The Real Effects of Monetary Shocks: Evidence from Micro Pricing Moments

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Abstract

We demonstrate an easy-to-use approach how to empirically evaluate potentially sufficient "micro" moments for the response of aggregate "macro" variables to policy shocks of interest. We do so entirely by example, by evaluating the sufficiency of micro pricing moments for the aggregate real effects of monetary policy shocks. First, while only 4 out of 8 candidate moments are informative about monetary non-neutrality when considered one at a time, only frequency of price changes is robustly informative. Second, none of our moments are empirically sufficient statistics for monetary non-neutrality because other variables are also informative for monetary non-neutrality. On the theory side, we show how our conditionally identified micro-macro moments can be used to make modeling choices and direct modeling efforts.

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I Introduction

A widely popular approach in recent years to discipline and evaluate models has been the use of micro data. In this context, we demonstrate an easy-to-use approach how to empirically evaluate potentially sufficient "micro" statistics for the response of aggregate "macro" variables to policy shocks of interest. We do so entirely by example, by evaluating the sufficiency of micro pricing moments for the aggregate real effects of monetary policy shocks, which is a first-order question in macroeconomics. However, our analysis can be also seen as an illustration of a more generally applicable way of using micro data to evaluate model predictions for a policy shock of interest.

Within our expository example, our analysis considers a large number of popular pricing moments: the frequency of price changes, kurtosis, kurtosis over frequency, average size, the standard deviation, the fraction of small price changes, the fraction of positive changes and the standard deviation of the price duration. Frequency is consistently informative and statistically significant for understanding monetary non-neutrality. Conditional on price change frequency, we find no evidence that higher order moments of the price change distribution are directly relevant for monetary non-neutrality. Other popular moments such as kurtosis of price changes have a relationship with monetary non-neutrality that is ambiguous and statistically insignificant. Kurtosis over frequency of price changes is informative about monetary non-neutrality but as we show only because frequency has a negative association.

Yet, even if some of these moments are informative about monetary non-neutrality, we show that none are sufficient statistics.[1] All the moments we consider are no sufficient statistics because they fail to pass a few simple hurdles inherent to any meaningful definition of sufficient statistics. First, we find that inclusion of other moments and variables is also informative about monetary non-neutrality. Moreover, any combination of moments we consider at best explains approximately half of the variation in monetary non-neutrality. This leaves the other half unaccounted for, and our moments insufficient.

On a positive note, however, such failure of pricing moments to serve as empirically

[1] What a sufficient statistic is in macroeconomics is surprisingly not precisely defined in the literature. While we do not aim to remedy this situation, our approach builds on the idea of a formula that sufficiently summarizes the response of a key variable of interest to an identified structural shock as in Nakamura and Steinsson (2018b). As a corollary, other variables should not add information to this sufficient summary nature. Statistically, in particular explanatory power of the formula with respect to the variable of interest should be extremely high and perfect in an ideal setting.

sufficient statistics does not mean that a focus on micro data is misguided when we try to evaluate the real effects of monetary policy, or make model choices. In fact, the opposite is true. Such failure calls for even more circumspect analysis using micro data. Our approach of tying micro to macro moments provides a way to do so: Conditional micro-macro moments are revealing about the question at hand – even if they have no differential effect. Modeling that only targets micro moments or macro moments may either draw macro implications that are not consistent with the data, or use a model micro mechanism that is empirically invalid. Consider for example the moment of kurtosis. There is no evidence from our data that increasing kurtosis leads to larger consumption responses. Therefore models that hinge on kurtosis to generate monetary non-neutrality are not consistent with the data. It is not kurtosis per se, but the model mechanism that generates excess kurtosis that can be related to monetary non-neutrality. We make exactly this point in detail in our model section.

An appealing feature of our approach for the policy-maker who aims at conducting counter-factual policy analysis may further lie in the following: Our approach is good at describing dynamics conditional on a small, specific shock in *normal* times. By contrast, model choice in practice that employs micro data is often made by requiring models to fit during particular, exceptional episodes – and unconditionally on a shock. For example, Gagnon (2009) evaluate the performance of Calvo versus menu costs for the Tequila crisis in Mexico, Alvarez et al. (2019) during hyperinflation in Argentina, Nakamura et al. (2018) for the Great Inflation in the U.S. in the 1970s, or Karadi and Reiff (2018) for VAT changes in Hungary. While these papers target momments in vey specific times, our approach provides moments that can be used to evaluate models more generally. We happily acknowledge however, that we may want our models to fit precisely in exceptional times - a necessity that depends on the policymaker's objective.

The details of our analysis are the following. Our analysis sets out by establishing empirical regularities for the response of prices and quantities, conditional on a monetary policy shock, but also conditional on micro moments. These conditional moments will be our "micro-macro" moments. As such, generating them necessarily involves both micro and macro data. On the macro side, we obtain a measure of monetary non-neutrality by computing the conditional impulse responses of prices. These impulse response functions to a monetary shock are estimated using standard methodologies, but also conditional on micro price moments. For example, we compute the impulse response of prices following a monetary shock when the kurtosis of price changes is above its median versus below its median in the data. The micro side comes in by conditioning on micro price moments when choosing the set of prices to compute impulse responses. For example, we compute the impulse response of prices following a monetary shock when the kurtosis of sectoral price changes is above its median versus below its median across sectors in the data.

We identify monetary policy shocks using three conventional identification schemes. First, we follow the Romer and Romer (2004) narrative approach of identifying the effect of monetary policy shocks. Second, we identify monetary policy shocks using a high-frequency approach as in Bernanke and Kuttner (2005), Gertler and Karadi (2015) or Nakamura and Steinsson (2018a). Finally, we employ a FAVAR approach as in Boivin et al. (2009) to identify the effect of changes in the federal funds rate.

We establish the nexus between monetary policy shocks and pricing moments in two ways. Both approaches imply the same message for the informativeness and sufficiency of moments.[2] The first approach presents a more aggregate summary while the second exploits the micro nature of the data. As our first approach, we classify the PPI inflation data into only two subsets, exploiting the micro price data that underlie the producer price index (PPI) at the Bureau of Labor Statistics (BLS). One subset is above and the other subset below the median of a proposed explanatory pricing moment. Here we compute pricing moments at the six-digit-NAICS-month level and then average the moment within a sector over time before sorting sectors. Next, we compute a weighted index of PPI inflation for each subset, for example, a price index for sectors with an above-median kurtosis of price changes. We then use these indices to compute impulse responses following a monetary policy shock, using the local projection methodology of Jordà (2005) and the single equation methodology of Romer and Romer (2004). In our FAVAR setting, we compute impulse responses for each six-digit NAICS sector and present results by averaging responses in each subset.

We find from all our analyses based on this first approach that prices are more responsive to monetary policy shocks for the index made up of sectors with an above-median frequency of price changes, compared to the index made up by sectors with a below-median frequency. Prices are less responsive for the index made up of sectors with

[2]Due to data restrictions, we are able to consider mainly 4 moments in parts of the anaysis.

a below-median kurtosis over frequency, or standard deviation of price spell durations. There is also a slightly stronger responses for an index made up of below-median fraction of positive price changes. However, the responsiveness of both indices sorted by kurtosis is almost identical when we use the narrative and the high-frequency approaches. From the FAVAR identification, the response of prices even goes in the opposite direction: prices in the high-kurtosis subset now respond by *more* and not by less. This result not only makes the kurtosis relation ambiguous but is also is at odds with the notion in the pricing literature[3] of larger real and smaller nominal responses when kurtosis is higher. In the FAVAR analysis, high or low average size, standard deviation of price changes and fraction of small price changes bear no differential relation with monetary non-neutrality.

Finally, as our key exercise, we use regression analysis to establish two results: First, only frequency has a robust relation with monetary non-neutrality. Second, however, none of our moments passes some basics hurdles to serve as sufficient statistics. These results follow from several steps. First, we regress each sectoral cumulative impulse response on each pricing moment individually. We tend to confirm the above aggregate relationships while also controlling for sectoral fixed effects. The regression results also reveal that frequency has a substantially higher explanatory power than any other moment, around 50%. Kurtosis in particular is not significant and explains the least variation while only average size and standard deviation of duration also have a significant relationship. Explanatory power far below 100% suggests that our moments are no quite sufficient. Second, when we throw in the kitchen sink of all moments plus additional covariates, only frequency retains a significant relationship, and we explain 59% of variation in monetary non-neutrality. However, this last step of analysis further emphasizes that neither of our 8 moments can be a sufficient statistic. For example, we find that profits or the persistence of sectoral shocks also can be significant and informative for monetary non-neutrality. They also add explanatory power to the regressions.

As our second approach, we solidify our results by exploiting the micro nature of our data. To this end, we regress real sales at the firm level on firm-level pricing statistics interacted with our measures of the monetary policy shock. The advantage of this firm-level analysis – beyond verifying results with a measure of real output rather than its nominal inflation complement – lies in our ability to control for firm-level fixed effects.

[3]See for example Vavra (2014): "Midrigan (2011) shows that greater kurtosis leads to a reduction in price flexibility."

The analysis also happens at a much finer level of disaggregation which illustrates the role of different aggregation levels. We find that exactly the same results hold as in the analysis that measures monetary non-neutrality using price responses at the six-digit NAICS level. For example, variation in the kurtosis of price changes given frequency has no significant interaction effect with monetary policy shocks.

Drawing on our empirical results, we demonstrate in our modeling part of the analysis how our micro-macro moments can be use to guide modeling and the selection of modeling ingredients. We show this through the lens of an important class of pricing models, menu cost models, and three key moments: frequency, kurtosis and kurtosis over frequency of price changes. In particular, kurtosis of price changes plays an important role in the menu cost literature, as it is understood to embody the extent of the so-called selection mechanism: When kurtosis is large, ceteris paribus, then monetary non-neutrality should be large. However, our results show that kurtosis may be empirically irrelevant for monetary non-neutrality. Can menu cost models still generate predictions in line with our empirical conditional impulse response functions?

We first show that menu cost models can indeed match our empirical price responses, in particular the model does not generate a strong positive association between kurtosis and monetary non-neutrality. We show this by calibrating a state-of-the-art menu cost model to match the CPI pricing moments in Vavra (2014). As we vary one target moment at a time, this variation enables assessment of how such variation changes the real effects following a monetary shock, just like in our empirical exercise. In particular, we shock the model for each calibration with a one month doubling of log nominal output of size 0.2%. First, we find a higher frequency of price changes leads to a smaller cumulative consumption response, in line with intuition. Second, an increase in kurtosis of price changes decreases monetary non-neutrality, unlike the notion in the literature but in line with our empirical findings, where the relation is ambiguous and can even have a negative sign. Third, the relationship of kurtosis over frequency with monetary non-neutrality is non-monotonic and can be negative. We further verify that these predictions also hold in a simplified model, the discrete-time version of Golosov and Lucas (2007).[4]

[4]While not the focus of our paper, we note that kurtosis can vary within the discrete-time version of the Golosov and Lucas (2007) model. Unlike in a continuous-time setting like Alvarez et al. (2016) where the mass of price changes at the Ss bands is always zero and kurtosis given frequency is always unity, this mass is not zero in discrete time. Hence, kurtosis of the distribution can vary with model parameters.

Next, our model exercise demonstrates the value of using our "micro-macro" moments to evaluate underlying model mechanisms. We do so by showing how to reconcile with our analysis the notion in the pricing literature that after conditioning on frequency, greater kurtosis leads to more monetary non-neutrality. The answer is simple: The use of random menu costs can generate this counterfactual relationship, by positively and directly linking kurtosis to the degree of Calvoness, and thus monetary non-neutrality in a model. When the fraction of random, small price changes increases as implied by the introduction of random menu costs, the larger mass of small price changes can increase kurtosis. But these random changes have zero selection by construction; they are not adjusting in response to a monetary shock. Therefore, they also increase monetary non-neutrality. These results show that the source of kurtosis through the model mechanisms is what matters, not the unconditional pricing moment itself. This insight incidentally validates our empirical findings of an unstable relationship of kurtosis, due to potentially differential technologies firms may use. Our results thus show how micro pricing moments when tied to the macro level can be helpful for evaluating what model ingredients are necessary. More generally, our analysis suggests that a fruitful test of models can be to link micro moments directly to macro moments.

We organize the paper as follows. Section II describes the underlying micro pricing data and our empirical methodology. Section III establishes the empirical regularities that compare impulse response functions across different values of micro moments. Section IV presents the modeling setup. Section V presents our model results, and Section VI concludes.

A. Literature review

Our main contribution lies in providing empirical insights about what micro pricing moments are informative for monetary non-neutrality following monetary policy shocks. In particular, we demonstrate that none of these moments take reasonable hurdles to be sufficient statistics. However, our analysis can also be seen as illustration of a more generally applicable way of using micro data to evaluate model predictions for a policy shock of interest.

As suggested, our analysis speaks most directly to the sufficient statistics approach for the effect of monetary policy shocks. This approach proposes sufficient statistics across a wide class of models to fully pin down monetary non-neutrality, as for example in recent work by Alvarez et al. (2016) and Baley and Blanco (2019).

Our contribution is to show how to empirically evaluate a large set of sufficient statistic candidates, by providing empirical impulse response functions in samples split along different values of the sufficient statistic as well as its components. These empirical impulse response functions allow us to evaluate whether this sufficient statistics approach is indeed sufficient with respect to empirically measured monetary non-neutrality (or any other object of interest). We show that empirically only frequency matters as expected. This finding stands in contrast to a large menu cost literate which sees kurtosis or higher moments as informative for monetary non-neutrality.[5]

We also relate to the recent literature that shows that conventional pricing moments may not even theoretically be sufficient statistics for monetary non-neutrality as proposed in the literature. Dotsey and Wolman (2018), Karadi and Reiff (2018) and Baley and Blanco (2019) analyze sophisticated menu costs models to make such arguments. We emphasize the fragility of kurtosis as a sufficient statistic by making clear in our theory section that small changes in modeling assumption relate to monetary non-neutrality, not simply kurtosis as a moment. On the one hand, even in a simple menu cost model, calibrated to CPI micro moments, kurtosis of price changes can predict lower monetary non-neutrality. On the other hand, we show why many models predict a positive relationship between kurtosis and non-neutrality. Menu cost models predict a positive relationship only when random menu costs are the source of excess kurtosis and the degree of Calvoness of the model.

Our analysis builds on advances by several papers that have pushed the modeling frontier. Building on the model of Golosov and Lucas (2007), work by Midrigan (2011) showed that menu cost models can generate large real effects. Key to this result is a multi-product setting where small price changes take place, as well as leptokurtic firm productivity which generates large price changes. Nakamura and Steinsson (2010) have further developed a Calvo-plus model featuring occasional nearly free price changes. This modeling trick generates price changes in the Calvo setting similar to a multi-product

[5] Alvarez et al. (2016) propose kurtosis given frequency as a sufficient statistic. However, a further sufficiency condition in their paper is that monetary shocks are normalized by the standard deviation of price changes as one moves cross calibrations or models. We interpret sufficiency based on a measure of monetary non-neutrality following the same sized shock across comparisons. Hence, when we consider kurtosis over frequency as one of our moments, we are not testing Alvarez et al. (2016).

menu cost model. Our model setup takes into account these advances in modeling assumptions.

Our work also contributes to the literature providing evidence on the interaction of sticky prices and monetary shocks. Gorodnichenko and Weber (2016) show that firms with high frequency of price change have greater conditional volatility of stock returns after monetary policy announcements. In contrast, Bils et al. (2003) find that when broad categories of consumer goods are split into flexible and sticky price sectors, that prices for flexible goods actually decrease relative to sticky prices after an expansionary monetary shock. Mackowiak et al. (2009) study the speed of response to aggregate and sectoral shocks and find that while higher frequency sectors respond faster to aggregate shocks, the relationship between sectoral shocks and frequency is weaker and potentially negative.

Finally, we also contribute to the large and growing literature that studies the heterogeneous response to monetary shocks. Cravino et al. (2018) is closest to our work, who empirically show that high-income households consume goods which have stickier, and less volatile prices than middle-income households. Kim (2016) presents related results.

II Data and Methodology

This section lays out how we use micro moments – which may be candidate sufficient statistics – to inform us about key policy variables of interest. Our key policy variable of interest is monetary non-neutrality following a monetary shock, and we have a set of 8 micro price moments. Our approach however is not restricted to the specifics we present here. Micro moments in any setting can analogously be related to the response of key policy variables to an identified shock.

Our general approach is to construct a measure of monetary non-neutrality, our key policy variable of interest and macro moment, and relate it to micro pricing moments. We do so by first generating empirical impulse response functions of the price level or output following a monetary policy shock, using several independent methodologies. However, we do not generate these impulse response functions conditionally on monetary shocks only. We generate the impulse responses to monetary shocks conditional on both high and low levels of pricing moments which we consider one at a time. Second, we also employ regression techniques to quantify the exact statistical relationship between measures of monetary non-neutrality and these moments at the firm and sectoral levels.

We next describe our data, and then how the specific methodologies use it.

A. Data

Our main dependent variables of interest are 154 producer price (PPI) inflation series from Boivin et al. (2009), which allow us to measure monetary non-neutrality. This dataset also includes various further macroeconomic indicators and financial variables. Some examples of these indicators are measures of industrial production, interest rates, employment and various aggregate price indices. We also include disaggregated data on personal consumption expenditure (PCE) series published by the Bureau of Economic Analysis, consistent with Boivin et al. (2009). Due to missing observations, we remove 35 real consumption series and are left with 194 disaggregated PCE price series. The resulting data set is a balanced panel of 653 monthly series, spanning 353 months from January 1976 to June 2005. As in Boivin et al. (2009), we transform each series to ensure stationarity.

We sort the 154 sectors for which we have PPI inflation rates into an above-median and below-median set according to these three moments of interest: Frequency of price changes, kurtosis of price changes, kurtosis over frequency, average size, standard deviation of price durations, the fraction of small price changes or the fraction of positive price changes. This requires us to have sectoral price-setting statistics. We obtain them by additionally exploiting the underlying micro price data from the PPI at the BLS. For each of the corresponding 154 series, we construct sector-level price statistics using PPI micro data from 1998 to 2005. We compute pricing moments at the sectoral-month level, and then take averages over time at the respective six-digit NAICS industry level, each of which corresponds to one of the 154 series. We can then assign sectors into above-median and below-median subsets for any given moment of interest and compute the average inflation rate in each subset.

We complement these sector-level inflation series with data at the firm-level that includes sales data and pricing moments. Due to data restrictions we compute 4 pricing moments: frequency, kurtosis, kurtosis over frequency and standard deviation of price durations. We compute the same three pricing moments using the PPI micro data for the 584 firms which were matched to Compustat data in Gilchrist et al. (2017). The pricing data is available from 2005 through 2014. Similar to the sectoral calculations above, we pool all price changes within a firm over time to calculate firm moments. We merge firm-level sales from Compustat into this dataset to get a measure of output for our subsequent analysis. In order to compute higher moments of the price change distribution, we restrict our sample to those firms with a minimum of 15 price changes over the full sample period leaving 309 firms in the analysis.

To avoid measurement error in the calculation of kurtosis as pointed out by Eichenbaum et al. (2014), we follow the approach suggested in Alvarez et al. (2016). We drop all price changes less than 1 cent and more than the 99th percentile of the absolute price change distribution. We disregard the $25 upper bound on price levels as in Alvarez et al. (2016) since it does not meaningfully apply to PPI micro data. We present several additional ways of addressing measurement error in our robustness section, including the instrumental variables approach in Gorodnichenko and Weber (2016). We also note that our analysis considers 2 different levels of aggregation – firms versus sectors – which allows us to see the effect of different levels of aggregation for the informativeness of pricing moments for measures of monetary non-neutrality.

Next, we describe the methodologies we use to relate pricing moments to the measures of monetary non-neutrality following monetary policy shocks. If there is data particular to each identification scheme for the effect of monetary policy shocks, we describe it in each subsection below.

B. Empirical Response to Romer and Romer Shocks

As a first approach to identify the effect of monetary policy shocks, we follow the narrative approach in Romer and Romer (2004). The original Romer and Romer (2004) monetary policy shocks are calculated as residuals from a regression of the change in the federal funds rate on the information set of Federal Reserve Greenbook forecasts. The original series is available from January 1969 to 1996. Using the same methodology, Wieland and Yang (2016) have extended the series up to December 2007. We use monthly industry level PPI inflation data from January 1976 to December 2007 for 154 six-digit NAICS industries.

We use the impulse response of prices to a monetary shock to measure monetary non-neutrality. We then sort prices into two bins according to high or low pricing moments. This sorting allows us to obtain differential responses for the prices by estimating the following local projections:

$$\begin{aligned} log(ppi_{j,t+h}) &= \beta_h + I_{PS>M}[\theta_{A,h} * MPshock_t + \varphi_{A,h} z_{j,t}] \\ &+(1 - I_{PS>M})[\theta_{B,h} * MPshock_t + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h} \end{aligned} \tag{1}$$

where $I_{PS>M}$ is a dummy variable that indicates if the price level is for the above-median set according to the three pricing moments of interest to generate a potentially differential response. $\theta_{j,h}$ is the impulse response of the price level to a Romer-Romer shock h months after the shock for the average industry in the above-median or below-median set indexed by j according to one of the three pricing moments of interest. $z_{j,t}$ are controls that include two lags of the RR shock, two lags of the Fed Funds rate, and current and two lags of the unemployment rate, industrial production, and price level. $MPshock_t$ refers to the extended Romer and Romer monetary shock series. The dependent variable is the average PPI in the high or low subsets described above in the data section. We have normalized the monetary shock such that an increase in the shock is expansionary.

As an alternative specification, we also follow the original Romer and Romer regression specification. This specification uses a lag structure instead of local projections, and inflation as a dependent variable:

$$\pi_{j,t} = \alpha_j + \sum_{k=1}^{11} \beta_{j,k} D_k + \sum_{k=1}^{24} \eta_{j,k} \pi_{j,t-k} + \sum_{k=1}^{48} \theta_{j,k} MP_{t-k} + \epsilon_{j,t} \tag{2}$$

We estimate each regression separately for the average industry inflation rate $\pi_{j,t}$ above and below the median value of each proposed pricing moment to estimate the differential inflationary responses following a monetary policy shock where j indexes above-median or below-median for each pricing moment. Following the estimation of the above specification, the estimated impulse response of interest is contained in the parameter estimates of $\theta_{j,k}$.

Considering the price response of the two subsets of the economy as informative for the relationship between monetary non-neutrality and pricing moments that differ across subsets is justified on the following grounds. Variations in pricing moments across subsets are indicative of variations in monetary non-neutrality as long as there are no strong general equilibrium effects and complementarities in the responses across subsets. We verify this approach in a calibrated two-sector model of the U.S. economy. Figure 10 in Appendix A illustrates the findings: Differences in key pricing moments are associated with distinct predictions for sectoral price impulse responses.[6]

C. Empirical Response to High Frequency Shock Identification

As a second approach to identify the effect of monetary policy shocks, we use the high frequency identified monetary shocks of Gertler and Karadi (2015). Their series is available from January 1990 through June of 2012. Complementary to this identification, we also use the series of high-frequency identified monetary policy shocks of Nakamura and Steinsson (2018). We use their data from January 1995 through March 2014.

We use the impulse response of prices to a monetary shock to measure monetary non-neutrality. We obtain responses for the prices sorted into two bins according to high or low pricing moments by estimating the following local projections:

$$\begin{aligned} log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} * MPshock_t + \varphi_{A,h} z_{j,t}] \\ +(1 - I_{PS>M})[\theta_{B,h} * MPshock_t + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h} \end{aligned} \tag{3}$$

where $I_{PS>M}$ is a dummy variable that indicates if the price level falls into the above-median set according to the three pricing moments of interest to generate a potentially differential response. $\theta_{j,h}$ is the impulse response of the price level to a high frequency identified shock h months after the shock for the average industry in the above-median or below-median set j according to one of the three pricing moments of interest. We control for the same variables as in the Romer and Romer identification above. $z_{j,t}$ are controls that include two lags of the monetary policy shock, two lags of the Fed Funds rate, and current and two lags of the unemployment rate, industrial production, and price level. The dependent variable is the average PPI in the high or low subsets described above in the data section.

To complement our sector-level analyses, we also estimate a firm-level specification that employs the high-frequency identification scheme, and focuses on output instead of

[6] We thank Adrien Auclert for pointing out the value of model guidance for our empirical strategy in this context. A similar result in Boivin et al. (2009) also supports our approach: The average of sectoral IRFs closely resembles the aggregate IRF following a monetary policy shock.

prices. We estimate the following specification:

$$log(sales_{j,t+h}) = \alpha_{th} + \alpha_{jh} + \theta_h * MPshock_t \times M_j + controls_t + \epsilon_{j,t+h} \tag{4}$$

where α_{th} are time fixed effects, α_{jh} are firm fixed effects, and $sales_{j,t+h}$ denotes firm j real sales at time t measured at quarterly frequency h months after the shock. We also include time and firm fixed effects, and monetary policy shocks are measured by the high-frequency identified shock. Controls further include 4 quarters of lagged log real sales, and current and 4 lags of log assets. M_j contains one of our three firm-level pricing moments: the firm-level frequency of price changes, the kurtosis of price changes, or the ratio of the two statistics. The estimated coefficients θ_h measure how the sales response to the monetary policy shock h months into the future depends on the firm's pricing moments M_j.

To assess the relative importance of frequency and kurtosis for monetary non-neutrality, we also include the interaction of monetary policy shocks with both frequency and kurtosis jointly on the right-hand side. This joint interaction allows us to understand the extent to which each pricing moment is jointly informative for monetary non-neutrality.

D. Empirical Responses to Monetary Shocks: FAVAR

Our third approach to obtain impulse response functions in the different subsets of the data follows the factor-augmented vector autoregressive model (FAVAR) in Boivin et al. (2009). In this third approach, we identify the monetary policy shock with a federal funds rate shock that drives the impulse responses. We refer the reader for details of the FAVAR approach to Boivin et al. (2009). The appeal of the FAVAR lies in drawing from a large set of variables containing information on macroeconomic and sectoral factors enabling us to better identify policy shocks than standard VARs.

We first use the FAVAR to generate PPI inflationary responses $\pi_{k,t}$ for each sector k:

$$\pi_{k,t} = \lambda'_k C_t + e_{k,t} \tag{5}$$

In the FAVAR setting, this sectoral inflationary response is given by the loading λ'_k on the VAR evolution of the common components C_t. This component in turn includes the evolution of the federal funds rate which we shock.

Monetary policy shocks are identified using the standard recursive assumption. The Fed Funds rate may respond to contemporaneous fluctuations in the estimated factors, but none of the common factors can respond within a month to unanticipated changes in monetary policy. Given the estimated FAVAR coefficients, we compute estimated impulse resposne functions for each of the k sectors. We then compute the mean of the impulse response at each horizon h in the two subsets of the data characterized as above-median and below-median according to each pricing moment of interest. These series embody the response of inflation following a monetary policy shock, conditional on high and low levels of a given micro moment.

Finally, we use the estimated sectoral impulse responses to more quantitatively assess the importance of our pricing moments for monetary non-neutrality. To do so, we regress the cumulative sectoral price responses on the pricing moments, taking into account broader industry fixed effects:

$$log(IRF_{k,h}) = a + \alpha_j + \beta' M_k + \gamma' X_j + \epsilon_{k,h} \tag{6}$$

where $log(IRF_{k,h})$ denotes the cumulative response of prices for an h-month horizon in sector k. α_j are six-digit NAICS fixed effects as additional control variables to control for any common factors across broad industries, and X_j are other industry level covariates such as profit. As before, M_k contains one of our industry-level pricing moments: the industry-level frequency of price changes, the kurtosis of price changes, the ratio of the two statistics, the average size of price changes, and the standard deviation of price change. To assess the relative importance of each pricing moment for monetary non-neutrality, we also include all moments jointly as explanatory variables. This joint interaction allows us to understand the extent to which each pricing moment is jointly informative for monetary non-neutrality.

As a specific test of sufficiency of our main moments, we also include the size of price changes and their dispersion, both individually and jointly with kurtosis and frequency. As additional controls, we also use profits and the persistence of idiosyncratic shocks from Boivin et al. (2009). None of these should be significant or informative if kurtosis, frequency or their ratio are indeed sufficient statistics.

III Empirical Results

In this section, we present our main empirical results. Among our 8 moments, 4 show a statistically significant relation with monetary non-neutrality when considered one at a time. However, only frequency of price changes has a robust relationship. Interestingly, kurtosis of price changes has none, or even a negative association, contrary to the notion in the literature. Kurtosis over frequency of price changes can, taken separately, be informative about monetary non-neutrality but only because the frequency has a strong negative association with non-neutrality. Neither pricing moment by itself or in combination is a sufficient statistic because they explain at best approximately half of the variation in monetary non-neutrality. In particular, inclusion of other variables also yields significant relationships with monetary non-neutrality and further explains variation.

A. Monetary Non-Neutrality and Pricing Moments

Across all of our three identification schemes and specifications, price-setting moments relate to monetary non-neutrality in very similar ways. We present our more aggregate results first, and then our firm-level and regression results.

A.1 Narrative Approach

First, both specifications that rely on the Romer and Romer identification scheme yield nearly identical results at the aggregate levels. We summarize the findings from the local projection specification in equation 1 in Figure 1 while Figure 10 summarizes the findings from the autoregressive specification in equation 2. Both figures present the response to a one percent decrease in the realization of the policy measure.

In terms of frequency, we find that low price change frequency sectors have a smaller price response to the monetary shock than the high frequency sectors. This implies that they have a larger real output response. Figure 1 and Figure 10 each show this relationship in Panels a. We note that monetary policy shocks begin to yield price responses with at least 24 months lag if we consider equation 1 which is consistent with the findings in Romer and Romer (2004).

In terms of kurtosis, we find what we call "irrelevance of kurtosis." Based on the local projection specification, results show that the price response in the high and the low kurtosis sectors is not statistically significantly different from one another. Figure 1 Panel b summarizes this result. The autoregressive specification makes a very similar if not stronger case for the irrelevance of kurtosis. Panel b in Figure 10 shows the associated impulse response.

In terms of kurtosis over frequency, our results show that high kurtosis over frequency has a positive association with monetary non-neutrality. High kurtosis over frequency sectors have a smaller price response to the monetary shock than the low kurtosis over frequency sectors. This implies that they have a larger real output response. Panel c in the figures summarizes the relevant price responses. We note that the impulse response functions are statistically only somewhat different from one another in the local projection specification while highly so in the autoregressive specification. Crucially, however, as the individual results for frequency and kurtosis suggest, the result for the ratio appears to be driven by the result for frequency. We show this point quantitatively rigorously further below using regression analysis.

In terms of our other pricing moments, we find the following results: As we consider Figures 1 and Figure 10, the only clear result arises in Panels d and h. Sectors with a below-median standard deviation of price durations show a statistically larger price response than above-median sectors. Also, sectors with a below-median fraction of small price changes tend to have a significantly stronger price response, at least at an intermediate horizon. Second, as Panel e through g illustrate, the relationship for the average size of price changes, their standard deviation, and the fraction of small price changes is generally not significantly different across above-median and below-median sets.

A.2 High-Frequency Approach

Second, using high-frequency identified shocks confirms the findings from the Romer and Romer identification scheme for frequency and kurtosis over frequency. However, our results further highlight the ambiguous relationship between kurtosis and monetary non-neutrality casting doubt on how informative the moment is for summarizing monetary non-neutrality. Figure 2 summarizes the findings from estimating equation 3, the high-frequency identified monetary shocks using a local projection specification. Panel a continues to show that low price change frequency sectors have a smaller price response to the monetary shock than the high-frequency sectors. Panel c continues to show that low kurtosis over frequency sectors exhibit a stronger price response compared to sectors with a high kurtosis over frequency. These results look quite similar to those from the Romer and Romer local projection shown above in Figure 1.

Strikingly, however, as Panel b shows, higher kurtosis is now associated with a *stronger* price response than lower kurtosis. This implies high-kurtosis sectors have a smaller real output response. This result is significant at most horizons and runs counter to the prevailing fundamental intuition in the menu cost literature. When we use our alternative high-frequency identified shocks following Nakamura and Steinsson (2018a), we find the same results as in Figure 2. Figure 20 in the Appendix presents these results.

Our analysis that uses the matched firm-level data confirms these findings as well. Due to inclusion of firm-level fixed effects in equation 4, these results are particularly robust to any additional cross-sectional variation down to the firm-level. Time fixed effects absorb common macroeconomic shocks, so the coefficient θ_h measures the differential impact of a monetary shock at horizon h depending on the pricing moment M_j. Figure 3 presents our findings. Panel a shows firms with high frequency of price changes have a smaller sales response following an expansionary monetary policy shock. Panel b establishes the "irrelevance of kurtosis" at the firm level. There is no significant difference from 0 in the sales response at most horizons as a function of firm-level kurtosis following a monetary policy shock. Panel c shows that firms with a higher kurtosis over frequency ratio have a larger real response to a monetary policy shock at all horizons. This finding is consistent with the predictions of the proposed statistic. Finally, in Panel d we estimate the specification with kurtosis and frequency jointly included, separately interacted with the monetary shock, to decompose the statistic and find that frequency has a significant negative impact on real sales, while kurtosis has no sigificant impact on real sales.[7]

[7] We confirm these firm-level findings using Romer and Romer shocks. Figure 14 in the Appendix displays the results.

A.3 FAVAR Approach

Third, using a FAVAR approach shows very similar results for the relationship between pricing moments and monetary non-neutrality. Figure 4 presents the implied impulse responses to a surprise 25 basis point, expansionary decrease in the federal funds rate. We plot the average response in the respective above-median set of sectors and in the below-median set of sectors.

In terms of the frequency of price changes, Panel a continues to show that the average impulse response function of the high-frequency sectors has a larger response to monetary shock than low-frequency sectors. This implies smaller real effects of monetary policy. In terms of kurtosis over frequency, Panel c continues to show that low kurtosis over frequency sectors exhibit a stronger price response compared to sectors with a high kurtosis over frequency. These two results look quite similar to those presented above. In terms of kurtosis, Panel b shows results similar to those from the high-frequency identified monetary shocks. Unlike the notion in the literature, high-kurtosis sectors have on average a *stronger* price response than low-kurtosis sectors implying less monetary non-neutrality. Finally, In terms of the standard deviation of price durations, Panel d shows that sectors with a relatively higher standard deviation show a larger price response.[8]

B. Further Results from Regression Analysis

Next, we present key cross-sectional results that confirm our findings in a quantitatively rigorous regression setting. While several moments individually have a statistically significant relationship with monetary non-neutrality, only the frequency of price changes is always robustly informative about monetary non-neutrality. Crucially, we also show that none of our moments take some basic hurdles to be sufficient statistics. Among all pricing moments considered, the specification with frequency alone has the highest explanatory power – but overall, explanatory power is only moderate across specifications. Further, if we include additional controls, they turn out to be informative about monetary non-neutrality too, and explanatory power increases. These findings suggest that neither pricing moment is an empirically sufficient statistic. We now show these results using

[8]As a robustness check, we show that our results continue to hold at more disaggregated levels. Instead of looking at above-median and below-median subsets of data, we present the results when looking at quartiles. Figure 17 in the Appendix shows the results are consistent with our main findings.

both sectoral and firm-level data.

First, we consider the sectoral level. We use as a measure of monetary non-neutrality our cumulated FAVAR estimates of price level responses 24 months after an expansionary monetary shock. We estimate the relationship of cumulated sectoral impulse responses with our key pricing moments in equation 6. We take into account three-digit fixed effects that absorb any systematic differences across sectors. We first estimate the relationships to moments individually, then jointly including frequency and kurtosis, and then pooling all moments. As a complement, we also include profits or the volatility of sector level shocks as controls. Table 1 shows our results.

Our main finding at the sectoral level is that individually, only 4 out of 8 moments have a statistically significant, informative relationship with monetary non-neutrality. These moments are the frequency of price changes, kurtosis over frequency, average size of price changes and the standard deviation of the duration of price spells. Kurtosis, a central moment in the pricing literature, is not significant. Statistical significance of individual moments with monetary non-neutrality is clearly a necessary statistical condition for moments to be sufficient statistics. Hence, 4 moments do not take this first hurdle to be a sufficient statistic.

Two simple further conditions for sufficiency lie in the robustness of the relationship of each moment with monetary non-neutrality, and high, near 100% explanatory power. In terms of robustness, columns (9) and (11) show two of our key results in this regard: In column (9), we include both frequency and kurtosis jointly. Only frequency has a significant relationship with non-neutrality, but not kurtosis, a central moment in the pricing literature. Hence, as our aggregate figures already suggested, it is frequency that drives the relation of frequency over kurtosis with monetary non-neutrality. In column (11), we include all moments jointly. Again, only frequency retains a strong, statistical significance, but no other moments such as kurtosis of price changes. In fact, in both columns (9) and (11), kurtosis exhibits a fragile relationship with monetary non-neutrality as it flips sign. Clearly, frequency is highly informative for monetary non-neutrality while all other moments are not, given frequency. They fail to take this simple first hurdle of robustness.

The importance of frequency is also reflected in the explanatory power across columns. Columns (1) - (8) show that frequency among all individual moments exhibits the highest explanatory power, with 50% of the variation in monetary non-neutrality explained. All other moments only add noise to the explanation of variation in monetary non-neutrality, given frequency. This result can be seen from three columns in particular: Column (1) shows that kurtosis over frequency only has an explanatory power of 43%, lower than frequency by itself in column (2) with 50%. Kurtosis just adds noise if we consider the ratio of frequency over kurtosis. Column (9) shows that including both frequency and kurtosis has approximately the same explanatory power as just frequency. Column (11) adds all moments as explanatory variables jointly. Now, explanatory power is still at 50%.

Does this mean that frequency is a sufficient statistic? Unfortunately, no. First, it should be noted that no pricing moments are completely informative and sufficient in the sense that they do not fully explain monetary non-neutrality. Approximately half of the variation in the price response remains unexplained – even for frequency. Second, even while highly informative, we find that other variables can still add information above and beyond frequency of price changes. The results in the last 2 columns show this result. Here, we include all moments together with additional sector level variables that Boivin et al. (2009) have found to affect the price response. We find that other variables such as profits or the volatility of sector level shocks are also significantly related to the price response, in addition to the frequency (but again not kurtosis).[9] Moreover, the R^2 increases to nearly 59%. If a pricing moment is a sufficient statistic, then no other variables should enter significantly and be informative as an explanatory variable. Clearly, this is not the case, not even for frequency of price changes.

Second, we consider the firm level. Here, decompose the determinants of monetary non-neutrality using our matched firm sample. We regress the log of firm-level sales four quarters after the shock on the interaction of one or multiple pricing moments with the high-frequency shock as in equation 4, including various controls and firm-fixed effects.

Again, findings at the firm level confirm our sectoral regression results from above. The frequency of price changes is the main moment associated with monetary non-neutrality. Table 2 shows the results. Column 0 reports the results when no pricing moment is included. Column 1 shows that higher kurtosis over frequency continues to be associated higher higher monetary non-neutrality, that is, sales. However, as Columns 2

[9]Profit is defined as the sector level average gross profit rate over the years 1997 through 2001. The volatility and persistence of sector level shocks are calculated from the FAVAR.

through 4 show this result is driven by the fact that higher frequency of price changes means lower sales. Kurtosis individually or jointly with frequency is not statistically significant. The percent of variation explained by pricing moments is low as seen by the specification with no pricing moments.

C. Robustness to Measurement Error

We now present several robustness exercises to confirm that our results are unaffected by potential measurement error in kurtosis and other micro moments.

First, we show that our calculations of moments change very little in the above-median and below-median subsets of the data under different trimming methods. Specifically, we examine the different permutations of trimming both small and large price changes as in Table 5 of Alvarez et al. (2016). The only difference is that we replicate the calculations separately for the above-median and below-median sets of each moment of interest. Table 6 in the Appendix shows robustness to various ways of trimming the data. We trim the data according to the type of trimming column. For example, case 0 is our baseline measure of trimming where price changes are dropped if they are less than 1 cent or more than the 99th percentile of the absolute price change distribution. Case 1 then changes the trimming of small price changes to drop them if they are less than 0.1 percent in absolute value, and cases 2 through 8 are similarly explained. We show that both the mean and median pricing statistic for a given subset of the data is stable across the trimming methods. The top panel shows the above and below-median frequency when the data is split by that moment. The middle panel shows the stability of kurtosis across trimming methods, and the bottom panel shows the kurtosis over frequency results. Across all three moments examined, the rankings show that the moment is well measured with regards to extreme price changes.

To further support the stability of the moments, we recompute impulse response functions under several versions of the trimming. In Figure 11 we present FAVAR estimated impulse response functions when the small price changes are instead dropped if they are less than 0.1 percent as in case 1. In Figure 12, we present impulses when price changes are trimmed at log(2) as in case 3. In both cases, results are nearly identical to the baseline case. Moreover, there is little overlap between the high and low moment groupings however we trim the data as large measurement error might imply. We find that when we construct the above and below median subsets, very few industries will switch between groups. Comparing case 1 trimming to our baseline methodology, 8 industries switch when we condition on frequency, 4 industries switch when we condition on kurtosis, and 8 industries switch when we condition on kurtosis over frequency. Comparing case 3 trimming to our baseline methodology, the results are the same as the previous comparison except for kurtosis where only 2 industries switch with each other.

Second, we address potential attenuation bias. Due to the large number of price changes, as seen in Table 10 with an average of 1,430 price changes per industry, we are able to correct for attenuation bias due to classical measurement error. Following Gorodnichenko and Weber (2016), we split our sample into an early and a late time period of approximately equal sizes. The sampling procedure of the BLS rotates and randomly samples products and establishments, so the sampling error should not be correlated across the early and late time periods. We repeat our key cross-sectional regression of the cumulative FAVAR price responses on pricing moments using the subsample moments for each moment separately (Table 7) and combining all moments (Table 8). These tables are shown in the Appendix. Column 1 and 2 simply replicate our baseline results from Table 1, with and without three-digit fixed effects.

To address the importance of measurement error for our analysis, we use an instrumental-variable approach. If there is idiosyncratic measurement error in each period, but each pricing moment is driven by the same fundamental, persistent characteristics, then the pricing moments from one subsample can be used as instruments for the same pricing moments in the other subsample. These results are shown in columns 3 through 6. In columns 3 and 4, we instrument for the early period moments with the late period moments, while in columns 5 and 6 we instrument for the late period moments with the early period moments. The estimated coefficients continue to be similar to our baseline estimates, suggesting that attenuation bias due to measurement error is not driving our results. In particular, our main message from the preceding analyses is also confirmed: Frequency of price changes is always significant. Kurtosis continues to be insignificant on its own in Table 11; In the top panel of table 12, kurtosis does become significant in both samples when frequency is the only other control variable. However, this result is an artifact of the lack of control variables. A the bottom panel shows only frequency retains significance when all moments act as controls.

Lastly, we show that the pricing moments are stable over time. While we pool the pricing moments in the time dimension to increase the size of the sample, we can calculate industry level pricing moments and compare them over time. In Figure 15 in the Appendix we calculate pricing moments at an annual frequency, and present the mean and interquartile range across industries for the three pricing moments. The panels show that the pricing moments are stable in value across time. In Figure 16 we do the same exercise but separate the high and low subsets for each pricing moment. We calculate the above and below median bin, and then plot the mean and interquartile range within each bin. It is clear that there is a substantial difference across time for the high and low bins in both frequency and kurtosis over frequency, while for the kurtosis of price change there is overlap of the interquartile range for the first year of the sample. Overall these figures show that the ordering of pricing moments across industries is stable over time.

IV General Equilibrium Pricing Model

The section demonstrates the importance of using conditionally identified micro-macro moments for making modeling choices. We do so by examining through the lens of menu cost models the role which 3 popular micro pricing moments – frequency, kurtosis, and kurtosis over frequency – play for monetary non-neutrality, our macro moment. Across several menu cost models that are common in the literature, we examine how the consumption response to the same size small monetary shock varies due to a perturbation in a pricing moment.[10] We find that frequency is always informative and has a monotonic negative relationship with monetary non-neutrality. Kurtosis of price change is not directly informative for monetary non-neutrality; rather the underlying model mechanism that generates excess kurtosis is what determines the price response to a monetary shock. Kurtosis over frequency is only informative through frequency, and generally does not have a monotonic relationship with monetary non-neutrality.

We first present a second-generation menu cost model in the spirit of Vavra (2014). When we calibrate it to CPI moments, the model can match our empirical results. Frequency has a negative relationship with monetary non-neutrality, and the model does

[10]This is not a direct test of the model of Alvarez et al. (2016) as they vary the size of the monetary shock.

not generate a positive association between kurtosis and monetary non-neutrality.[11] The role of kurtosis over frequency is ambiguous. These results also hold in the most simplified version of the model which is a discrete-time version of the Golosov and Lucas (2007) model.

Finally, we examine how a commonly used version of random menu costs can flip the sign of the relationship between kurtosis and monetary non-neutrality, just like in the data.. The random menu cost mechanism generates random, free price changes that increases the Calvoness of the model, while also raising the kurtosis in the model through a higher fraction of random, small price changes. As a result, the relationship between kurtosis and monetary non-neutrality flips sign, The frequency of price changes continues to have a negative relationship with non-neutrality. Only by linking micro moments to macro moments can we draw these conclusions. Simply targeting micro moments is not sufficiently informative about the behavior of identified macro moments.

A. Model Setup

Our general equilibrium model nests both a menu cost model as well as the Calvo pricing model. This aspect of the model follows Nakamura and Steinsson (2010) where there is some probability of a free Calvo price change. The model also includes leptokurtic idiosyncratic productivity shocks as in Midrigan (2011) as well as aggregate productivity shocks. Removing these features reduces the model down to the Golosov and Lucas (2007) model.

A.1 Households

The household side of the model is standard. Households maximize current expected utility, given by

$$E_t \sum_{\tau=0}^{\infty} \beta^t \big[log(C_{t+\tau}) - \omega L_{t+\tau}\big] \tag{7}$$

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

[11] See for example our Figures 1-5 for the empirical counterparts. Also in our regression analyses, frequency has a positive relation with the price response and hence a negative one with output. Kurtosis is insignificant and has ambiguous signs.

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz \right]^{\frac{\theta}{\theta-1}} \tag{8}$$

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

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta} \tag{9}$$

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

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

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

$$P_t C_t + E_t[D_{t,t+1} B_{t+1}] \leq B_t + W_t L_t + \int_0^1 \pi_t(z) dz \tag{11}$$

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, $\pi_t(i)$ is the profit of firm i in period t. 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

$$D_{t,t+1} = \beta \left(\frac{C_t P_t}{C_{t+1} P_{t+1}} \right) \tag{12}$$

$$\frac{W_t}{P_t} = \omega C_t \tag{13}$$

where equation (12) describes the relationship between asset prices and consumption, and

(13) describes labor supply.

A.2 Firms

In the model there are a continuum of firms indexed by i. The production function of firm i is given by

$$y_t(i) = A_t z_t(i) L_t(i) \tag{14}$$

where $L_t(i)$ is labor rented from households. A_t are aggregate productivity shocks and $z_t(i)$ are idiosyncratic productivity shocks.

Firm i maximizes the present discounted value of future profits

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau} \pi_{t+\tau}(i) \tag{15}$$

where profits are given by:

$$\pi_t(i) = p_t(i) y_t(i) - W_t L_t(i) - \chi(i) W_t I_t(i) \tag{16}$$

$I_t(i)$ is an indicator function equal to one if the firm changes its price and equal to zero otherwise. $\chi(i)$ is the menu cost of changing prices. The final term indicates that firms must hire an extra $\chi(i)$ units of labor if they decide to change prices with probability $1 - \alpha$, or may change their price for free with probability α.[12] This is the "CalvoPlus" parameter from Nakamura and Steinsson (2010) that enables the model to encapsulate both a menu cost as well as a pure Calvo model, as well as allows us to match the random menu cost set up in Alvarez et al. (2016). In the menu cost model this parameter is set such that a small probability of receiving a free price change enables the model to generate small price changes, while in the Calvo model set up it is calibrated to the frequency of price changes with an infinite menu cost.

Total demand for good i is given by:

$$y_t(i) = Y_t \left(\frac{p_t(i)}{P_t} \right)^{-\theta} \tag{17}$$

The firm problem is to maximize profits in (24) subject to its production function (22), demand for its final good product (25), and the behavior of aggregate variables.

[12]This is a reduced form modeling device representing multiproduct firms like in Midrigan (2011).

Aggregate productivity follows an AR(1) process:

$$log(A_t) = \rho_A log(A_{t-1}) + \sigma_A \nu_t \tag{18}$$

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

The log of firm productivity follows a mean reverting AR(1) process with shocks that arrive infrequently according to a Poisson process:

$$logz_t(i) = \begin{cases} \rho_z logz_{t-1}(i) + \sigma_z \epsilon_t(i) & \text{with probability } p_z \\ logz_{t-1}(i) & \text{with probability } 1 - p_z, \end{cases} \tag{19}$$

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

Nominal aggregate spending follows a random walk with drift:

$$log(S_t) = \mu + log(S_{t-1}) + \sigma_s \eta_t \tag{20}$$

where $S_t = P_t C_t$ and $\eta_t \sim$ N(0,1).

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, we assume that firms use a forecasting rule of the form:

$$log\left(\frac{P_t}{S_t}\right) = \gamma_0 + \gamma_1 logA_t + \gamma_2 log\left(\frac{P_{t-1}}{S_t}\right) + \gamma_3\left(log\left(\frac{P_{t-1}}{S_t}\right) * logA_t\right) \tag{21}$$

The accuracy of the rule is checked using the maximum Den Haan (2010) statistic in a dynamic forecast. The model is solved recursively by discretization and simulated using the non-stochastic simulation method of Young (2010).

B. Calibration

For all variations of the model that follow, we use 2 sets of parameters. The first set of parameters is common to all model calibrations. Our model is a monthly model so the discount rate is set to $\beta = (0.96)^{\frac{1}{12}}$. The elasticity of substitution is set to $\theta = 4$ as in Nakamura and Steinsson (2010).[13] The nominal shock process is calibrated to match the mean growth rate of nominal GDP minus the mean growth rate of real GDP and the standard deviation of nominal GDP growth over the period of 1998 to 2012. This implies $\mu = 0.002$ and $\sigma_s = 0.0037$. Finally the model is linear in labor so we calibrate the productivity parameters to match the quarterly persistence and standard deviation of average labor productivity from 1976-2005. This gives $\rho_A = 0.8925$ and $\sigma_A = 0.0037$.

The second set of parameters is calibrated internally to match micro pricing moments. These are the menu cost χ, the probability of an idiosyncratic shock, p_z, the volatility of idiosyncratic shocks σ_z, the persistence of idiosyncratic shocks ρ_z, and the probability of a free price change α. Their values will be discussed in the next section.

V Model Results

This section presents our main model results. It illustrates by example how conditional pricing moments can be informative for guiding modeling choices. First, we show that a standard, second-generation menu cost model is able to generate our main empirical findings. It generates the negative relationship between frequency and monetary non-neutrality, and does not generate a strong positive association between kurtosis and monetary non-neutrality. Second, we establish that the same relationships also hold in the simplest, discrete-time version of a menu cost model, Golosov and Lucas (2007).

We then show how the conditional micro-macro moments can be used to evaluate underlying model mechanisms. Models that rely on a strong positive relationship between kurtosis and monetary non-neutrality are at odds with the empirically identified relationship. We show how instead the use of random menu costs can generate this counterfactual relationship, by positively linking kurtosis of price changes to perfectly random price changes. These results show that the source of kurtosis through the model mechanisms is what matters, not the unconditional pricing moment itself. This insight also validates our empirical methodology given the unstable relationship of kurtosis, and the potentially differential technologies firms use.

[13]While other papers in the literature set the elasticity of substitution to higher numbers such as 7 in Golosov and Lucas (2007), this lowers the average mark up, but the ordered price level response across models to a monetary shock would not change.

A. Baseline Model Results

First, we first show that our baseline menu cost model is able to generate our main empirical findings: The negative relationship between frequency and monetary non-neutrality, and does not generate a strong positive association between kurtosis and monetary non-neutrality. There is no clear relationship between the ratio of kurtosis over frequency of price changes and monetary non-neutrality.

The baseline model, described in detail in the previous section, is calibrated to match price-setting statistics from the CPI micro data during the period 1988-2012 documented by Vavra (2014).[14] We then undertake a comparative static exercise where we vary one pricing moment at a time to understand the importance of each moment for monetary non-neutrality. The moments we examine are the frequency and kurtosis of price changes. In addition to a baseline calibration that matches the data, we consider 4 alternative specifications: a case of high, and a case of low frequency of price changes that holds kurtosis constant, and a case of low kurtosis, and a case of medium kurtosis that hold frequency constant. Tables 3 and 4 summarize the moments and parameters associated with each case. The ratio of kurtosis over frequency is the same in the high frequency and the low kurtosis cases, allowing this exercise to demonstrate if ratio of kurtosis over frequency is a sufficient statistic in this simple menu cost model, or rather a function of one of the underlying moments.

Our outcome variable of interest, as in the empirical analysis, continues to be monetary non-neutrality. We measure it by examining the impact of a one-time permanent expansionary monetary shock on real output. We implement this with a monetary shock that increases nominal output by 0.002, a doubling of the monthly nominal output growth rate. The real effects of this monetary shock are given by the cumulative consumption response.

As we vary one pricing moment at a time, while holding all others fixed, we confirm our two main empirical findings. Figure 5 summarizes the results graphically. First, we find that monetary non-neutrality is a negative function of frequency in our menu cost model, holding kurtosis constant. This result which we illustrate in Panel a confirms the conventional notion that more frequent price adjustment is associated with smaller

[14]We define the fraction of small price changes as those less than 1% in absolute value and take this data from Luo and Villar (2015) This definition allows comparison across different pricing data sets.

real output effects. Second, the impulse response functions in Panel b also show that, holding frequency constant, an increase in kurtosis of price changes decreases monetary non-neutrality.[15]

A key result lies in the role of kurtosis over frequency. Kurtosis over frequency does not provide clear predictions for monetary non-neutrality. As Panel c in Figure 5 shows, kurtosis over frequency does not map one to one into monetary non-neutrality. Varying frequency or kurtosis while holding their ratio constant leads to different cumulative consumption responses. A comparison of the high frequency and low kurtosis calibration illustrates this finding. The ratio of kurtosis over frequency is 42 for both calibrations, but the high frequency calibration in the red dashed line with a frequency of .15 and kurtosis of 6.4 exhibits a lower consumption response than the low kurtosis calibration in the grey circled linewith a frequency of .11 and kurtosis of 4.7. The reason is that increasing frequency and decreasing kurtosis can individually both decrease the ratio of kurtosis over frequency relative to the baseline. But, at the same time, they cause the total consumption response to move in opposite directions. Frequency dominates this movement in our exercise.

The analysis of this simple one-sector menu cost model shows that the frequency of price changes exhibits a strong negative relationship with monetary non-neutrality, just like in the data. The model does not generate a positive association between kurtosis of price changes and monetary non-neutrality: Kurtosis has a weaker negative relationship with monetary non-neutrality than frequency. Moreover, the ratio of kurtosis over frequency has a non-monotonic relationship with monetary non-neutrality. The results also suggest that a naive reading of kurtosis over frequency of price changes does not fully encapsulate the real effects of monetary shocks and is therefore not sufficient. Rather one has to pay close attention to changes in even small modeling assumptions that underlie its derivation as we demonstrate next.

[15]We repeat this exercise using the model of Midrigan (2011) who more explicitly models firm multi-product pricing. We find the same relationship as in our model, that monetary non-neutrality falls as kurtosis increases while holding frequency of regular price changes constant. In the quantitative model of Dotsey and Wolman (2018), they vary the autocorrelation of idiosyncratic productivity shocks to change pricing moments and study the relationship of monetary non-neutrality with the ratio of kurtosis over frequency. They also find that as kurtosis over frequency increases the monetary non-neutrality in the model falls.

B. Why Is Kurtosis Not Informative?

This section illustrates how the conditional micro-macro moments can be used to discipline model mechanisms. Specifically, we show how a popular unconditional micro pricing moment, kurtosis, can now counterfactually have a strong positive associated with monetary non-neutrality, our identified macro moment. The unstable relationship across models and tenuous relationship in the data suggests kurtosis is not a particularly informative moment for monetary non-neutrality.

We show how a common random menu cost set up can generate a strong positive relationship between kurtosis and monetary non-neutrality, at odds with the identified empirical relationship. Our main insight is that the fraction of random, small price changes, embodying the degree of Calvoness, is key for the sign of the relationship. This fraction is both positively associated with kurtosis of price changes and monetary non-neutrality. A small change in price setting assumptions, the assumption of random menu costs – rather than a fixed menu cost – can create such random small price changes.

In order to establish these results, we start with a simplified version of our baseline model such that it represents a discrete-time version of the Golosov and Lucas (2007) model. We find that kurtosis can have a negative relationship while it also varies in a discrete-time version of the Golosov-Lucas model due to the difference between discrete time and continuous time.[16] In order to generate the posited positive relationship between kurtosis over frequency and monetary non-neutrality, we find that we need to add one assumption that is specific to the assumptions in Alvarez et al. (2016) but not Golosov and Lucas (2007) - random rather than fixed menu costs. We establish this finding by considering the relationship between kurtosis and monetary non-neutrality in the discrete-time Golosov-Lucas model with fixed menu costs, and then reconsider it after we add the random menu cost assumption.

First, to simplify our baseline model to the Golosov and Lucas (2007) model, we remove several model ingredients from our baseline model. We remove aggregate productivity shocks and leptokurtic idiosyncratic productivity shocks, remove trend inflation, and turn the idiosyncratic productivity shocks into random walk processes.

[16]This is in contrast to Alvarez et al. (2016), who show that it should be equal to unity in continuous time. The reason is that there is always a non-negligible mass at the Ss bands in discrete time while that mass is always 0 in continuous time. Changes in the model parameters therefore change the mass at the bounds and hence the steady-state distribution of price changes and the kurtosis of the distribution.

We set the Calvo plus parameter to zero, implying no free price changes. Parameter calibrations for the Golosov-Lucas model are shown in Table ??.[17] The same small expansionary monetary shock is used as in the previous model simulation exercise to generate consumption impulse response functions as a measure of monetary non-neutrality.

We find that an increase in kurtosis in the Golosov and Lucas (2007) model is associated with a decrease in monetary non-neutrality, contrary to the intuition in the literature. Panel a in Figure 6 illustrates this result. As kurtosis of price changes increases, the consumption impact of a monetary shock falls. Increasing kurtosis from 1.4 to 2.2 decreases monetary non-neutrality by 47 percent as measured by the cumulative consumption response over 12 months. The reason that monetary non-neutrality falls as kurtosis rises is due to the concurrent effect on the average size of price changes. We increase kurtosis while holding frequency fixed by decreasing the size of the menu cost from 0.115 to 0.0054, as well as the volatility of idiosyncratic productivity shocks from 0.11 to 0.01. Intuitively, these changes decrease the average size of price changes while increasing the number of firms that have prices close to the inaction band of changing prices. Therefore when a monetary shock occurs in the high-kurtosis case, it triggers more price changes and selection, decreasing monetary non-neutrality. Panels a and b in Figure 7 illustrates this shift in the simulated distribution of price changes closer to the Ss bands.

Next, we add the random menu cost assumption from Alvarez et al. (2016) to the simplified, discrete-time Golosov and Lucas (2007) model. We find that this small change in model assumption is enough to flip the sign of the relationship between kurtosis and monetary non-neutrality. Under random menu costs, firms are randomly selected to receive a free price change, implying that these prices have zero selection into changing. This feature is implemented by setting the Calvo plus parameter to a positive number. Table ?? shows our exact specific parameter calibrations. Panel b in Figure 6 illustrates this striking result, as kurtosis increases, monetary non-neutrality now increases.

What is the deeper intuition for this result? What is evident from the calibration and the model moments in Table ?? is that the fraction of random, free price changes $\mathcal{L}$ plays a key role. From a modeling standpoint, as the fraction of random, free price

[17] Specifically we set the $\rho_z = 1$ to generate random walk productivity shocks. The probability of receiving an idiosyncratic shock is set to 1 ($p_z = 1$), and the drift of nominal GDP is set to 0 ($\mu = 0$).

changes increases from 73% to 91%, the degree of Calvoness of the model increases. These price changes have no selection effect in them, decreasing the overall selection effect, causing monetary non-neutrality to rise. At the same time, the random, small price changes draw mass towards zero and therefore increases the kurtosis of the price change distribution, holding the frequency constant. Hence, when kurtosis is positively affected by the fraction of free prices changes in a random menu cost model, kurtosis can also have a positive relationship with monetary non-neutrality. Given the negative empirical relationship between kurtosis and monetary non-neutrality, it would seem to suggest this is not a promising model ingredient.

Figure 8 illustrates these effects. As Panel a shows, the random menu costs increase the number of small price changes, relative to the fixed menu cost model of Golosov and Lucas (2007) in Panel a of Figure 7. Panel b illustrates that an increase in Calvoness can moreover increase the number of small price changes, hence monetary non-neutrality, and kurtosis at the same time.

This section shows that models that hinge on kurtosis to generate monetary non-neutrality are not informative due to the unstable relationship across models. The model results make clear the value in using conditional micro-macro pricing moments, directly linking unconditional pricing moments to monetary shocks, to evaluate monetary models. Results show that unconditional pricing moments, such as kurtosis, are not directly informative about monetary non-neutrality. Rather, the model ingredient that generates excess kurtosis is what matters. This distinction about kurtosis and monetary non-neutrality illustrates the value of our empirical methodology given the unstable relationship of kurtosis.

VI Conclusion

Using micro price data, we have empirically evaluated in this paper what price-setting moments are informative for monetary non-neutrality, our identified macro moment. Our analysis presents an example for a generally applicable way of evaluating the informativeness of micro moments for identified macro moments of interest. We show that kurtosis of price changes is not a sufficient statistic for monetary non-neutrality. Contrary to the notion in the literature, kurtosis and monetary non-neutrality have none, or even a negative association in the data. Only frequency has an empirically robust relationship with monetary non-neutrality.

We show that menu cost models can match empirical price responses that are jointly conditional on a monetary policy shock and key pricing moments. Menu cost models predict a positive relationship of kurtosis and monetary non-neutrality as posited in the literature only when random menu costs are the source of excess kurtosis and raise the Calvoness of the model at the same time.

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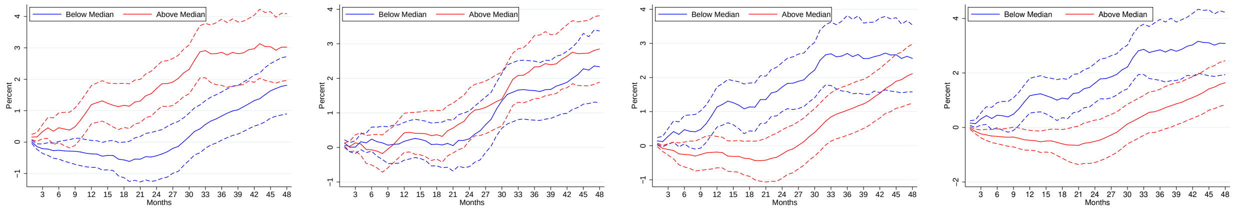
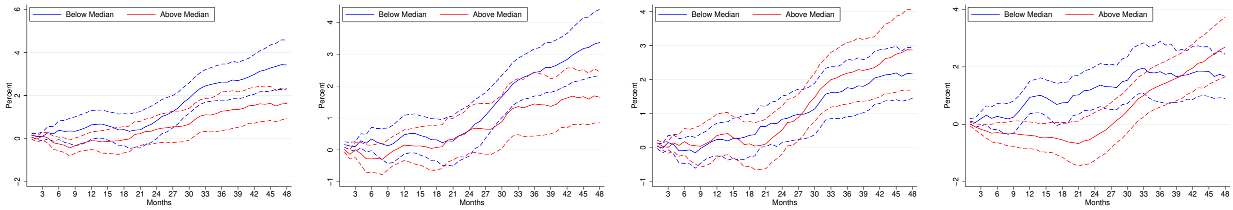
VII Figures



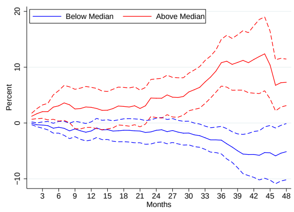
(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency (d) S.D. Duration



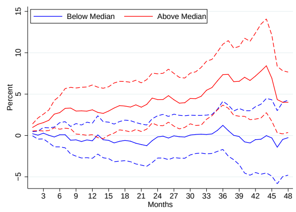
(e) Average Size (f) Standard Deviation (g) Fraction Small (h) Fraction Positive

Figure 1: Romer and Romer Monetary Policy Shock IRF

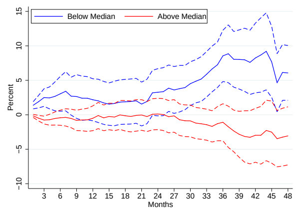
NOTE: In the above figures, we plot the respectively estimated coefficients $\theta_{A,h}$ and $\theta_{B,h}$ from the following specification: $Log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} * MPshock_t + \varphi_{A,h} z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} * MPshock_t + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h}$ where $ppi_{j,t+h}$ is the price level for industries in the "Above Median" or "Below Median" set according to the pricing moment of interest, at time t measured at monthly frequency, h months into the future. Controls include two lags of the RR shock, two lags of the Fed Funds rate, and current and two lags of the unemployment rate, industrial production, and price level. Standard errors are constructed using the Newey-West correction for serial autocorrelation. Dashed lines present 68% standard error bands.



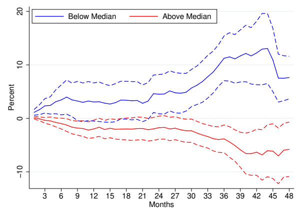
(a) Frequency



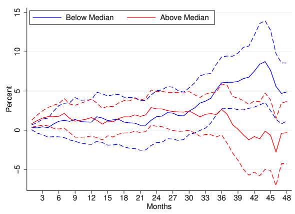
(b) Kurtosis



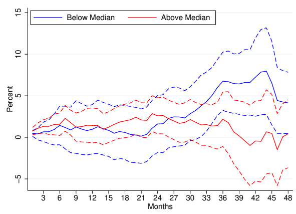
(c) Kurtosis/Frequency



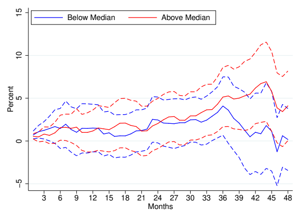
(d) S.D. Duration



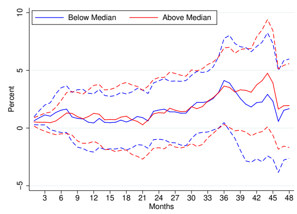
(e) Average Size



(f) Standard Deviation



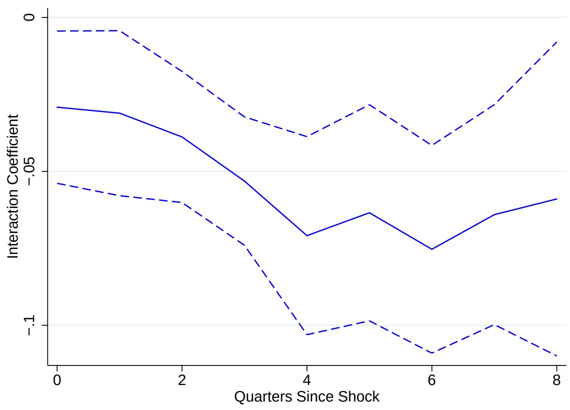
(g) Fraction Small



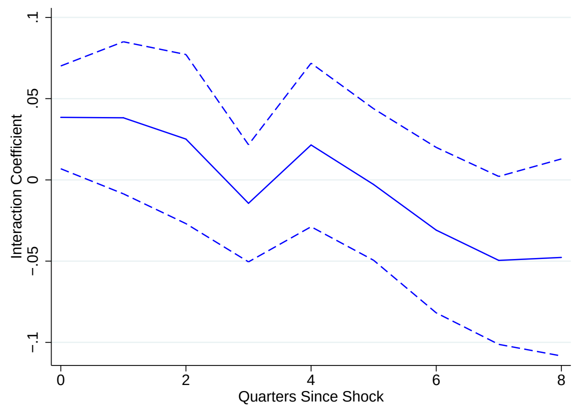
(h) Fraction Positive

Figure 2: High Frequency Identified Monetary Policy Shock IRF

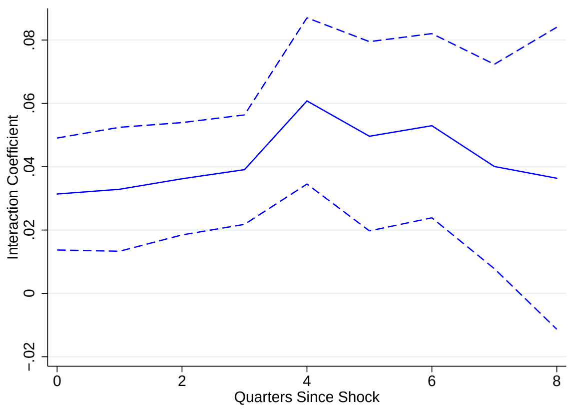
NOTE: In the above figures, we plot the respectively estimated coefficients $\theta_{A,h}$ and $\theta_{B,h}$ from the following specification: $Log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} * MPshock_t + \varphi_{A,h} z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} * MPshock_t + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h}$ where $ppi_{j,t+h}$ is the price level for industries in the "Above Median" or "Below Median" set according to the pricing moment of interest, at time t measured at monthly frequency, h months into the future. Controls include two lags of the high frequency identified shock, two lags of the Fed Funds rate, and current and two lags of the unemployment rate, industrial production, and price level. Standard errors are constructed using the Newey-West correction for serial autocorrelation. Dashed lines present 68% standard error bands.



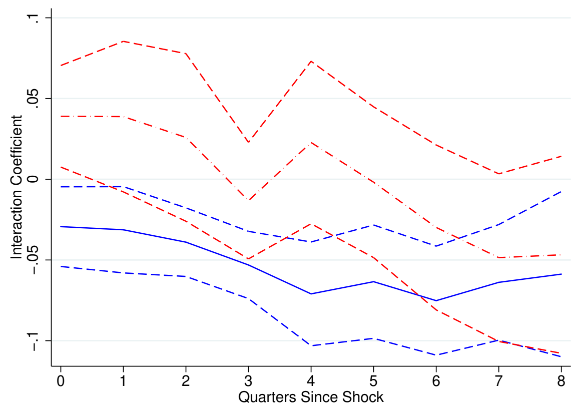
(a) Frequency



(b) Kurtosis



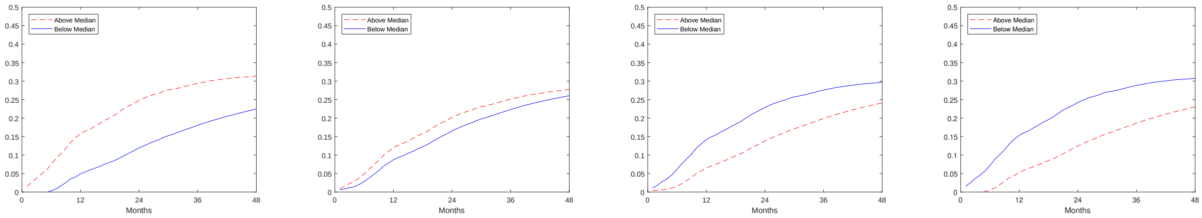
(c) Kurtosis/Frequency



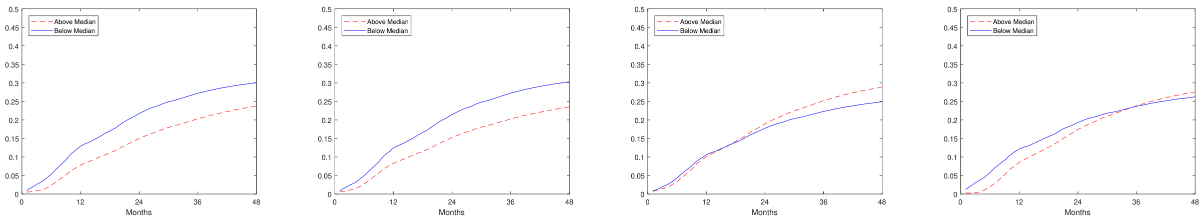
(d) Kurtosis (Dash-Dot) and Frequency (Solid)

Figure 3: High Frequency Identified Monetary Policy Shock IRF

NOTE: In the above panels, we plot the respectively estimated coefficients θ_h from the following specification: $Log(sales_{j,t+h}) = \alpha_{th} + \alpha_{jh} + \theta_h * MPshock_t \times M_j + controls_t + \epsilon_{j,t+h}$ where $sales_{j,t+h}$ denotes firm j real sales at time t measured at quarterly frequency, h months into the future. Controls further include 4 quarters of lagged log real sales, and current and 4 quarters of lagged log assets. Monetary policy shocks are measured by the high-frequency shock. M_j contains one of our three firm-level pricing moments: frequency, kurtosis, the ratio of the two statistics, or both statistics individually. In panel d, the solid blue line is the frequency interaction coefficient and the dash-dot red line is the kurtosis interaction coefficient. Heteroskedasticity and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Driscoll and Kraay (1998) with a lag length equal to forecast horizon of h. Dashed lines present 90% standard error bands.



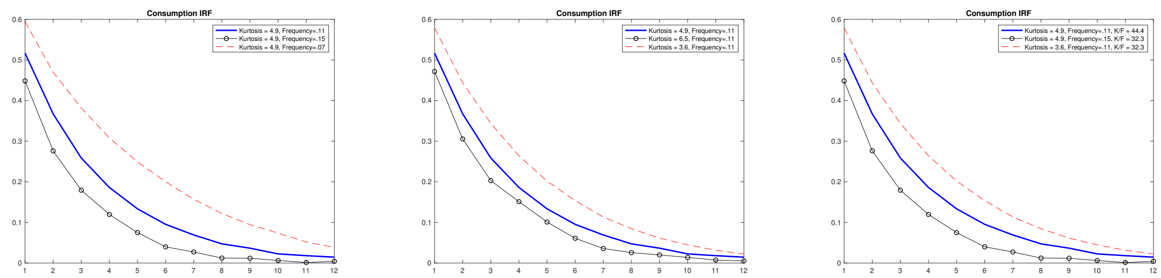
(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency (d) S.D. Duration



(e) Average Size (f) Standard Deviation (g) Fraction Small (h) Fraction Positive

Figure 4: FAVAR Monetary Policy Shock IRF

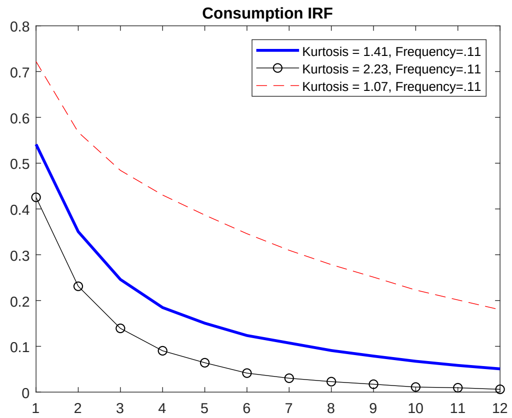
Note: In the above panels, "Above Median" and "Below Median" refer to the impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. FAVAR estimated impulse responses of sectoral prices in percent to an identified 25 basis point unexpected Federal Funds rate decrease are shown.



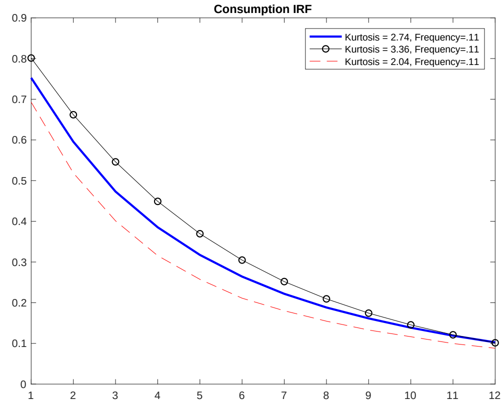
(a) Frequency Variation (b) Kurtosis Variation (c) Kurtosis/Frequency Variation

Figure 5: Consumption IRF Comparison

Note: Impulse response of consumption to a one time permanent increase in log nominal output of size 0.002 for different calibrations of our baseline monthly model. The percent increase in consumption due to the expansionary shock is plotted where the shock occurs at the horizon labeled 1. The results are based on simulations of 3500 economies.



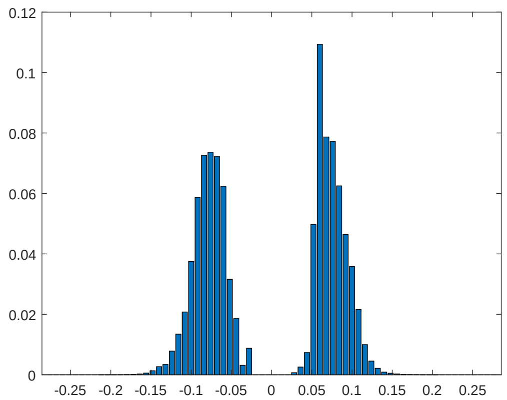
(a) Golosov-Lucas Model



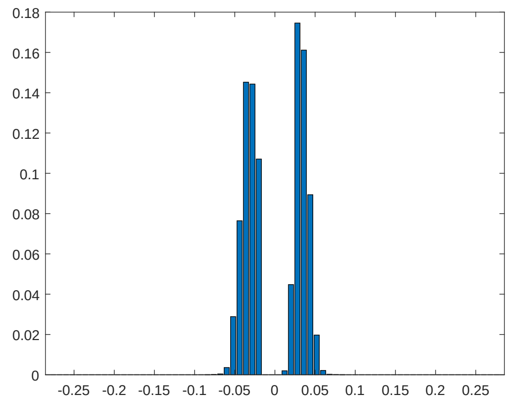
(b) Random Menu Cost Model

Figure 6: Consumption IRF Comparison

NOTE: Impulse response of consumption to a one time permanent increase in log nominal output of size 0.002 for different calibrations in each of the two models. The percent increase in consumption due to the expansionary shock is plotted where the shock occurs at the horizon labeled 1. The results are based on simulations of 3500 economies.



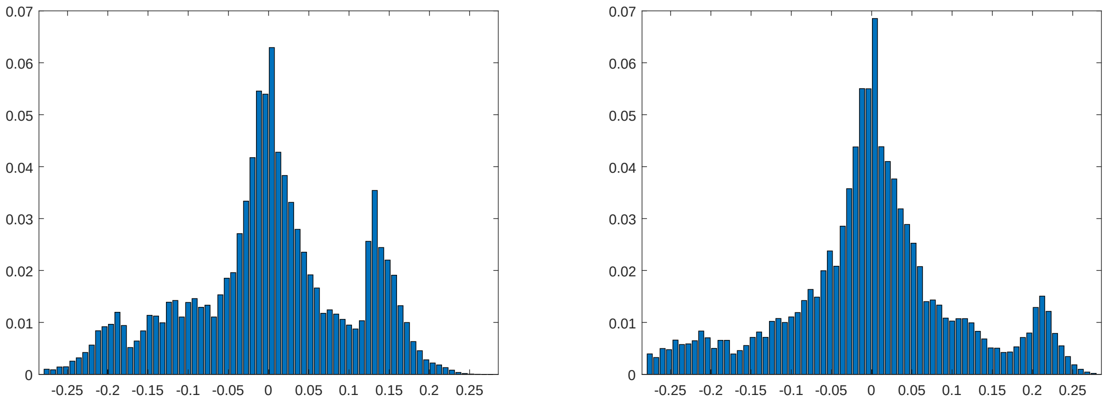
(a) Baseline



(b) High Kurtosis

Figure 7: Model Price Distributions - GL

NOTE: Price change distribution in Golosov-Lucas model calibrations.



(a) Baseline (b) High Kurtosis

Figure 8: Model Price Distributions - Random Menu Costs

Note: Price change distribution in random menu cost model calibrations.

VIII Tables

Cross-Sectional Determinants of Sectoral Price Response													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$	-0.250***												
	(0.074)												
Log Frequency		0.422***							0.476***	0.332***	0.441**	0.411***	0.274**
		(0.073)							(0.074)	(0.126)	(0.184)	(0.102)	(0.134)
Log Kurtosis			0.138						-0.151		-0.189	-0.166	-0.113
			(0.119)						(0.112)		(0.142)	(0.132)	(0.131)
Log Avg. Size				-0.316**							-0.252	-0.202	-0.111
				(0.148)							(0.221)	(0.232)	(0.203)
Log S.D.					-0.158						0.117	0.014	-0.136
					(0.127)						(0.189)	(0.195)	(0.152)
Log Frac. Small						0.017					-0.105	-0.106	-0.096
						(0.077)					(0.078)	(0.074)	(0.064)
Log Frac. Pos.							-0.334				0.160	0.070	0.020
							(0.382)				(0.426)	(0.434)	(0.343)
Log S.D. Duration								-0.462***		-0.144	-0.090		
								(0.084)		(0.129)	(0.188)		
Log Profit												-0.439**	-0.298
												(0.195)	(0.194)
SD(e_k)													10.283
													(12.401)
$\rho(e_k)$													0.570***
													(0.116)
NAICS 3 FE	X	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.429	0.502	0.394	0.407	0.393	0.372	0.391	0.477	0.509	0.505	0.506	0.520	0.594
N	148	148	148	148	148	146	148	148	148	148	146	145	145

Table 1: Decomposing Monetary Non-Neutrality

Note: This tables uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following specification: $log(IRF_{k,h}) = a + \alpha_j + \beta' M_k + \gamma' X_j + \epsilon_{k,h}$. Where $Log(IRF_{k,h})$ is the log of the 24-month cumulative sectoral response of prices to a monetary shock from our FAVAR analysis. M_k contains one of our industry-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average size, and standard deviation of price changes, or the full set of pricing moments. α_j are three-digit NAICS industry fixed effects and are included in all specifications. X_j are sector-level controls including gross profit rate, the volatility of sector level shocks, and the autocorrelation of sector level shocks. Robust standard errors in parentheses. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Cross-Sectional Determinants of Firm-Level Sales Responses					
	(0)	(1)	(2)	(3)	(4)
Log Kurtosis/Frequency		.061**			
		(0.024)			
Log Frequency			-.071***		-.071***
			(0.027)		(0.027)
Log Kurtosis				0.021	0.023
				(0.040)	(0.039)
Firm Controls	X	X	X	X	X
Firm FE	X	X	X	X	X
Time FE	X	X	X	X	X
R^2	0.762	0.762	0.762	0.762	0.762
N	19,315	19,315	19,315	19,315	19,315

Table 2: Decomposing Monetary Non-Neutrality

Note: This tables uses regression analysis to test the informativeness of three pricing moments for monetary non-neutrality. We estimate the following specification: $Log(sales_{j,t+4}) = \alpha_{th} + \alpha_{jh} + \theta_h * MPshock_t \times M_j + controls_t + \epsilon_{j,t+h}$. M_j contains one of our three firm-level pricing moments: frequency, kurtosis, the ratio of the two statistics, and both jointly interacted with the high-frequency shock. α_t and α_j are firm and time fixed effects. Other controls are 4 quarters of lagged log sales, and current and 4 quarters of lagged log assets. Column 0 reports the specification with controls and fixed effects included, but no pricing moments. Within R^2 is reported. Heteroskedasticity and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Driscoll and Kraay (1998) with a lag length equal to forecast horizon of h. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Moment	Data	Baseline	High Frequency	Low Frequency	High Kurtosis	Low Kurtosis
			Baseline Calibration			
Frequency	0.11	**0.11**	**0.15**	**0.07**	**0.11**	**0.11**
Fraction Up	0.65	**0.63**	**0.61**	**0.67**	**0.64**	**0.62**
Average Size	0.077	**0.077**	**0.077**	**0.077**	**0.077**	**0.077**
Fraction Small	0.13	**0.13**	**0.13**	**0.13**	**0.13**	**0.13**
Kurtosis	4.9	**4.9**	**4.9**	**4.9**	**6.5**	**3.6**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	58.2	44.4	32.3	68.1	57.4	32.3
		Golosov-Lucas Model with Random Walk and No Trend Inflation				
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Up	0.65	0.51	0.51	0.51	0.49	0.51
Average Size	0.077	**0.077**	0.077	0.077	0.033	0.23
Fraction Small	0.13	0.00	0.00	0.00	0.00	0.00
Kurtosis	4.9	1.41	**1.40**	**1.44**	**2.23**	**1.07**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	12.8	9.39	18.1	20.3	9.7
		Random Menu Cost Model with Random Walk and No Trend Inflation				
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Up	0.65	0.51	0.51	0.51	0.51	0.51
Average Size	0.077	**0.077**	**0.077**	**0.077**	**0.077**	**0.077**
Fraction Small	0.13	**0.13**	0.14	0.013	0.14	0.12
Kurtosis	4.9	2.74	**2.73**	**2.74**	**3.36**	**2.04**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	25.0	18.2	32.6	30.2	18.6
$\mathcal{L}$		0.73	0.74	0.76	0.91	0.55

Table 3: Model Moments

NOTE: The table shows the model moments that are internally targeted for each economy. All monthly CPI data moments are taken from Vavra (2014) and are calculated using data from 1988-2014. Fraction of small price changes less than 1 percent in absolute value taken from Luo and Villar (2017). Bolded moments are targeted. In the Golosov-Lucas and Random menu cost models, kurtosis of 4.9 is the kurtosis of standardized price changes from Vavra (2013). $\mathcal{L}$ is defined as the fraction of price changes that are free.

Parameter	Baseline	High Frequency	Low Frequency	High Kurtosis	Low Kurtosis
		Baseline Calibration			
χ	0.0095	0.0048	0.022	0.0055	0.02
p_z	0.072	0.115	0.025	0.053	0.01
σ_z	0.13	0.143	0.116	0.144	0.103
ρ_z	0.75	0.99	0.65	0.65	0.75
α	0.029	0.036	0.022	0.022	0.036
		Golosov-Lucas Calibration			
χ	0.0241	0.0181	0.034	0.0054	0.115
p_z	1.0	1.0	1.0	1.0	1.0
σ_z	0.029	0.0345	0.0243	0.01	0.11
ρ_z	1.0	1.0	1.0	1.0	1.0
α	0.0	0.0	0.0	0.0	0.0
		Random Menu Cost Calibration			
χ	0.195	0.14	0.25	0.7	0.089
p_z	1.0	1.0	1.0	1.0	1.0
σ_z	0.044	0.051	0.0383	0.062	0.037
ρ_z	1.0	1.0	1.0	1.0	1.0
α	0.08	0.1106	0.061	0.10	0.06

Table 4: Model Parameters

NOTE: The table shows the model parameters that are internally calibrated for each economy. χ denotes the menu cost of adjusting prices, p_z the probability that log firm productivity follows an AR(1) process with standard deviation σ_z, ρ_z the persistence of idiosyncratic probability shocks, and α is the probability of a free price change.

A Model Appendix

A. Multi-Sector Pricing Model

This section now presents a multi-sector pricing model that demonstrates that our empirical identification is consistent with aggregate monetary non-neutrality and that general equilibrium effects do not reverse the ordering of the impulse response functions.

It is the same as our baseline model in section IV but allows for heterogeneity between sectors. The quantitative pricing model nests both a second generation menu cost model as well as the Calvo pricing model. The multi-sector model follows Nakamura and Steinsson (2010) where there is some probability of a free Calvo price change and each sector has sector specific pricing behavior. It also includes leptokurtic idiosyncratic productivity shocks as in Midrigan (2011) as well as aggregate productivity shocks.

A.1 Households

The household side of the model is the same as in the one sector version in section *A.1*.

A.2 Firms

In the model there are a continuum of firms indexed by i and industry j. The production function of firm i is given by

$$y_t(i) = A_t z_t(i) L_t(i) \tag{22}$$

where $L_t(i)$ is labor rented from households. A_t are aggregate productivity shocks and $z_t(i)$ are idiosyncratic productivity shocks.

Firm i maximizes the present discounted value of future profits

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau} \pi_{t+\tau}(i) \tag{23}$$

where profits are given by:

$$\pi_t(i) = p_t(i) y_t(i) - W_t L_t(i) - \chi_j(i) W_t I_t(i) \tag{24}$$

$I_t(i)$ is an indicator function equal to one if the firm changes its price and equal to zero otherwise. $\chi_j(i)$ is the sector specific menu cost. The final term indicates that firms must hire an extra $\chi_j(i)$ units of labor if they decide to change prices with probability $1-\alpha_j$, or may change their price for free with probability α_j.

Total demand for good i is given by:

$$y_t(i) = Y_t\left(\frac{p_t(i)}{P_t}\right)^{-\theta} \tag{25}$$

The firm problem is to maximize profits in (24) subject to its production function (22), demand for its final good product (25), and the behavior of aggregate variables.

Aggregate productivity follows an AR(1) process:

$$log(A_t) = \rho_A log(A_{t-1}) + \sigma_A \nu_t \tag{26}$$

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

The log of firm productivity follows a mean reverting AR(1) process with shocks that arrive infrequently according to a Poisson process:

$$logz_t(i) = \begin{cases} \rho_z logz_{t-1}(i) + \sigma_{z,j}\epsilon_t(i) & \text{with probability } p_{z,j} \\ logz_{t-1}(i) & \text{with probability } 1-p_{z,j}, \end{cases} \tag{27}$$

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

Nominal aggregate spending follows a random walk with drift:

$$log(S_t) = \mu + log(S_{t-1}) + \sigma_s \eta_t \tag{28}$$

where $S_t = P_t C_t$ and $\eta_t \sim$ N(0,1).

B. Multi-Sector Model Results

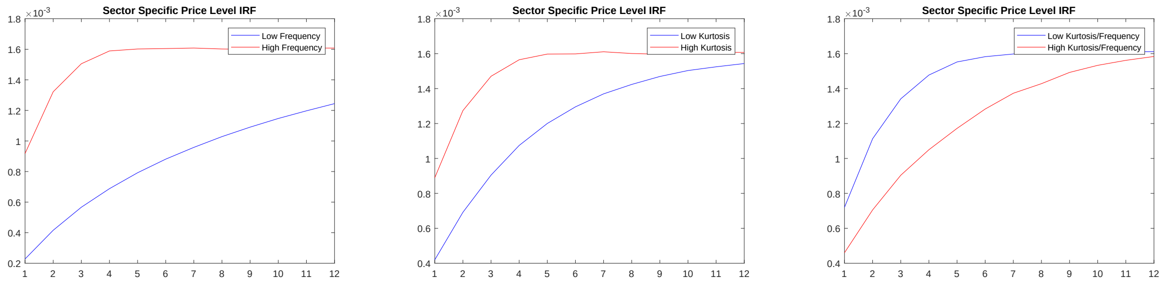
Figure 9 shows the results from the multi-sector menu cost model when industries are split by a pricing moment of interest. The model is calibrated to data is trimmed when price changes are less than \$.01 or greater than log(2) in absolute value. The model moments are in Table 5.

The left panel shows that the high frequency sector has a stronger response to a monetary shock. In the middle panel the high kurtosis sector has a stronger response to

Frequency Calibration				
	Low Frequency Sector		High Frequency Sector	
Moment	Data	MC	Data	MC
Frequency	0.06	0.06	0.28	0.28
Average Size	0.088	0.090	0.057	0.057
Fraction Small	0.11	0.15	0.19	0.19
Kurtosis	3.1	3.2	4.9	5.2
$\frac{\text{Kurtosis}}{\text{Frequency}}$	46.1	52.4	24.2	18.9
Kurtosis Calibration				
	Low Kurtosis Sector		High Kurtosis Sector	
Moment	Data	MC	Data	MC
Frequency	0.11	0.11	0.23	0.24
Average Size	0.082	0.082	0.066	0.068
Fraction Small	0.15	0.11	0.16	0.16
Kurtosis	2.5	2.7	5.6	5.9
$\frac{\text{Kurtosis}}{\text{Frequency}}$	29.5	24.3	41.0	24.9
Kurtosis/Frequency Calibration				
	Low Kurtosis/Frequency Calibration Sector		High Kurtosis/Frequency Calibration Sector	
Moment	Data	MC	Data	MC
Frequency	0.25	0.25	0.10	0.10
Average Size	0.065	0.066	0.082	0.081
Fraction Small	0.17	0.17	0.13	0.14
Kurtosis	3.5	3.8	4.5	4.8
$\frac{\text{Kurtosis}}{\text{Frequency}}$	17.9	14.9	52.7	49.6

Table 5: Multi-sector Pricing Moments

NOTE: Monthly pricing moments calculated using PPI data from 1998-2005. For all calibrations, each pricing moment is calculated at the 6 digit NAICS level. The average pricing moment is then calculated for industries above and below the median statistic of interest. Fraction small is the fraction of price changes less than one percent in absolute value.



(a) Frequency Menu Cost (b) Kurtosis Menu Cost (c) Kurtosis/Frequency Menu Cost

Figure 9: Multi-Sector Model Monetary Policy Shock IRF

NOTE: In all six figures, "Above Median" and "Below Median" refer to the impulse response function of the sector calibrated to match the pricing moments above or below the median value of the statistic for all industries. Model calibration noted under each figure. Impulse responses of sectoral prices in response to a permanent increase in money.

a monetary shock, and in the right panel the high kurtosis over frequency sector has a lower response to an expansionary monetary shock.

B Empirical Appendix

In this appendix we show summary statistics and additional robustness checks for time period of interest, type of monetary shock, and level of disaggregation.

In Tables 9 and 10, we present the summary statistics for pricing moments of interest.

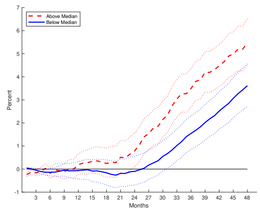
In Figure 17 we show FAVAR estimated impulse response functions when the industries are quartile subsets of the data rather than above and below median. Panel a shows that as frequency of price changes increases across quartiles, there is a larger price response to the monetary shock. Panel b shows that as the kurtosis of price changes increases across quartiles, the price response remains ambiguous. The response increases overall but also slightly goes down between the second and third quartiles. When we consider the ratio of kurtosis over frequency in panel c, the ordering is consistent across quartiles. Greater kurtosis over frequency is associated with a smaller price response.

In Figures 18 and 19, we show under both local projection and lag structure methodology that the Romer and Romer shock results continue to hold when we restrict the data to 1976 to 2007. Choice of the high frequency identified shock also does not affect our results. Rather than using the Gertler and Karadi (2015) version of the shock series, we examine the series from Nakamura and Steinsson (2018a). We use their data from January 1995 through March 2014. Results are in Figure 20 and are consistent with what we found with the Gertler and Karadi (2015) version of the shocks.

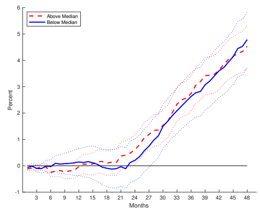
	Low Frequency			High Frequency			
Type of Trimming	Mean	Median	N Obs	Mean	Median	N Obs	Case
< P99	0.057	0.055	38092	0.262	0.223	160974	0
> 0.1%	0.060	0.057	40244	0.280	0.227	170598	1
< log(10/3)	0.058	0.056	38606	0.263	0.223	161499	2
< log(2)	0.058	0.056	38220	0.263	0.223	161145	3
< 100%	0.058	0.056	38510	0.263	0.223	161431	4
> 0%	0.061	0.058	40986	0.283	0.230	173172	5
> 0.5%	0.057	0.054	37437	0.266	0.211	158419	6
> 1.0%	0.054	0.051	36377	0.250	0.190	141862	7
> 0.1%, < log(2)	0.054	0.051	36510	0.251	0.190	142030	8
	Low Kurtosis			High Kurtosis			
Type of Trimming	Mean	Median	N Obs	Mean	Median	N Obs	Case
< P99	2.36	2.32	31315	4.85	4.31	167751	0
> 0.1%	2.43	2.41	30287	5.03	4.46	180555	1
< log(10/3)	2.42	2.47	31081	5.33	4.68	169024	2
< log(2)	2.37	2.32	29363	5.00	4.45	170002	3
< 100%	2.41	2.43	30515	5.23	4.67	169426	4
> 0%	2.46	2.47	33583	5.09	4.51	180575	5
> 0.5%	2.34	2.32	29271	4.73	4.29	166585	6
> 1.0%	2.24	2.24	26091	4.45	4.12	152148	7
> 0.1%, < log(2)	2.26	2.25	26172	4.57	4.16	152368	8
	Low Kurtosis/ Frequency			High Kurtosis / Frequency			
Type of Trimming	Mean	Median	N Obs	Mean	Median	N Obs	Case
< P99	17.11	17.75	136640	49.80	42.98	62426	0
> 0.1%	17.07	17.60	146225	49.44	42.90	64617	1
< log(10/3)	17.76	18.61	116696	51.96	45.79	83409	2
< log(2)	17.30	17.75	116413	50.42	43.49	82952	3
< 100%	17.63	18.19	116647	51.47	44.78	83294	4
> 0%	17.06	17.75	128030	49.38	43.03	86128	5
> 0.5%	17.03	17.34	135421	49.80	43.53	60435	6
> 1.0%	17.09	17.69	121119	50.34	44.16	57120	7
> 0.1%, < log(2)	17.29	17.69	120798	50.87	44.16	57742	8

Table 6: Pricing Moment Robustness

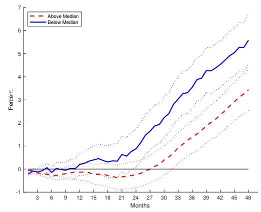
NOTE: The table shows the average and median price change moment by above-median and below-median bin, under various trimming methods. The top panel reports mean and median price change frequency by above-median and below-median set, the middle panel reports mean and median price change kurtosis by above-median and below-median set, and the bottom panel reports mean and median price change kurtosis over frequency by above-median and below-median set. Moments are computed by standardizing price changes at 6 digit NAICS industry level. N Obs is the number of observations in each set for each trimming method. Each row describes a different sub-sample of the data applying the filter described in the column "Type of Trimming."' The subsample for case 0 is the baseline sample in the main text of the paper: price changes are included if they are larger in absolute value than $0.01 and lower in value than the 99^{th} percentile of changes. Each additional row describes the impact of changing one of the upper or lower thresholds in the "Type of Trimming." The second row changes the lower trimming threshold such that the sample now includes price changes if they are larger in absolute value than 0.1% and lower in value than the 99^{th} percentile of changes. Case 8 changes both the upper and lower thresholds.



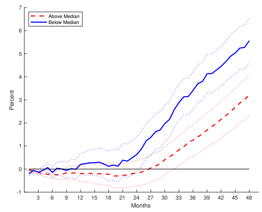
(a) Frequency



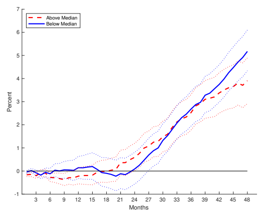
(b) Kurtosis



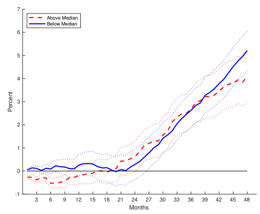
(c) Kurtosis/Frequency



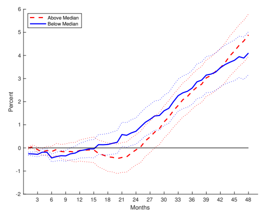
(d) S.D. Duration



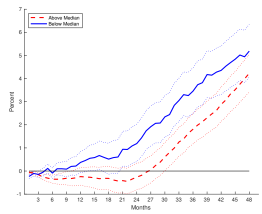
(e) Average Size



(f) Standard Deviation



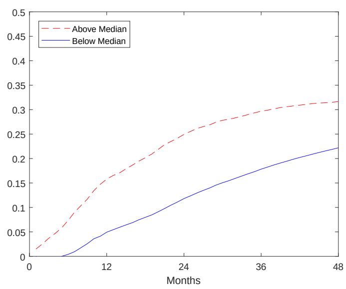
(g) Fraction Small



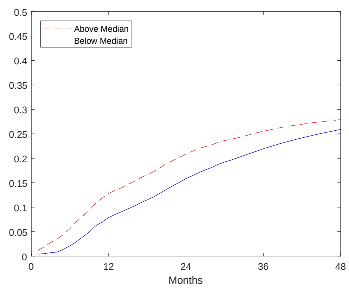
(h) Fraction Positive

Figure 10: Romer and Romer Monetary Policy Shock IRF

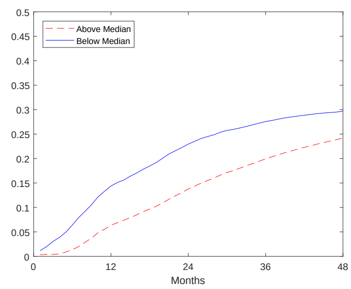
NOTE: In the above figures, we plot the impulse response functions calculated from the following specification: $\pi_{j,t} = \alpha_j + \sum_{k=1}^{11} \beta_{j,k} D_k + \sum_{k=1}^{24} \eta_{j,k}\pi_{j,t-k} + \sum_{k=1}^{48} \theta_{j,k} MP_{t-k} + \epsilon_{j,t}$ where $\pi_{j,t}$ is the inflation rate for industries in the "Above Median" or "Below Median" set according to the pricing moment of interest, at time t measured at monthly frequency. Dashed lines present 68% bootstrapped standard error bands.



(a) Frequency



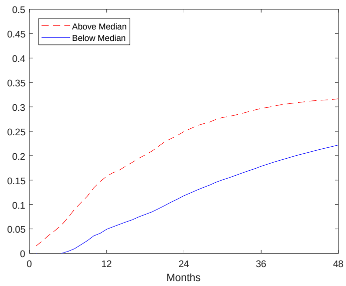
(b) Kurtosis



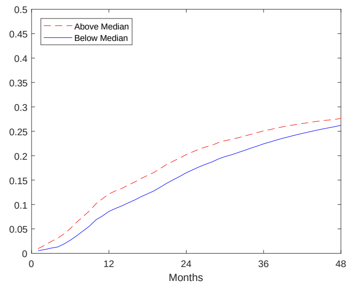
(c) Kurtosis/Frequency

Figure 11: FAVAR Monetary Policy Shock IRF - Robustness to Small Price Changes

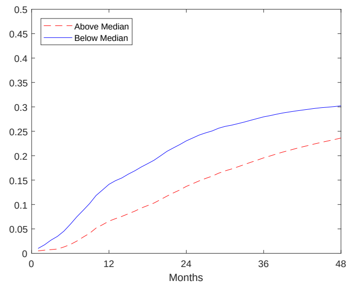
NOTE: In the above panels, "Above Median" and "Below Median" refer to the impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. Data are trimmed as in Case 1 in Table 6. Different from our baseline sample, small price changes are trimmed when they are less than 0.1 percent in absolute value. FAVAR estimated impulse responses of sectoral prices in percent to an identified 25 basis point unexpected Federal Funds rate decrease are shown.



(a) Frequency



(b) Kurtosis



(c) Kurtosis/Frequency

Figure 12: FAVAR Monetary Policy Shock IRF - Robustness to Large Price Changes

NOTE: In the above panels, "Above Median" and "Below Median" refer to the impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. Data are trimmed as in Case 3 in Table 6. Relative from our baseline sample, large price changes are trimmed when they are greater than log(2) in absolute value. FAVAR estimated impulse responses of sectoral prices in percent to an identified 25 basis point unexpected Federal Funds rate decrease are shown.

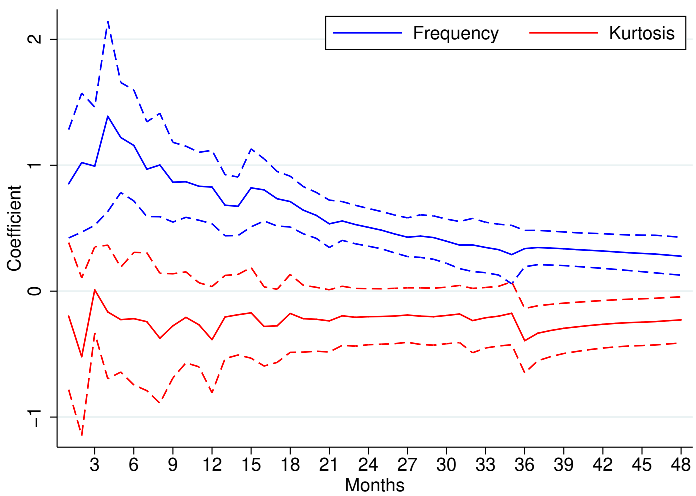
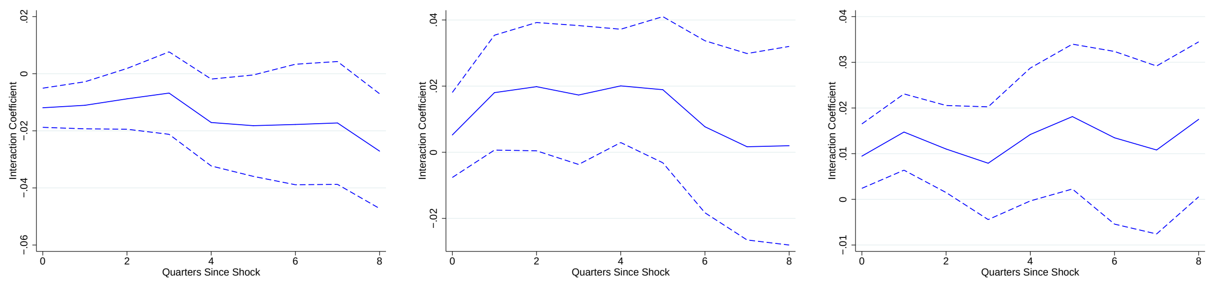


Figure 13: FAVAR Cross-Sectional Regression Coefficients

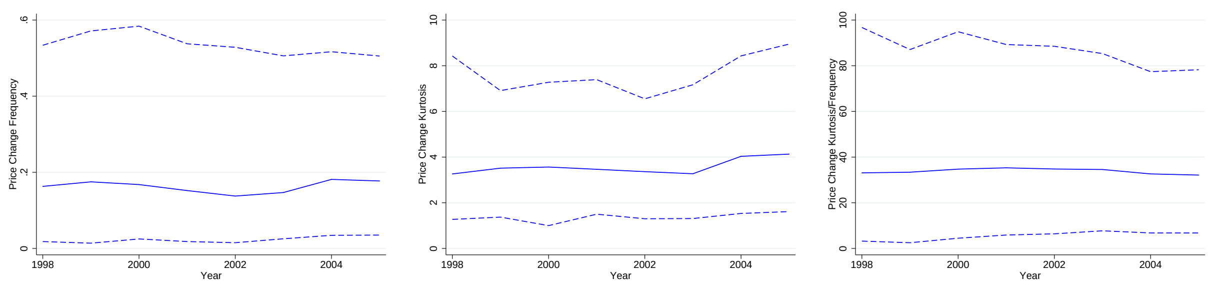
NOTE: The above figure shows the relationship of the full horizon response for the FAVAR estimated price level response to an expansionary monetary shock to the key pricing moments. The coefficient values are estimated from $log(IRF_{k,h}) = a + \beta_h' M_k + \alpha_{j,h} + \epsilon_{k,h}$ where the horizon h is varied 1 to 48 months after the monetary shock, and the covariates are the log frequency, log kurtosis, log average size, log standard deviation of price changes, fraction of small price changes, fraction of positive price changes, and 3-digit NAICS fixed effects. Dashed lines present 90% standard error bands.



(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency

Figure 14: Romer and Romer Monetary Policy Shock IRF

NOTE: In the above panels, we plot the respectively estimated coefficients θ_h from the following specification: $Log(sales_{j,t+h}) = \alpha_{th} + \alpha_{jh} + \theta_h * MPshock_t \times M_j + controls_t + \epsilon_{j,t+h}$ where $sales_{j,t+h}$ denotes firm j sales at time t measured at quarterly frequency, h months into the future. Controls further include 4 quarters of lagged log sales, and current and 4 quarters of lagged log assets. Monetary policy shocks are measured by the Romer and Romer shock. M_j contains one of our three firm-level pricing moments: frequency, kurtosis, or the ratio of the two statistics. Heteroskedasticity and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Driscoll and Kraay (1998) with a lag length equal to forecast horizon of h. Dashed lines present 90% standard error bands.



(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency

Figure 15: Annual Average Pricing Moments

NOTE: Each monthly pricing moment is calculated at the industry-month, averaged within an industry at an annual frequency, and then presented as a cross-sectional average. The dotted lines are the 25th and 75th percentiles of each moment.

Cross-Sectional Determinants of Sectoral Price Response Univariate Specifications						
	Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1	
	(1)	(2)	(3)	(4)	(5)	(6)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$	-0.420***	-0.250***	-0.493***	-0.335***	-0.448***	-0.269***
	(0.060)	(0.074)	(0.066)	(0.074)	(0.071)	(0.077)
NAICS 3 FE		X		X		X
N	148	148	147	147	147	147
Log Frequency	0.448***	0.422***	0.470***	0.454***	0.507***	0.521***
	(0.056)	(0.073)	(0.060)	(0.078)	(0.067)	(0.094)
NAICS 3 FE		X		X		X
N	148	148	148	148	148	148
Log Kurtosis	0.289***	0.138	0.303**	0.072	0.301**	0.181
	(0.106)	(0.119)	(0.131)	(0.129)	(0.124)	(0.122)
NAICS 3 FE		X		X		X
N	148	148	147	147	147	147
Log Avg. Size	-0.594***	-0.316**	-0.497***	-0.313	-1.065***	-0.536**
	(0.120)	(0.148)	(0.182)	(0.231)	(0.205)	(0.234)
N	148	148	148	148	148	148
Log Std. Dev.	-0.456***	-0.158	-0.444**	-0.236	-0.687***	-0.181
	(0.141)	(0.127)	(0.184)	(0.169)	(0.241)	(0.252)
NAICS 3 FE		X		X		X
N	148	148	147	147	147	147
Log Frac. Small	0.034	0.017	0.150	0.136	0.098	0.134
	(0.071)	(0.077)	(0.092)	(0.088)	(0.099)	(0.093)
NAICS 3 FE		X		X		X
N	146	146	136	136	136	136
Log Frac. Pos.	-0.702**	-0.334	-0.775	-0.694	-0.950	-0.260
	(0.304)	(0.382)	(0.575)	(0.716)	(0.585)	(0.836)
NAICS 3 FE		X		X		X
N	148	148	148	148	148	148

Table 7: Decomposing Monetary Non-Neutrality IV and Subsample

Note: This tables uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following specification: $log(IRF_{k,h}) = a + \beta' M_k + \alpha_j + \epsilon_{k,h}$. Where $Log(IRF_{k,h})$ is the log of the 24-month cumulative sectoral response of prices to a monetary shock from our FAVAR analysis. M_k contains one of our industry-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average size, and standard deviation of price changes, or the full set of pricing moments. α_j are three-digit NAICS industry fixed effects and are included in columns (2), (4), and (6). The pricing moments are calculated over the full sample in columns (1) and (2). In columns (3) through (6), the data set is split into an early and late subsample and the two subsamples are used as instruments for each other. Robust standard errors in parentheses. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Cross-Sectional Determinants of Sectoral Price Response Multivariate Specifications						
	Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Frequency	0.520***	0.476***	0.561***	0.549***	0.623***	0.601***
	(0.056)	(0.074)	(0.062)	(0.074)	(0.072)	(0.099)
Log Kurtosis	-0.222**	-0.151	-0.237*	-0.223*	-0.313**	-0.220*
	(0.104)	(0.112)	(0.127)	(0.120)	(0.125)	(0.118)
NAICS 3 FE		X		X		X
N	148	148	147	147	147	147
Log Frequency	0.527***	0.507***	0.867***	0.630***	0.596**	0.620***
	(0.088)	(0.091)	(0.222)	(0.126)	(0.273)	(0.197)
Log Kurtosis	-0.221	-0.203	-0.399	-0.198	-0.742	-0.711
	(0.139)	(0.135)	(0.326)	(0.258)	(0.475)	(0.519)
Log Avg. Size	-0.182	-0.225	0.724	0.378	-2.623*	-2.369
	(0.263)	(0.222)	(1.039)	(0.861)	(1.479)	(1.586)
Log Std. Dev.	-0.083	0.097	-0.374	-0.093	1.671	2.065
	(0.227)	(0.185)	(0.853)	(0.727)	(1.434)	(1.674)
Log Frac. Small	-0.149**	-0.104	0.125	0.102	-0.514**	-0.249
	(0.068)	(0.078)	(0.206)	(0.149)	(0.228)	(0.174)
Log Frac. Pos.	0.252	0.210	1.940*	0.433	-0.275	-0.326
	(0.406)	(0.415)	(1.083)	(0.749)	(1.522)	(1.392)
NAICS 3 FE		X		X		X
N	146	146	136	136	136	136

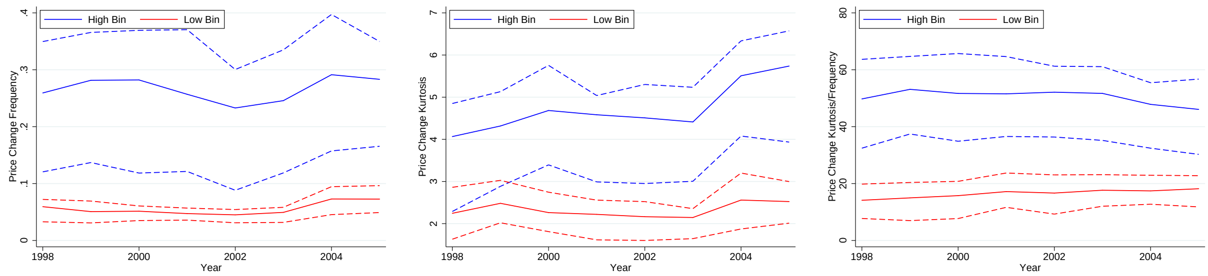
Table 8: Decomposing Monetary Non-Neutrality IV and Subsample

NOTE: This tables uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following specification: $log(IRF_{k,h}) = a + \beta' M_k + \alpha_j + \epsilon_{k,h}$. Where $Log(IRF_{k,h})$ is the log of the 24-month cumulative sectoral response of prices to a monetary shock from our FAVAR analysis. M_k contains one of our industry-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average size, and standard deviation of price changes, or the full set of pricing moments. α_j are three-digit NAICS industry fixed effects and are included in columns (2), (4), and (6). The pricing moments are calculated over the full sample in columns (1) and (2). In columns (3) through (6), the data set is split into an early and late subsample and the two subsamples are used as instruments for each other. Robust standard errors in parentheses. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

	Mean	SD	P50
Frequency	0.19	0.21	0.09
Kurtosis	5.58	3.57	4.70
Kurtosis/ Frequency	73.74	78.16	50.00
Number of Price Changes	157.9	251.2	69.0
Firms		309	

Table 9: Firm Level Pricing Statistics

NOTE: This table shows the mean, standard deviation, and median firm level pricing moments for our Compustat-PPI matched sample using monthly data from 2005 through 2014.



(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency

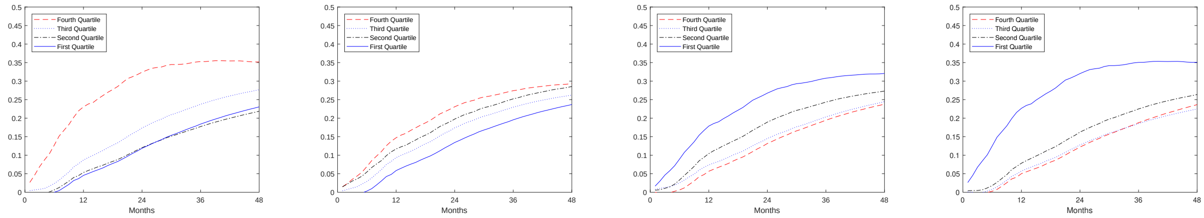
Figure 16: Annual Average Pricing Moments within Bin

NOTE: Each monthly pricing moment is calculated at the industry-month, averaged within an industry at an annual frequency, and then presented as a cross-sectional average within the above and below median subsets. The dotted lines are the 25th and 75th percentiles of each moment within each subset.

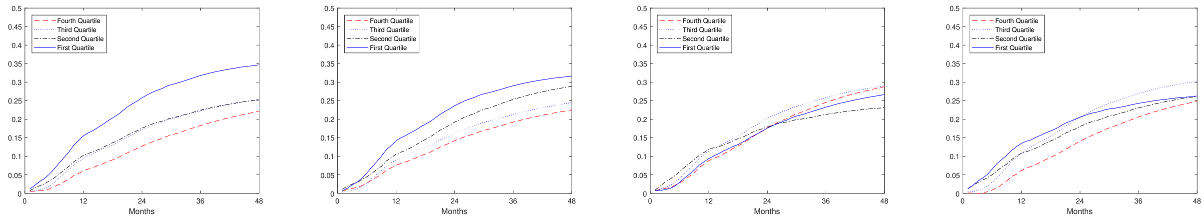
	Mean	SD	P50
Frequency	0.16	0.16	0.09
Kurtosis	4.0	2.6	3.5
Kurtosis/ Frequency	34.7	23.2	28.8
Number of Price Changes	1431	2844	634
Industries		154	

Table 10: Industry Level Pricing Statistics

NOTE: This table shows the mean, standard deviation, and median industry level pricing moments for the PPI sample using monthly data from 1998 through 2005.



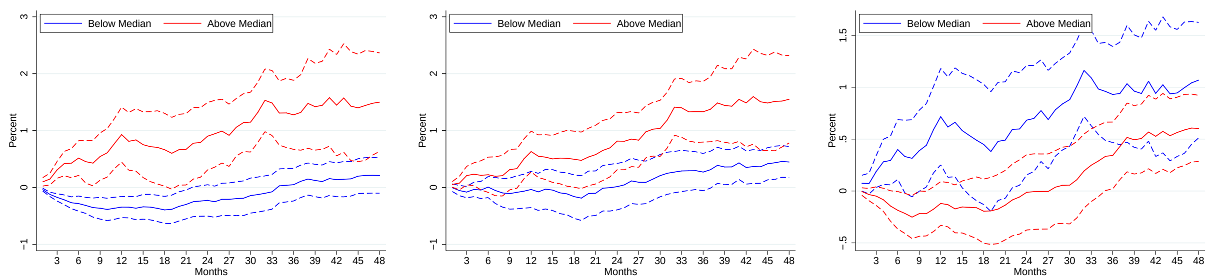
(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency (d) S.D. Duration



(e) Average Size (f) Standard Deviation (g) Fraction Small (h) Fraction Positive

Figure 17: FAVAR Monetary Policy Shock IRF - Robustness to Disaggregation

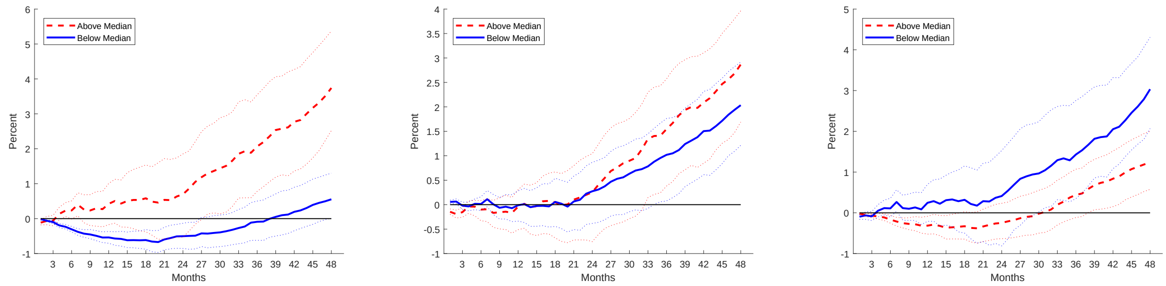
Note: In the above panels, "Quartile" refers to the impulse response function of industries whose pricing moment is included in a given quartile subset for the value of that statistic for all industries. Estimated impulse responses of sectoral prices in percent to an identified 25 basis point unexpected Federal Funds rate decrease are shown.



(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency

Figure 18: Romer and Romer Monetary Policy Shock IRF 1976-2007

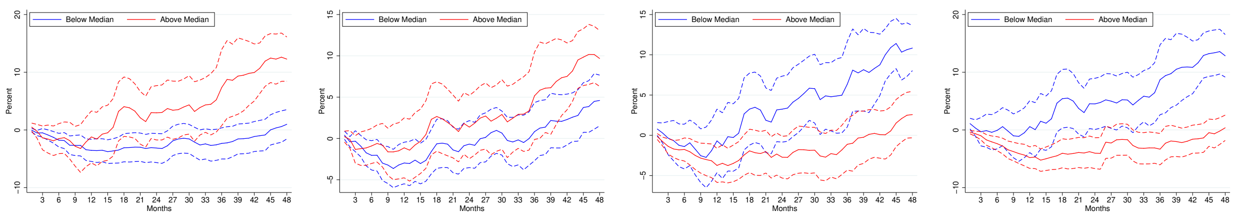
Note: In the above figures, we plot the respectively estimated coefficients $\theta_{A,h}$ and $\theta_{B,h}$ from the following specification: $Log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} * MPshock_t + \varphi_{A,h} z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} * MPshock_t + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h}$ where $ppi_{j,t+h}$ is the price level for industries in the "Above Median" or "Below Median" set according to the pricing moment of interest, at time t measured at monthly frequency, h months into the future. Controls include two lags of the RR shock, two lags of the Fed Funds rate, and current and two lags of the unemployment rate, industrial production, and price level. Standard errors are constructed using the Newey-West correction for serial autocorrelation. Dashed lines present 68% standard error bands.



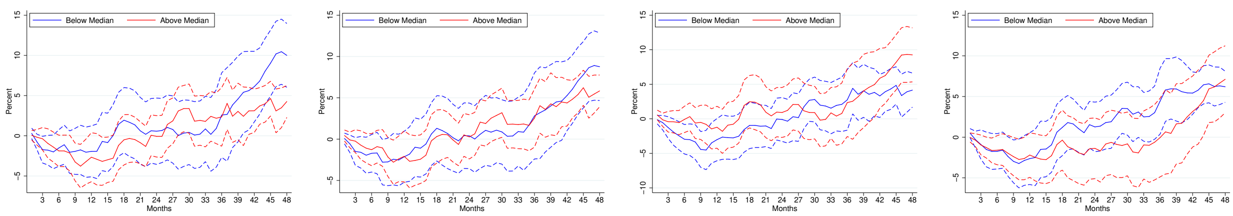
(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency

Figure 19: Romer and Romer Monetary Policy Shock IRF

NOTE: In the above figures, we plot the impulse response functions calculated from the following specification: $\pi_{j,t} = \alpha_j + \sum_{k=1}^{11} \beta_{j,k} D_k + \sum_{k=1}^{24} \eta_{j,k}\pi_{j,t-k} + \sum_{k=1}^{48} \theta_{j,k} MP_{t-k} + \epsilon_{j,t}$ where $\pi_{j,t}$ is the inflation rate for industries in the "Above Median" or "Below Median" set according to the pricing moment of interest, at time t measured at monthly frequency. Dashed lines present 68% bootstrapped standard error bands.



(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency (d) S.D. Duration



(e) Average Size (f) Standard Deviation (g) Fraction Small (h) Fraction Positive

Figure 20: High Frequency Identified Monetary Policy Shock IRF- Nakamura and Steinsson Series

NOTE: In the above figures, we plot the respectively estimated coefficients $\theta_{A,h}$ and $\theta_{B,h}$ from the following specification: $Log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} * MPshock_t + \varphi_{A,h} z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} * MPshock_t + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h}$ where $ppi_{j,t+h}$ is the price level for industries in the "Above Median" or "Below Median" set according to the pricing moment of interest, at time t measured at monthly frequency, h months into the future. Controls include two lags of the high frequency identified shock, two lags of the Fed Funds rate, and current and two lags of the unemployment rate, industrial production, and price level. Standard errors are constructed using the Newey-West correction for serial autocorrelation. Dashed lines present 68% standard error bands.