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

Gee Hee Hong*, Matthew Klepacz†, Ernesto Pasten‡, and Raphael Schoenle§

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Abstract

Using micro price data, we empirically evaluate what price-setting moments are informative for monetary non-neutrality. Kurtosis of price changes has none, or even a negative association, 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. Neither pricing moment is a sufficient statistic, explaining little variation in monetary non-neutrality. We show that menu cost models can match empirical price responses, in particular the negative association between kurtosis and monetary non-neutrality. Menu cost models predict a positive relationship as posited in the literature only if random menu costs are the source of excess kurtosis and raise the "Calvo-ness" of the model.

JEL classification: E13, E31, E32

Keywords: Price-setting, Calvo pricing, menu cost, micro moments, sufficient statistics

*International Monetary Fund. e-Mail: GHong@imf.org

†College of William and Mary. e-Mail: mtklepacz@wm.edu

‡Central Bank of Chile and Toulouse School of Economics. e-Mail: ernesto.pasten@tse-fr.eu

§Brandeis University. e-Mail: schoenle@brandeis.edu.

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I Introduction

One of the central questions in macroeconomics is to what extent monetary policy shocks can affect real output and consumption. The answer of course depends on the extent to which nominal variables such as prices also absorb these shocks. While it is well known that frequency of price changes is of vital importance for monetary non-neutrality, a recent literature has summarized the extent of aggregate price flexibility, and hence monetary non-neutrality, with a sufficient statistics approach. The focus there typically lies on 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 2006, Midrigan 2011): When a shock triggers price adjustment and a lot of prices are very far from their desired price level, then adjusting prices move by a lot and so does the overall price level, rather than real quantities. Alvarez et al. (2016) formalize this argument by showing that a sufficient statistic in a wide class of models only depends on the ratio of two pricing moments, the kurtosis of price changes and the frequency of price changes.

The main contribution of this paper lies on the empirical side: We evaluate what price-setting moments are informative for monetary non-neutrality. Kurtosis of price changes has none, or even a negative association with monetary non-neutrality, contrary to the widely held notion in the literature. Kurtosis over frequency of price changes is informative about monetary non-neutrality, but only because frequency has a strong negative association. Neither pricing moment is a fully sufficient statistic because they explain little variation in monetary non-neutrality in a statistical sense.

We show these results by establishing three facts for the response of prices and quantities, conditional a monetary policy shock: First, the response of prices goes up with the frequency of price changes while the response of output decreases. Second, there is no statistical difference in the conditional price response as a function of kurtosis. Even worse, when kurtosis of price changes is high, prices may even respond by *more* than when kurtosis is low. The response of output goes down as kurtosis increases. These results go counter the fundamental notion in the literature that higher kurtosis of price changes means smaller price and larger real output responses. Third, the response of prices decreases in the ratio of kurtosis over frequency, while the response of output increases. This result confirms the informativeness of the ratio presented in the literature in particular by Alvarez et al. (2016). However, we show that its informativeness is driven

by the strong relationship of frequency with monetary non-neutrality, not by kurtosis. Crucially, we also find low explanatory power in terms of R^2 statistics of all three pricing moments for monetary non-neutrality, leaving room for other statistics to claim sufficiency status.

Second, these empirical findings open up questions for theory: Can menu cost models generate predictions in line with the empirical conditional impulse response functions? How do we reconcile the commonly held notion that higher kurtosis leads to higher monetary non-neutrality – distilled most clearly in the sufficient statistic proposed by Alvarez et al. (2016) – with the empirical findings? We show that a state-of-the-art menu cost model as well as a discrete-time version of the Golosov and Lucas (2007) model can predict the empirical conditional impulse response functions. In particular, both models predict the negative relationship from the data between kurtosis and monetary non-neutrality. By contrast, we find that the models predict a positive relationship as posited in the literature only if random menu costs are a model feature. These random menu costs create random, free price changes, in effect raising both kurtosis and Calvo-ness of the model, and hence monetary non-neutrality.[1]

Our empirical analysis proceeds by exploiting micro price data from the Bureau of Labor Statistics (BLS) on producer prices to evaluate the relation between pricing moments, such as the kurtosis of price changes, and monetary non-neutrality. To this end, our approach computes conditional impulse response functions of output and prices as a measure of monetary non-neutrality – crucially, we condition in this step not only on a monetary policy shock as is standard, but also jointly on micro price moments. In particular, we consider three micro price moments: the kurtosis of price changes, the frequency of price changes and the ratio of these two 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.

This approach embodies a simple test of proposed sufficient statistics: It allows one to evaluate the interaction of pricing moments with monetary policy shocks on monetary non-neutrality. If there is no interaction or it has the wrong sign relative to what is

[1] 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).

proposed, then the proposed moment may not be appropriate as a sufficient statistic for the policy question of interest. We further evaluate if the explanatory power of a proposed pricing moment is near 100%, as it should be if the moment is a sufficient statistic.

We identify monetary policy shocks using three conventional identification schemes. First, we follow the Romer and Romer (2000) 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) or Gertler and Karadi (2015). 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 NAICS six-digit level into two subsets: one subset above, and the other below the median of a proposed sufficient statistic. Here we compute pricing moments by pooling all price changes in each NAICS sector-month 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, and conduct regression analysis using the identification schemes of Romer and Romer (2000) and Jorda (2005). In our FAVAR setting, we compute impulse responses for each six-digit sector and present results by averaging responses in each subset. Where possible, we include four-digit sectoral fixed effects to capture other cross-sectional determinants.

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 above-median frequency of price changes, compared to the index made up by sectors with 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. In the FAVAR setup, the response of prices even goes in the wrong direction: prices in the high-kurtosis subset respond by *more* and not by less, as the theoretical notion of larger real and smaller nominal responses for higher kurtosis implies. Finally, and most importantly, we decompose the effects of monetary non-neutrality into kurtosis and frequency and find

that it is entirely driven by frequency.

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. 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.

Next, we show that menu cost models can match our empirical price responses, in particular the negative 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). In particular, we vary one target moment at a time and assess how such variation changes real effects following a monetary policy shock. First, we find a higher frequency of price changes leads to a smaller cumulative consumption response. 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. Third, the relationship of kurtosis over frequency with monetary non-neutrality is non-monotonic. 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 can not be a sufficient statistic as posited.

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 widely held notion that kurtosis should have a positive relationship with monetary non-neutrality. Our main insight is that the degree of Calvo-ness, embodied in the fraction of random, small price changes, is key. This fraction is both positively associated 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. At the same time, the random nature of these price changes decreases the selection effect and increases monetary non-neutrality. While there may be many ways to implement this mechanism we show that a small change in price setting assumptions of the Golosov and Lucas (2007) can create such random small price changes. What is needed is the assumption of random menu costs such as in Alvarez et al. (2016) – rather than a fixed menu cost. We implement

random menu costs in our model through the Calvo plus parameter, following exactly the way Alvarez et al. (2016) model random menu costs.

We organize the paper as follows: Section II establishes the empirical regularities that compare impulse response functions across different values of micro moments. Section IV presents the modeling setup. Section V demonstrates how we discriminate across models, and Section VI 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. Our analysis can also be seen as a way to use 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, Le Bihan and Lippi (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 find that instead 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 if random menu costs are the source of excess kurtosis and the degree of Calvo-ness 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 shocks which generate 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 Micro Moments and Monetary Non-Neutrality

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.

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 inflation 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 also conditional on both high and low levels of pricing moments – here: also candidate sufficient statistics – which we consider one at a time: frequency, kurtosis and kurtosis over frequency of price changes. In particular, 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 we use to measure monetary non-neutrality are 154 producer price (PPI) inflation series from Boivin et al. (2009). 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 sectoral level price statistics using PPI micro data from 1998 to 2005. We compute pricing moments at the good 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 550 firms which were matched to Compustat data in Gilchrist et al. (2017). Similar to the sectoral calculations above, we compute pricing moments at the good level, and then take averages over time at the respective firm level. We include firm-level sales from Compustat into this dataset to get a measure of output for our subsequent analysis.

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

B. Empirical Response to Romer and Romer Shocks

As a first approach to identify the effect of monetary policy shocks, we follow the narrative approach in Romer and Romer (2004). The original Romer and Romer (2004) monetary policy shocks are calculated as residuals from a regression of the federal funds rate on its lagged values and 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 (2017) have extended the series up to December 2007. We use monthly industry level PPI inflation data from January 1976 to December 2007.

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

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

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 in the future for the average industry in the above-median or below-median set according to one of the three pricing moments of interest. $z_{j,t}$ are controls that include two lags of the RR shock, two lags of the Fed Funds rate, and current and two lags of the unemployment rate, industrial production, and price level. $MPshock_t$ refers to the extended Romer and Romer monetary shock series. The dependent variable is the average PPI in the high or low subsets described above in the data section.

We have normalized the monetary shock such that an increase in the shock is expansionary.

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

$$
\pi_t^c = \alpha^c + \sum_{k=1}^{11} \beta_k^c D_k + \sum_{k=1}^{24} \eta_k^c \pi_{t-k}^c + \sum_{k=1}^{48} \theta_k^c MP_{t-k} + \epsilon_t^c \tag{2}
$$

We run each regression separately for the average industry inflation rate π_t^c above and below the median value of each proposed pricing moment to estimate the differential inflationary responses following a monetary policy shock. Following the estimation of the above specification, the estimated impulse response of interest is contained in the parameter estimates of θ_k.

C. Empirical Response to High Frequency Shock Identifcation

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). The series are available from January 1990 to June of 2012.

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

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

where $I_{PS>M}$ is a dummy variable that indicates if the price level 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 high frequency identified shock h months in the future for the average industry in the above-median or below-median set 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:

$$Log(sales_{j,t+h}) = \alpha_t + \alpha_j + \theta_h * MPshock \times M_j + controls + \epsilon_{j,t} \tag{4}$$

where α_t are time fixed effects, α_j are firm fixed effects, and $sales_{j,t+h}$ denotes firm j sales at time t measured at quarterly frequency h months into the future. As before, we also include time and firm fixed effects, and monetary policy shocks are measured by the high-frequency shock. Controls further include up to 4 quarters of lagged log sales, and log assets and up to 4 quarters of lagged log assets. M_j contains one of our three firm-level pricing moments: the firm-level frequency of price changes, the kurtosis of price changes, or the ratio of the two statistics. The estimated coefficients θ_h summarize the impulse response of sales to the monetary policy shock h months into the future for the average firm.

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 cuts 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 of (slow-moving) macro variables and (fast-moving) financial variables, enabling us to better identify policy shocks than standard VARs.

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

$$\pi_{k,t} = \lambda_k C_t + e_{k,t} \tag{5}$$

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

Given the estimated FAVAR coefficients, we compute the mean of the $\{\pi_{k,t}\}$ – the inflationary responses following a monetary policy shock – 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 micro moments.

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 sectoral fixed effects:

$$log(IRF_{k,h}) = \beta M_k + FEs + \epsilon_{k,h} \tag{6}$$

where $log(IRF_{k,h})$ denotes the cumulative response of prices for an h-month horizon. We also include two-digit NAICS fixed effects as additional control variables. As before, 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. To assess the relative importance of frequency and kurtosis for monetary non-neutrality, we also include 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.

III Empirical Regularities

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 is a sufficient statistic because they also explain little variation in monetary non-neutrality.

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 1 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 is likely to be driven by the result for frequency. We quantify this extent further below.

A.2 High-Frequency Approach

Second, using high-frequency identification not only confirms the findings from the Romer and Romer identification scheme. Instead, 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, 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 kurtosis over frequency. These two 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.

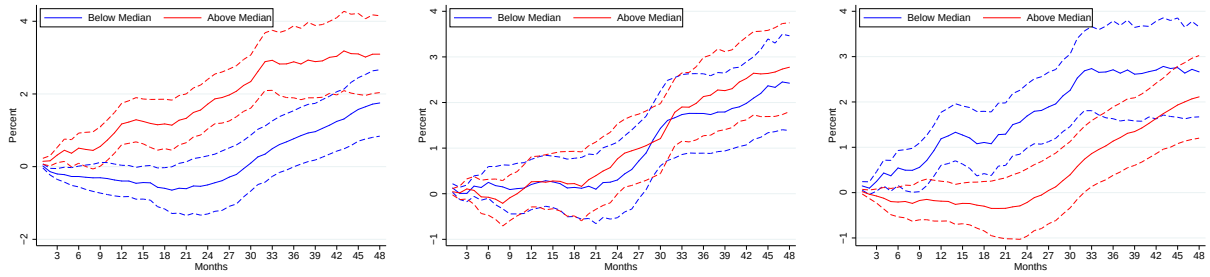
Our analysis that uses the matched firm-level data confirms these findings. Because we include firm-level fixed effects (see equation 4), these results are particularly robust to any cross-sectional variation at the firm-level. Figure 4 presents our findings. Panel a shows an increase in frequency of price changes is associated with a larger drop in firm-level sales following a contractionary 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 any horizon as a function of firm-level kurtosis following a monetary policy shock. Panel c shows that for a higher kurtosis over frequency ratio, firms pass through less of a monetary policy shock into sales at any horizon. Again, this findings is at odds with the predictions of the proposed statistic.

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 across all sectoral impulse response (black line), the response in the respective above-median set of sectors (red dashed line) and in the below-median set of sectors (solid blue line).

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 identification: Unlike the notion in the literature, high-kurtosis sectors have on average a *stronger* price response that low-kurtosis sectors implying less monetary non-neutrality.

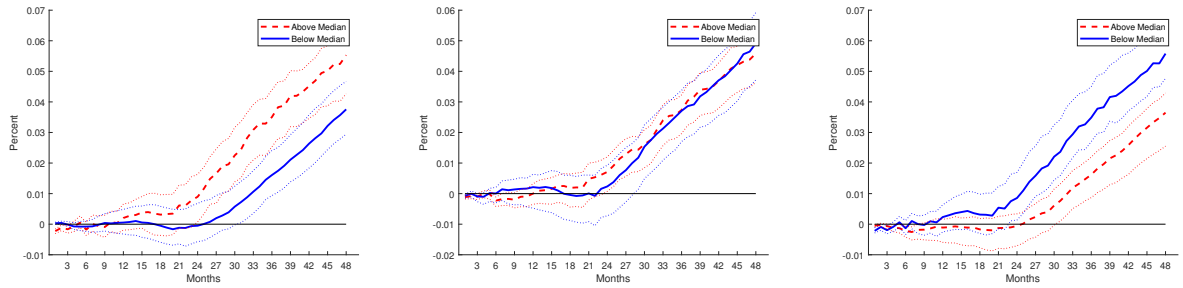
First, we decompose the sectoral determinants of monetary non-neutrality by examining the cross-sectional relationship between pricing moments and the identified price responses. We use as measure of monetary non-neutrality our cumulated FAVAR estimates of price level responses 24 months after an expansionary monetary shock. We estimate the relationship of cumulated sectoral impulse responses with our key pricing



a Frequency b Kurtosis c Kurtosis/Frequency

Figure 1: Romer and Romer Monetary Policy Shock IRF

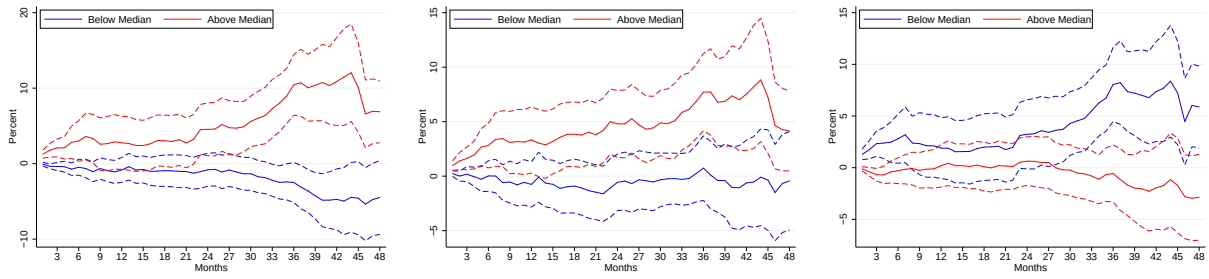
NOTE: In all three figures, "Above Median" and "Below Median" refer to the impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. Standard errors are constucted using the Newey-West correction for serial autocorrelation. Dashed lines present 68% standard error bands.



a Frequency b Kurtosis c Kurtosis/Frequency

Figure 2: Romer and Romer Monetary Policy Shock IRF

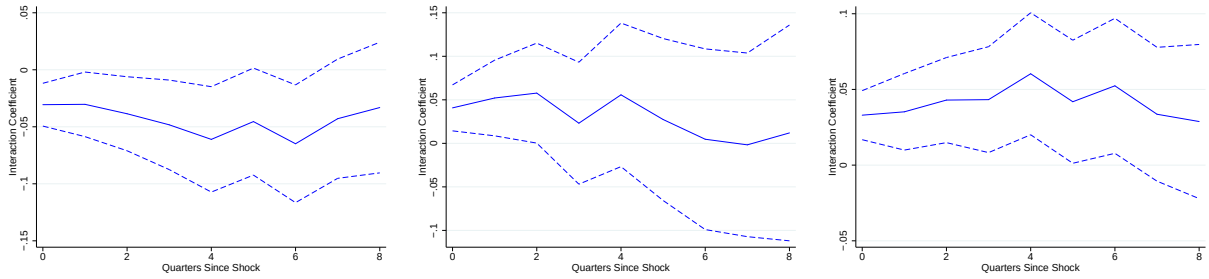
NOTE: In all three figures, "Above Median" and "Below Median" refer to the impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. Dashed lines present 68% bootstrapped standard error bands.



a Frequency b Kurtosis c Kurtosis/Frequency

Figure 3: High Frequency Identified Monetary Policy Shock IRF

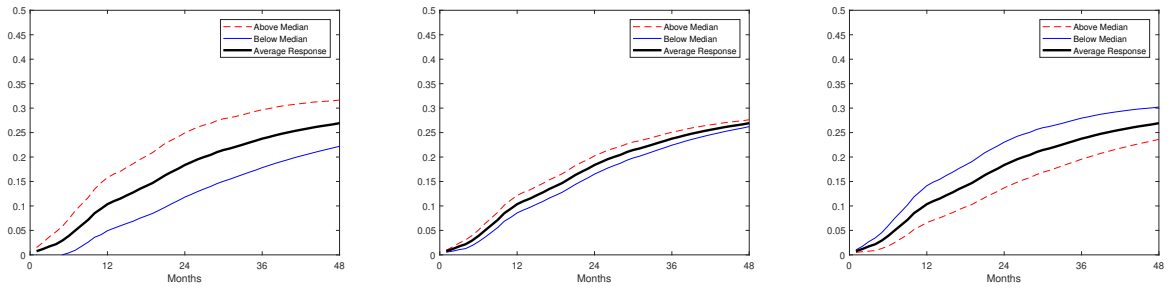
NOTE: In all three figures, "Above Median" and "Below Median" refer to the impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. Standard errors are constucted using the Newey-West correction for serial autocorrelation. Dashed lines present 68% standard error bands.



a Frequency b Kurtosis c Kurtosis/Frequency

Figure 4: High Frequency Identified Monetary Policy Shock IRF

NOTE: In the above panels, we plot the respectively estimated coefficients θ_h from the following specification: $Log(sales_{j,t+h}) = \alpha_t + \alpha_j + \theta_h * MPshock \times M_j + controls + \epsilon_{j,t}$ where $sales_{j,t+h}$ denotes firm j sales at time t measured at quarterly frequency, h months into the future. Controls further include up to 4 quarters of lagged log sales, and log assets and up to 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, or the ratio of the two statistics. Dashed lines present 90% standard error bands.



a Frequency b Kurtosis c Kurtosis/Frequency

Figure 5: FAVAR Monetary Policy Shock IRF

NOTE: In all three figures, "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. Estimated impulse responses of sectoral prices in percent to an identified 25 basis point unexpected Federal Funds rate decrease are shown.

moments as in equation (6).

B. Further Results from Regression Analysis

Next, we show two results: Not only do our findings go through in a more quantitative regression setting. Moreover, when we jointly relate pricing moments to monetary non-neutrality in the cross section of firms and sectors, only frequency comes out significant as the plots in the previous subsection have already suggested. All statistics have very low explanatory power. We show these results using both sectoral and firm-level data.

First, we decompose the sectoral determinants of monetary non-neutrality by examining the cross-sectional relationship between pricing moments and the identified price responses. We use as 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 as in equation (6).

Our main finding is that only frequency of price changes is always significantly related to monetary non-neutrality. Table 1 shows our results. Column 1 shows that overall kurtosis over frequency has a statistically significant, negative relationship with the cumulative price response. This confirms the prediction of Alvarez et al. (2016). However, when we add 2-digit sector fixed effects in Column 2, the relationship becomes insignificant. Next, when we look at the relationships of frequency and kurtosis

individually in Columns 3-6, then the price response has a positive relationship with both price change frequency and kurtosis regardless of whether or not we include two-digit sector fixed effects. However, only the relationship with frequency is statistically significant. Moreover, the positive sign for kurtosis is at odd with what the notion in the menu cost literature suggests.

Strikingly, when we jointly relate the log 24-month cumulative response of prices to both log frequency and log kurtosis, only the frequency of price changes is relevant. Columns (7) and (8) show these results. In particular, they continue to hold when we control for industry fixed effects. We note that the explanatory power is always low across all columns. This latter finding in particular casts doubt on the ability of any of the moments to be sufficient statistics.

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 ahead 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 (1) shows that higher kurtosis over frequency continues to be associated higher sales as predicted by Alvarez et al. (2016). However, as Columns (2)-(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.

IV General Equilibrium Pricing Model

This section demonstrates the importance of taking into account our empricial 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: Both frequency and kurtosis have a negative relationship with monetary non-neutrality. The role of kurtosis over frequency is ambiguous. Second, we introduce random menu costs to reconcile the model with the notion in the literature of a positive relation between kurtosis

Cross-Sectional Determinants of Sectoral Price Response								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Kurtosis/Frequency	-.137*	-0.134						
	(0.076)	(0.081)						
Log Frequency			0.152**	0.160**			0.170**	0.186**
			(0.063)	(0.072)			(0.071)	(0.081)
Log Kurtosis					0.090	0.070	-0.058	-0.079
					(0.116)	(0.117)	(0.131)	(0.130)
Industry FE		X		X		X		X
R^2	0.019	0.035	0.036	0.053	0.004	0.021	0.037	0.055
N	148	148	148	148	148	148	148	148

Table 1: Decomposing Monetary Non-Neutrality

NOTE: This tables uses regression analysis to test the informativeness of three pricing moments for monetary non-neutrality. We regress the log of the 24-month cumulative sectoral response of prices to a monetary shock from our FAVAR analysis on log frequency over kurtosis, log frequency, log kurtosis of price changes and both jointly, as well as two-digit sectoral fixed effects.

Cross-Sectional Determinants of Firm-Level Sales Responses				
	(1)	(2)	(3)	(4)
Log Kurtosis/Frequency	.060**			
	(0.024)			
Log Frequency		-.061**		-.061**
		(0.028)		(0.028)
Log Kurtosis			0.056	0.057
			(0.050)	(0.050)
R^2	59.20%	59.19%	59.18%	59.20%
N	19,522	19,522	19,522	19,522

Table 2: Decomposing Monetary Non-Neutrality

NOTE: This tables uses regression analysis to test the informativeness of three pricing moments for monetary non-neutrality. We regress the log of sales four quarters ahead on the interaction of log frequency over kurtosis, log frequency, log kurtosis of price changes and both jointly with the high-frequency shock. We also include firm-level and time fixed effects, up to 4 quarters of lagged log sales, and log assets and up to 4 quarters of lagged log assets. Standard errors are clustered by firm.

and monetary non-neutrality. Random menu costs generate random, free price changes: This introduction increases the "Calvo-ness" of the 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

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

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

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

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

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

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

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

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

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

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

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

The first-order conditions of the household maximization problem are

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

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

where equation (12) describes the relationship between asset prices and consumption, and (13) describes labor supply.

A.2 Firms

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

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

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

Firm i maximizes the present discounted value of future profits

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

where profits are given by:

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

$I_t(i)$ is an indicator function equal to one if the firm changes its price and equal to zero otherwise. $\chi(i)$ is the menu cost of changing prices. The final term indicates that firms must hire an extra $\chi(i)$ units of labor if they decide to change prices with probability $1-\alpha$, or may change their price for free with probability α.[2] This is the "CalvoPlus" parameter from Nakamura and Steinsson (2010) that enables the model to encapsulate both a menu cost as well as a pure Calvo model, as well as allows us to match the random menu cost set up in Alvarez et al. (2016). In the menu cost model this parameter is set such that a small probability of receiving a free price change enables the model to generate small price changes, while in the Calvo model set up it is calibrated to the frequency of price changes with an infinite menu cost.

Total demand for good i is given by:

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

The firm problem is to maximize profits in (16) subject to its production function (14), demand for its final good product (17), and the behavior of aggregate variables.

Aggregate productivity follows an AR(1) process:

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

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

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

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

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

Nominal aggregate spending follows a random walk with drift:

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

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

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

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

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

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

B. Calibration

For all variations of the model that follow, we use 2 sets of parameters. The first set of parameters is common to all model calibrations. Our model is a monthly model so the discount rate is set to $\beta = (0.96)^{\frac{1}{12}}$. The elasticity of substitution is set to $\theta = 4$ as in Nakamura and Steinsson (2010).[3] The nominal shock process is calibrated to match the mean growth rate of nominal GDP minus the mean growth rate of real GDP and the standard deviation of nominal GDP growth over the period of 1998 to 2012. This implies $\mu = 0.002$ and $\sigma_s = 0.0037$. Finally the model is linear in labor so we calibrate the productivity parameters to match the quarterly persistence and standard deviation of average labor productivity from 1976-2005. This gives $\rho_A = 0.8925$ and $\sigma_A = 0.0037$.

The second set of parameters is calibrated internally to match micro pricing moments. These are the menu cost χ, the probability of an idiosyncratic shock, p_z, the volatility of

[3]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 to a monetary shock would not change.

idiosyncratic shocks σ_z, and the probability of a free price change α. Their values will be discussed in the next section.

V Model Results

This section presents our main model results. First, we first show that a standard, second-generation menu cost model is able to generate our main empirical findings: The negative relationship between frequency and monetary non-neutrality, as well as the negative relationship between kurtosis and monetary non-neutrality. Second, we establish that the same relationships also hold in the simplest version of a menu cost model, Golosov and Lucas (2007).

Crucially, we then show how to reconcile these predictions with the widely held 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 Golosov and Lucas (2007) model, reverses the relationship between kurtosis and monetary non-neutrality. Relative to a fixed menu cost, this introduction creates "Calvo-ness" through random, small price changes while also generating excess kurtosis. Increasing the fraction of small price changes leads to both more random Calvo-ness and less selection, as well as higher kurtosis.

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, as well as the negative relationship 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).[4] 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

[4]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.

Moment	Data	Baseline	High Frequency	Low Frequency	Low Kurtosis	Medium Kurtosis
Frequency	0.11	0.11	0.15	0.08	0.11	0.11
Fraction Up	0.65	0.65	0.62	0.67	0.63	0.64
Average Size	0.077	0.077	0.077	0.077	0.077	0.077
Fraction Small	0.13	0.16	0.13	0.13	0.13	0.14
Kurtosis	6.4	6.4	6.4	6.4	4.7	5.5
$\frac{\text{Kurtosis}}{\text{Frequency}}$	58.2	57.6	42.6	81.8	42.2	50.1

Table 3: Baseline Comparative Static

NOTE: Monthly CPI data moments taken from Vavra (2014) and are calculated using data from 1988-2014.

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 cases: a case of high, and a case of low frequency of price changes that holds kurtosis constant, and a case of low, and a case of medium kurtosis that holds 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 demonstrates 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 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

Parameter	Baseline	High Frequency	Low Frequency	Low Kurtosis	Medium Kurtosis
χ	0.0071	0.0033	0.014	0.0107	0.0087
p_z	0.053	0.086	0.037	0.076	0.0652
σ_z	0.16	0.173	0.138	0.126	0.147
ρ_z	0.65	0.98	0.65	0.75	0.78
α	0.03	0.03	0.018	0.03	0.03

Table 4: Model Parameters CPI Calibration

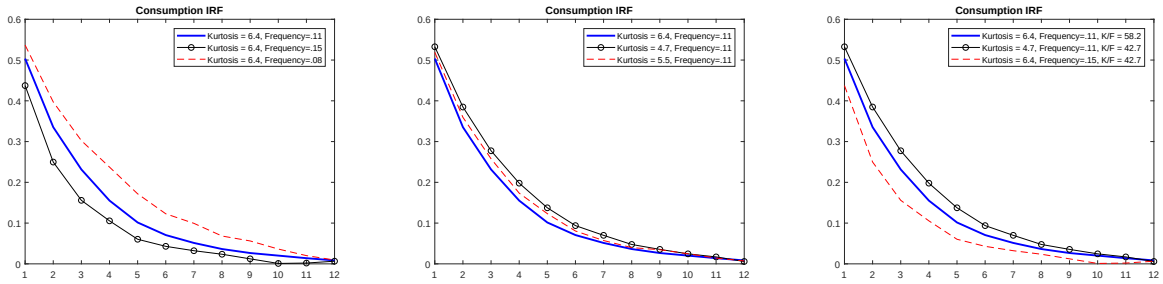
NOTE: The table shows the model parameters that are internally calibrated for each economy. χ denotes the menu cost of adjusting prices, p_z the probability that log firm productivity follows an AR(1) process with standard deviation σ_z, ρ_z the persistence of idiosyncratic probability shocks, and α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

non-neutrality[5].

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 response. 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 (red dashed line, frequency of .15 and kurtosis of 6.4) exhibits a lower consumption response that the low kurtosis calibration (grey, circled line, 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.

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. Kurtosis of price changes has a weaker negative relationship with monetary non-neutrality. Moreover, 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

[5]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.



a Frequency Variation b Kurtosis Variation c Kurtosis/Frequency Variation

Figure 6: Consumption IRF Comparison

NOTE: Impulse response of output to a one time permanent increase in log nominal output of size 0.002 for different calibrations.

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 makes 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 degree of "Calvo-ness", embodied in the fraction of random, small price changes, 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 an increase in kurtosis given frequency should theoretically lead to higher monetary non-neutrality. However, to generate this positive relationship, 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 next considering the relationship between kurtosis and monetary non-neutrality in the Golosov-Lucas setting, and then reconsider it after we add the

random menu cost assumption.

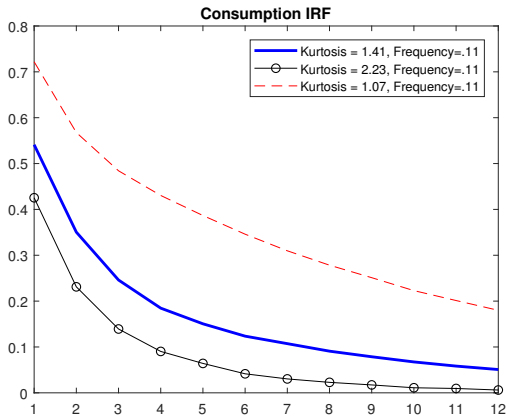
First, to simplify our baseline model to the Golosov and Lucas (2007) model, we remove several model ingredients from our baseline model. We remove aggregate productivity shocks and leptokurtic idiosyncratic productivity shocks, remove trend inflation, and turn the idiosyncratic productivity shocks into 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.[6] The same small expansionary monetary shock is used as in the previous model simulation exercise to generate consumption impulse response functions as a measure of monetary non-neutrality.

We find that an increase in kurtosis in the Golosov and Lucas (2007) model is associated with a decrease in monetary non-neutrality, contrary to the intuition in the literature and the theoretical results in Alvarez et al. (2016). 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. 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 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, it triggers more price changes and decreases monetary non-neutrality.

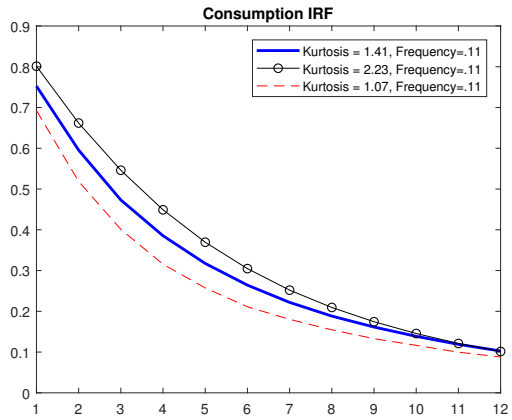
Next, we add the random menu cost assumption from Alvarez et al. (2016) to the simplified Golosov and Lucas (2007) model. We find that this small change in model assumption is enough to flip the sign of the relationship between kurtosis and monetary non-neutrality. Under random menu costs, firms are randomly selected to receive a free price change, implying that these prices have zero selection into changing. Mechanically, 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

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



a Golosov-Lucas Model



b Random Menu Cost Model

Figure 7: Consumption IRF Comparison

NOTE: Impulse response of output to a one time permanent increase in log nominal output of size 0.002 for different calibrations in each of the two models.

Parameter	Baseline	High Frequency	Low Frequency	High Kurtosis	Low Kurtosis
χ	0.0241	0.0181	0.034	0.0054	0.115
p_z	1.0	1.0	1.0	1.0	1.0
σ_z	0.029	0.0345	0.0243	0.01	0.11
ρ_z	1.0	1.0	1.0	1.0	1.0
α	0.0	0.0	0.0	0.0	0.0

Table 5: Model Parameters Golosov-Lucas Calibration

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

Moment	Data	Baseline	High Frequency	Low Frequency	High Kurtosis	Low Kurtosis
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Up	0.65	0.51	0.51	0.51	0.49	0.51
Average Size	0.077	**0.077**	0.077	0.077	0.033	0.23
Fraction Small	0.13	0.00	0.00	0.00	0.00	0.00
Kurtosis	4.9	1.41	**1.40**	**1.44**	**2.23**	**1.07**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	12.8	9.39	18.1	20.3	9.7

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

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).

Parameter	Baseline	High Frequency	Low Frequency	High Kurtosis	Low Kurtosis
χ	0.195	0.14	0.25	0.7	0.089
p_z	1.0	1.0	1.0	1.0	1.0
σ_z	0.044	0.051	0.0383	0.062	0.037
ρ_z	1.0	1.0	1.0	1.0	1.0
α	0.08	0.1106	0.061	0.10	0.06

Table 7: Model Parameters Random Menu Cost Calibration

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

Moment	Data	Baseline	High Frequency	Low Frequency	High Kurtosis	Low Kurtosis
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Up	0.65	0.51	0.51	0.51	0.51	0.51
Average Size	0.077	**0.077**	**0.077**	**0.077**	**0.077**	**0.077**
Fraction Small	0.13	**0.13**	0.14	0.013	0.14	0.12
Kurtosis	4.9	2.74	**2.73**	**2.74**	**3.36**	**2.04**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	25.0	18.2	32.6	30.2	18.6
$\mathcal{L}$		0.73	0.74	0.76	0.91	0.55

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

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.

and the model moments in Table 8 is that the fraction of random, free price changes plays a key role. From a modeling standpoint, as the fraction of random, free price changes increases from 73% to 91%, the degree of "Calvo-ness" of the model increases. These price changes have not selection effect in them, decreasing the overall selection effect, causing monetary non-neutrality rises. 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.

VI Conclusion

Using micro price data, we have empirically evaluated in this paper what price-setting moments are informative for monetary non-neutrality. 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 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 if random menu costs are the source of excess kurtosis and raise the "Calvo-ness" of the model.

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