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

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Abstract

Cross-sectional variation in micro data can be used to empirically evaluate sufficient statistics for the response of aggregate variables to policy shocks of interest. We demonstrate an easy-to-use approach through a detailed example. We evaluate the sufficiency of micro pricing moments for the aggregate real effects of monetary policy shocks. Our analysis shows how a widely held notion about the kurtosis of price changes, as sufficient for summarizing the selection effect, turns out not to hold empirically. On theoretical grounds, we show how a small change in assumptions - removing random menu costs - can nonetheless reconcile the predictions of the existing theoretical literature with our empirical regularities.

Resumen

Este artículo propone una metodología basada en micro datos para evaluar candidatos de estadísticos suficientes propuestos para cuantificar la respuesta de variables agregadas a shocks de política. Esa metodología se ilustra usando un ejemplo: la relación entre estadísticas de datos micro de precios y el efecto agregado de la política monetaria. El principal resultado es que no hay evidencia de la validez empírica de la importancia de un estadístico suficiente ampliamente aceptada en modelos de costos de menú, la razón de curtosis de la distribución de cambios de precios sobre la frecuencia de dichos cambios. Teóricamente, se muestra que una variación en el modelo estándar puede reconciliar las predicciones del modelo con la evidencia encontrada.

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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.

Our expository example focuses on a recent literature that has summarized the extent of aggregate output effects following monetary policy shocks – monetary non-neutrality – with a sufficient statistics approach. After conditioning on price stickiness, given by price change frequency, the focus here typically lies with a key pricing moment, the kurtosis of price changes. Kurtosis of price changes can be a sufficient statistic because it embodies the so-called “selection effect” (Golosov and Lucas (2007), Midrigan (2011)): When a monetary shock occurs, prices that were already very far from their desired levels are more likely to adjust and by a large amount, even if the shock is relatively small.1 As a result, the overall price level is flexible in response to aggregate shocks rather than real quantities, reducing the real effects of monetary policy. The resulting steady-state distribution of price changes will exhibit low kurtosis because very large price changes have been “cut out” relative to a normal distribution due to the presence of strong such selection. Alvarez et al. (2016) have formalized this notion with a sufficient statistics approach. They show that the degree of monetary non-neutrality can be pinned down in a wide class of models by the ratio of two pricing moments, the kurtosis of price changes and the frequency of price changes.2

1Throughout the rest of the paper when we discuss the sufficiency of kurtosis of price changes, it is after conditioning on price change frequency.
2“We show that the ratio of kurtosis to the frequency of price changes is a sufficient statistics for the real effects of monetary shocks, measured by the cumulated output response following a monetary shock.” Alvarez et al. (2016) The notion goes back at least to the work of Midrigan (2007) who points out that how large the real effects of monetary policy shocks are “depends on higher-order moments of the distribution of idiosyncratic disturbances in the economy.” Alvarez et al. (2016) argue in their introduction that kurtosis is sufficient since “We show that this statistic embodies the extent to which “selection” of price changes occurs. [. . . ] This paper shows that the selection concerning the timing is also encoded in the kurtosis of price changes.”
We demonstrate how cross-sectional variation in micro data can be used to empirically evaluate candidate sufficient statistics, here in the realm of price-setting and with a focus on monetary non-neutrality. Our analysis in particular shows how kurtosis of price changes fails to summarize monetary non-neutrality as posited when we take it to the data. Instead, the relationship with monetary non-neutrality is ambiguous or has an unexpected sign. Kurtosis over frequency of price changes is informative about monetary non-neutrality but only because frequency has a strong negative association. While frequency is consistently informative and significant for understanding monetary non-neutrality, neither pricing moment is a completely sufficient statistic: Inclusion of other moments and variables is also informative about monetary non-neutrality, and any combination of moments we consider only explains approximately half of the variation in monetary non-neutrality, leaving the other half unaccounted for.3

Our contribution more generally lies in showing how empirical regularities can be used to validate key modeling mechanisms, in our example in the pricing literature. In particular, we show in this context how to reconcile the commonly held notion that higher kurtosis leads to higher monetary non-neutrality with our empirical findings. We find that both a discrete-time version of the Golosov and Lucas (2007) model – a model in the class of Alvarez et al. (2016) – and an off-the-shelf, state-of-the-art menu cost model do in fact predict the negative association of kurtosis and monetary non-neutrality from the data. However, a small difference in assumptions, the assumption of random menu costs, generates the flip in sign in the predictions of Alvarez et al. (2016). The reason is that this assumption is closely tied to the fraction of random, small price changes as we show below.

Our analysis sets out by establishing the above empirical regularities for the response of prices and quantities, conditional on a monetary policy shock. To this end, we exploit micro price data from the Bureau of Labor Statistics (BLS) on producer prices to evaluate the relation between pricing moments, namely kurtosis of price changes, frequency of price changes and the ratio of the two, and monetary non-neutrality. In particular, our approach

3What a sufficient statistic is in macroeconomics is surprisingly not precisely defined in the literature. We take it to be 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 the explanatory power of the formula with respect to the variable of interest should be extremely high. Our methodology shows what pricing moments are empirically informative for monetary non-neutrality and therefore are helpful for evaluating what model ingredients are necessary.
computes conditional impulse response functions of output and prices as a measure of monetary non-neutrality. Impulse response functions are estimated to a monetary policy shock as is standard, 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.

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 relationship between monetary policy shocks and pricing moments, which can be candidate sufficient statistics, in two ways. As our first approach, we use the micro price data that underlie the producer price index (PPI) at the Bureau of Labor Statistics (BLS) to classify the PPI inflation data published at the six-digit NAICS level into two subsets. One subset is above and the other subset below the median of a proposed explanatory pricing moment. Here we compute pricing moments at the sector-month level and then average the moment within a sector over time before sorting them. Such pooling avoids sensitivity to outliers. 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 at the six-digit NAICS level 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. 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 wrong direction: prices in the high-kurtosis subset respond by more and not by less. This is at odds with the
theoretical notion of larger real and smaller nominal responses when kurtosis is higher.

Finally, and most importantly, we use regression analysis to decompose the effects of monetary non-neutrality into kurtosis and frequency. We find that it is entirely driven by frequency. Frequency is always a significant variable, and explains about 50% of the variation in monetary non-neutrality by itself. Kurtosis is not significant and explains the least variation, thus adding noise to the informativeness of the kurtosis of frequency ratio. This result continues to hold when we add other moments and variables as controls. However, our analysis also shows that neither kurtosis nor frequency nor their ratio taken individually can be a completely sufficient statistic. For example, we find that profits or the persistence of idiosyncratic shocks also can be significant and informative for monetary non-neutrality.

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. 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.

These empirical regularities open up questions for theory which we address: How do we reconcile the commonly held notion that higher kurtosis leads to higher monetary non-neutrality – distilled most clearly in the sufficient statistic approach – with the empirical findings? And in particular, can menu cost models generate predictions in line with the 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 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 enables assessment of how such variation changes the real effects following a monetary policy shock. 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 or has an unexpected sign. Third, the relationship of kurtosis over frequency
with monetary non-neutrality is non-monotonic and can be negative. We verify that these
predictions also hold in a discrete-time version of Golosov and Lucas (2007), which falls
into the class of models covered by the analysis of Alvarez et al. (2016). These results
imply that kurtosis of price changes cannot be a sufficient statistic.

Next, we show how to reconcile the negative relationship between kurtosis and
monetary non-neutrality in the data and these two menu cost models with the held
notion that kurtosis should have a positive relationship with monetary non-neutrality.
Our main insight is that the degree of Calvoness, embodied in the fraction of random,
small price changes, is key. This fraction is both positively linked with kurtosis of price
changes and monetary non-neutrality. When the fraction of random, small price changes
increases, the larger mass of small price changes can increase kurtosis. But these random
price changes have zero selection by construction; they are not adjusting in response to
a monetary shock and therefore they also increase monetary non-neutrality. The random
menu costs in Alvarez et al. (2016) that are used to encapsulate models from Golosov
and Lucas (2007) at one extreme to the Calvo model at the other, link kurtosis and
monetary non-neutrality. We emphasize that our example shows what pricing moments
are empirically informative for monetary non-neutrality and therefore are 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

\footnote{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 the continuous-time setting where the mass of price changes at the \( S_s \) 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.}

\footnote{While there are many formulations of random menu costs in the literature such as Dotsey and Wolman (2018) or Ball and Mankiw (1995), we follow Alvarez et al. (2016) exactly in how we model random menu costs: Each period, firms get to change prices for free with an exogenously given probability. This formulation is the same as the CalvoPlus model of Nakamura and Steinsson (2010).}
concludes.

A. Literature review

Our main contribution lies in providing empirical insights about what price-setting moments are informative for monetary non-neutrality following monetary policy shocks. In particular, we focus on the notion that kurtosis of price changes is a key moment for monetary non-neutrality. 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.

First, our analysis speaks 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. The approach has recently been pioneered by the important theoretical contribution by Alvarez et al. (2016). This paper establishes that across a large class of models, the ratio of kurtosis over frequency of price changes is a sufficient statistic of monetary non-neutrality. Our contribution is to empirically evaluate the proposed sufficient statistic, 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. We show that empirically only frequency matters as expected. The underlying notion that kurtosis is positively associated with monetary non-neutrality does not hold in the data.

Moreover, 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 show that even in a simple menu cost model, calibrated to CPI micro moments, one specific pricing moment, kurtosis of price changes, is not a sufficient statistic as proposed in the literature. We instead find that increasing kurtosis can predict lower monetary non-neutrality. What further distinguishes our analysis is that we show why Alvarez et al. (2016) 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 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 pricing 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 policy shock. 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
Our general approach is to construct a measure of monetary non-neutrality, our key policy variable of interest, 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: frequency, kurtosis and kurtosis over frequency of price changes. 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, or kurtosis over frequency. 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. 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
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 obtain responses for the prices sorted into two bins according to high or low pricing moments by estimating the following local projections:

$$\log(ppi_{j, t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} * MP_{shock_t} + \varphi_{A,h} z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} * MP_{shock_t} + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h}$$  \hspace{1cm} (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. $MP_{shock_t}$ 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:

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

11
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.\(^6\) We also note that the Alvarez et al. (2016) model, whose predictions we test, abstracts from complementarities and general-equilibrium effects so that sectoral relations between pricing moments and monetary non-neutrality are informative. In a multi-sector version of their model, aggregate monetary non-neutrality is a function of the expenditure weighted average of the sectoral moments.

\section*{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{equation}
\log(p_{ji,(t+h)}) = \beta_h + I_{PS>M}[\theta_{A,h}*MP_{s,t+h} + \varphi_{A,h}z_{j,t}] \\
+ (1 - I_{PS>M})[\theta_{B,h}*MP_{s,t+h} + \varphi_{B,h}z_{j,t}] + \epsilon_{j,t+h}
\end{equation}

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

\(^6\)We thank Adrien Auclert for pointing out the value of model guidance for our empirical strategy in this context. A similar result in BGM (2009) also supports our approach: The average of sectoral IRFs closely resembles the aggregate IRF following a monetary policy shock.
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 prices. We estimate the following specification:

$$\log(sales_{j,t+h}) = \alpha_{th} + \alpha_{jh} + \theta_{h} \times MP_{shock_{t}} \times M_{j} + controls_{t} + \epsilon_{j,t+h}$$

(4)

where $\alpha_{th}$ are time fixed effects, $\alpha_{jh}$ 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 $\theta_{h}$ 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 $k$:

$$\pi_{k,t} = \lambda_k' C_t + \epsilon_{k,t}$$  \hspace{1cm} (5)

In the FAVAR setting, this sectoral inflationary response is given by the loading $\lambda_k'$ 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 response 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:

$$\log(\text{IRF}_{k,h}) = a + \alpha_j + \beta' M_k + \gamma' X_j + \epsilon_{k,h}$$  \hspace{1cm} (6)

where $\log(\text{IRF}_{k,h})$ denotes the cumulative response of prices for an $h$-month horizon in sector $k$. $\alpha_j$ are three-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. Kurtosis of price changes has none, or even a negative association, with our measures of monetary non-neutrality, contrary to the notion in the literature. Kurtosis over frequency of price changes is 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.

A.1 Narrative Approach

First, both specifications that rely on the Romer and Romer identification scheme yield nearly identical results. We summarize the findings from the local projection specification in equation 1 in Figure 1 while Figure 2 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 2 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 2 shows the associated impulse response.

In terms of kurtosis over frequency, our results tend to confirm that the association between the moment and monetary non-neutrality has the correct sign as predicted by Alvarez et al. (2016). 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 quantify this relationship further below.

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 3 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 3. 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 $\theta_h$ measures the differential impact of a monetary shock at horizon $h$ depending on the pricing moment $M_j$. Figure 4 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 significant impact on real sales.7

A.3 FAVAR Approach

Third, using a FAVAR approach shows very similar results for the relationship between pricing moments and monetary non-neutrality. Figure 5 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

7We confirm these firm-level findings using Romer and Romer shocks. Figure 14 in the Appendix displays the results.
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 shows 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.\(^8\)

\[\text{B. Further Results from Regression Analysis}\]

Next, we present key cross-sectional results that confirm our findings in a quantitatively more rigorous setting. Our main message is that the frequency of price changes is always informative about monetary non-neutrality, as the previous subsection already suggested. The ratio of kurtosis over frequency is informative but only because frequency is informative. Kurtosis by itself has the wrong sign and loses significance once fixed effects or further explanatory variables are included. Other moments when included also turn out to be significant and informative. Among all pricing moments considered, the specification with frequency alone has the highest explanatory power while overall, explanatory power is moderate across specifications. These last two findings suggest that neither pricing moment is an empirically completely sufficient statistic. We now show these results using 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. Table 1 shows our results.

Our main finding at the sectoral level is that frequency of price changes and kurtosis over frequency are always significantly related to monetary non-neutrality in a way

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\(^8\)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.
consistent with the literature. The informativeness of frequency completely drives the informativeness of the ratio. Kurtosis of price changes has an ambiguous relationship, never enters significantly and has low explanatory power. Column 1 shows that overall kurtosis over frequency has a statistically significant, negative relationship with the cumulative price response. This is in line with the prediction of Alvarez et al. (2016). Next, we look at the relationships of frequency and kurtosis individually in Columns 2 and 3, and other pricing moments such average size and the standard deviation of price changes in columns 4 and 5. The price response has a positive and significant relationship with the price change frequency – but not kurtosis which enters insignificantly. The positive sign for kurtosis is moreover at odds with the notion suggested in the menu cost literature suggests: higher kurtosis is associated at a higher price response and hence, less monetary non-neutrality. The moment summarizing the absolute size of price changes is significantly associated with an overall lower price response while the standard deviation of price changes carries no significance.

When we jointly relate the log 24-month cumulative response of prices to both log frequency and log kurtosis, the frequency of price changes remains significantly related with a very similar magnitude, but kurtosis flips sign and becomes insignificant. Column 6 shows this result, and the same results holds in column 7 when we include all pricing moments together: only frequency matters. Among all the pricing moments in columns 2 through 5, frequency considered separately has the highest explanatory power for monetary non-neutrality with an $R^2$ of 50%, kurtosis the lowest with 39%. The ratio of kurtosis over frequency in column 1 only explains 43% of the variation in monetary non-neutrality, indicating that kurtosis adds noise to the information contained in the frequency of price changes. All pricing moments taken together in column 7 explain only 51% of the total variation.

These results show 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. The results in the last 3 columns cast further doubt on the idea that any of the pricing moments are sufficient.

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9Figure 13 shows the estimated coefficients for the full impulse response horizon to an expansionary monetary shock for specification (7). The figure shows that frequency of price change has a stronger impact on the price response at shorter horizons before tapering off. Kurtosis of price change has little to no effect for the full horizon.
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 in 2 out of 3 columns, 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).\footnote{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.} If a pricing moment is a sufficient statistic, then no other variables should enter significantly and be informative as an explanator. Clearly, this is not the case.

Second, we decompose the determinants of monetary non-neutrality at the firm level, 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 sales as predicted by Alvarez et al. (2016). However, as Columns 2 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.

\section*{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 10 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 14 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 11) and combining all moments (Table 12). 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: Kurtosis comes out with an insignificant coefficient while the frequency of price changes is always significant and turns out to be the driver behind the significance of the ratio of kurtosis over frequency.

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

This section demonstrates the importance of taking into account our empirical pricing moments for understanding monetary non-neutrality in a menu cost model. 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 not generate a positive association between kurtosis and monetary non-neutrality. 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 which belongs to the class of models covered by Alvarez et al. (2016). Second, we introduce random menu costs to reconcile the model with the notion in the literature of a positive relation between kurtosis and monetary non-neutrality. Random menu costs generate random, free price changes. This mechanism increases the Calvoness of the most simplified model, the Golosov and Lucas (2007) model, while also raising the kurtosis in the model through a higher fraction of random, small price changes.

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

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

(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.

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11See 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.
\[ C_t = \left[ \int_0^1 c_t(z)^{\frac{1}{\sigma} - 1} \, dz \right]^{\frac{1}{1-\sigma}} \]  

(8)

where \( \theta \) 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

\[ c_t(z) = C_t \left( \frac{p_t(z)}{P_t} \right)^{-\theta} \]  

(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

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

(10)

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

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

(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

\[ D_{t,t+1} = \beta \left( \frac{C_tP_t}{C_{t+1}P_{t+1}} \right) \]  

(12)

\[ \frac{W_t}{P_t} = \omega C_t \]  

(13)

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

$$y_t(i) = A_t z_t(i) L_t(i)$$

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

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

where profits are given by:

$$\pi_t(i) = p_t(i) y_t(i) - W_t L_t(i) - \chi(i) W_t I_t(i)$$

$I_t(i)$ 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 $\alpha$.\textsuperscript{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:

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

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.

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\textsuperscript{12}This is a reduced form modeling device representing multiproduct firms like in Midrigan (2011).
Aggregate productivity follows an AR(1) process:

\[ \log(A_t) = \rho_A \log(A_{t-1}) + \sigma_A \nu_t \]  

(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:

\[
\log z_t(i) = \begin{cases} 
\rho_z \log z_{t-1}(i) + \sigma_z \epsilon_t(i) & \text{with probability } p_z \\
\log z_{t-1}(i) & \text{with probability } 1 - p_z,
\end{cases}
\]  

(19)

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

Nominal aggregate spending follows a random walk with drift:

\[ \log(S_t) = \mu + \log(S_{t-1}) + \sigma_s \eta_t \]  

(20)

where \( S_t = P_tC_t \) 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:

\[
\log \left( \frac{P_t}{S_t} \right) = \gamma_0 + \gamma_1 \log A_t + \gamma_2 \log \left( \frac{P_{t-1}}{S_t} \right) + \gamma_3 \left( \log \left( \frac{P_{t-1}}{S_t} \right) * \log A_t \right)
\]  

(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 $\beta = (0.96)^{1/12}$. The elasticity of substitution is set to $\theta = 4$ as in Nakamura and Steinsson (2010). 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 $\chi$, the probability of an idiosyncratic shock, $p_z$, the volatility of idiosyncratic shocks $\sigma_z$, and the probability of a free price change $\alpha$. Their values will be discussed in the next section.

V Model Results

This section presents our main model results. 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 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 to reconcile these predictions with the notion in the literature that the relationship between kurtosis and monetary non-neutrality should be positive. The introduction of random menu costs, as for example in Alvarez et al. (2016), to the discrete-time Golosov and Lucas (2007) model, reverses the relationship between kurtosis and monetary non-neutrality. Relative to a fixed menu cost, this introduction creates Calvoness through random, small price changes while also generating excess kurtosis. Increasing the fraction of small price changes leads to both more random Calvoness and less selection, as well as higher kurtosis.

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 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). 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 6 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.\footnote{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.}

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 6 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 line with 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. 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. These latter findings cast doubt on the notion in the literature that kurtosis has a positive relationship with monetary non-neutrality even in a simple, quite standard menu cost model. 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.
B. Why Is Kurtosis Not Sufficient?

This section now explores what can make kurtosis an informative pricing moment in menu cost models for monetary non-neutrality, conditional on the frequency of price changes. Our main insight is that the fraction of random, small price changes, embodying the degree of Calvoness, is key. 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. According to Alvarez et al. (2016), the Golosov-Lucas model belongs to the class of models for which kurtosis given frequency should theoretically have a positive relation with monetary non-neutrality, with the value of kurtosis always at unity in the continuous-time analysis. We find that kurtosis can have a negative relationship while it actually also varies in a discrete-time version of the Golosov-Lucas model due to the difference between discrete time and continuous time.\(^\text{16}\) 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. We set the Calvo plus parameter to zero, implying no free price changes. Parameter calibrations for the Golosov-Lucas model are shown in Table 5.\(^\text{17}\) The same small

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\(^\text{16}\)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.

\(^\text{17}\)Specifically we set the \(p_z = 1\) 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 (\(\mu = 0\)).
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 7 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 8 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 7 shows our exact specific parameter calibrations. Panel b in Figure 7 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 8 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 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 9 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 8. 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.

VI Conclusion

Using micro price data, we have empirically evaluated in this paper what price-setting moments are informative for monetary non-neutrality. Our analysis presents an example for a generally applicable way of evaluating the informativeness of micro moments for 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. At the same time, kurtosis over frequency is a sufficient statistic as posited, but only because the frequency of price changes has a strong negative association 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 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.
References


of the Federal Reserve System, Finance and Economics Discussion Series.


VII Figures

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: 

$$\log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} \cdot MP_{shock_t} + \varphi_{A,h}z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} \cdot MP_{shock_t} + \varphi_{B,h}z_{j,t}] + \epsilon_{j,t+h}$$

where $ppi_{j,t}$ 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.

Figure 2: 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.
Figure 3: 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: $\log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} \cdot MPshock_t + \varphi_{A,h}z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} \cdot MPshock_t + \varphi_{B,h}z_{j,t}] + \epsilon_{j,t+h}$ 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.
Figure 4: High Frequency Identified Monetary Policy Shock IRF

Note: In the above panels, we plot the respectively estimated coefficients $\theta_h$ from the following specification: $\log(sales_{j,t+h}) = \alpha_{th} + \alpha_{jh} + \theta_h \times MPshock_t \times M_j + controls_t + \epsilon_{j,t+h}$ 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.
Figure 5: 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.

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 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 500 economies.
Figure 7: 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 500 economies.

Figure 8: Model Price Distributions - GL

Note: Price change distribution in Golosov-Lucas model calibrations.
Figure 9: Model Price Distributions - Random Menu Costs

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

<table>
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<td>0.476***</td>
<td>0.471***</td>
<td>0.385***</td>
<td>0.252***</td>
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<td>(0.074)</td>
<td>(0.084)</td>
<td>(0.093)</td>
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<td>-0.138</td>
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<td>0.053</td>
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<td>(0.138)</td>
<td>(0.149)</td>
<td>(0.124)</td>
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<td></td>
<td>(0.154)</td>
<td>(0.145)</td>
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Table 1: Decomposing Monetary Non-Neutrality

**Note:** This table uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following specification: 

\[ \log(\text{IRF}_{k,h}) = a + \alpha_j + \beta'_M k + \gamma' X_j + \epsilon_{k,h}. \]

Where \(\log(\text{IRF}_{k,h})\) 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. \(\alpha_j\) 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.
Table 2: Decomposing Monetary Non-Neutrality

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<th>Moment</th>
<th>Data</th>
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<th>Low Frequency</th>
<th>Low Kurtosis</th>
<th>Medium Kurtosis</th>
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<td>Frequency</td>
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<td>0.11</td>
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<td>0.077</td>
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<tr>
<td>Kurtosis</td>
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<td>6.4</td>
<td>6.4</td>
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<tr>
<td>Kurtosis Frequency</td>
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<td>42.6</td>
<td>81.8</td>
<td>42.2</td>
<td>50.1</td>
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Table 3: Baseline Comparative Static

Note: Monthly CPI data moments taken from Vavra (2014) and are calculated using data from 1988-2014.
### Table 4: Model Parameters CPI Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
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<th>Low Frequency</th>
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<td>$\chi$</td>
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<td>0.0107</td>
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<tr>
<td>$p_z$</td>
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<td>0.086</td>
<td>0.037</td>
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<td>$\sigma_z$</td>
<td>0.16</td>
<td>0.173</td>
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<td>$\rho_z$</td>
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<td>0.65</td>
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<td>$\alpha$</td>
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<td>0.03</td>
<td>0.018</td>
<td>0.03</td>
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**Note:** The table shows the model parameters that are internally calibrated for each economy. $\chi$ denotes the menu cost of adjusting prices, $p_z$ the probability that log firm productivity follows an AR(1) process with standard deviation $\sigma_z$, $\rho_z$ the persistence of idiosyncratic probability shocks, and $\alpha$ is the probability of a free price change.

### Table 5: Model Parameters Golosov-Lucas Calibration

<table>
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<tr>
<th>Parameter</th>
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<th>Low Frequency</th>
<th>Low Kurtosis</th>
<th>Low Kurtosis</th>
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<tr>
<td>$\chi$</td>
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<td>0.0181</td>
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<td>$p_z$</td>
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<td>1.0</td>
<td>1.0</td>
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<tr>
<td>$\sigma_z$</td>
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<td>0.0345</td>
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<tr>
<td>$\alpha$</td>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
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</table>

**Note:** The table shows the model parameters that are internally calibrated for each economy. $\chi$ denotes the menu cost of adjusting prices, $p_z$ the probability that log firm productivity follows an AR(1) process with standard deviation $\sigma_z$, $\rho_z$ the persistence of idiosyncratic probability shocks, and $\alpha$ is the probability of a free price change.

### Table 6: Golosov-Lucas Model with Random Walk and No Trend Inflation

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<tr>
<th>Moment</th>
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<tbody>
<tr>
<td>Frequency</td>
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<td><strong>0.11</strong></td>
<td><strong>0.15</strong></td>
<td><strong>0.08</strong></td>
<td><strong>0.11</strong></td>
<td><strong>0.11</strong></td>
<td><strong>0.11</strong></td>
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<td>Fraction Up</td>
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<tr>
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<td>Kurtosis</td>
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<td><strong>1.44</strong></td>
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<td>Kurtosis Frequency</td>
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</table>

**Note:** Data is from the one sector version of the CPI. Bolded moments are targeted. Fraction of small price changes less than 1 percent in absolute value taken from Luo and Villar (2017).
### Table 7: Model Parameters Random Menu Cost Calibration

<table>
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<td>$\chi$</td>
<td>0.195</td>
<td>0.14</td>
<td>0.25</td>
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</tr>
<tr>
<td>$p_z$</td>
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<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>$\sigma_z$</td>
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<td>0.051</td>
<td>0.0383</td>
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<td>1.0</td>
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<tr>
<td>$\alpha$</td>
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<td>0.1106</td>
<td>0.061</td>
<td>0.10</td>
<td>0.06</td>
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</table>

**Note:** The table shows the model parameters that are internally calibrated for each economy. $\chi$ denotes the menu cost of adjusting prices, $p_z$ the probability that log firm productivity follows an AR(1) process with standard deviation $\sigma_z$, $\rho_z$ the persistence of idiosyncratic probability shocks, and $\alpha$ is the probability of a free price change.

### Table 8: Random Menu Cost Model with RW and no trend inflation

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<tr>
<th>Moment</th>
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<th>Baseline Frequency</th>
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<td>0.11</td>
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<td>0.51</td>
<td>0.51</td>
<td>0.51</td>
<td>0.51</td>
</tr>
<tr>
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<td>0.077</td>
<td>0.077</td>
<td>0.077</td>
<td>0.077</td>
</tr>
<tr>
<td>Fraction Small</td>
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<td>0.13</td>
<td>0.14</td>
<td>0.013</td>
<td>0.14</td>
<td>0.12</td>
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<td>Kurtosis</td>
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<td><strong>2.73</strong></td>
<td><strong>2.74</strong></td>
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<td><strong>2.04</strong></td>
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<tr>
<td>Kurtosis Frequency</td>
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<td>25.0</td>
<td>18.2</td>
<td>32.6</td>
<td>30.2</td>
<td>18.6</td>
</tr>
</tbody>
</table>

**Note:** Bolded moments are targeted. Fraction of small price changes less than 1 percent in absolute value taken from Luo and Villar (2017). 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.
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

\[ y_t(i) = A_t z_t(i) L_t(i) \]  

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

\[ E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau} \pi_{t+\tau}(i) \]  

where profits are given by:

\[ \pi_t(i) = p_t(i)y_t(i) - W_t L_t(i) - \chi_j(i) W_t I_t(i) \]  

\( I_t(i) \) 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 $\alpha_j$.

Total demand for good $i$ is given by:

$$y_t(i) = Y_t \left( \frac{p_t(i)}{P_t} \right)^{-\theta}$$  \hspace{1cm} (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:

$$\log(A_t) = \rho_A \log(A_{t-1}) + \sigma_A \nu_t$$  \hspace{1cm} (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:

$$\log z_t(i) = \begin{cases} 
\rho_z \log z_{t-1}(i) + \sigma_{z,j} \epsilon_t(i) & \text{with probability } p_{z,j} \\
\log z_{t-1}(i) & \text{with probability } 1 - p_{z,j},
\end{cases}$$  \hspace{1cm} (27)

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

Nominal aggregate spending follows a random walk with drift:

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

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

**B. Multi-Sector Model Results**

Figure 10 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 9.

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

<table>
<thead>
<tr>
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<th>MC</th>
<th>Data</th>
<th>MC</th>
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<td>0.06</td>
<td>0.28</td>
<td>0.28</td>
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<tr>
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<td>0.090</td>
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### Kurtosis Calibration

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<td>Kurtosis</td>
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<td>Kurtosis/Frequency</td>
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### Kurtosis/Frequency Calibration

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<td>Average Size</td>
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<td>Kurtosis/Frequency</td>
<td>17.9</td>
<td>14.9</td>
<td>52.7</td>
<td>49.6</td>
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Table 9: 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.
Figure 10: 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 13 and 14, 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.
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<th>N Obs</th>
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Table 10: 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 99th 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 99th percentile of changes. Case 8 changes both the upper and lower thresholds.
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 10. 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.

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 10. 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 $\log(\text{IRF}_{k,h}) = a + \beta_h M_k + \alpha_{j,h} + \epsilon_{k,h}$ 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, and 3-digit NAICS fixed effects. Dashed lines present 90% standard error bands.

Figure 14: Romer and Romer Monetary Policy Shock IRF

**Note:** In the above panels, we plot the respectively estimated coefficients $\theta_h$ from the following specification: $\log(\text{sales}_{j,t+h}) = \alpha_{th} + \alpha_{j,h} + \theta_h * \text{MPshock}_t \times M_j + \text{controls}_t + \epsilon_{j,t+h}$ 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.
### Cross-Sectional Determinants of Sectoral Price Response Univariate Specifications

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<th>Sample 2, IV (4)</th>
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<td>-0.493***</td>
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<td>-0.448***</td>
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<tr>
<td></td>
<td>(0.060)</td>
<td>(0.074)</td>
<td>(0.066)</td>
<td>(0.074)</td>
<td>(0.071)</td>
<td>(0.077)</td>
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<td>0.130</td>
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<td>0.213</td>
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<td>0.448***</td>
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<td>0.470***</td>
<td>0.454***</td>
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<td>0.521***</td>
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<td>Log Kurtosis</td>
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<td>0.301***</td>
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<td>Log Std. Dev.</td>
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<td>0.355</td>
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Table 11: Decomposing Monetary Non-Neutrality IV and Subsample

**Note:** This table uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following specification: $\log(\text{IRF}_{k,h}) = a + \beta M_k + \alpha_j + \epsilon_{k,h}$. Where $\log(\text{IRF}_{k,h})$ 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. $\alpha_j$ 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

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<th>Baseline (1)</th>
<th>Sample 1, IV (2)</th>
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<th>Sample 2, IV (5)</th>
<th>Sample 2, IV (6)</th>
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<td>0.520***</td>
<td>0.476***</td>
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<td>0.549***</td>
<td>0.623***</td>
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<td>-0.223*</td>
<td>-0.313**</td>
<td>-0.220*</td>
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<td>(0.104)</td>
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<td>(0.120)</td>
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<tr>
<td>$R^2$</td>
<td>0.320</td>
<td>0.509</td>
<td>0.277</td>
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<tr>
<td>Log Frequency</td>
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<td>0.471***</td>
<td>0.668***</td>
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<td>0.594***</td>
<td>0.581***</td>
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<td>(0.074)</td>
<td>(0.084)</td>
<td>(0.111)</td>
<td>(0.121)</td>
<td>(0.107)</td>
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<tr>
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<td>(0.201)</td>
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<td>0.212</td>
<td>-0.161</td>
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<tr>
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<td>(0.212)</td>
<td>(0.207)</td>
<td>(0.278)</td>
<td>(0.326)</td>
<td>(0.296)</td>
<td>(0.279)</td>
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<tr>
<td>Log Std. Dev.</td>
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<td>0.033</td>
<td>-0.597</td>
<td>-0.387</td>
<td>-0.052</td>
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<td>(0.156)</td>
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<td>$R^2$</td>
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</tbody>
</table>

Table 12: Decomposing Monetary Non-Neutrality IV and Subsample

Note: This table uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following specification: $\log(\text{IRF}_{k,h}) = a + \beta' M_k + \alpha_j + \epsilon_{k,h}$. Where $\log(\text{IRF}_{k,h})$ 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. $\alpha_j$ 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.

<table>
<thead>
<tr>
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<td>0.09</td>
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<tr>
<td>Kurtosis</td>
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<td>3.57</td>
<td>4.70</td>
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<td>Kurtosis/Frequency</td>
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<td>Number of Price Changes</td>
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<td>251.2</td>
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<td>Firms</td>
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Table 13: 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.
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.

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.

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<tr>
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<th>Mean</th>
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<td>0.16</td>
<td>0.16</td>
<td>0.09</td>
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<td>Kurtosis</td>
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<td>Kurtosis/Frequency</td>
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<td>Industries</td>
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</table>

Table 14: 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.
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.

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: $\log(p_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} \times MP_{shock_t} + \varphi_{A,h} z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} \times MP_{shock_t} + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h}$ where $p_{j,t+h}$ 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.
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: \( \pi_{j,t} = \alpha_j + \sum_{k=1}^{44} \beta_{j,k} D_k + \sum_{k=1}^{48} \eta_{j,k} \pi_{j,t-k} + \sum_{k=1}^{48} \theta_{j,k} M_{t-k} + \epsilon_{j,t} \) 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.

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: \( \log(ppi_{j,t+h}) = \beta_h + I_{PS>M} [\theta_{A,h} \cdot MP_{shock} + \phi_{A,h} z_{j,t}] + (1 - I_{PS>M}) [\theta_{B,h} \cdot MP_{shock} + \phi_{B,h} z_{j,t}] + \epsilon_{j,t+h} \) 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.
<table>
<thead>
<tr>
<th>Documentos de Trabajo</th>
<th>Working Papers</th>
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<td>Banco Central de Chile</td>
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