.8%

Table 13: Inflation-Output Stabilization Tradeoff

model also experiences an increase in oil price volatility, 45.9% of the increase in nominal output goes into output while 54.1% goes into the increase in price level.

This result suggests that increases in an aggregate cost shock do not substantially increase the trade off between output stabilization and inflation. During periods of high oil price volatility only 1% less of the increase in nominal output goes into output. Contrasting with this result is the implications of the baseline menu cost model, where 10% less of the increase in nominal output goes into inflation. 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, which causes more of the nominal output change to be incorporated into the price level.

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 baseline 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 load more on the common realization of the 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 Wiederholt (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 to oil usage, I show that the increase in price change dispersion is larger for sectors with more oil usage. In order to match this relationship in the data, the selection effect in a menu cost model must be reduced. I do this by introducing random and heterogeneous menu costs, which induces randomness in which prices can change in a given period. This enables the model to match the key empirical relationship between price change dispersion. 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 react more strongly because they believe it is an increase in idiosyncratic volatility that may dampen effectiveness, they may over react during periods of high volatility and cause unnecessary inflation.

An important future research question should ask if other aggregate volatility shocks affect price setting behavior in the same manner as oil volatility. In particular, does increased monetary policy volatility cause price changes to be more disperse and affect it's effectiveness? During 1979 to 1982 the FOMC targeted the quantity of money rather than a federal funds target rate, which increased the observed volatility of the federal funds rate. Policy uncertainty, such as that about taxation or affecting future demand, is another common shock to firms that could affect price setting behavior.

References

[1] Bachmann, Rudiger, Benjamin Born, Steffan Elstner, and Christiane Grimme (2013). "Time-Varying Business Volatility, Price Setting, and the Real Effects of Monetary Pol-

icy" Mimeo.

[2] Baley, Isaac and Julio Blanco (2016). "Menu Costs, Uncertainty Cycles, and the Propagation of Nominal Shocks." Working Paper.

[3] Bartik, Timothy (1991). "Who Benefits From State and Local Economic Development Policies." W.E. Upjohn Institute for Employment Research: Kalamazoo, Mich.

[4] Baumeister, Christiane and Lutz Kilian (2015). "Understanding the Decline in the Price of Oil since June 2014." Journal of the Association of Environmental and Resource Economist.

[5] Baumeister, Christiane and Lutz Kilian (2016). "Fourty Years of Oil Price Fluctuations: Why the Price of Oil May Still Surprise Us." Journal of Economic Perspectives, Volume 30, Winter 2016, pp. 139-160.

[6] Berger, David and Joseph Vavra (2015). "Volatility and Pass-Through." National Bureau of Economic Research Working Paper Series, 2015, No. 19651.

[7] Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. "How Much Should We Trust Differences-In-Differences Estimates." Quarterly Journal of Economics, 119, 249-275.

[8] Bhattarai, Saroj and Raphael Schoenle (2014). "Multiproduct Firms and Price-Setting: Theory and Evidence from U.S. Producer Prices." Journal of Monetary Economics. Volume 66, September 2014.

[9] Blanchard, Olivier, and Jordi Gali (2008). "The Macroeconomic Effects of Oil Price Shocks: Why are the 2000s so different from the 1970s" NBER, International Dimensions of Monetary Policy.

[10] Blanco, Julio (2016). "Optimal Inflation Target in an Economy with Menu Costs and Zero Lower Bound." Working Paper.

[11] Bloom, Nicholas (2009). "The Impact of Uncertainty Shocks" Econometrica, May 77, pp. 623-685.

[12] Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, Stephen Terry (2012). "Really Uncertain Business Cycles." NBER Working Paper 18245, July.

[13] Born, Benjamin and Johannes Pfeifer. "Policy Risk and the Business Cycle." Journal of Monetary Economics. Volume 68, November 2014: 68-85.

[14] Chen, Shiu-Sheng (2009). “Oil Price Pass-Through into Inflation.” Energy Economics, Volume 31, 126-133.

[15] Clark, Todd and Stephen Terry (2010). “Time Variation in the Inflation Passthrough of Energy Prices.” Journal of Money, Credit and Banking, Vol. 42, No. 7.

[16] Davis, Steven J. and John C. Haltiwanger (2001). “Sectoral job creation and destruction responses to oil price changes.” Journal of Monetary Economics, 48(3):465-512.

[17] Den Haan, Wouter J. (2010). “Assessing the Accuracy of the Aggregate Law of Motion in Models with Heterogeneous Agents.” Journal of Economic Dynamics and Control, 32, 79-99.

[18] Dotsey, Michael, Robert G. King, and Alexander J. Wolman (1999). “State Dependent Pricing and the General Equilibrium Dynamics of Money and Output.” Quarterly Journal of Economics, 114(2), 655-690.

[19] Drenik, Andres and Diego Perez (2016). “Price Setting Under Uncertainty About Inflation.” Working Paper.

[20] Fernandez-Villaverde, Jesus and Juan Rubio-Ramirez (2007). “Estimating Macroeconomic Models: A Likelihood Approach.” Review of Economic Studies 74(4), 1059-1087.

[21] Fernandez-Villaverde, Jesus, Pablo Guerron-Quintana, Keith Kuester, and Juan Rubio-Ramirez (2015). “Fiscal Volatility Shocks and Economic Activity.” American Economic Review, 105(11): 3352-3384.

[22] Gilchrist, Simon, Raphael Schoenle, Jae Sim, and Egon Zakrajsek (2015). “Inflation Dynamics during the Financial Crisis.” Finance and Economics Discussion Series 2015-012. Washington: Board of Governors of the Federal Reserve System.

[23] Gertler, Mark and John Leahy (2008). “A Phillips Curve With an Ss Foundation.” Journal of Political Economy, 116, 533-572.

[24] Goldberg, Pinelopi K. and Rebecca Hellerstein (2009). “How Rigid Are Producer Prices?” Staff Report No. 407, Federal Reserve Bank of New York.

[25] Gilchrist, Simon and Egon Zakrajsek (2012). “Credit Spreads and Business Cycle Fluctuations.” American Economic Review, 102(4):1692-1720.

[26] Godsill, Simon J. Arnaud Doucet, and Mike West (2004). "Monte Carlo Smoothing for Nonlinear Time Series." Journal of the American Statistical Association 99 (465), 156-168.

[27] Gopinath, Gita and Oleg Itskhoki (2010). "Frequency of Price Adjustment and Pass Through." Quarterly Journal of Economics (2010) 125 (2): 675-727.

[28] Gorodnichenko, Yuriy, and Michael Weber. "Are sticky prices costly? Evidence from the stock market." The American Economic Review 106.1 (2016): 165-199.

[29] Hall, Robert (1988). "The Relation between Price and Marginal Cost in U.S. Industry." Journal of Political Economy, Vol 96, No. 5.

[30] Hamilton, James D (2009). "Causes and Consequences of the Oil Shock of 2007-2008." Brookings Papers on Economic Activity, 1, Spring, pg. 215-283.

[31] Jo, Soojin (2012). "The Effects of Oil Price Uncertainty on the Macroeconomy." Bank of Canada Working Paper 2012-40.

[32] Karadi, Peter and Adam Reiff. "Menu Costs, Aggregate Fluctuations, and Large Shocks." Working paper, February 2016.

[33] Kilian, Lutz (2008). "The Economic Effects of Energy Price Shocks." Journal of Economic Literature, Volume 90, pg 216-240.

[34] Kilian, Lutz (2009). "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market." American Economic Review, 99(3):1053-1069.

[35] Kilian, Lutz and Bruce Hicks (2013). "Did Unexpectedly Strong Economic Growth Caue the Oil Price Shock of 2003-2008?" Journal of Forecasting 32(5): 385-54.

[36] Kilian, Lutz and Thomas K. Lee (2014). "Quantifying the Speculative Component in the Real Price of Oil: The Role of Global Oil Inventories." Journal of International Money and Finance 42: 71-87.

[37] Kilian, Lutz and Daniel P. Murphy (2014). "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil." Journal of Applied Econometrics 29(3):454-78.

[38] Kilian, Lutz and Robert Vigfusson (2010). "Nonlinearities in the oil price-output relationship." Macroeconomic Dynamics, 15:337-363, 2010.

[39] Kilian, Lutz and Robert Vigfusson (2011). "Are the responses of the U.S. economy asymmetric in energy price increases and decreases?" Quantitative Economics, 2(3):419-453.

[40] Kilian, Lutz and Robert Vigfusson (2013). "Do oil prices help forecast U.S. Real GDP? the role of nonlinearities and asymmetries." Journal of Business and Economic Statistics, 31(1):78-93.

[41] Klenow, Peter J. and Oleksiy Krystov (2008). "State Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation?" Quarterly Journal of Economics, 123(3), 863-904.

[42] Knotek, Edward and Stephen Terry (2008). "Alternative Methods of Solving State-Dependent Pricing Models." Federal Reserve Bank of Kansas City Working Paper No. 08-10.

[43] Levy, Daniel, Mark Bergen, Shantanu Dutta, and Robert Venable. "The Magnitude of Menu Costs: Direct Evidence from Large U.S. Supermarket Chains." Quarterly Journal of Economics, 112(3): 791-824.

[44] Luo, Shaowen and Daniel Villar (2015). "The Skewness of the Price Change Distribution: A New Touchstone for Sticky Price Models". Working Paper.

[45] Mackowiak, Bartosz and Mirko Wiederhold (2009). "Optimal Sticky Prices under Rational Inattention." American Economic Review, 99(3): 769-803.

[46] Menkulasi, Jeta (2009). "Rational Inattention and Changes in Macroeconomic Volatility." University of Maryland, mimeo.

[47] Midrigan, Virgiliu. (2011) "Menu Costs, Multiproduct Firms, and Aggregate Fluctuations" Econometrica July 79.

[48] Nakamura, E. and J. Steinsson (2008). "Five Facts about prices: A reevaluation of menu cost models" Quarterly Journal of Economics 123(4).

[49] Nakamura, E. and J. Steinsson (2010). "Monetary Non-neutrality in a multi-sector menu cost model" Quarterly Journal of Economics 125(3).

[50] Nekarda, Chris and Valerie Ramey (2011). "Industry Evidence on the Effects of Government Spending" American Economic Journal: Macroeconomics 3 January 2011.

[51] Perotti, Robert (2008). "In Search of the Transmission Mechanism of Fiscal Policy." In NBER Macroeconomics Annual 2007, ed. Daron Acemoglu, Kenneth Rogoff, and Michael Woodford, 169-226. Chicago: University of Chicago Press.

[52] Plante, Michael, and Nora Traum (2012). "Time-Varying Oil Price Volatility and Macroeconomic Aggregates" Center for Applied Economics and Policy Research Working Paper 2012-002.

[53] Roberts, G O, A Gelman, and W R Gilks. (1996) "Efficient Metropolis Jumping Rules." Bayesian Statistics, 5:599-607.

[54] Shea, John (1993). "Do Supply Curves Slope Up?" Quarterly Journal of Economics, 108(1): 1-32.

[55] Stella, Andrea (2013). "The Magnitude of Menu Costs: A Structural Estimation." Meeting Papers 2014 (No. 436). Society for Economic Dynamics.

[56] Vavra, Joe (2014). "Inflation Dynamics and Time Varying Volatility: New Evidence and an SS Interpretation" Quarterly Journal of Economics.

[57] Yellen, Janet (2016). "Current Conditions and the Outlook for the U.S. Economy." The World Affairs Council of Philadelphia, 6 June 2016, Philadelphia PA.

[58] Young, Eric (2010). "Solving the incomplete markets model with aggregate uncertainty using the Krusell-Smith algorithm and non-stochastic simulations." Journal of Economic Dynamics Control 34: 36-41.

[59] Zhang, Fang (2016). "Rational Inattention in Uncertain Business Cycles." Journal of Money, Credit, and Banking, forthcoming.

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.

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

Then using equation (21) I substitute out for $O_t(z)$ which gives after simplification

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

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 $L_t(z)$.

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t}\Big)y_t(z) - \Big(\frac{W_t + s_o P_t^o}{P_t}\Big)\frac{y_t(z)}{A_t(z)} - \chi(z)\frac{W_t}{P_t}I_t(z) \tag{33}$$

Now I substitute in the firm's demand curve (20) and labor supply (16) to give

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

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

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

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

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{P_t} - \frac{1}{A_t(z)}\frac{W_t + s_o P_t^o}{P_t}\Big)\Big(\frac{p_t(z)}{P_t}\Big)^{-\theta}C_t - \chi(z)(\omega C_t)I_t(z) \tag{36}$$

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 (26) I can write $\frac{P_t}{S_t}$ as

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

and we can write C_t as

$$C_t = e^{-\big(\gamma_0 + \gamma_1 log P_t^o + \gamma_2\sigma_t + \gamma_3 log(\frac{P_{t-1}}{S_t}) + \gamma_4(log(\frac{P_{t-1}}{S_t}) * log P_t^o) + \gamma_5(log(\frac{P_{t-1}}{S_t}) * \sigma_t)\big)} \tag{38}$$

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

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

then use (16) to replace the real wage in terms of consumption.

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

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

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

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

$$\pi_t^R(z) = \Big(\frac{p_t(z)}{S_t}e^{-(\Theta)} - \frac{1}{A_t(z)}(\omega e^{-(\Theta)} + s_o P_t^o\Big)\Big(\frac{p_t(z)}{S_t}\Big)^{-\theta}(e^{(\Theta)})^{\theta-1} - \chi(z)(\omega e^{-(\Theta)})I_t(z) \tag{42}$$

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

$$D_{t,t+1}^R = \beta\frac{C_t}{C_{t+1}} = \beta\frac{e^{-\Big(\gamma_0+\gamma_1 logP_t^o+\gamma_2\sigma_t+\gamma_3 log(\frac{P_{t-1}}{S_t})+\gamma_4(log(\frac{P_{t-1}}{S_t})*logP_t^o)+\gamma_5(log(\frac{P_{t-1}}{S_t})*\sigma_t)\Big)}}{e^{-\Big(\gamma_0+\gamma_1 logP_{t+1}^o+\gamma_2\sigma_{t+1}+\gamma_3 log(\frac{P_t}{S_{t+1}})+\gamma_4(log(\frac{P_t}{S_{t+1}})*logP_{t+1}^o)+\gamma_5(log(\frac{P_t}{S_{t+1}})*\sigma_{t+1})\Big)}} \tag{43}$$

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 and 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 (27).

3. Given the policy function from step 2, the model is simulated using non-stochastic simulation. This implies that the aggregate variables P_t^O, 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 $\chi(z)$. 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 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 $\mid DH_{iter+1}^{max} - DH_{iter}^{max} \mid < .0001$. After this criterion is met the aggregate law of motion has converged and model equilibrium is reached.

A.3 Menu Cost Model alternative calibration

I show that the baseline menu cost model calibrated to match a large fraction of small price changes continues to imply a negative price change dispersion oil price volatility relationship. The model is calibrated to match the price setting moments from the random menu cost model, specifically the calibration closely matches the random menu cost moments:

Price Setting Statistic	Data	MC	Random MC
Frequency	0.154	0.154	0.153
Average Size of Price Change	0.071	0.098	0.098
Fraction Small Price Changes	0.074	0.374	0.368
Standard Deviation Price Changes	0.125	0.125	0.125
Fraction Price Increases	0.602	0.651	0.648

Table 14: Menu Cost Model: Alternative Calibration

The middle column shows the moments from this new calibration. In this menu cost model calibration, a one standard deviation oil price volatility increase causes price change dispersion to fall by 2.93% while price change frequency will increase 8.87%. This result shows that the menu cost model with a large fraction of small price changes still does not match the salient price change dispersion and oil price relationship, and that this is not the key price setting moment for generating this relationship.

B Data Appendix

B.1 Stochastic Volatility Model

The stochastic volatility model is given by

$$logP_t^o = \rho_p logP_{t-1}^o + e^{\sigma_t}\nu_t \tag{44}$$

$$\sigma_t = (1-\rho_\sigma)\overline{\sigma} + \rho_\sigma \sigma_{t-1} + \phi\nu_{\sigma,t} \tag{45}$$

The process for σ_t is latent, and following Plante and Traum (2012), Fernandez-Villaverde et al. (2011), and Born and Pfeifer (2014), a sequential importance resampling particle filter is used to evaluate the likelihood function due to the nonlinearity in the SV model. Once the likelihood function of the data is constructed, a random walk Metropolis-Hastings algorithm is used to compute the posterior distribution of the four parameters. Uniform priors are used for each parameter. The particle filter uses 40,000 particles to construct the likelihood, while 150,000 draws are used in the RWMH algorithm with the first 50,000 discarded. The final acceptance ratio of proposals is 0.32, within the recommended window of 15% to 40% in Roberts, Gelman and Gilks (1996). In order to obtain the volatility series of the data, the backwards-smoothing routine of Godsill 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^{ϕ}-1) $\times$ 100%= 15%. [27]

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:

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

$$p(P_o^T;\Theta) = \prod_{t=1}^{T} p(P_o^t|P_o^{t-1};\Theta)$$
$$= \int \frac{1}{e^{\sigma_0}\sqrt{2\pi}} exp\Bigg[-\frac{1}{2}(\frac{P_o^1-\rho_p P_o^0}{e^{\sigma_0}})^2\Bigg] d\sigma_0$$
$$\times \prod_{t=2}^{T} \frac{1}{e^{\sigma_t}\sqrt{2\pi}} exp\Bigg[-\frac{1}{2}(\frac{P_o^t-\rho_p P_o^{t-1}}{e^{\sigma_0}})^2\Bigg] p(\sigma^t|P_o^{t-1};\Theta) d\sigma_t \tag{46}$$

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:

$$p(\sigma_t|P_o^t;\Theta) \cong \sum_{i=0}^{N} \omega_t^i \delta_{\sigma_t^i}(\sigma_t) \tag{47}$$

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 (45) we 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 (45) 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

$$\tilde{\omega}_t^i = \frac{\omega_t^i}{\sum_{i=1}^{N}\omega_t^i} \tag{48}$$

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

$$\begin{aligned} p(P_o^T;\Theta) \cong \frac{1}{N}\sum_{i=1}^{N} \frac{1}{e^{\sigma_0^i}\sqrt{2\pi}} exp\Bigg[-\frac{1}{2}(\frac{P_o^1-\rho_p P_o^0}{e^{\sigma_0^i}})^2\Bigg] \\ \times \prod_{t=2}^{T}\frac{1}{N}\sum_{i=1}^{N} \frac{1}{e^{\sigma_{t|t-1}^i}\sqrt{2\pi}} exp\Bigg[-\frac{1}{2}(\frac{P_o^t-\rho_p P_o^{t-1}}{e^{\sigma_{t|t-1}^i}})^2\Bigg] \end{aligned} \tag{49}$$

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

$$p(\sigma^T|P_o^t;\Theta) = p(\sigma_T|P_o^t;\Theta)\prod_{t=1}^{T-1} p(\sigma_t|\sigma_{t+1:T},P_o^T;\Theta) \tag{50}$$

The second factor is then simplified to

$$\begin{aligned} p(\sigma_t|\sigma_{t+1:T},P_o^T;\Theta) &= p(\sigma_t|\sigma_{t+1},P_o^t;\Theta) \\ &= \frac{p(\sigma_t|P_o^t;\Theta)f(\sigma_{t+1}|\sigma_t)}{p(\sigma_{t+1}|P_o^t)} \\ &\propto p(\sigma_t|P_o^t;\Theta)f(\sigma_{t+1}|\sigma_t) \end{aligned} \tag{51}$$

The first equality comes from the Markovian properties of the model, f is the state transition density from 45. Equation 47 allows us to construct $p(\sigma_t|P_o^t;\Theta)$ by forward filtering, therefore we can approximate the above equation RHS by

$$p(\sigma_t|\sigma_{t+1},P_o^t;\Theta) \cong \sum_{i=0}^{N} \omega_{t|t+1}^i \delta_{\sigma_t^i}(\sigma_t) \tag{52}$$

The weights are given by

$$\omega_{t|t+1}^i = \frac{\omega_t^i f(\sigma_{t+1}|\sigma_t^i)}{\sum_{i=1}^N \omega_t^i f(\sigma_{t+1}|\sigma_t^i)} \tag{53}$$

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 53.

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

$\Theta^{prop}_{j+1} = \Theta^{prop}_j + cN(0,1)$, j=1,...,150,000

where j is the number of draws and c is a scaling parameter set to induce an acceptance ratio between 0.15 and 0.40 (Need to check) suggested in Roberts, Gelman, and Gilks (1997).

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

$$logP^o_t = \rho_p logP^o_{t-1} + \epsilon_t \tag{54}$$

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

$$\sigma^2_t = \omega + \alpha\epsilon^2_{t-1} + \beta\sigma^2_{t-1} \tag{55}$$

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 oil prices are used for robustness. This is a weighted average of domestic and imported oil. This data is available monthly.

Both 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 (2008b), 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:

$$\pi_{j,t} = \alpha_j + \alpha_t + \sum_{i=0}^{12} b_i \big(s_{o,j} * \Delta log P^o_{t-i}\big) + \epsilon_{j,t} \tag{56}$$

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 15.

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

TABLE 15: 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 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 16 along with the four digit industries with the largest oil share.

Table 16: 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

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 17. 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.

Next, in table 18 are the results that correspond to 6 but for interquartile range rather than price change standard deviation. The table shows oil price volatility still has a positive correspondence with a robust measure of price change dispersion.

The main industry results with GARCH and Realized oil price volatility are listed in tables 19 and 20.

The next robustness check is in table 21. It includes zeros in the calculation of price change dispersion. We see that even after including price changes of zero, that oil price volatility increases price change dispersion. Lastly, table 22 includes controls for lags of all variables and reports the sum. The reported total effect is similar to a one period regression.

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

$$Y_{j,t} = \eta * (so,j * \Delta log(P^o_{t-1})) + \lambda * (so,j * \sigma_{t-1}) + \gamma' X_{j,t} + \alpha_j + \alpha_t + \epsilon_{jt} \tag{57}$$

where $Y_{j,t}$ is industry level price change frequency. The results are in table 23. There is no evidence that oil price volatility affects price change frequency.

Using a higher level of aggregation does not impact the baseline results. Table 24 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 more heterogeneity within an industry due to aggregation.

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 17: 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 *** $p < .01$.

B.9 Price Data Comparison

Figure 9 shows producer price inflation plotted against consumer price inflation for the sample period. The month over month producer inflation rate is more volatile than the consumer inflation rate. The correlation between the two series is 0.82. The price setting statistics are broadly similar except for a lower fraction of small price changes in the PPI. 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 are 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

Dependent Variable: IQR of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	-0.268**	-0.271**	-0.267**	-0.228*
	(0.118)	(0.119)	(0.131)	(0.119)
$s_{o,j} * \sigma_{t-1}$	2.168**	2.177**	2.184*	1.945**
	(1.007)	(1.009)	(1.112)	(0.967)
$\pi_{j,t}$		0.029	0.018	0.018
		(0.106)	(0.085)	(0.082)
$\Delta IP_{j,t}$			0.003	0.002
			(0.008)	(0.008)
$\text{PriceDisp}_{j,t-1}$				0.133***
				(0.042)
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	10,939

Table 18: Industry Specific Coefficient: IQR

Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	-0.043	-0.052	-0.127	-0.097
	(0.113)	(0.115)	(0.114)	(0.109)
$s_{o,j} * \sigma_{t-1}$	2.624***	2.676***	2.894**	2.693**
	(0.956)	(0.980)	(1.083)	(1.014)
$\pi_{j,t}$		0.085	0.091	0.091
		(0.116)	(0.111)	(0.109)
$\Delta IP_{j,t}$			0.000	-0.003
			(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

Table 19: GARCH Oil Price Volatility

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

Dependent Variable: Standard Deviation of Price Change

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.134	0.127	0.014	0.039
	(0.127)	(0.127)	(0.092)	(0.088)
$s_{o,j} * \sigma_{t-1}$	1.747***	1.766***	1.502***	1.428***
	(0.578)	(0.586)	(0.518)	(0.493)
$\pi_{j,t}$		0.080	0.081	0.082
		(0.117)	(0.114)	(0.111)
$\Delta IP_{j,t}$			0.002	-0.002
			(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 20: Realized Oil Price Volatility

Dependent Variable: Standard Dev of Price Change with Zeros

	(1)	(2)	(3)	(4)
$s_{o,j} * \Delta log(P^o_{t-1})$	0.002	-0.018	-0.043	-0.025
	(0.036)	(0.043)	(0.044)	(0.040)
$s_{o,j} * \sigma_{t-1}$	2.114***	2.175***	2.254***	2.031***
	(0.693)	(0.731)	(0.815)	(0.731)
$\pi_{j,t}$		0.196***	0.195***	0.194
		(0.071)	(0.070)	(0.068)
$\Delta IP_{j,t}$			0.004	0.002
			(0.007)	(0.007)
$\text{PriceDisp}_{j,t-1}$				0.112***
				(0.018)
Time & Industry FE	Yes	Yes	Yes	Yes
Number of Industries	81	81	63	63
N	13,606	13,606	10,946	10,939

Table 21: Stochastic Volatility of Oil Prices

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.

Table 22: Oil Volatility and Price Setting Behavior-NAICS 4

Dependent Variable: Standard Deviation of Price Change

	SV		RV		GARCH	
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=0}^{3} \theta_j \Delta log(P^o_{t-i})$	-0.561		-0.416		-0.548	
	(0.360)		(0.305)		(0.328)	
$\sum_{i=0}^{3} \theta_j \sigma_{t-i}$	2.658**		2.155**		3.370***	
	(1.002)		(1.028)		(1.255)	
$\sum_{i=0}^{3} \pi_{j,t-i}$	0.039		0.026		0.054	
	(0.127)		(0.131)		(0.123)	
$\sum_{i=0}^{3} \Delta IP_{j,t-i}$	-0.010		-0.008		-0.014	
	(0.054)		(0.054)		(0.055)	
$\sum_{i=1}^{3} \theta_j \Delta log(P^o_{t-i})$		-0.227		-0.265		-0.397
		(0.249)		(0.196)		(0.260)
$\sum_{i=1}^{3} \theta_j \sigma_{t-i}$		2.771***		1.771*		2.601**
		(0.980)		(0.097)		(1.180)
$\sum_{i=1}^{3} \pi_{j,t-i}$		0.041		0.036		0.059
		(0.127)		(0.128)		(0.121)
$\sum_{i=1}^{3} \Delta IP_{j,t-i}$		-0.012		-0.013		-0.016
		(0.054)		(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

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

Dependent Variable: Frequency of Price Change

	(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)
PriceDisp$_{j,t-1}$				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 23: Oil Volatility and Price Setting Behavior

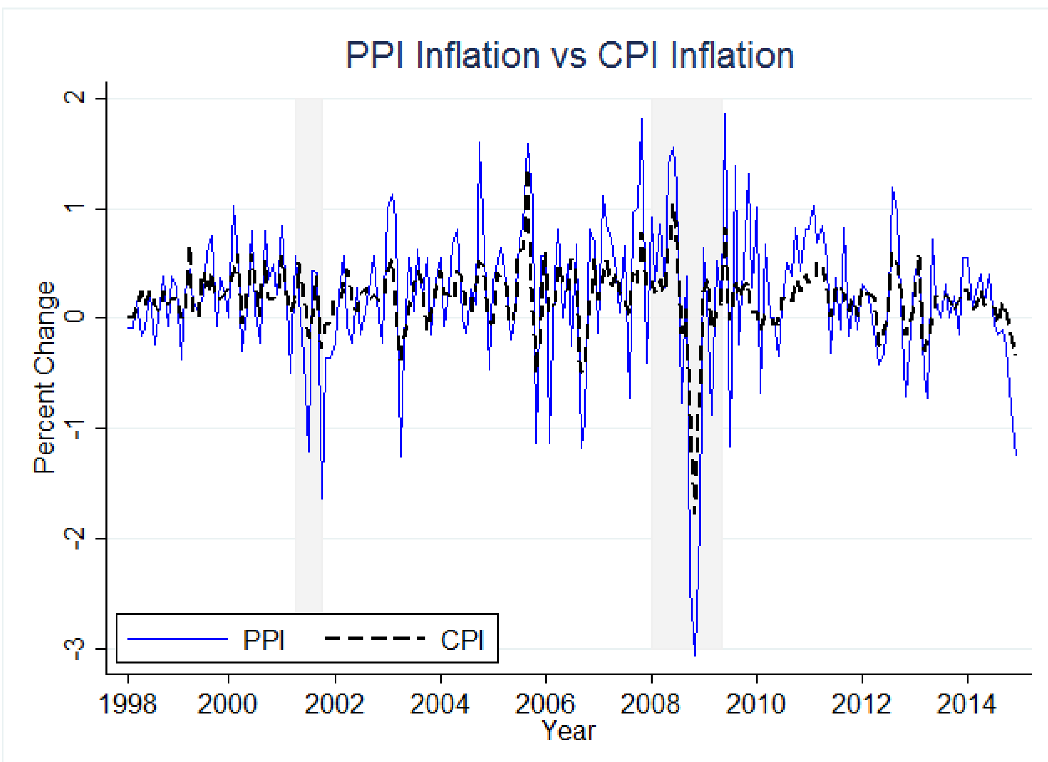


FIGURE 9: Monthly PPI Inflation and CPI Inflation
NOTE: Consumer Price index for all Urban Consumers and Producer Price Index by Commodity for Finished Goods. Both indices are seasonally adjusted.

Table 24: 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)
$\theta_j \Delta log(P^o_{t-1})$	-0.047	-0.025	-0.019	0.010	0.113	0.115	-0.128	-0.126	-0.118
	(0.158)	(0.206)	(0.207)	(0.175)	(0.222)	(0.223)	(0.158)	(0.202)	(0.203)
$\theta_j \sigma_{t-1}$	2.265*	2.551**	2.492***	1.433	2.218***	2.174***	2.760***	2.621***	2.551***
	(1.196)	(1.007)	(0.991)	(0.894)	(0.508)	(0.490)	(0.725)	(0.793)	(0.774)
$\pi_{j,t-1}$		-0.155	-0.167		-0.154	-0.165		-0.152	-0.164
		(0.12)	(0.118)		(0.119)	(0.117)		(0.118)	(0.117)
$\Delta IP_{j,t}$			0.056			0.055			0.056
			(0.043)			(0.043)			(0.043)
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. Robust asymptotic standard errors reported in parentheses are clustered at the industry level: * $p < .10$; ** $p < .05$; and *** $p < .01$.