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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 first-order question in macroeconomics concerns the degree of monetary non-neutrality – do monetary policy shocks have real output effects or do they tend to be absorbed by inflationary responses? How price-setting is modeled matters for answering these questions. The use of micro price data, following the pioneering work of Bils and Klenow (2004) and Nakamura and Steinsson (2008), has been a highly successful approach to discipline pricing models and gauge the associated degree of monetary non-neutrality. However, evidence is scarce about the empirical relationship between the micro price moments used to discipline models and monetary non-neutrality.

This paper evaluates the informativeness of popular pricing moments for monetary non-neutrality. Empirically, frequency of price changes is the only robustly significant pricing moment. This result is in line with the predictions of basic models of price rigidities. Further, we show our empirical findings can guide modeling efforts in the domain of price-setting by focusing on the role that the ratio of kurtosis over frequency plays for monetary non-neutrality. This is a moment that Alvarez et al. (2016a, 2020) have proven to be a theoretically sufficient statistic for monetary non-neutrality in a wide class of pricing models. We instead find in a quantitative menu cost model that this ratio has an ambiguous relationship with monetary non-neutrality. We show which modeling ingredients are behind this discrepancy with previous theoretical work, aligning theoretical and empirical results.

Our analysis starts by establishing four main empirical results. First, frequency of price changes is the only one among eight popular pricing moments that has a robust, statistically significant relationship with monetary non-neutrality.[1] As kurtosis of price changes bears no significant relationship with the degree of monetary non-neutrality, it is the frequency of price changes that makes the ratio of kurtosis over frequency take on statistical significance. We establish these results using a multitude of regression specifications. They include placebo exercises where other, insignificant pricing moments

[1]We rely a broad set of alternative but empirically highly correlated measures of monetary non-neutrality, using the response of either prices or real sales to monetary policy shocks identified under three alternative approaches: FAVAR as in Boivin et al. (2009), narrative as in Romer and Romer (2004) with the extended sample of Wieland and Yang (2020), and high-frequency as in Nakamura and Steinsson (2018). The pricing moments include frequency, kurtosis, the ratio of kurtosis over frequency, average size, standard deviation, fraction of small and fraction of positive price changes, and the standard deviation of price durations.

become significant once divided by frequency. Our results are robust to the use of alternative measures of monetary non-neutrality, fixed effects, instruments to account for measurement error, and specifications in levels or logs.

Second, frequency of price changes is the only *pricing* moment analyzed that is highly informative for explaining variation in the degree of monetary non-neutrality. Frequency univariately explains around 30 percent of the observed variation in monetary non-neutrality across finely disaggregated sectors. Other pricing moments explain less. For instance, kurtosis or the ratio of kurtosis over frequency univariately explain 4 percent and 17 percent. All pricing moments together account for 33 percent of total variation. Inclusion of non-pricing moments increases R^2 from 33 percent to 52 percent.

Third, two *non-pricing* moments stand out as significant for monetary non-neutrality: profit rates, and the persistence of sectoral shocks. As in Boivin et al. (2009), profit rates can be understood to measure the extent of competition in a sector, while the persistence of sectoral shocks may affect the strength of the selection effect as in Golosov and Lucas (2007). These non-pricing moments explain a substantial fraction of variation in monetary non-neutrality and influence the significance of pricing moments. For example, upon their inclusion, the ratio of kurtosis over frequency can become statistically insignificant.

Last, our empirical results suggest that the search for an empirically relevant sufficient statistic encapsulating monetary non-neutrality is unlikely to end with any single pricing moment. Except for frequency, the pricing moments considered are not robustly statistically significant for monetary non-neutrality, a necessary condition for sufficiency. In addition, sufficient statistics should fully summarize the relationship with monetary non-neutrality such that no other pricing or non-pricing variable contains additional information.[2] However, omitted variable bias is present for all pricing moments. We apply formal tests following Oster (2019), among other checks, to confirm the scope for omitted variable bias.[3]

Although our goal is to broadly evaluate the empirical informativeness of popular pricing and non-pricing moments in the micro data, a particular angle of our analysis is

[2]See for example Fisher (1922): "No other statistic that can be calculated from the same sample provides any additional information as to the value of the parameter."

[3]This procedure considers changes in explanatory power we observe along with the instability of coefficients across specifications. The insight that ties together omitted variable bias and informativeness is that concern for omitted variable bias lessens only as a model gets closer to explaining all of the variation in the dependent variable – that is, as R^2 increases towards its upper bound.

that it provides evidence on whether the ratio of kurtosis over frequency of price changes is an empirically sufficient statistic for monetary non-neutrality, as posited by Alvarez et al. (2016a, 2020). As presented above, the ratio of kurtosis over frequency is informative for monetary non-neutrality in some specifications, but it is not an empirically sufficient statistic. Its significance stems from the significance of frequency, while kurtosis only adds noise. Significance can be lost altogether when other, non-pricing moments are included. Additionally, we find limited evidence that the estimated coefficients of kurtosis and frequency, included as separate regressors, bear an equal but opposite sign as predicted by theory. In short, our results point towards a gap between assumptions in theoretical work and the empirical environment where its findings can be assessed.

Our theoretical analysis gives our empirical findings a positive note. As we trace out which modeling assumptions have which consequences for the relation of pricing moments and monetary non-neutrality, our findings can guide modeling choices. To make our point, we concentrate attention on menu cost models and three pricing moments: kurtosis, frequency, and their ratio. Our baseline model is an augmented version of Nakamura and Steinsson (2010) calibrated in standard quantitative fashion. Set in discrete time, it features trend inflation, stochastic aggregate productivity and monetary shocks, leptokurtic idiosyncratic productivity shocks, menu costs and Calvo-plus free price changes, among other model ingredients.[4] The model predicts that both frequency and kurtosis have negative relationships with monetary non-neutrality. As a result, their ratio has a non-monotonic relation with monetary non-neutrality. We compute these relationships by comparing steady-state pricing moments and monetary non-neutrality across different calibrations.[5]

Next, starting from the simplest model nested in our setup, we add each of the above assumptions sequentially to show how they determine the relation of pricing moments with monetary non-neutrality. In particular, this stepwise addition clarifies which assumptions

[4]We note that the model does not fit in the class of models studied by Alvarez et al. (2016a, 2020).

[5]First, for a given calibration, we simulate the steady state distribution by simulating a time series of 1000 periods after a burn-in of 500 periods. In each period we compute a moment of interest and use the average moment over time as the steady state pricing moment. Second, we compute the associated monetary non-neutrality after we shift the steady-state distribution with a one-time expansionary monetary shock, averaging the change in consumption across 3500 simulations. Third, we repeat these steps for different calibrations to obtain potentially different steady state distributions and monetary non-neutrality. In order to vary the moments we consider, we change the size of menu costs, the size of idiosyncratic shocks, the CalvoPlus parameter and the extent of leptokurtic shocks.

are behind the different predictions of our quantitative menu cost model compared to Alvarez et al. (2016a, 2020). This simplest nested model is the Golosov-Lucas model set in discrete time, featuring fixed menu costs, no aggregate shocks, Gaussian idiosyncratic productivity shocks and no trend inflation. To start with, we implement a monetary shock as an unexpected, one-time shift in the distribution of price gaps. This model falls into the class of models in Alvarez et al. (2016a, 2020), except that we do not use a second-order approximation for firm flow profits and solve a discrete-time setting. As a consequence, alternative calibrations cannot generate variation in kurtosis as predicted by their theory although kurtosis does not precisely equal 1.[6] However, once we add in stochastic monetary shocks, variation in kurtosis emerges. Both frequency and kurtosis bear a negative relationship with monetary non-neutrality and the ratio has an ambiguous relation, as in our full model. This result carries significance for a widely used modeling technique that may apply beyond the price setting focus in this paper: It matters for model predictions if we allow for stochastic aggregate shocks, or if we implement an aggregate shock as an unexpected one-time shift in relative prices.

As we enrich the list of modeling assumptions further, we find that adding random menu costs reverses the sign of the relation between kurtosis and monetary non-neutrality. Random menu costs can mechanically increase kurtosis and make some price changes not subject to selection (Golosov and Lucas (2007)), so monetary non-neutrality coincidentally increases. Now, the ratio of kurtosis over frequency has a positive relation with non-neutrality as in Alvarez et al. (2016a, 2020), who also assume random menu costs. However, adding in leptokurtic idiosyncratic shocks once more reverses the sign of the relation of kurtosis with monetary non-neutrality, working through a similar mechanism as in Karadi and Reiff (2019). At the same time, this addition generates an ambiguous relation of the ratio with monetary non-neutrality. Finally, the addition of the remaining model ingredients has no further effect on the sign of the relationship. In particular, the addition of 2 percent trend inflation has little additional effect in line with Baley and Blanco (2021).

As these exercises show, the relation of frequency with monetary non-neutrality is robust across modeling assumptions, but the relation of kurtosis and the ratio of kurtosis

[6]The reason lies in the discrete-time approximation of our setting. In Appendix A, we show that using a quadratic loss function approximation of firm flow profit does not change our results. Figure 11 illustrates this.

over frequency is not, just as in the data. Likely, sectors differ in practice in the extent to which assumptions from our exercise apply. In some sectors, fixed menu costs or aggregate shocks may dominate, implying a negative relation between kurtosis and non-neutrality, while random menu costs may dominate in other sectors, implying the opposite sign. The presence of different price setting mechanisms across sectors implies that a multi-sector model would always generate a positive relationship between frequency and monetary non-neutrality, but an unstable relationship between kurtosis and monetary non-neutrality depending on sectoral weights.

Literature. Our analysis contributes to a large empirical literature that has used micro pricing moments to analyze the effects of monetary policy shocks, starting with the work of Bils and Klenow (2004), Nakamura and Steinsson (2008) and Midrigan (2011). Another approach to discipline models has been to use specific episodes. For example, Gagnon (2009) evaluates the performance of Calvo versus menu cost models based on the Tequila crisis in Mexico, Alvarez et al. (2019) based on hyperinflation in Argentina, Nakamura et al. (2018) for the Great Inflation in the US, or Karadi and Reiff (2019) for VAT changes in Hungary. Gopinath and Itskhoki (2010) study the interaction between price flexibility and exchange rate shocks affecting price responses. Our work shows that the extent to which variation in micro pricing moments across sectors drives monetary non-neutrality can additionally be used to discipline models. By diving into sectoral and firm-level data, we exploit such variation.

Another literature our paper touches upon argues that conventional pricing moments may not be sufficient statistics for monetary non-neutrality in quantitative models. Dotsey and Wolman (2020), Karadi and Reiff (2019), Alexandrov (2020), Bonomo et al. (2020), or Bonomo et al. (2021) make such arguments. We make two contributions in this context: First, we provide direct empirical evidence in this regard. Second, we emphasize that pricing moments per se do not sufficiently summarize monetary non-neutrality. We show how different model ingredients affect the relation of pricing moments with monetary non-neutrality by going through our list of modeling assumptions. This analysis builds on several advances that have pushed the modeling frontier in menu cost models, such as Golosov and Lucas (2007), Caballero and Engel (2007), Nakamura and Steinsson (2010) and Midrigan (2011). Our list of modeling assumptions can be extended further as the above papers show, for example to take into account empirical phenomena such as price adjustment synchronization (Bonomo et al. (2020)). Without exhaustively doing so, the broader point of our analysis remains to emphasize the challenges that theory faces in light of a complex empirical environment.

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. Henkel (2020) finds the response of industrial production to monetary shocks varies with price stickiness while Meier and Reinelt (2020) show markup dispersion increases in response to monetary shocks. Castro (2020) uses regional variation in price stickiness to study monetary non-neutrality.

Finally, in related work subsequent to ours, Alvarez et al. (2021) have used an empirical strategy similar in spirit to ours, although with many important differences such as the use of French rather than US data. Our paper addresses the major concerns that the authors shared with us,[7] while also including many other robustness checks.

The rest of the paper proceeds as follows. Section II discusses the data, empirical methodology, and results. Section III presents the menu cost model. Section IV presents the model results and Section V concludes.

II Empirical Analysis

This section describes our data and the methodology we use to test which micro pricing moments are informative about the price or output response following an identified monetary shock, as well as our findings.

[7] Among other highly correlated measures, our empirical section also uses the monetary non-neutrality measure they propose. We also explain how R^2 and testing for omitted variable bias are tied together. We report results with and without fixed effects. While our model section shares the broader motivation of our empirical analysis, we clarify why our model predictions differ from Alvarez et al. (2016a, 2020). We also show that normalization for large shocks is not responsible for our findings.

A Data

Our main dependent variables are 154 producer price (PPI) inflation series from Boivin et al. (2009). This dataset on which we build also includes various further macroeconomic indicators and financial variables. Some examples 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). 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 first sort the 154 sectors into an above-median and a below-median set according to 8 pricing moments of interest: Frequency, kurtosis, the ratio of kurtosis over frequency, average size, standard deviation, fraction of small and fraction of positive price changes, and the standard deviation of price durations. This sorting requires us to have sectoral price-setting statistics. We obtain them by using the micro price data that underlie the construction of 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 by pooling price changes at the sector-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. Summary statistics are in Table 1. We assign sectors into above-median and below-median subsets for any given moment of interest and compute the average inflation rate in each subset.

As an important complement to these sector-level series, we use firm-level data on real sales and pricing moments. First, we compute 5 firm-level moments: frequency, kurtosis, the kurtosis over frequency ratio, average size, and standard deviation of price change. We compute these pricing moments using the PPI micro data for the 584 firms that Gilchrist et al. (2017) match to Compustat data. The pricing data are available from 2005 through 2014 for these calculations. As with the sectoral calculations, we pool all price changes within a firm over time to calculate firm pricing moments. Second, we merge firm-level sales from Compustat into this dataset to obtain a measure of output. Whenever we compute pricing moments, we restrict our sample to firms with a minimum of 5 price changes over the full sample period, which leaves 420 firms in the analysis. Summary statistics are in Table 11 in Appendix B.

To avoid measurement error in kurtosis as pointed out by Eichenbaum et al. (2014), we follow the approach suggested in Alvarez et al. (2016a) in both the industry and the firm exercises. We drop all price changes of 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. (2016a) since it does not meaningfully apply to PPI micro data. We present additional ways of addressing measurement error in our robustness section, including the instrumental variables approach in Gorodnichenko and Weber (2016).

B Identification of Monetary Policy Shocks

We rely on several commonly used schemes of identifying monetary policy shocks. Our two primary ones are the FAVAR approach as in Boivin et al. (2009) and the Romer and Romer (2004) narrative approach. We refer the reader to the respective papers for details. The approaches have various advantages and disadvantages that have been discussed elsewhere but are orthogonal to the purpose of our analysis. Our analysis uses the original data associated with these two identification schemes, from January 1976 to June 2005 for the FAVAR, and from January 1969 to December 2007 for the narrative scheme with the extension by Wieland and Yang (2020). Appendix B further shows robustness to using the high-frequency approach as in Nakamura and Steinsson (2018) using data from January 1995 through March 2014.

C Aggregated Approach

We first estimate the importance of our micro pricing moments for monetary non-neutrality at an aggregate level, depending on whether sectors fall into one of two bins: The first (second) bin contains all sectors with pricing moments above (below) the median value of the specific moment being evaluated. Then, we produce an impulse response for either set. Methodological details vary slightly by identification scheme, but across bins and identification schemes, we find a robust relationship of frequency of price changes with monetary non-neutrality and a tenuous one for kurtosis.

In the FAVAR monetary shock identification, we compute estimated price impulse responses $IRF_{k,h}$ for each of the k sectors at each monthly horizon h.[8] 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.

In the monetary shock identification following Romer and Romer (2004), we obtain differential impulse responses for an above-median and below-median set 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 pricing moments of interest. $\theta_{j,h}$ denotes the impulse response of the price level to an identified monetary policy shock h months after the shock for the average industry in the above-median or below-median set indexed by j. $z_{j,t}$ denotes controls that include two lags of the 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. We have normalized the monetary shock such that an increase in the shock is expansionary.[9]

Across all identification schemes and specifications, we find that pricing moments systematically relate to monetary non-neutrality as Figures 1 and 2 illustrate.[10] Low-frequency sectors have a smaller price response to the monetary shock than high-frequency sectors, regardless of the identification scheme. This result implies that low-frequency sectors have larger cumulative output responses.

In turn, the price responses in the high- and the low-kurtosis sectors are at best not significantly different from one another, as the Romer and Romer identification shows.

[8] We specifically follow Boivin et al. (2009) in the FAVAR methodology. We first use the FAVAR to generate PPI inflationary responses $\pi_{k,t}$ for each sector k: $\pi_{k,t} = \lambda_k' C_t + e_{k,t}$; in this setting the sectoral inflationary response is given by the loading λ_k' on the VAR evolution of the common components C_t. This component in turn includes the evolution of the federal funds rate which we shock. Monetary policy shocks are identified using the standard recursive assumption. The fed funds rate may respond to contemporaneous fluctuations in the estimated factors, but none of the common factors can respond within a month to unanticipated changes in monetary policy. Given the estimated FAVAR coefficients, we compute estimated impulse response functions for each of the k sectors.

[9] We additionally estimate the OLS specification of Romer and Romer (2004) in Figure 15 in Appendix B. The results are consistent using this alternative estimation method. Figure 16 in Appendix B shows the impulses estimated using data from 1976 through 2007. Results show the same patterns during this time period.

[10] Results using high-frequency shocks show the same patterns and are in Figure 12 in Appendix B.

The FAVAR analysis shows that high-kurtosis sectors have an even *stronger* price response than low-kurtosis sectors – which implies less monetary non-neutrality. This fragility in the relationship persists in subsequent exercises. In the model sections we show how this fragility can arise naturally in quantitative menu cost models.

In terms of the ratio of kurtosis over frequency of price changes, we find that the strong negative relationship of frequency with monetary non-neutrality dominates the relationship in this aggregate setup, despite the fragility inherent in the kurtosis relationship. The sectors with high kurtosis over frequency ratios have a smaller price response to the monetary shock than those with low kurtosis over frequency ratios. This suggests that they have a larger real output response. This finding holds across identification schemes.

Carvalho and Schwartzman (2015) show in that dispersion of the duration of price spells is a sufficient statistic for monetary non-neutrality in some time-dependent pricing models after conditioning on the frequency of price changes. We consistently find that a low dispersion of durations is associated with a higher price response, implying low monetary non-neutrality. This finding holds across our identification schemes. The reason for this result lies in the negative empirical relationship of the frequency of price adjustment with the dispersion of price durations.[11] However, after conditioning on price change frequency, it does not predict the price response as the next section shows.

The other pricing moments we study do not have clear univariate relationships with monetary non-neutrality across identification schemes.

D Detailed Regression Approach

We now exploit detailed variation in pricing moments at the industry- and firm-level, and find that the same results obtained in our aggregate approach emerge in both univariate and multivariate regression settings with richer sets of controls. In contrast to the specifications in the preceding subsection, the multivariate setting combines all pricing and non-pricing moments. This combination allows us to learn about the *relative* informativeness of individual pricing moments and other predictors of monetary non-neutrality.

[11] The correlation between frequency of price adjustment with the dispersion of price durations is -0.74 across industries. Due to this strong negative collinearity, we do not include it in some multivariate specifications in the following sections.

Our regression analysis follows two approaches to gauging the effects of pricing behavior on monetary non-neutrality. First, we use sectoral price responses h periods after an identified monetary shock as a direct measure of monetary non-neutrality, which we regress on the pricing moments taking into account broad industry fixed effects:

$$log(IRF_{k,h}) = a_h + \alpha_{j,h} + \beta' M_k + \gamma' X_k + \epsilon_{k,h} \tag{2}$$

where $log(IRF_{k,h})$ denotes the response of prices at a 24-month horizon in six-digit NAICS sector k from the FAVAR analysis.[12] $\alpha_{j,h}$ represent three-digit NAICS fixed effects as additional control variables to capture any common factors across broad industries j, and X_k represent other industry level covariates, such as profits or the persistence of shocks that can potentially affect monetary non-neutrality. Such common factors are for example sectoral exposure to oil, market structure, variations in strategic complementarity or any other source of unobserved heterogeneity. M_k contains one or more of the 8 industry pricing moments we study.

To provide guidance for modeling, one needs to gauge the relative importance of pricing moments, and the stability of their relationship with monetary non-neutrality. We do so by evaluating the effect of including multiple moments and controls on informativeness by considering goodness-of-fit statistics such as R^2, the log likelihood, and the approach in Oster (2019). This approach ties an assessment of coefficient stability to changes in informativeness of various specifications. The idea is that concern for omitted variable bias only lessens as the model gets closer to explaining all of the variation in the dependent variable — that is, as R^2 increases towards its upper bound. Hence, when evaluating specifications for omitted variable bias, one should simultaneously normalize any observed coefficient changes by changes in explanatory power.

In particular, we perform the Oster (2019) test by focusing on individual pricing moments relative to multivariate specifications that contain all pricing moments together. We also consider frequency, or kurtosis, against a specification with kurtosis and frequency; and kurtosis, frequency or their ratio against the multivariate specifications.

[12]Figure 19 in the Appendix shows the full horizon response from the FAVAR estimated price-level response for all univariate specifications and several multivariate specifications. The coefficient values are estimated from $log(IRF_{k,h}) = a_h + \alpha_{j,h} + \beta_h' M_k + \gamma_h X_k + \epsilon_{k,h}$ where the horizon h is varied from 1 to 48 months. The results are consistent with Table 2. The figure shows that frequency of price change has a greater impact on the price response at shorter horizons before slowly decaying in importance. Kurtosis of price change has no estimated effect for the full impulse.

This approach allows us to establish the scope for omitted variable bias when explaining monetary non-neutrality.

Second, we use an interaction approach. Here, the effect on monetary non-neutrality is gauged indirectly. We interact sectoral micro pricing moments in our regressions with Romer and Romer shocks and estimate potentially differential impulse responses to monetary policy shocks. Again, we include multiple moments in the interaction to assess their joint relationship with monetary non-neutrality. We estimate the following specification:

$$log(ppi_{k,t+h}) = \alpha + \alpha_k + \alpha_t + \beta' M_k * MP_t + \gamma' X_k * MP_t + \epsilon_{k,t+h} \tag{3}$$

where $log(ppi_{k,t+h})$ is the log sectoral price level 48 months after the monetary policy shock. As an alternative dependent variable, we use the same methodology with firm-level real sales in the next subsection. MP_t denotes the Romer and Romer identified monetary policy shocks. M_k represents one or several of our industry-level pricing moments.Other industry-level controls X_k include gross profit rates, and the volatility and persistence of sectoral shocks. α_k represent six-digit NAICS industry fixed effects, while α_t denote time fixed effects at a monthly frequency. Both are included in all specifications.

Across these two approaches, we continue to find that univariately, frequency of price changes is significantly related to monetary non-neutrality as in the univariate industry-level regression setup. Kurtosis of price changes is not statistically significantly related to monetary non-neutrality and has an unstable sign when compared to multivariate specifications. As in the previous subsection, the strength of the relationship of frequency with monetary non-neutrality dominates and generates a significant and negative univariate relation of the ratio of kurtosis over frequency with monetary non-neutrality. Other moments are not significant or come with an unstable sign. Table 2, and Table 10 in the Appendix, summarize the results in Columns 1-8, the first for the FAVAR and the second for the Romer and Romer shocks. Figure 3 plots the full impulse response in Panels (a) through (h) for the Romer and Romer shocks.

A further insight from the univariate specifications in Columns 1-8 of Table 2 lies in the measures of informativeness for the various moments: Frequency of price changes is clearly the most informative pricing moment. We compute as measures of fit R^2, adjusted R^2, the log likelihood, and the Bayesian information criterion, not taking into account industry fixed effects, in order to gauge the contribution of individual moments to overall explanatory power. We see, for example, that the explanatory power (R^2) of frequency of price changes is the highest among all moments with 30 percent while others, such as kurtosis of price changes, are quite uninformative in comparison, with an R^2 of approximately 4 percent. The ratio of kurtosis over frequency compared to frequency alone has a much lower explanatory power of 17 percent, suggesting that kurtosis adds noise to the information contained just in the frequency of price changes. The low levels of R^2 are important below when assessing evidence for omitted variable bias following the procedure in Oster (2019). The other measures of fit provide a similar picture.

Then we turn to a multivariate setting. Here, our main results emerge in a richer setup. We find, consistent with our previous results, that the frequency of price changes is consistently statistically significant when we include all pricing moments. This result remains when all pricing moments plus non-pricing moments are included — in particular, gross profit rates, the standard deviation and persistence of sectoral shocks. Profit rates can be understood to capture the extent of competition in the sector, while the persistence of sectoral shocks might affect the strength of the selection effect. We find that other pricing moments are not significant or consistently significant across specifications. This holds for kurtosis of price changes, which always remains statistically insignificant, but also for the ratio of kurtosis over frequency, which can lose significance in the multivariate settings. Whether we include fixed effects or not does not alter these conclusions. Table 2 summarizes these multivariate results in Columns 9-13 for the FAVAR approach, while Columns 8-11 in Table 10 display the results for the Romer and Romer approach.

A particular multivariate specification pertaining to the sufficient statistic proposed by Alvarez et al. (2016a, 2020) will be discussed further in Section F. This specification is a bivariate regression setup with kurtosis and frequency as the only two explanatory variables. As shown in Column 9 of Table 2 and Table 10, a previously implicit result from the aggregate analysis is now directly validated. Frequency, and not kurtosis, is the driver for the informativeness of the ratio of kurtosis over frequency for monetary non-neutrality. Frequency is highly statistically significant in this bivariate regression, while kurtosis is not statistically significant. A formal likelihood ratio test confirms the result: We cannot reject the null at a 5 percent significance level that a model with just frequency explains the data as well as a model with both frequency and kurtosis. But we can reject the null at a 1 percent significance level that a model with only kurtosis fits equally well. This result is shown in the row denoted "LR test 1" in Table 2.

In general, these richer multivariate specifications reveal two insights: First, measured informativeness in the regressions with all pricing moments, or with only kurtosis and frequency, is very similar to that found in the univariate frequency of price change specification. Hence, frequency is the most informative pricing moment. Second, when we include further variables, such as the volatility and persistence of shocks or profit rates, the informativeness of the specifications in the FAVAR setup improves. For example, the simple R^2 measure goes up to 52 percent if we additionally include volatility and persistence of shocks compared to 30 percent if we only include frequency, or 33 percent if we include all pricing moments. This finding suggests that single or multiple pricing moments are not robust in summarizing monetary non-neutrality. These results can be seen by comparing the univariate, bivariate and multivariate results in Tables 2 and 10.

More formally, we gauge the extent of omitted variable bias by computing the δ test statistic in Oster (2019), for all pricing moments in the FAVAR setup relative to fuller specifications. The results are summarized in the rows denoted by "δ" in Table 2. The first row tests each individual moment or the ratio of kurtosis over frequency against the richer models (that is, against Columns 12 and 14, respectively, and in the case of the standard deviation of price durations against Column 10). The complementary second row compares kurtosis or frequency, respectively, to the specification that jointly includes only kurtosis and frequency of price changes (Column 9). Rows 3 and 4 present robustness checks where we assume the true R^2 is 0.8. We find that δ is much below unity or even negative for kurtosis. This finding suggests that selection on unobservables does not have to be large to explain away our regression results due to omitted variable bias.

Finally, we also formally compare the model fit of each univariate specification against our more complex multivariate specifications using likelihood ratio tests for each specification in Columns 1-8 against the saturated specifications in Columns 12 and 14, reported in the row labeled "LR test 2." We always reject the null that a model with just a single pricing moment fits the data equally well as a model with the saturated specification. These findings underline the fragility that is associated with using univariate pricing moments as summary statistics for monetary non-neutrality.

D.1 Firm-Level Regression Results

Our main findings also emerge robustly from our firm-level regressions using Romer and Romer shocks. These highly disaggregated specifications allow us to take into account time and detailed firm-level fixed effects while also controlling for four quarters of lagged log sales. Moreover, these specifications use firm-level real sales as a dependent variable, which allows us to confirm our previous findings for a dependent variable that measures monetary non-neutrality using quantities rather than prices. In this exercise, we restrict our attention to the ratio of kurtosis over frequency, kurtosis, frequency, the standard deviation and the average size of price changes as moments of interest.

Specifically, we continue to use the interaction approach used above with the Romer and Romer shocks where the effect on monetary non-neutrality is gauged indirectly. We include multiple moments in the interaction to assess their joint relationship with monetary non-neutrality. We estimate the following specification:

$$log(sales_{j,t+h}) = \alpha + \alpha_t + \alpha_j + \theta_h * MP_t * M_j + \gamma' X_{j,t} + \epsilon_{j,t+h} \tag{4}$$

where $log(sales_{j,t+h})$ is the log firm-level real sales h quarters after the Romer and Romer shock where we use h=4. MP_t denotes the Romer and Romer identified monetary policy shocks. M_j represents one or several of our firm-level pricing moments. Firm-level controls $X_{j,t}$ include four quarters of lagged log sales. α_j and α_t denote firm and time fixed effects.

Consistent with the results from our previous industry and aggregate analyses, we find that frequency is individually highly significant, while kurtosis is statistically insignificant. The standard deviation and the average size of price changes are not statistically significant. The ratio of kurtosis over frequency has a positive and significant sign as predicted by theory. But in a bivariate setting that includes frequency and kurtosis as explanatory variables, it again shows that frequency is the only informative component behind the ratio of kurtosis over frequency. Only frequency is statistically significant in this bivariate specification while kurtosis is insignificant. In a multivariate setting that includes all individual moments jointly, only frequency is again statistically significant. Table 3 summarizes the regression results while Figure 4 plots the full impulse response for each specification.[13]

In terms of informativeness, a simple regression of our dependent variable on fixed effects and controls already explains much of the variation with an R^2 of more than 60 percent, with most variation explained by the control variables as shown in Column 0. Adding any pricing moments in an interaction with monetary policy shocks does not increase R^2. This is a well-known result for specifications with autoregressive components. This finding reinforces the conclusion that pricing moments are not the only informative summaries for the response of key variables of interest to monetary policy shocks.

E Robustness to Measurement Error

This section shows that results are unaffected by potential measurement error in kurtosis and other micro moments. First, a simple fact lessens concerns about measurement error: Key moments are very stable and persistent over time. As Table 1 shows in its last column, the correlation of pricing moments between 1998 to 2003 and 2004 to 2005 at the industry level is quite high. It ranges between 0.39 for the average size of price changes and 0.91 for the frequency of price changes. Kurtosis has a correlation of 0.85. The same results hold true for the entire time series. Figure 20 in the Appendix shows that pricing moments and the ordering across industries are remarkably stable over time.

Second, our aggregate results appear quite robust when applying different trimming methods for small and large price changes.[14] We focus our analysis on kurtosis and frequency in this exercise because kurtosis is particularly prone to measurement issues as shown by Eichenbaum et al. (2014). Table 9 in the Appendix presents the results. Each row corresponds to a type of trimming. Across moments and types of trimming, pricing moments including kurtosis appear to be well measured with regard to extreme price changes, and invariant. Because kurtosis is in practice most susceptive to measurement error, its stability is reassuring also for all other moments.

Third, we show that an instrumental variables approach to address attenuation bias – due to classical measurement error – does not change our key regression results. To

[13] In the Appendix, we show that these results are robust to a horizon of 8 quarters after the shock in Table 12, and to using the high-frequency identified shocks of Nakamura and Steinsson (2018) as shown in Tables 13 and 14 and Figure 13.

[14] We follow the trimming methodology exactly as in Table 5 in the appendix of Alvarez et al. (2016b). The only difference is that we replicate their calculations separately for above-median and below-median sets of each pricing moment.

implement such an approach, we follow Gorodnichenko and Weber (2016) and split our sample into an early and a late time period of approximately equal size. We then use moments from one period as instruments for moments in the other period. We find that the instrumented coefficient estimates continue to be similar to our baseline estimates, suggesting that attenuation bias due to measurement error is not driving our results. Our main message from the preceding analyses re-emerges: Frequency of price changes is always significant, across univariate, bivariate, and multivariate settings. Kurtosis is now significant in some of the univariate and bivariate specifications, but not in the multivariate settings. The ratio of kurtosis over frequency becomes insignificant in all multivariate specifications. The specific results are shown in Table 15 for the univariate setting, and in Table 16 for the multivariate case.

F Relation to Alvarez et al. (2016a, 2020)

Although our analysis has broader motivation, it also has a straightforward connection to Alvarez et al. (2016a, 2020). They prove that the ratio of kurtosis and frequency of price changes is a sufficient statistic for monetary non-neutrality in a large class of models. This ratio is one of the pricing moments we study. This section recapitulates the main result in Alvarez et al. (2016a, 2020). We discuss how results previously presented, in combination with additional exercises, shed light on the empirical application of their theory. A reader interested in the details of these results can read the self-contained section, or otherwise can skip ahead to the model analysis in Section III.

F.1 The Sufficient Statistic in Alvarez et al. (2016a, 2020)

The analytical menu cost model in Alvarez et al. (2016a, 2020) is set in continuous time and features random menu costs, Gaussian idiosyncratic productivity shocks, no stochastic monetary shocks, no trend inflation, and firm quadratic objective functions, among other ingredients. This model captures the essence of many pricing models including Taylor (1980), Calvo (1983), Reis (2006), Golosov and Lucas (2007), Nakamura and Steinsson

(2010), Midrigan (2011) and Alvarez and Lippi (2014).[15] In Alvarez et al. (2016a, 2020), they summarize monetary non-neutrality $\mathcal{M}$ by the following expression when monetary shocks are small:

$$\mathcal{M} = \frac{\delta}{6\epsilon} \frac{kurtosis}{frequency} \tag{5}$$

where $\mathcal{M}$ denotes the integral of the output response following a once-and-for-all monetary shock, $kurtosis$ the steady-state kurtosis of price changes, $frequency$ the steady-state frequency of price changes, $\frac{1}{\epsilon}$ the supply elasticity of labor to the real wage, and δ the size of a small monetary shock.

When monetary shocks are large, Alvarez et al. (2016a, 2020) show that this relationship must be adjusted by another pricing moment, the steady-state standard deviation of price changes denoted by $Std(\Delta p)$, such that $\mathcal{M}$ is

$$\mathcal{M} = \tilde{\mathcal{M}} \left(\frac{\delta}{Std(\Delta p)} \right) Std(\Delta p) \tag{6}$$

where $\tilde{\mathcal{M}}$ is the expression in (5) for small shocks, and $Std(\Delta p)$ enters in two ways, dividing the size of monetary shocks and as a re-scaling factor.

Our regressions relate in a straight-forward way to either equation (5) or (6). We start by describing a comprehensive set of empirical measures of monetary non-neutrality we investigate. First, to evaluate the relation between monetary non-neutrality and pricing moments, we use an indirect time-series specification that regresses a panel of prices or real sales on interactions of monetary shocks with kurtosis and frequency, as well as their ratio, plus controls. Second, we use direct, cross-sectional measures of monetary non-neutrality, that is, we use as a measure of $\tilde{\mathcal{M}}$ the price response of sector k at a horizon h, of which we take logs.[16] We also use a specification in levels where the measure

[15] However, strictly speaking, many of these models do include stochastic aggregate shocks. By contrast, Alvarez et al. (2016a, 2020) assume that only idiosyncratic shocks generate the distribution of price changes from which pricing moments are computed. While a useful theoretical simplification, it is inconsistent with pricing moments measurable in the data. Our theory in Section IV suggests that this assumption is important for understanding the relationship between kurtosis and monetary non-neutrality in a quantitative menu cost model.

[16] The associated specification is the following, based on equation (5) above:

$$\log \mathcal{M} = \log \delta - \log 6\epsilon + \log kurtosis - \log frequency \tag{7}$$

of monetary non-neutrality is cumulative, denoted by CIR^P. Alvarez et al. (2021) show this is the specification that their theory implies, once a constant is included into the regression and kurtosis and frequency are normalized by their means. These measures pick up different features of the impulse response function. However, in practice, we find CIR^P and our measure are highly correlated, with a correlation coefficient of 0.9965 in levels and 0.87 in logs. These high correlations explain why the results from specifications in logs are robust to using CIR^P, or a specification in levels. A comparison of Table 2 in logs with Tables 17 and 18 using CIR^P illustrates this robustness.

In addition, we report results after adjusting for large shocks, as prescribed by theory. When we estimate specification (3) using the normalized narrative and high-frequency identification schemes, we additionally control for the standard deviation of price changes in our specifications expecting it to enter negatively and significantly. However, no adjustment is necessary in our FAVAR analysis as this setup is linear in nature. The standard deviation for price changes in the numerator of the adjustment factor cancels out with the standard deviation of price changes that divides the shock.

We use this battery of specifications to gauge the evidence for the statistical significance of the ratio of kurtosis over frequency for monetary non-neutrality. This analysis is complemented by a placebo test where we regress our measures of monetary non-neutrality on the ratio of frequency and any other pricing moment instead of kurtosis. Separately, we check the prediction that coefficients on kurtosis and frequency of price changes have equal but opposite signs as implied by equations (5) and (6).

To complete the test of sufficiency, we check for omitted variable bias. Here we include additional pricing moments and non-pricing moments, such as the persistence of shocks, into our specifications. We also allow for fixed effects to filter out sources of unobserved heterogeneity. We equally report results without fixed effects. But tests of omitted variable bias are also where our analysis goes beyond tests of significance by assessing the strength of the link between the strict theoretical setup and the empirical environment.

Our analysis does so in two ways: First, we run model comparisons between equation (7) against more restricted statistical models where only frequency or only kurtosis is the explanatory variable. Furthermore, we run model comparisons against richer statistical models with additional explanatory variables. The goal of these tests is to gauge the goodness of fit of the sufficient statistic in the data. It may well be the case that statistically, a single moment or the addition of further variables significantly improves our understanding of what drives monetary non-neutrality in the actual data. Second, we include the formal test by Oster (2019) to tie together our assessment of omitted variable bias to an assessment of changes in informativeness.

F.2 Evaluating the Sufficient Statistics Result

Our main conclusion is that the theoretically sufficient statistic in Alvarez et al. (2016a, 2020) is not sufficient in a statistical sense. The same conclusion applies to all of the pricing moments we evaluate: They all fail to pass several empirical tests for sufficiency status. While frequency emerges as the informative driver of the ratio of kurtosis over frequency, other pricing and non-pricing moments are also informative for monetary non-neutrality in the data.

We start with results from the univariate setting, which appear to confirm Alvarez et al. (2016a, 2020): The ratio of kurtosis over frequency has a robust statistical relation to measures of monetary non-neutrality. However, as we have shown in a bivariate setting, it is frequency of price changes in the ratio that contains the information generating the significant relation to monetary non-neutrality while kurtosis actually adds noise. We reach this conclusion based on several pieces of evidence. First, a statistical model with just frequency as an explanatory variable is more informative with respect to the data than a model with the ratio of kurtosis over frequency in it, or a model with only kurtosis in it. Second, a placebo exercise where the ratio of any of our pricing moments over frequency appears significant reinforces this conclusion as Table 20 in Appendix B summarizes. Each such ratio is statistically related to monetary non-neutrality, but driven by frequency.

Our multivariate specifications reinforce these findings. The significance of kurtosis over frequency of price changes is driven by the frequency of price changes. Frequency of price changes is robustly informative about monetary non-neutrality. Kurtosis remains insignificant. This insight about the importance of the frequency of price changes holds true when we use a comprehensive set of pricing moments, or include non-pricing moments, such as the persistence of sectoral shocks. Further, we also find that kurtosis and frequency do not always emerge from the regression results with equal but opposite signs in the FAVAR analysis as the F-tests in Tables 2, 17, and 18 indicate. However the null hypothesis of equality is not rejected using Romer and Romer shocks in Table 3. The ratio of kurtosis over frequency, which was statistically significant in the univariate setting, becomes insignificant when included along with other pricing moments and non-pricing moments. The multivariate columns of Tables 2 and 17 illustrate this result, while Tables 3 and 18 show that it may remain marginally significant in some cases.

An instrumental variables approach confirms these findings while correcting for potential measurement error, as shown in Tables 16 and 19. In these specifications, we also find that non-pricing moments turn out to be informative about monetary non-neutrality. This latter finding is important because it contradicts the definition of a sufficient statistic — that no other variable is informative. Results when we perform an adjustment for large shocks are consistent as shown in Panels A and B in Table 4.

Statistical evaluation along two dimensions suggests that omitted variable bias is reason for concern. First, when we add explanatory variables, we find that additional information turns out to be important not just in terms of affecting statistical significance, but also when we consider the predictive power of our specifications. Our measures of informativeness show a strong increase as we go from the univariate specifications to the bivariate and multivariate ones. In line with these results, a likelihood ratio test formally rejects the version of the sufficient statistic including just frequency and kurtosis as in equation 6 against our fullest specification, as Tables 2, 17 and 18 indicate in the line labeled "LR Test 2." Similarly, a likelihood ratio test rejects the specification with only the ratio of kurtosis over frequency against the specification with the ratio and all other moments and controls. Second, near-zero or even negative δ estimates for all pricing moments in tests following Oster (2019) more broadly suggest that none of our pricing moments can be sufficient statistics. Tables 2, 17, and 18 summarize these results.

III General Equilibrium Pricing Model

This section and the next show how the sign of the theoretical relationship between micro pricing moments and monetary non-neutrality can depend on small changes in modeling assumptions. We concentrate our attention on menu cost models and kurtosis, frequency, and their ratio. In our baseline quantitative model, both frequency and kurtosis have negative relationships with non-neutrality such that their ratio is characterized by an ambiguous, non-monotonic relationship. As we add assumptions sequentially, going from a simple nested model up to our full baseline model, the result for frequency remains robust, while kurtosis and their ratio of kurtosis over frequency exhibit a fragile relationship with monetary non-neutrality. In particular, we find that the sufficient statistic result in Alvarez et al. (2016a, 2020) only holds under certain assumptions.

This section presents our baseline model, while the subsequent Section IV presents quantitative exercises and provides intuition for our findings.

A Model Setup

Our model encompasses a generalized setup that nests several model variants. Our baseline setup presents a second-generation menu cost model that follows Nakamura and Steinsson (2010). It includes elements of menu cost and Calvo price setting, idiosyncratic leptokurtic productivity shocks as in Midrigan (2011), and aggregate productivity and monetary shocks. Our setup also encapsulates the Golosov and Lucas (2007) model.

A.1 Households

This modelling block is standard. Households maximize expected utility, given by

$$E_t \sum_{\tau=0}^{\infty} \beta^t \left[log(C_{t+\tau}) - \omega L_{t+\tau}\right] \tag{8}$$

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,

$$C_t = \left[\int_0^1 c_t(i)^{\frac{\theta-1}{\theta}} di\right]^{\frac{\theta}{\theta-1}} \tag{9}$$

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

Households decide each period how much to consume of each differentiated good by choosing the consumption bundle that yields the highest level of the consumption index C_t. This implies that household demand for differentiated good i is

$$c_t(i) = C_t \left(\frac{p_t(i)}{P_t}\right)^{-\theta} \tag{10}$$

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

$$P_t = \left[\int_0^1 p_t(i)^{1-\theta} di \right]^{\frac{1}{1-\theta}} \tag{11}$$

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

$$P_t C_t + E_t[D_{t,t+1} B_{t+1}] \leq B_t + W_t L_t + \int_0^1 \pi_t(i) di \tag{12}$$

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

$$D_{t,t+1} = \beta \left(\frac{C_t P_t}{C_{t+1} P_{t+1}} \right) \tag{13}$$

$$\frac{W_t}{P_t} = \omega C_t \tag{14}$$

where equation (13) describes the relationship between asset prices and consumption, and (14) describes labor supply.

A.2 Firms

There is a continuum of firms indexed by i. The production function of firm i is given by

$$y_t(i) = A_t z_t(i) L_t(i) \tag{15}$$

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

Firm i maximizes the present discounted value of future profits,

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau} \pi_{t+\tau}(i) \tag{16}$$

where profits are given by:

$$\pi_t(i) = p_t(i)y_t(i) - W_t L_t(i) - \chi(i) W_t I_t(i) \tag{17}$$

$I_t(i)$ 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. This is the "CalvoPlus" parameter from Nakamura and Steinsson (2010) that enables the model to encapsulate both a menu cost and a pure Calvo model. In the case of the baseline menu cost setup, this parameter is set such that a small probability of receiving a free price change enables the model to generate small price changes.

Total demand for good i is given by:

$$y_t(i) = Y_t \left(\frac{p_t(i)}{P_t} \right)^{-\theta} \tag{18}$$

The firm's problem is to maximize profits in (17) subject to its production function (15), demand for its final good product (18), and the behavior of aggregate variables.

Aggregate productivity follows an AR(1) process with $\nu_t \sim$ N(0,1):

$$log(A_t) = \rho_A log(A_{t-1}) + \sigma_A \nu_t \tag{19}$$

The log of firm productivity follows a mean reverting AR(1) process with shocks that arrive infrequently according to a Poisson process with $\epsilon_t(i) \sim$ N(0,1):

$$log z_t(i) = \begin{cases} \rho_z log z_{t-1}(i) + \sigma_z \epsilon_t(i) & \text{with probability } p_z \\ log z_{t-1}(i) & \text{with probability } 1 - p_z, \end{cases} \tag{20}$$

Nominal aggregate spending $S_t = P_t C_t$ is a random walk with a drift and $\eta_t \sim$ N(0,1):

$$log(S_t) = \mu + log(S_{t-1}) + \sigma_s \eta_t \tag{21}$$

The state space of the firm's 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. Thus, we assume 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 the forecasting rule:

$$log\left(\frac{P_t}{S_t}\right) = \gamma_0 + \gamma_1 logA_t + \gamma_2 log\left(\frac{P_{t-1}}{S_t}\right) + \gamma_3\left(log\left(\frac{P_{t-1}}{S_t}\right) * logA_t\right) \tag{22}$$

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

We use two complementary sets of parameters in all subsequent model calibrations. 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 $\theta = 6.8$ as in Vavra (2014). 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 from 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, and is used to parameterize our baseline model. The relevant parameters are the menu cost χ, the probability of an idiosyncratic shock, p_z, the volatility of idiosyncratic shocks σ_z, the persistence of idiosyncratic shocks ρ_z, and the probability of a free price change α. Their values will be discussed in the next section.

IV Model Results

This section illustrates how modeling assumptions determine the relationship between pricing moments and monetary non-neutrality.

A Model Predictions

In a first step, we calibrate the baseline model, described in detail in the previous section, to match price-setting statistics from the CPI micro data during the period 1988-2012 documented by Vavra (2014).[17] This part of the exercise is in line with conventional calibration approaches in the literature. However, next we undertake a comparative statics exercise where we vary one pricing moment at a time to understand its respective importance for monetary non-neutrality. The moments we examine are the frequency and kurtosis of price changes, as well as their ratio. We consider four alternative specifications: a case of high and a case of low frequency of price changes that hold kurtosis and other moments constant, as well as a case of high, and a case of low kurtosis that hold frequency and other moments constant. We set the ratio of kurtosis over frequency to be the same in the high-frequency and the low-kurtosis cases. This choice allows us to study if the ratio of kurtosis over frequency is a sufficient statistic in this off-the-shelf menu cost model. Tables 5 and 6 summarize the moments and parameters associated with each case.

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

When we vary one pricing moment at a time, while holding all others fixed, we find three main results. The top row of Figure 5 summarizes them graphically. First, we find that monetary non-neutrality is a negative function of frequency in our menu cost model, conditional on kurtosis. 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) show that an increase in kurtosis conditional on frequency decreases monetary non-neutrality.

Third, we show that the ratio of kurtosis over frequency has a non-monotonic relationship with monetary non-neutrality. Panel (c) in Figure 5 illustrates this finding graphically. Varying either frequency or kurtosis while holding their ratio constant leads to different cumulative consumption responses. A comparison of the high-frequency and

[17] We define the fraction of small price changes as those less than 1 percent in absolute value and take these data from Luo and Villar (2021). This definition allows comparison across different pricing data sets.

low-kurtosis calibration illustrates this finding: The ratio of kurtosis over frequency is 32 for both calibrations, but the high-frequency calibration with a frequency of 0.15 and kurtosis of 4.9 exhibits a lower consumption response than the low-kurtosis calibration with a frequency of 0.11 and kurtosis of 3.6. 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.

In a second step, we analyze what predictions between pricing moments and monetary non-neutrality arise in the Golosov and Lucas (2007) model. The Golosov-Lucas model is nested in our baseline model after we remove aggregate productivity shocks and turn leptokurtic idiosyncratic productivity shocks into walk processes. We set trend inflation to zero and the Calvo plus parameter to zero so there are no free price changes. Table 6 summarizes our parameter choices.[18] We use the same small one-time expansionary monetary shock as in the previous model simulation exercise to generate consumption impulse response functions as a measure of monetary non-neutrality.

The same three predictions as in the baseline model also arise in this setup. First, frequency conditional on kurtosis is negatively associated with monetary non-neutrality. Panel (d) in Figure 5 illustrate this result. Second, an increase in kurtosis in the Golosov and Lucas (2007) model, conditional on frequency, is associated with a decrease in monetary non-neutrality. Panel (e) in Figure 5 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, holding frequency constant, decreases monetary non-neutrality by 43 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 0.0241 to 0.0054, as well as the volatility of idiosyncratic productivity shocks from 0.029 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 6 illustrates this shift in the simulated

[18]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 ($\mu = 0$).

distribution of price changes closer to the Ss bands. Third, we find that an increase in the ratio of kurtosis over frequency is associated with a non-monotonic response of monetary non-neutrality. Panel (f) of Figure 5 illustrates this result.[19]

These predictions of the Golosov-Lucas model may appear surprising because Alvarez et al. (2016a, 2020) have shown that kurtosis always equals unity in their Golosov-Lucas setup, leaving no room to vary kurtosis in the first place. However, this conclusion does not apply in our setting. First, in discrete time, there is always a non-negligible mass at the Ss bands while that mass is always 0 in continuous time. Changes in the model parameters change the mass at the bounds, and hence potentially the steady-state distribution of price changes and the kurtosis of the distribution. More discreteness can exacerbate the findings that kurtosis can vary. Accordingly, we find that our result becomes more pronounced as we increase the extent of discreteness from monthly to quarterly and to semi-annual sampling frequencies. Table 7 illustrates this finding.

Second, the main reason, however, lies in how we implement monetary shocks in the setup. Our simulations allow for both stochastic monetary and idiosyncratic productivity shocks. Both determine the steady-state distribution of price changes. In this setup, we implement a common monetary shock with an unexpected one-time permanent monetary expansion. Different parameter values, including those for aggregate and idiosyncratic volatility, can generate the same frequency of price changes but different values of kurtosis. This is due to the different implied steady-state price change distributions as Figure 6 shows. Our setup is in line with the setup in Golosov and Lucas (2007). Alvarez et al. (2016a, 2020), by contrast, study a setting with a one-time permanent monetary shift, but no stochastic monetary shocks. If we remove stochastic monetary shocks, we approximately replicate the predictions in Alvarez et al. (2016a, 2020). In particular, kurtosis no longer varies.[20] The consumption response to a monetary shock divided by the standard deviation of price changes is also approximately the same.

The reason for these findings is as Alvarez et al. (2016a, 2020) argue: A one-time

[19] We confirm these results if the monetary shock is considered "large" as defined by Alvarez et al. (2016a, 2020). For this exercise, we hold the frequency of price changes constant across both calibrations. We then shock the model with a monetary shock standardized by the standard deviation of price changes, $\frac{\delta}{Std(\Delta p)}$, in both calibrations, and normalize the size of the impulse response by the standard deviation of price changes. Figure 10 in Appendix A displays our results.

[20] In this setup without stochastic monetary shocks, kurtosis is fixed at 1.3 across the baseline, high and low kurtosis calibrations. This compares to variation in kurtosis of 1.35 to 2.2 in our baseline Golosov-Lucas model with stochastic monetary shocks.

monetary shock only rescales distributions based on otherwise purely idiosyncratic shocks, but leaves kurtosis and frequency invariant. This makes the ratio of these moments a sufficient statistic in their setup, a result that no longer applies if one allows for stochastic variation in the aggregate monetary process. This result suggests a potential gap between micro pricing moments in their model and those measurable in the data, when monetary shocks are stochastic.[21]

B Reconciling Models and Data

The previous analysis has shown that both frequency and kurtosis of price changes have a negative relationship with monetary non-neutrality across several workhorse models, and thus their ratio has a non-monotonic relationship. This result depends on the details of how monetary shocks are implemented, as we illustrated. Now we show how the addition of assumptions leads us from the simple Golosov-Lucas model to the full baseline model and how each assumption matters. First, a simple change in the assumption about price setting from fixed to random menu costs can flip the sign of the relationship between kurtosis and monetary non-neutrality. Second, another modeling assumption about leptokurtic shocks can make the sign of the relationship between kurtosis and monetary non-neutrality reverse once more, without affecting frequency. But then, no further changes in the assumptions affect the relationships of moments with monetary non-neutrality. These findings suggest that small variations in modeling assumptions may reconcile model predictions with the fragility of kurtosis as well as robustness of frequency in our empirical analysis.

The simple change in price setting assumptions that makes the details of the monetary process discussed above irrelevant lies in how we set up menu costs. If we add in random menu costs in our variation of the Golosov and Lucas (2007) model, this small change in price setting assumptions is enough to reverse the sign of the relationship between kurtosis and monetary non-neutrality, conditional on the frequency of price changes. 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 6 displays our specific parameter

[21]Including stochastic aggregate productivity shocks instead of monetary shocks also allows kurtosis to vary and also generates a negative relationship between kurtosis and monetary non-neutrality.

calibrations. Panel (b) in Figure 8 illustrates this reversal: As kurtosis increases, monetary non-neutrality now increases. It is now positive. This sign reversal for the relationship of kurtosis and monetary non-neutrality as a result generates a strictly positive relation between the ratio of kurtosis over frequency and monetary non-neutrality.

What is the deeper intuition for this result? What is evident from the calibration and the model moments in Table 5 is that the fraction of random, free price changes, denoted by $\mathcal{L}$, plays a key role. From a modeling standpoint, as the fraction of random, free price changes increases from 73 percent to 91 percent, 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 increase the kurtosis of the price change distribution, holding the frequency constant. Hence, when kurtosis is positively affected by the fraction of free price changes in a random menu cost model, kurtosis can also have a positive relationship with monetary non-neutrality.

Figure 7 illustrates the effects of the random menu cost assumption by considering the distribution of price changes. As Panel (a) shows, the random menu costs increase the number of small price changes, relative to our version of the fixed menu cost model of Golosov and Lucas (2007) in Panel (a) of Figure 6. 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.

Which additional modeling assumption(s) can resurrect the negative relation of kurtosis and the non-monotonic relation of the ratio of kurtosis over frequency with monetary non-neutrality in the baseline model? We find, in line with the results, for example, in Bonomo et al. (2020) or Karadi and Reiff (2019), that the introduction of leptokurtic shocks leads to a negative relation of kurtosis with monetary non-neutrality and an ambiguous relation of the ratio with non-neutrality. Frequency has a robust negative relation with monetary non-neutrality. No further addition from the list of assumptions leading up to the baseline model changes the relation of kurtosis, frequency, or their ratio with monetary non-neutrality. Figure 8 illustrates this finding. Table 8 summarizes the sign of the relationship between kurtosis, frequency or their ratio and monetary non-neutrality as we add one assumption at a time.[22]

[22]Figure 9 in Appendix A illustrates the findings for frequency.

We take away from our modeling results two insights: First, on a positive note, we have found a robust, negative relation of frequency with monetary non-neutrality across models consistent with our empirical evidence. Second, the theoretical relationship between popular pricing moments and monetary non-neutrality is closely linked to modeling details. We have shown this result in the context of kurtosis, frequency and their ratio, and by going through a long list of modeling assumptions. This list could be extended further, for example to take into account empirical phenomena like price adjustment synchronization (Bonomo et al. (2020)). Without exhaustively doing so, the broader point of our analysis is to emphasize the challenges that theory faces in light of a complex empirical environment.

The dependence of results on modeling assumptions is also a welcome model feature. Likely, it presents a mirror image of differences across sectors in reality. In some sectors, for example, fixed menu costs or aggregate shocks may dominate, implying a negative relation between kurtosis and monetary non-neutrality. Random menu costs may dominate in other sectors, implying the opposite sign. This scenario implies that a multi-sector model that weights different model assumptions across sectors would always generate a negative relation between frequency and monetary non-neutrality, but an unstable relationship between kurtosis and monetary non-neutrality. Hence, our empirical null result in the aggregate for the relation between kurtosis and monetary non-neutrality conditional on frequency, and the frequent insignificance of kurtosis over frequency in our regressions present themselves as manifestations of sectoral heterogeneity in modeling assumptions.

V Conclusion

Using micro price data, we have empirically evaluated what price-setting moments are informative for monetary non-neutrality. We exploit sectoral and firm-level variation in pricing moments to show empirically that among a set of eight popular pricing moments, only frequency has an empirically robust relationship with monetary non-neutrality, and also drives whatever information is contained in the ratio of kurtosis over frequency. Kurtosis over frequency is not a sufficient statistic for monetary non-neutrality.

On the theory side, we show that small changes in modeling assumptions can have important effects on the sign of the relationship between pricing moments and monetary non-neutrality. For this reason, pricing moments per se do not sufficiently encapsulate monetary non-neutrality. Future empirical work may investigate variation in price setting assumptions across sectors of the economy.

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VI Tables

	Mean	Median	Standard Dev.	25th Percentile	75th Percentile	Corr(Early,Late)
$\frac{Kurtosis}{Frequency}$	34.73	28.75	23.16	18.61	45.11	0.89
Frequency	0.16	0.09	0.16	0.06	0.23	0.91
Kurtosis	3.97	3.45	2.57	2.47	4.73	0.85
Average Size	0.07	0.07	0.03	0.06	0.09	0.45
S.D.	0.08	0.08	0.03	0.06	0.10	0.39
Frac. Small	0.12	0.09	0.09	0.05	0.18	0.69
Fraction Pos.	0.62	0.60	0.11	0.53	0.69	0.51
S.D. Duration	10.75	10.61	5.50	6.19	14.77	
N	154	154	154	154	154	

Table 1: Industry-Level Summary Statistics

NOTE: This table summarizes the pricing moments listed in each row. S.D. Duration denotes the standard deviation of the duration of price spells; all other statistics are moments based on log price changes. The last column reports the correlation for a given moment computed in 1998-2003 and 2004-2005.

Cross-Sectional Determinants of Sectoral Price Response

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$	-0.250***													-0.127	-0.129
	(0.074)													(0.111)	(0.093)
Log Frequency		0.422***							0.476***	0.441**	0.411***	0.274**	.206*		
		(0.073)							(0.074)	(0.184)	(0.102)	(0.134)	(0.115)		
Log Kurtosis			0.138						-0.151	-0.189	-0.166	-0.113	-0.151		
			(0.119)						(0.112)	(0.142)	(0.132)	(0.131)	(0.108)		
Log Avg. Size				-0.316**						-0.252	-0.202	-0.111	-0.091	-0.356	-0.280
				(0.148)						(0.221)	(0.232)	(0.203)	(0.216)	(0.220)	(0.173)
Log S.D.					-0.158					0.117	0.014	-0.136	-0.198	-0.015	-0.112
					(0.127)					(0.189)	(0.195)	(0.152)	(0.150)	(0.203)	(0.168)
Log Frac. Small						0.017				-0.105	-0.106	-0.096	-0.093	-0.107	-0.114*
						(0.077)				(0.078)	(0.074)	(0.064)	(0.059)	(0.067)	(0.062)
Log Frac. Pos.							-0.334			0.160	0.070	0.020	0.080	-0.130	-0.030
							(0.382)			(0.426)	(0.434)	(0.343)	(0.311)	(0.339)	(0.310)
Log S.D. Duration								-0.593***		-0.090					
								(.076)		(0.188)					
Log Profit											-0.439**	-0.298	-.406**	-0.341	-0.420**
											(0.195)	(0.194)	(0.172)	(0.201)	(0.169)
SD(e_k)												10.283	10.445	13.895	12.565
												(12.401)	(10.042)	(12.020)	(9.458)
$\rho(e_k)$												0.570***	.678***	0.602***	0.709***
												(0.116)	(0.103)	(0.111)	(0.102)
constant	-.855***	-.963***	-1.803***	-2.459***	-1.996***	-1.552***	-1.792***	-.803***	-.652**	-1.034	-2.150**	-2.625**	2.840***	-3.489***	-3.479***
	(0.246)	(0.182)	(0.227)	(0.456)	(0.367)	(0.211)	(0.275)	(0.196)	(0.265)	(0.834)	(1.010)	(0.853)	(1.061)	(0.750)	(1.006)
R^2	0.1773	0.303	0.042	0.106	0.067	0.002	0.031	0.295	0.320	0.327	0.389	0.594	0.524	0.579	0.516
adj. R^2	0.1717	0.298	0.035	0.100	0.061	< 0.000	0.024	0.290	0.311	0.293	0.367	0.500	0.492	0.486	0.487
log likelihood	-142.570	-130.274	-153.863	-148.688	-151.844	-153.161	-154.713	-131.157	-128.483	-121.447	-117.771	-84.835	-96.302	-87.449	-97.567
BIC	295.134	270.543	317.720	307.370	313.682	316.289	319.420	272.308	271.957	282.708	265.485	309.018	242.370	333.164	239.924
										$H0: \beta^{freq} = -\beta^{kurt}$					
F-stat									8.08	1.79	3.27	1.53	0.20		
p-value									0.005	0.183	0.073	0.219	0.652		
LR test 1		3.58	50.76												
		(0.0584)	(< 0.000)												
LR test 2	90.01	62.75	109.93	102.24	108.55	111.19	114.29	67.18	59.17						
	(< 0.000)	(< 0.000)	(< 0.000)	(< 0.000)	(< 0.000)	(< 0.000)	(< 0.000)	(< 0.000)	(< 0.000)						
δ	0.159	0.165	-0.187	0.102	-0.066	-0.594	-0.051	0.026							
δ		0.355	-0.252												
$\delta(R^2_{max} = 0.8)$	0.300	0.311	-0.367	0.167	-0.109	-0.971	-0.084	0.043							
$\delta(R^2_{max} = 0.8)$		0.523	-0.414												
NAICS 3 FE	X	X	X	X	X	X	X	X	X	X	X	X	-	X	-
N	148	148	148	148	148	146	148	148	148	146	145	145	145	145	145

Table 2: Drivers of Monetary Non-Neutrality (FAVAR Approach)

NOTE: This table uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality based on the FAVAR specification. We estimate the following specification: $log(IRF_{k,h}) = a_h + \alpha_{j,h} + \beta' M_k + \gamma' X_k + \epsilon_{k,h}$ where $log(IRF_{k,h})$ is the response of prices at a 24-month horizon in a six-digit NAICS sector k in our FAVAR analysis. M_k contains one of our industry-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average size, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, and standard deviation of price duration, or the full set of pricing moments. $\alpha_{j,h}$ denotes three-digit NAICS industry j fixed effects, included in all specifications. X_k denotes sector-level controls, including the gross profit rate, the volatility of sector-level shocks, and the auto-correlation of sector-level shocks. Two log likelihood ratio tests are computed: LR test 1 compares specifications (2) or respectively (3) against (9), while LR test 2 compares (1) through (7) as well as (9) against (13), and (8) against (13) with the standard deviation of price durations included. Log likelihood ratio tests and measures of fit are computed excluding industry fixed effects and robust standard errors, except in columns (12) and (14). Log likelihood ratio tests and measures of fit are computed excluding industry fixed effects and robust standard errors, except in columns (12) and (14). δ denotes the test statistic in Oster (2019), while $\delta(R^2_{max=0.8})$ computes this statistic for a maximum possible R^2 of 80%. The first and third δ rows comprise a test of (2) and (3) against (12), (1) against (14), and (4) through (8) against (10), and the second and fourth δ rows a test of (2) and (3) against (9). Robust standard errors in parentheses. *** denotes significance at the 1 percent level, ** significance at the 5 percent level, * significance at the 10 percent level.

Cross-Sectional Determinants of Firm-Level Sales Responses									
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$*MP$_t$		1.853**							1.666*
		(0.845)							(0.865)
Log Frequency*MP$_t$			-1.893**				-1.999**	-1.858*	
			(0.947)				(0.918)	(0.976)	
Log Kurtosis*MP$_t$				-0.012			0.901	0.671	
				(1.997)			(1.940)	(1.981)	
Log S.D.*MP$_t$					-2.696			-1.286	-1.802
					(2.183)			(3.755)	(3.665)
Log Avg. Size*MP$_t$						-4.050		-2.254	-1.270
						(3.028)		(5.725)	(5.145)
							$H0 : \beta^{freq} = -\beta^{kurt}$		
F-stat							0.26	0.27	
p-value							0.611	0.605	
Firm Controls	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X	X
R^2	0.608	0.608	0.608	0.608	0.608	0.608	0.608	0.608	0.608
N	26,122	26,122	26,122	26,122	26,122	26,122	26,122	26,122	26,122

Table 3: Firm-Level Drivers of Monetary Non-Neutrality (Romer and Romer Approach)

NOTE: This table uses regression analysis at the firm-level to test the informativeness of five pricing moments for monetary non-neutrality based on the Romer and Romer identification. We estimate the following specification: $log(sales_{j,t+4}) = \alpha + \alpha_t + \alpha_j + \theta_h * MP_t * M_j + \gamma' X_{j,t} + \epsilon_{j,t+4}$, where $log(sales_{j,t+4})$ is the log firm-level real sales 4 quarters after the Romer and Romer shock. M_j contains one of our five firm-level pricing moments: frequency, kurtosis, the ratio of the two statistics, standard deviation of price changes, the average size of price changes, or multiple moments interacted with the Romer and Romer shock denoted by MP_t. α_t and α_j are firm and time fixed effects. Four quarters of lagged log sales are included as additional controls in X_t. Column 0 reports the specification with controls and fixed effects included, but no pricing moments. Within R^2 is reported. Standard errors are two-way clustered by firms and month. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

	A. Non-normalized MP			
	(1)	(2)	(3)	(4)
Log$\frac{Kurt}{Freq}$*MP$_t$	-1.680**			-2.372***
	(0.655)			(0.774)
Log Freq*MP$_t$		1.798***	2.289***	
		(0.653)	(0.743)	
Log Kurt*MP$_t$		-0.682	-1.096	
		(0.758)	(0.663)	
Log SD*MP$_t$			0.791	3.257***
			(0.658)	(0.946)
Log Frac. Small*MP$_t$			0.049	-0.284
			(0.319)	(0.380)
Log Frac. Pos.*MP$_t$			2.404	2.739
			(3.352)	(3.023)
Log Avg*MP$_t$			0.154	-3.305***
			(0.897)	(1.118)
	$H0: \beta^{freq} = -\beta^{kurt}$			
F-stat		3.37	1.94	
p-value		0.069	0.165	
R^2	0.001	0.001	0.001	0.001
N	60,672	60,672	59,904	59,904
	B. Normalized MP			
Log$\frac{Kurt}{Freq}$*$MP_{norm,t}$	-0.069*			-0.131***
	(0.039)			(0.048)
Log Freq*$MP_{norm,t}$		0.067**	0.121***	
		(0.033)	(0.046)	
Log Kurt*$MP_{norm,t}$		-0.004	-0.038	
		(0.047)	(0.039)	
Log SD*$MP_{norm,t}$	-0.042**	-0.033*	-0.137*	0.032
	(0.018)	(0.020)	(0.070)	(0.036)
Log Frac. Small*$MP_{norm,t}$			0.022	-0.008
			(0.026)	(0.029)
Log Frac. Pos.*$MP_{norm,t}$			0.118	0.138
			(0.226)	(0.182)
Log Avg*$MP_{norm,t}$			0.047	-0.150**
			(0.047)	(0.058)
	$H0: \beta^{freq} = -\beta^{kurt}$			
F-stat		3.82	6.58	
p-value		0.05	0.01	
Industry FE	X	X	X	X
Time FE	X	X	X	X
R^2	0.000	0.000	0.001	0.001
N	60,672	60,672	59,904	59,904

Table 4: Non-normalized vs. Normalized Shocks (Romer and Romer Approach)

NOTE: This table uses regression analysis to evaluate the role of shock normalization for the informativeness of pricing moments for monetary non-neutrality. In Panel A, we focus on "non-normalized monetary shocks." In Panel B, we use "normalized monetary shocks," defined as $MP^{norm}_{k,t} = \frac{MP_t}{SD_k}$, where SD_k is the standard deviation of price changes for each sector k. In Panel A, we estimate the following regressions: $log(ppi_{k,t+h}) = \alpha + \alpha_k + \alpha_t + \beta' M_k * MP_t + \gamma' X_k * MP_t + \epsilon_{k,t+h}$,where $log(ppi_{k,t+h})$ is the log of the h-month cumulative sectoral response of price to the Romer and Romer monetary policy shock denoted by MP_t, where h=48, M_k contains one of our industry-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average size, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, or the full set of pricing moments. α_k and α_t denote six-digit NAICS industry fixed effects and time fixed effects at monthly frequency. Both are included in all specifications. For Panel B, we use the following specification: $log(ppi_{k,t+h}) = \alpha + \alpha_k + \alpha_t + \beta' M_k * MP^{norm}_{k,t} + \gamma' X_k * MP^{norm}_{k,t} + \epsilon_{k,t+h}$. Standard errors are two-way clustered by firms and month. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Moment	Data	Baseline	High Frequency	Low Frequency	High Kurtosis	Low Kurtosis
			Golosov-Lucas			
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Positive	0.65	0.51	0.51	0.51	0.49	0.51
Average Size	0.077	**0.077**	**0.077**	**0.077**	0.033	0.154
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**	**1.35**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	12.8	9.39	18.1	20.3	9.7
		Golosov-Lucas with Random Menu Costs				
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Positive	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	0.13	0.14	0.12
Kurtosis	4.9	2.7	**2.7**	**2.7**	**3.4**	**2.0**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	25.0	18.2	32.6	30.2	18.6
$\mathcal{L}$		0.73	0.74	0.76	0.91	0.55
		Golosov-Lucas with Random Menu Costs and Leptokurtic Shocks				
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Positive	0.65	0.50	0.50	0.50	0.50	0.51
Average Size	0.077	**0.077**	**0.077**	**0.077**	**0.077**	**0.077**
Fraction Small	0.13	**0.13**	**0.13**	**0.13**	**0.13**	**0.13**
Kurtosis	4.9	**4.9**	**4.9**	**4.9**	**6.8**	**2.5**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	44.9	32.2	62.8	62.6	22.1
		Golosov-Lucas with Random Menu Costs, Leptokurtic Shocks, and Trend Inflation				
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Positive	0.65	0.69	0.67	0.73	0.72	0.67
Average Size	0.077	**0.077**	**0.077**	**0.077**	**0.077**	**0.077**
Fraction Small	0.13	**0.13**	**0.13**	**0.13**	**0.13**	**0.13**
Kurtosis	4.9	**4.9**	**4.9**	**4.9**	**6.7**	**3.8**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	45.0	32.6	61.6	60.9	34.6
		Golosov-Lucas with Random Menu Costs, Leptokurtic Shocks, Trend Inflation, and Aggregate TFP Shocks				
Frequency	0.11	**0.11**	**0.15**	**0.08**	**0.11**	**0.11**
Fraction Positive	0.65	0.63	0.67	0.67	0.64	0.63
Average Size	0.077	**0.07**	**0.077**	**0.077**	**0.077**	**0.077**
Fraction Small	0.13	**0.13**	**0.13**	**0.13**	**0.13**	**0.13**
Kurtosis	4.9	**4.9**	**4.9**	**4.9**	**6.9**	**3.8**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	44.5	43.6	62.1	32.6	61.5	34.9
			Baseline			
Frequency	0.11	**0.11**	**0.15**	**0.07**	**0.11**	**0.11**
Fraction Positive	0.65	**0.63**	**0.61**	**0.67**	**0.64**	**0.62**
Average Size	0.077	**0.077**	**0.077**	**0.077**	**0.077**	**0.077**
Fraction Small	0.13	**0.13**	**0.13**	**0.13**	**0.13**	**0.13**
Kurtosis	4.9	**4.9**	**4.9**	**4.9**	**6.5**	**3.6**
$\frac{\text{Kurtosis}}{\text{Frequency}}$	58.2	44.4	32.3	68.1	57.4	32.3

Table 5: Model Moments

NOTE: The table shows the model moments that are internally targeted for each economy. All monthly CPI data moments are taken from Vavra (2014) and are calculated using data from 1988-2014. Fraction of small price changes less than 1 percent in absolute value taken from Luo and Villar (2021). Boldface moments are targeted. $\mathcal{L}$ is defined as the fraction of price changes that are free.

Parameter	Baseline	High Frequency	Low Frequency	High Kurtosis	Low Kurtosis
			Golosov-Lucas		
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
			Golosov-Lucas with Random Menu Costs		
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
			Golosov-Lucas with Random Menu Costs and Leptokurtic Shocks		
χ	0.00215	0.001	0.0048	0.00115	0.0353
p_z	0.084	0.117	0.06	0.06	0.20
σ_z	0.148	0.14	0.146	0.16	0.082
ρ_z	1.0	1.0	1.0	1.0	1.0
α	0.017	0.009	0.0132	0.085	0.035
			Golosov-Lucas with Random Menu Costs, Leptokurtic Shocks, and Trend Inflation		
χ	0.0074	0.003	0.0225	0.0039	0.0175
p_z	0.083	0.115	0.0605	0.06	0.11
σ_z	0.156	0.16	0.0383	0.197	0.124
ρ_z	1.0	1.0	1.0	1.0	1.0
α	0.03	0.035	0.028	0.023	0.036
			Golosov-Lucas with Random Menu Costs, Leptokurtic Shocks, Trend Inflation, and Aggregate TFP Shocks		
χ	0.0095	0.005	0.02	0.0055	0.02
p_z	0.086	0.115	0.0605	0.06	0.11
σ_z	0.1425	0.1455	0.14	0.173	0.118
ρ_z	1.0	1.0	1.0	1.0	1.0
α	0.029	0.036	0.026	0.022	0.036
			Baseline		
χ	0.0095	0.0048	0.022	0.0055	0.02
p_z	0.072	0.115	0.025	0.053	0.01
σ_z	0.13	0.143	0.116	0.144	0.103
ρ_z	0.75	0.99	0.65	0.65	0.75
α	0.029	0.036	0.022	0.022	0.036

Table 6: Model Parameters

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

Moment	Monthly	Quarterly	Bi-annual
Frequency	0.11	0.31	0.51
Fraction Positive	0.51	0.54	0.59
Average Size	0.077	0.077	0.078
Fraction Small	0.0	0.02	0.06
Kurtosis	1.40	1.55	2.01

Table 7: Model Moments: Horizon Variation

Note: The table shows the moments of the Golosov-Lucas model at different sampling horizons. The model is solved at a monthly frequency and then simulated with a panel of 10,000 firms. Moments are then calculated by sampling price changes at monthly, quarterly, and bi-annual frequency.

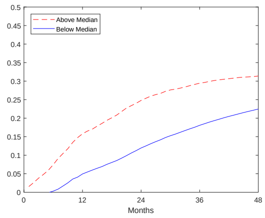
Model	Correlation between Monetary Non-Neutrality and Kurtosis	and Frequency	and $\frac{\text{Kurtosis}}{\text{Frequency}}$
Golosov-Lucas, no stochastic monetary shocks	None	Negative	Positive
Golosov-Lucas, with stochastic monetary shocks	Negative	Negative	Ambiguous
+ RMC	Positive	Negative	Positive
+ Leptokurtic Shocks	Negative	Negative	Ambiguous
+ Trend Inflation	Negative	Negative	Ambiguous
+ Aggregate Productivity Shocks	Negative	Negative	Ambiguous
Baseline Model	Negative	Negative	Ambiguous

Table 8: Model Assumptions: Moment Effects

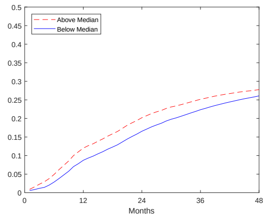
Note: The table summarizes the sign of the relationship between kurtosis, frequency, or their ratio and monetary non-neutrality as we add additional model parameters to the Golosov-Lucas model with stochastic monetary shocks in the steady-state. The first row shows the correlations in the Golosov-Lucas model without stochastic monetary shocks in the steady-state. We compute the correlation between moments and monetary non-neutrality in several steps: First, for a given calibration, we simulate the steady state distribution by simulating a time series of 1000 periods after a burn-in of 500 periods. In each period we compute a moment of interest and use the average moment over time as the steady state pricing moment. Second, we compute the associated monetary non-neutrality after we shift the steady-state distribution with a one-time expansionary monetary shock, averaging the change in consumption across 3500 simulations. Third, we repeat these steps for different calibrations to obtain potentially different steady state distributions and monetary non-neutrality.

VII Figures

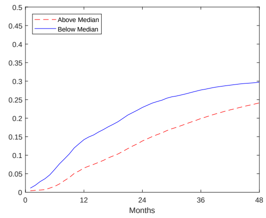
A Aggregated Results



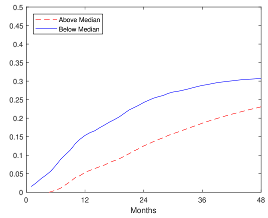
(a) Frequency



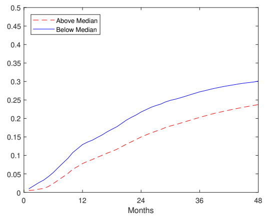
(b) Kurtosis



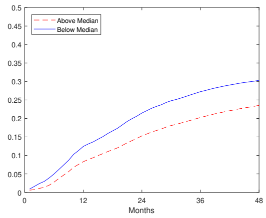
(c) Kurtosis/Frequency



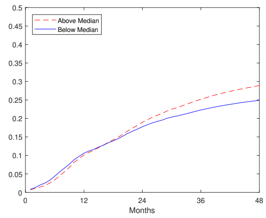
(d) S.D. Duration



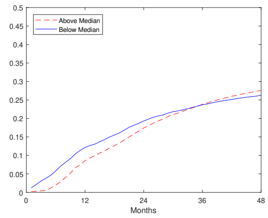
(e) Average Size



(f) Standard Deviation



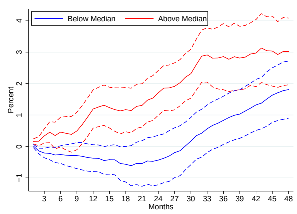
(g) Fraction Small



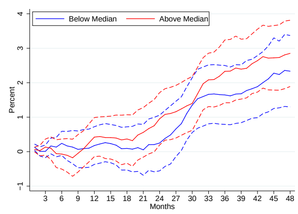
(h) Fraction Positive

Figure 1: FAVAR Monetary Policy Shock Impulse Responses

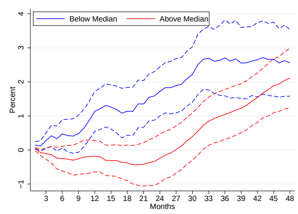
NOTE: In the above panels, “Above Median” and “Below Median” refer to the average impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. All panels show the estimated impulse responses of sectoral prices in percent to an identified 25-basis-point unexpected decrease in the federal funds rate.



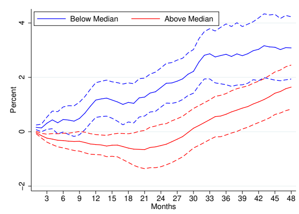
(a) Frequency



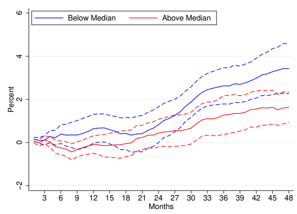
(b) Kurtosis



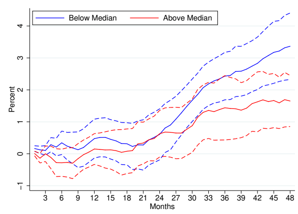
(c) Kurtosis/Frequency



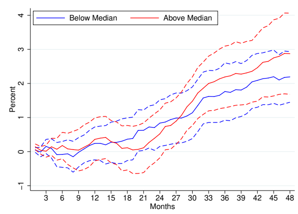
(d) S.D. Duration



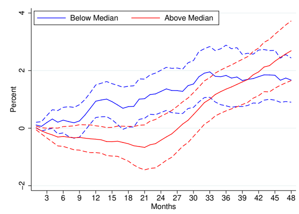
(e) Average Size



(f) Standard Deviation



(g) Fraction Small

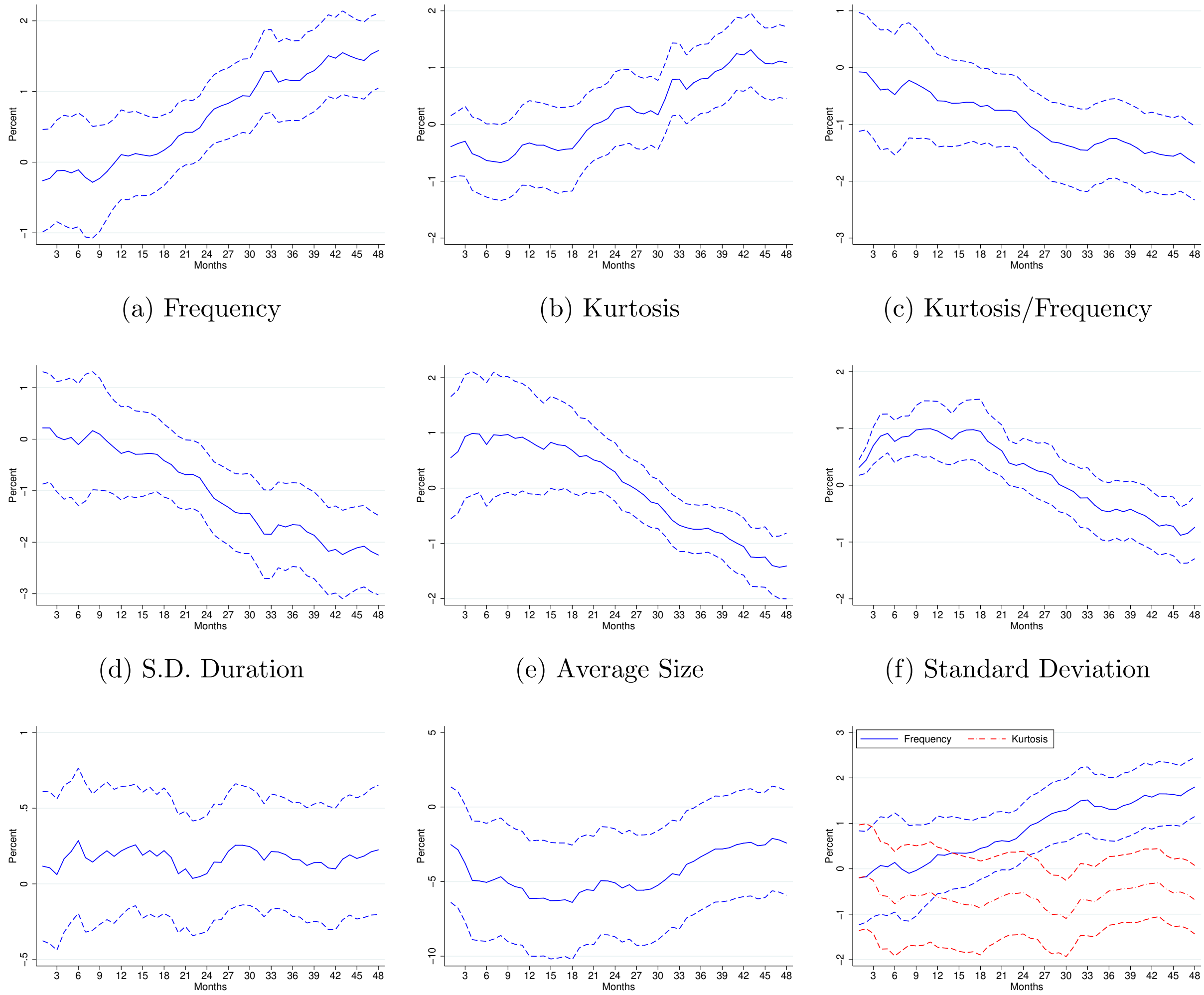


(h) Fraction Positive

Figure 2: Romer and Romer Monetary Policy Shock Aggregated Impulse Responses

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

B Sectoral and Firm-Level Results



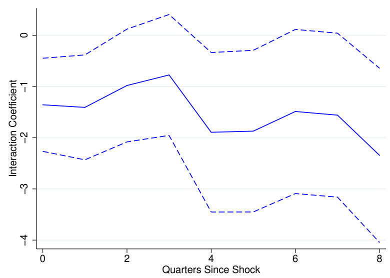
(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency

(d) S.D. Duration (e) Average Size (f) Standard Deviation

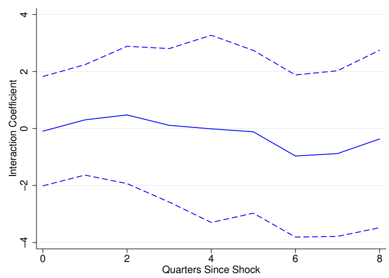
(g) Fraction Small (h) Fraction Positive (i) Frequency and Kurtosis

Figure 3: Romer and Romer Monetary Policy Shock, Industry-Level Impulse Responses

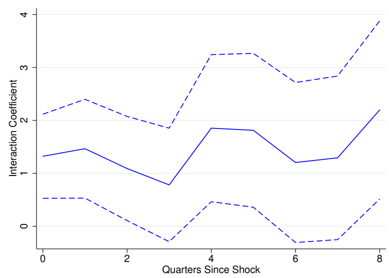
Note: In the above panels, we plot the respectively estimated coefficients θ_h from the following specification: $log(ppi_{k,t+h}) = \alpha + \alpha_{th} + \alpha_{kh} + \beta_h' M_k * MP_t + \gamma_h' X_k * MP_t + \epsilon_{k,t+h}$ where $log(ppi_{k,t+h})$ denotes industry k's price response at time t measured at monthly frequency, h months into the future. Time and 6-digit NAICS fixed effects are included in all specifications. M_k contains the log of one or more of the industry-level pricing moments: frequency, kurtosis, kurtosis over frequency, average size, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, or the standard deviation of price duration. Panel (i) controls for frequency and kurtosis separately. Standard errors are two-way clustered by industry and month. Dashed lines present 68% standard error bands.



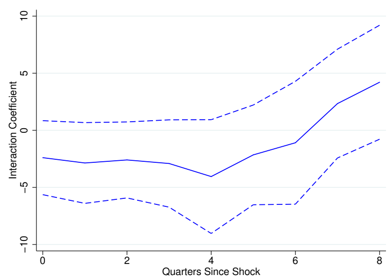
(a) Frequency



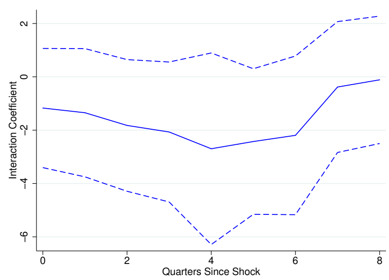
(b) Kurtosis



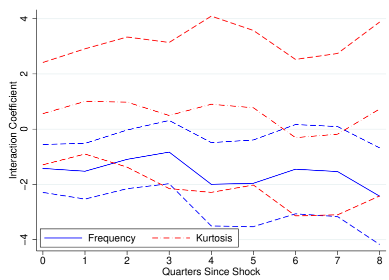
(c) Kurtosis/Frequency



(d) Average Size



(e) Standard Deviation

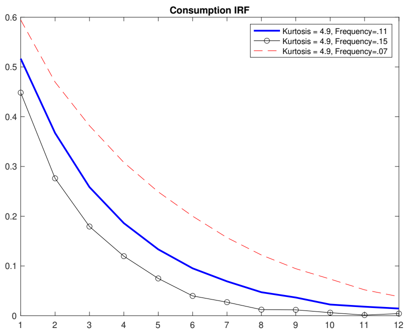


(f) Frequency and Kurtosis

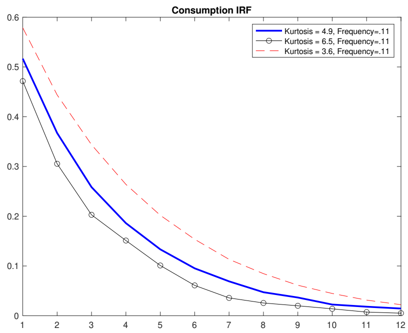
Figure 4: Romer and Romer Monetary Policy Shock Firm-Level Impulse Responses

NOTE: In the above panels, we plot the respectively estimated coefficients θ_h from the following specification: $Log(sales_{j,t+h}) = \alpha + \alpha_{th} + \alpha_{jh} + \theta_h * M_j * MP_t + \gamma_h' X_{j,t} + \epsilon_{j,t+h}$ 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. Monetary policy shocks are measured by the Romer and Romer series. M_j contains the log of one or more of the firm-level pricing moments: frequency, kurtosis, kurtosis over frequency, average size, or the standard deviation of price change. In panel (f), the solid blue line is the frequency interaction coefficient and the dash-dot red line is the kurtosis interaction coefficient with only those pricing moments included. Standard errors are two-way clustered by firms and month. Dashed lines present 90% standard error bands.

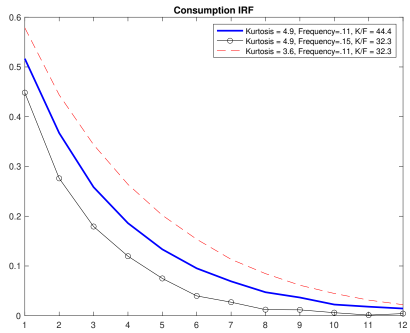
C Model Results



(a) Frequency Variation

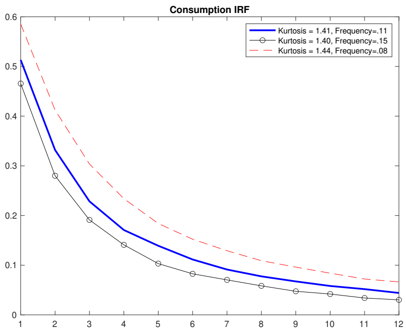


(b) Kurtosis Variation

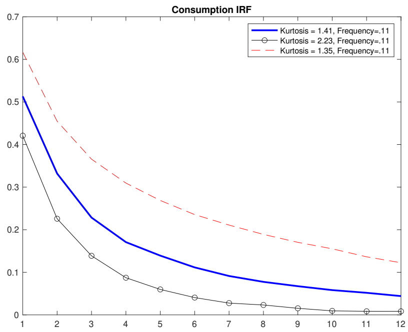


(c) Kurtosis/Frequency Variation

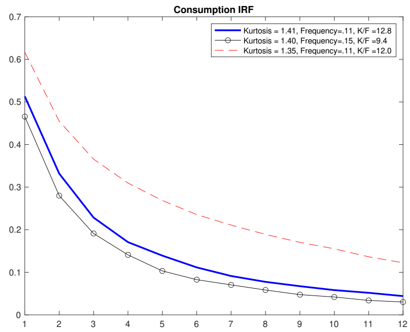
Baseline Model



(d) Frequency Variation



(e) Kurtosis Variation

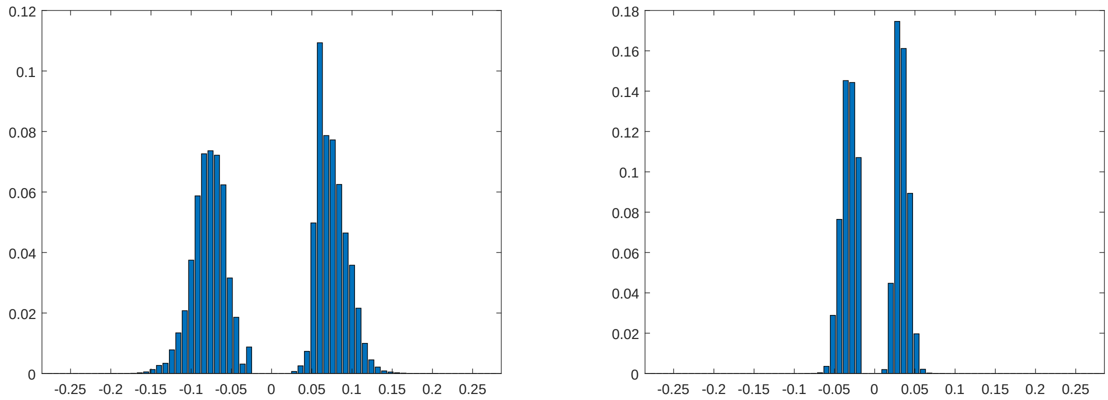


(f) Kurtosis/Frequency Variation

Golosov-Lucas Model

Figure 5: Consumption Impulse Responses

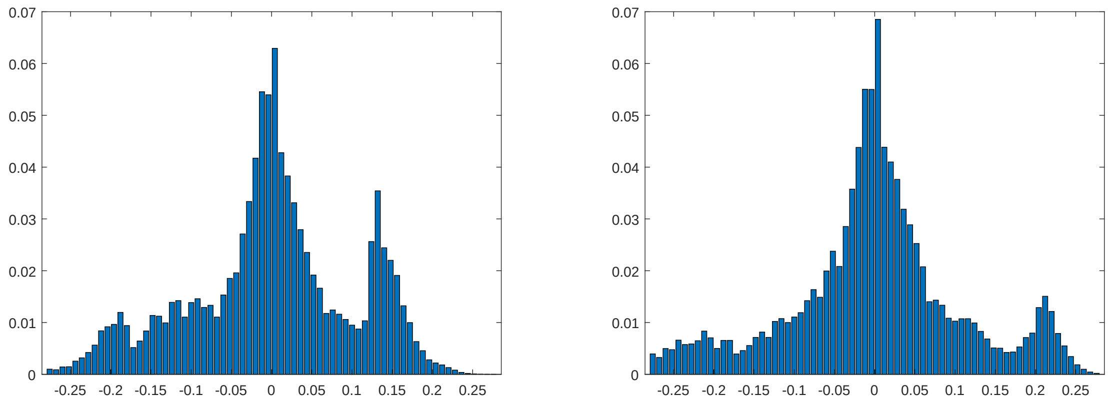
NOTE: Impulse responses of consumption to a one-time permanent increase in log nominal output of size 0.002 for different calibrations of our baseline monthly menu cost model are shown in the top row, while different calibrations of the Golosov-Lucas model are shown in the bottom row. The percent increase in consumption due to the expansionary shock is plotted where the shock occurs at the horizon labeled 1. The results are based on simulations of 3500 economies.



(a) Baseline (b) High Kurtosis

Figure 6: Model Price Distributions - Golosov-Lucas Model

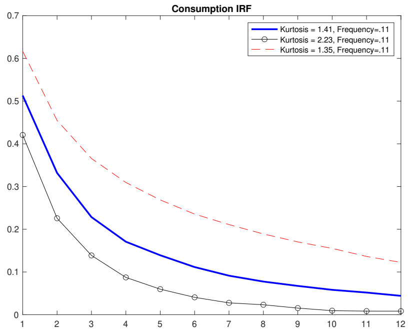
NOTE: Price change distribution in two calibrations of the Golosov-Lucas model are shown above. Panel (a) displays the baseline model calibration distribution while Panel (b) shows the high kurtosis calibration model distribution.



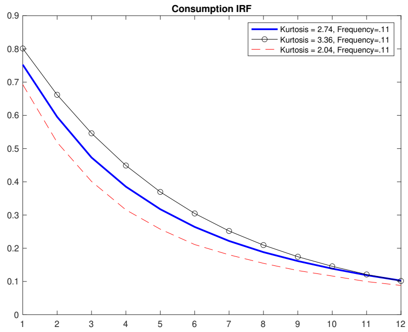
(a) Baseline (b) High Kurtosis

Figure 7: Model Price Distributions - Golosov-Lucas Model with Random Menu Costs

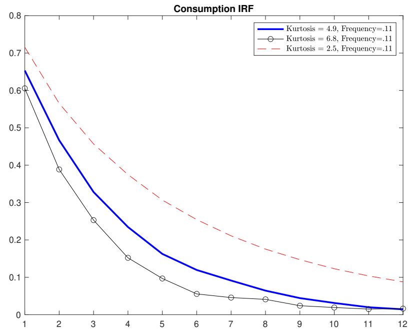
NOTE: Price change distribution in two calibrations of the Golosov-Lucas model with random menu costs are shown above. Panel (a) displays the baseline model calibration distribution while Panel (b) shows the high kurtosis calibration model distribution.



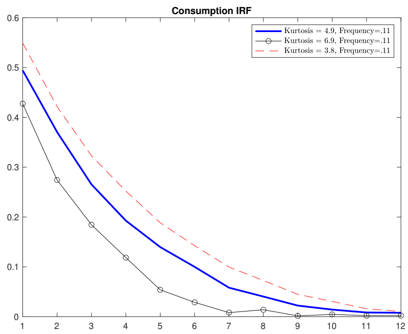
(a) Golosov-Lucas



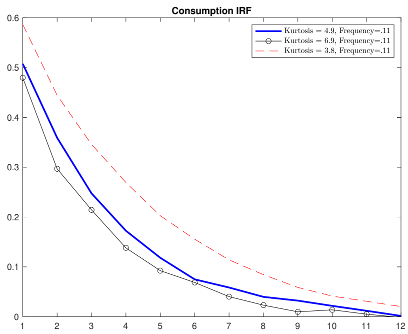
(b) Golosov-Lucas with Random Menu Costs



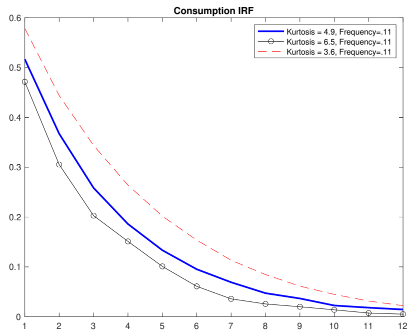
(c) Golosov-Lucas with Random Menu Costs and Leptokurtic Shocks



(d) Golosov-Lucas with Random Menu Costs, Leptokurtic Shocks, and Trend Inflation



(e) Golosov-Lucas with Random Menu Costs, Leptokurtic Shocks, Trend Inflation, and Aggregate TFP Shocks



(f) Full Model

Figure 8: Model Assumptions: Kurtosis Effects

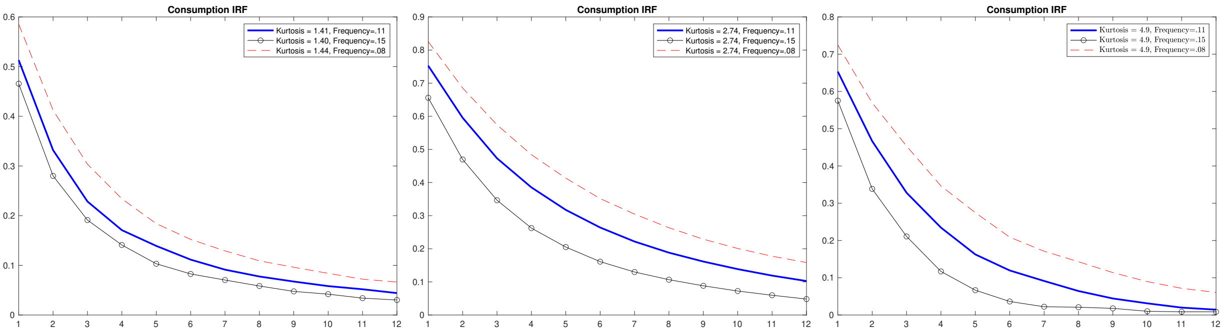
NOTE: Impulse responses of consumption to a one-time permanent increase in log nominal output of size 0.002 for different calibrations as we vary one modeling assumption at a time. The percent increase in consumption due to the expansionary shock is plotted where the shock occurs at the horizon labeled 1. The results are based on simulations of 3500 economies.

A Model Appendix

A Golosov-Lucas Frequency Comparative Statics

This section presents additional model results.

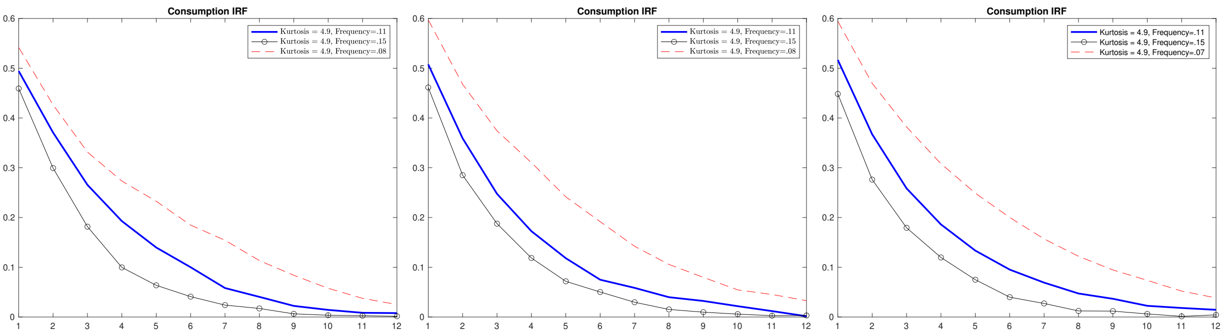
First, it shows the comparative statics exercise under different model assumptions when frequency is allowed to vary holding kurtosis fixed. As frequency increases, the cumulative consumption impact decreases in all models. The results are shown in Figure 9.



(a) Golosov-Lucas

(b) Golosov-Lucas with Random Menu Costs

(c) Golosov-Lucas with Random Menu Costs and Leptokurtic Shocks



(d) Golosov-Lucas with Random Menu Costs, Leptokurtic Shocks, and Trend Inflation

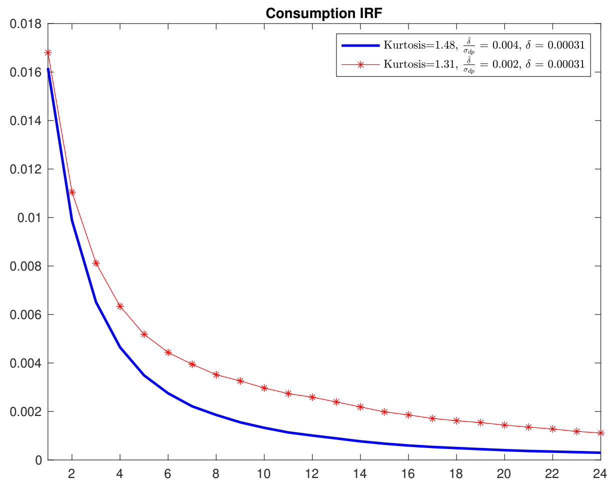
(e) Golosov-Lucas with Random Menu Costs, Leptokurtic Shocks, Trend Inflation, and Aggregate TFP Shocks

(f) Full Model

Figure 9: Model Assumptions: Frequency Effects

NOTE: Impulse responses of consumption to a one-time permanent increase in log nominal output of size 0.002 for different calibrations as we vary one modeling assumption at a time. The percent increase in consumption due to the expansionary shock is plotted where the shock occurs at the horizon labeled 1. The results are based on simulations of 3500 economies.

Next, Figure 10 shows the scaled impulse response function when the monetary shock is considered “large” as defined by Alvarez et al. (2016a, 2020), and confirms that the small shock results continue to hold in this environment. For this exercise, we hold the frequency of price changes constant across both calibrations. We then shock the model with a monetary shock standardized by the standard deviation of price changes, $\frac{\delta}{Std(\Delta p)}$, in both calibrations, and normalize the size of the impulse response by the standard deviation of price changes. The figure shows that when kurtosis is lower, the scaled monetary non-neutrality is higher. This result establishes that whether monetary shocks are standardized or not is not the reason why monetary non-neutrality differs among calibrations in our Golosov-Lucas model.

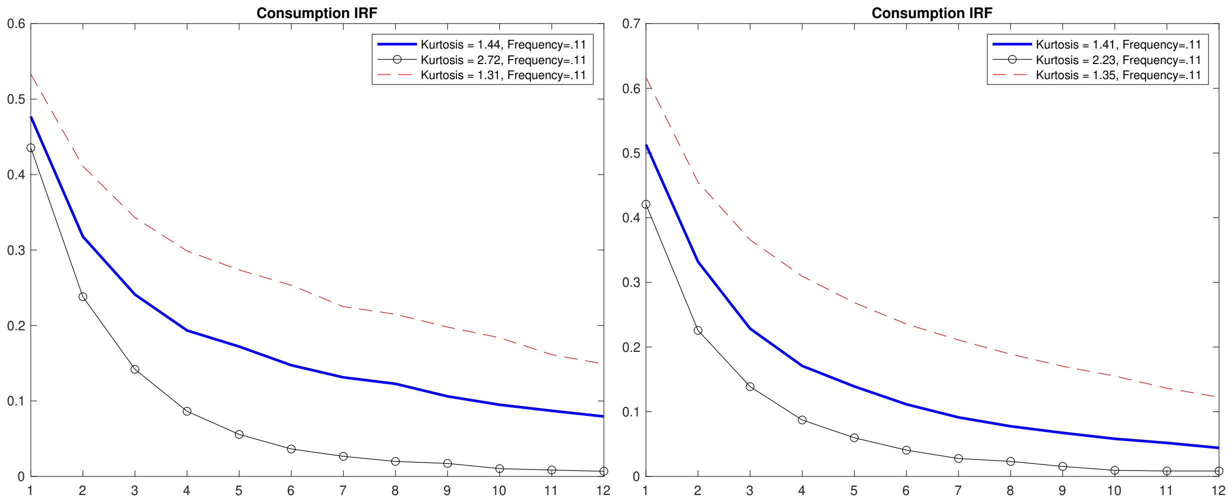


(a) Golosov-Lucas Model

Figure 10: Large Shock Consumption Impulse Responses, Golosov-Lucas Model

NOTE: Impulse responses of consumption to a one-time permanent increase in log nominal output of size 0.00031 divided by the standard deviation of price change for different calibrations and resulting impulse responses normalized by the standard deviation of price changes in each of the two model simulations. The percent increase in consumption due to the expansionary shock is plotted where the shock occurs at the horizon labeled 1. The results are based on simulations of 3500 economies.

Last, Figure 11 shows that the negative relationship between kurtosis and monetary non-neutrality holds in the Golosov-Lucas model with stochastic monetary shocks when we solve it with the exact firm flow profit function, or if the firm flow profit function it is approximated by a quadratic loss function as in Alvarez et al. (2016a). In the model without stochastic monetary shocks where the firm profit function is approximated by a quadratic loss function, kurtosis does not vary in alternative calibrations.



(a) Quadratic Approximation

(b) Exact Solution

Figure 11: Consumption Impulse Responses, Golosov-Lucas Model

NOTE: Impulse responses of consumption to a one-time permanent increase in log nominal output of size 0.002 for different variations of the Golosov-Lucas model. In panel (a), firm flow profit is approximated by a quadratic loss function. In panel (b), firm flow profit is not approximated. The percent increase in consumption due to the expansionary shock is plotted where the shock occurs at the horizon labeled 1. The results are based on simulations of 3500 economies.

B Empirical Appendix

In this Appendix, we show summary statistics and additional robustness checks for different time periods of interest, measurement error, type of monetary shock, measures of monetary non-neutrality, and levels of disaggregation.

Table 9 considers different trimming methods for small and large price changes, and calculates moments by above-median and below-median sets of each pricing moment. Table 10 presents regression estimates of Equation (3) using the Romer and Romer shocks. In Table 11 we present the summary statistics for pricing moments of interest at the firm-level. Table 12 shows that the firm-level results are the same if we lengthen the horizon from 4 to 8 quarters using Romer and Romer monetary shocks. Tables 13 and 14 present firm-level results using the Nakamura and Steinsson high-frequency monetary shocks from January 1995 through March 2014. Table 15 presents instrumental variable results for the univariate part of Table 2, while Table 16 presents the main multivariate results. Table 17 replicates Table 2 with the dependent variable given by the cumulated impulse price response, CIR^P, as defined in Alvarez et al. (2021) and in logs. Table 18 estimates the same specification in levels and based on normalized explanatory variables. Table 19 presents multivariate results from an instrumental variables approach using the cumulated price response, CIR^P, as in Alvarez et al. (2021), both in logs and in levels, and standardized pricing moments in the level regressions. Table 20 shows the results of a placebo test that combines the frequency of price changes with any of the pricing moments instead of the kurtosis of price changes.

The Appendix also contains several figures. Figures 12 and 13 illustrate our main aggregate and firm-level results using the monetary shock series from Nakamura and Steinsson (2018), based on data from January 1995 through March 2014. Figure 14 uses the Gertler and Karadi (2015) version of the monetary shock series from January 1990 to June 2014. Figure 15 presents estimates from the OLS specification of Romer and Romer (2004). In Figure 16 we show that the Romer and Romer shock results continue to hold when we restrict the data to 1976 to 2007. Figures 17 and 18 present robustness checks of the FAVAR exercise to trimming small and large price changes, while Figure 19 present sensitivity results to the choice of horizon for Table 2. Figure 20 plots the raw pricing moments over time.

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

Table 9: Pricing Moments 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 the 6-digit NAICS industry level. N is the number of observations in each set for each trimming method. Each row describes a different subsample of the data applying the filter described in the column "Type of Trimming." The subsample for case 0 is the baseline sample in the main text of the paper: price changes are included if they are larger in absolute value than \$0.01 and lower in value than the 99^{th} percentile of changes. Each additional row describes the impact of changing one of the upper or lower thresholds in the "Type of Trimming." The second row changes the lower trimming threshold such that the sample now includes price changes if they are larger in absolute value than 0.1% and lower in value than the 99^{th} percentile of changes. Case 8 changes both the upper and lower thresholds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Cross-Sectional Determinants of Sectoral Price Response											
Log $\frac{Kurt}{Freq}$*MP$_t$	-1.680**											-1.098**
	(0.655)											(0.549)
Log Frequency*MP$_t$		1.579***							1.798***	2.289***	0.837**	
		(0.532)							(0.653)	(0.743)	(0.379)	
Log Kurtosis*MP$_t$			1.086*						-0.682	-1.096	-0.749	
			(0.638)						(0.758)	(0.663)	(0.551)	
Log S.D.*MP$_t$				-0.741						0.791	0.285	1.232**
				(0.555)						(0.658)	(0.339)	(0.581)
Log Frac. Small*MP$_t$					0.225					0.049	0.079	-0.029
					(0.430)					(0.319)	(0.311)	(0.317)
Log Frac. Pos.*MP$_t$						-2.415				2.404	1.813	2.172
						(3.522)				(3.352)	(3.611)	(3.107)
Log Avg. Size*MP$_t$							-1.409**			0.154	-0.228	-1.274*
							(0.598)			(0.897)	(0.579)	(0.767)
Log S.D. Duration*MP$_t$								-2.249***				
								(0.775)				
Log Profit*MP$_t$											-1.671	-1.584
											(1.141)	(1.023)
SD(e_k) *MP$_t$											77.577***	72.392**
											(29.304)	(34.960)
$\rho(e_k)$ *MP$_t$											1.001	1.018
Industry FE	X	X	X	X	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X	X	X	X	X
R^2	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.001
N	60,672	60,672	60,672	60,672	59,904	60,672	60,672	60,672	60,672	59,904	57,490	57,490
										$H0: \beta^f = -\beta^{kurt}$		
F-stat									3.37	1.94	0.01	
p-value									0.069	0.165	0.904	

Table 10: Drivers of Monetary Non-Neutrality (Romer and Romer Approach)

NOTE: This table uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality using Romer and Romer monetary policy shocks. We estimate the following specification: $log(ppi_{k,t+h}) = \alpha + \alpha_k + \alpha_t + \beta' M_k * MP_t + \gamma' X_k * MP_t + \epsilon_{k,t+h}$, where $log(ppi_{k,t+h})$ is the log sectoral price level h months after the Romer and Romer shock denoted by MP_t, where h=48. M_k contains one of our industry-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average size, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, standard deviation of price duration, or the full set of pricing moments. X_k are sector-level controls, including the gross profit rate, the volatility of sector-level shocks, and the autocorrelation of sector-level shocks. α_k are six-digit NAICS industry fixed effects and are included in all specifications. α_t are time fixed effects at monthly frequency and are included in all specifications. Standard errors are two-way clustered by firms and month. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

	Mean	SD	p50
Frequency	0.15	0.19	0.07
Kurtosis	4.82	2.99	4.10
$\frac{Kurtosis}{Frequency}$	84.56	80.08	58.62
S.D.	0.08	0.06	0.07
Avg. Size	0.07	0.03	0.06
Number of Price Changes	118.30	225.26	37.00
Firms		420	

Table 11: Firm-Level Summary 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.

Cross-Sectional Determinants of Firm-Level Sales Responses									
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$*MP$_t$		2.198**							2.062**
		(1.023)							(1.021)
Log Frequency*MP$_t$			-2.345**				-2.430**	-2.007*	
			(1.035)				(1.063)	(1.113)	
Log Kurtosis*MP$_t$				-0.366			0.730	2.328	
				(1.893)			(1.914)	(2.173)	
Log S.D.*MP$_t$					-0.111			-4.544	-4.380
					(1.452)			(3.528)	(3.050)
Log Avg. Size*MP$_t$						4.212		10.894	10.625*
						(3.034)		(6.937)	(5.976)
							$H0: \beta^{freq} = -\beta^{kurt}$		
F-stat							0.75	0.02	
p-value							0.389	0.894	
Firm Controls	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X	X
R^2	0.434	0.434	0.434	0.434	0.434	0.434	0.434	0.435	0.435
N	25,869	25,869	25,869	25,869	25,869	25,869	25,869	25,869	25,869

Table 12: Firm Sales Response at Long Horizon (Romer and Romer Approach)

NOTE: This table uses regression analysis at the firm level to test the informativeness of five pricing moments for monetary non-neutrality based on the Romer and Romer identification. We estimate the following specification: $log(sales_{j,t+8}) = \alpha + \alpha_{th} + \alpha_{jh} + \theta_h * MP_t * M_j + \gamma' X_{j,t} + \epsilon_{j,t+8}$, where $log(sales_{j,t+8})$ is the log firm-level real sales $h = 8$ quarters after the Romer and Romer shock. M_j contains one of our five firm-level pricing moments: frequency, kurtosis, the ratio of the two statistics, standard deviation of price changes, the average size of price changes, and multiple moments interacted with the Romer and Romer shock denoted by MP_t. α_t and α_j are firm and time fixed effects. Four quarters of lagged log sales are included as additional controls in X_t. Column 0 reports the specification with controls and fixed effects included, but no pricing moments. Within R^2 is reported. Standard errors are two-way clustered by firms and month. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cross-Sectional Determinants of Firm-Level Sales Responses									
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$*MP$_t$		6.420*							6.493*
		(3.470)							(3.623)
Log Frequency*MP$_t$			-9.824**				-9.576**	-10.604**	
			(4.526)				(4.420)	(4.423)	
Log Kurtosis*MP$_t$				-7.515			-6.137	-9.236	
				(8.784)			(8.518)	(9.854)	
Log S.D.*MP$_t$					-0.821			9.615	0.875
					(7.614)			(16.220)	(15.800)
Log Avg. Size*MP$_t$						-1.004		-18.377	-0.220
						(13.691)		(29.908)	(28.146)
							$H0 : \beta^{freq} = -\beta^{kurt}$		
F-stat							2.17	2.84	
p-value							0.147	0.098	
Firm Controls	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X	X
R^2	0.471	0.471	0.472	0.471	0.471	0.471	0.472	0.472	0.471
N	17,542	17,542	17,542	17,542	17,542	17,542	17,542	17,542	17,542

Table 13: Firm Sales Response (High-Frequency Approach)

Note: This table uses regression analysis at the firm level to test the informativeness of five pricing moments for monetary non-neutrality based on the Nakamura and Steinsson high-frequency identification. We estimate the following specification: $log(sales_{j,t+4}) = \alpha + \alpha_{th} + \alpha_{jh} + \theta_h * MP_t * M_j + \gamma' X_{j,t} + \epsilon_{j,t+4}$, where $log(sales_{j,t+4})$ is the log firm-level real sales $h = 4$ quarters after the Nakamura and Steinsson high-frequency shock. M_j contains one of our five firm-level pricing moments: frequency, kurtosis, the ratio of the two statistics, standard deviation of price changes, the average size of price changes, and multiple moments interacted with the high-frequency shock denoted by MP_t. α_{th} and α_{jh} are firm and time fixed effects. Four quarters of lagged log sales are included as additional controls in X_t. Column 0 reports the specification with controls and fixed effects included, but no pricing moments. Within R^2 is reported. Standard errors are two-way clustered by firms and month. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Cross-Sectional Determinants of Firm-Level Sales Responses									
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$*MP$_t$		6.188**							6.518*
		(2.905)							(3.314)
Log Frequency*MP$_t$			-9.652***				-9.387***	-10.172***	
			(3.289)				(3.250)	(3.570)	
Log Kurtosis*MP$_t$				-7.918			-6.561	-7.525	
				(7.399)			(7.276)	(8.444)	
Log S.D.*MP$_t$					2.545			7.616	-0.343
					(6.528)			(12.866)	(12.814)
Log Avg. Size*MP$_t$						7.582		-6.517	9.998
						(12.349)		(25.766)	(23.075)
							$H0 : \beta^{freq} = -\beta^{kurt}$		
F-stat							3.75	3.58	
p-value							0.058	0.064	
Firm Controls	X	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X	X
Time FE	X	X	X	X	X	X	X	X	X
R^2	0.311	0.311	0.311	0.311	0.311	0.311	0.311	0.311	0.311
N	17,330	17,330	17,330	17,330	17,330	17,330	17,330	17,330	17,330

Table 14: Firm Sales Response at Long Horizon (High-Frequency Approach)

NOTE: This table uses regression analysis at the firm level to test the informativeness of five pricing moments for monetary non-neutrality based on the Nakamura and Steinsson high-frequency identification. We estimate the following specification: $log(sales_{j,t+8}) = \alpha + \alpha_{th} + \alpha_{jh} + \theta_h * MP_t * M_j + \gamma' X_{j,t} + \epsilon_{j,t+8}$, where $log(sales_{j,t+8})$ is the log firm-level real sales $h = 8$ quarters after the Nakamura and Steinsson high-frequency shock. M_j contains one of our five firm-level pricing moments: frequency, kurtosis, the ratio of the two statistics, standard deviation of price changes, the average size of price changes, and multiple moments interacted with the high-frequency shock denoted by MP_t. α_{th} and α_{jh} are firm and time fixed effects. four quarters of lagged log sales are included as additional controls in X_t. Column 0 reports the specification with controls and fixed effects included, but no pricing moments. Within R^2 is reported. Standard errors are two-way clustered by firms and month. *** 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 Univariate Specifications						
	Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1	
	(1)	(2)	(3)	(4)	(5)	(6)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$	-0.420***	-0.250***	-0.493***	-0.335***	-0.448***	-0.269***
	(0.060)	(0.074)	(0.066)	(0.074)	(0.071)	(0.077)
NAICS 3 FE		X		X		X
N	148	148	147	147	147	147
Log Frequency	0.448***	0.422***	0.470***	0.454***	0.507***	0.521***
	(0.056)	(0.073)	(0.060)	(0.078)	(0.067)	(0.094)
NAICS 3 FE		X		X		X
N	148	148	148	148	148	148
Log Kurtosis	0.289***	0.138	0.303**	0.072	0.301**	0.181
	(0.106)	(0.119)	(0.131)	(0.129)	(0.124)	(0.122)
NAICS 3 FE		X		X		X
N	148	148	147	147	147	147
Log Avg. Size	-0.594***	-0.316**	-0.497***	-0.313	-1.065***	-0.536**
	(0.120)	(0.148)	(0.182)	(0.231)	(0.205)	(0.234)
N	148	148	148	148	148	148
Log Std. Dev.	-0.456***	-0.158	-0.444**	-0.236	-0.687***	-0.181
	(0.141)	(0.127)	(0.184)	(0.169)	(0.241)	(0.252)
NAICS 3 FE		X		X		X
N	148	148	147	147	147	147
Log Frac. Small	0.034	0.017	0.150	0.136	0.098	0.134
	(0.071)	(0.077)	(0.092)	(0.088)	(0.099)	(0.093)
NAICS 3 FE		X		X		X
N	146	146	136	136	136	136
Log Frac. Pos.	-0.702**	-0.334	-0.775	-0.694	-0.950	-0.260
	(0.304)	(0.382)	(0.575)	(0.716)	(0.585)	(0.836)
NAICS 3 FE		X		X		X
N	148	148	148	148	148	148

Table 15: Measurement Error: Instrumental Variables Univariate Specification

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

Cross-Sectional Determinants of Sectoral Price Response Multivariate Specifications																		
	Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1		Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1		Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$													-0.129	-0.127	-0.201	-0.144	-0.132	-0.227
													(0.093)	(0.112)	(0.143)	(0.166)	(0.209)	(0.239)
Log Frequency	0.520***	0.476***	0.561***	0.549***	0.623***	0.601***	0.527***	0.507***	0.867***	0.630***	0.596**	0.620***						
	(0.056)	(0.074)	(0.062)	(0.074)	(0.072)	(0.099)	(0.088)	(0.091)	(0.222)	(0.126)	(0.273)	(0.197)						
Log Kurtosis	-0.222**	-0.151	-0.237*	-0.223*	-0.313**	-0.220*	-0.221	-0.203	-0.399	-0.198	-0.742	-0.711						
	(0.104)	(0.112)	(0.127)	(0.120)	(0.125)	(0.118)	(0.139)	(0.135)	(0.326)	(0.258)	(0.475)	(0.519)						
Log S.D.							-0.083	0.097	-0.374	-0.093	1.671	2.065	-0.112	-0.015	0.130	0.311	0.570	1.037
							(0.227)	(0.185)	(0.853)	(0.727)	(1.434)	(1.674)	(0.168)	(0.203)	(0.491)	(0.539)	(0.852)	(1.133)
Log Avg. Size							-0.182	-0.225	0.724	0.378	-2.623*	-2.369	-0.280	-0.356	-0.265	-0.447	-1.391**	-1.744*
							(0.263)	(0.222)	(1.039)	(0.861)	(1.479)	(1.586)	(0.173)	(0.220)	(0.510)	(0.588)	(0.651)	(0.906)
Log Frac. Small							-0.149**	-0.104	0.125	0.102	-0.514**	-0.249	-0.114*	-0.107	0.036	0.034	-0.345**	-0.296**
							(0.068)	(0.078)	(0.206)	(0.149)	(0.228)	(0.174)	(0.062)	(0.067)	(0.134)	(0.129)	(0.149)	(0.148)
Log Frac. Pos.							0.252	0.210	1.940*	0.433	-0.275	-0.326	-0.030	-0.130	0.363	-0.301	-1.206	-1.222
							(0.406)	(0.415)	(1.083)	(0.749)	(1.522)	(1.392)	(0.310)	(0.339)	(0.694)	(0.633)	(0.975)	(0.908)
Log Profit													-0.420**	-0.341*	-0.472***	-0.374*	-0.523***	-0.349*
													(0.169)	(0.201)	(0.178)	(0.197)	(0.182)	(0.191)
SD(e_k)													12.565	13.895	7.118	8.441	1.347	7.245
													(9.458)	(12.021)	(9.662)	(11.591)	(10.136)	(11.613)
$\rho(e_k)$													0.709***	0.603***	0.738***	0.507***	0.627***	0.518***
													(0.102)	(0.111)	(0.125)	(0.114)	(0.128)	(0.141)
constant	-0.424*	-0.652**	-0.260	-0.408	-0.160	-0.381	-1.347	-1.015	3.014	0.970	-3.823	-1.668	-3.489***	-3.479***	-2.041	-2.528	-5.787***	-5.280**
	(0.219)	(0.265)	(0.255)	(0.285)	(0.272)	(0.284)	(0.833)	(0.833)	(2.915)	(1.789)	(2.969)	(2.547)	(0.750)	(1.006)	(1.585)	(1.864)	(2.073)	(2.257)
NAICS 3 FE		X		X		X		X		X		X		X		X		X
R^2	0.320	0.509	0.277	0.481	0.331	0.501	0.331	0.505	-0.111	0.500	-0.045	0.283	0.516	0.579	0.503	0.601	0.319	0.455
N	148	148	147	147	147	147	146	146	136	136	136	136	145	145	135	135	135	135

Table 16: Measurement Error: Instrumental Variables Multivariate Specification I

NOTE: This table uses regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following specification: $log(IRF_{k,h}) = a + \alpha_{j,h} + \beta' M_k + \epsilon_{k,h}$ where $log(IRF_{k,h})$ is the response of prices at a 24-month horizon in six-digit NAICS sector k in our FAVAR analysis. M_k contains one of our industry-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average size, standard deviation of price changes, fraction of small price changes, or fraction of positive price changes. $\alpha_{j,h}$ are three-digit NAICS industry fixed effects. The pricing moments are calculated over the full sample in columns (1)-(2), (7)-(8), and (13)-(14). In columns (3)-(6), (9)-(12), and (15)-(18), 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						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log $\frac{Kurtosis}{Frequency}$	-.199***						-0.193
	(0.074)						(0.132)
Log Frequency		.334***		.346***	.441**	.266**	
		(0.087)		(0.108)	(0.189)	(0.131)	
Log Kurtosis			0.172	-0.037	-0.185	-0.091	
			(0.114)	(0.132)	(0.135)	(0.129)	
Log Avg. Size					-0.064	0.0362	-0.287
					(0.234)	(0.207)	(0.210)
Log S.D.					0.288	0.061	0.290
					(0.210)	(0.195)	(0.304)
Log Frac. Small					0.007	0.012	-0.001
					(0.105)	(0.095)	(0.092)
Log Frac. Pos.					0.941	0.801	0.763
					(0.696)	(0.685)	(0.720)
Log S.D. Duration					-0.064		
					0.191		
Log Profit						-0.058	-0.078
						(0.228)	(0.236)
$SD(e_k)$						14.600	16.340
						(11.169)	(10.758)
$\rho(e_k)$						.536***	.562***
						(0.157)	(0.150)
constant	2.757***	2.666***	1.908***	2.741***	4.362***	2.988*	2.585
	(0.243)	(0.186)	(0.221)	(0.352)	(1.408)	(1.787)	(1.907)
R^2	0.113	0.234	0.062	0.234	0.265	0.411	0.397
adj. R^2	0.107	0.228	0.0551	0.224	0.228	0.372	0.362
log likelihood							-127.546
BIC							299.944
				$H0 : \beta^f = -\beta^{kurt}$			
F-stat				8.56	2.02	2.21	
p-value				0.004	0.158	0.140	
LR test 1		18.36	32.14				
		< 0.0000	< 0.0000				
LR test 2	67.77	49.3	79.48	49.14			
	< 0.000	< 0.000	< 0.000	< 0.000			
δ	0.117	0.095	-0.017				
δ		0.153	-0.032				
$\delta(R^2_{max} = 0.8)$	0.175	0.141	-0.026				
$\delta(R^2_{max} = 0.8)$		0.195	-0.043				
NAICS 3 FE	X	X	X	X	X	X	X
N	149	149	149	149	147	146	146

Table 17: Drivers of Monetary Non-Neutrality - Log Cumulated Price Response (FAVAR Approach)

Note: This table replicates Table 2, columns (1)-(3), (9), (12) and (13). The only difference is that the dependent variable is given by the cumulated impulse price response, $CIR^P_{h,k}$, as defined in Alvarez et al. (2021), over $h = 48$ months, for each six-digit NAICS sector k. We thus estimate a specification in logs using $log(CIR^P_{k,h}) = a + \alpha_{j,h} + \beta' M_k + \epsilon_{k,h}$ where M_k contains the log of the ratio of frequency over kurtosis, or the log of one of our industry-level pricing moments: frequency, kurtosis, average size, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, or standard deviation of price duration.

	Cross-Sectional Determinants of Sectoral Price Response					
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{Kurtosis}{Frequency}$	-1.494***					-.906*
	(0.445)					(0.471)
Frequency		2.387***		2.624***	1.828**	
		(0.608)		(0.679)	(0.880)	
Kurtosis			0.464	-0.782	-1.084	
			(0.702)	(0.686)	(0.713)	
S.D.					0.933	0.604
					(1.553)	(1.655)
Avg. Size					-2.260	-2.015
					(1.654)	(1.645)
Frac. Small					0.002	-0.264
					(0.713)	(0.744)
Frac. Pos.					5.521**	5.342**
					(2.478)	(2.626)
Profit					-1.399	-2.006
					(1.476)	(1.504)
$SD(e_k)$					1.638	2.201*
					(1.207)	(1.135)
$\rho(e_k)$					-.120***	-.119***
					(0.033)	(0.032)
constant	11.786***	5.751***	9.554***	6.463***	2.466	5.138
	(1.299)	(1.479)	(1.767)	(1.513)	(3.978)	(4.188)
R^2	0.48	0.52	0.44	0.53	0.60	0.59
adj. R^2	0.292	0.433	0.253	0.464	0.554	0.404
log likelihood	-393.983	-376.808	-398.07	-371.975	-350.266	-373.576
BIC	888.706	854.355	896.878	849.726	846.414	882.973
				$H0 : \beta^f = -\beta^{kurt}$		
F-stat				8.29	1.17	
p-value				0.005	0.282	
LR test 1		1.79	46.55			
		(0.1814)	(< 0.0000)			
LR test 2	74.42	108.72	102.06	55.51		
	<(0.0000)	<(0.0000)	<(0.0000)	<(0.0000)		
δ		0.175	-0.260			
δ	0.136	0.265	-0.403			
$\delta(R^2_{max} = 0.8)$		0.152	-0.132			
$\delta(R^2_{max} = 0.8)$	0.206	0.19‘	-0.181			
NAICS 3 FE	X	X	X	X	X	X
N	154	154	154	154	153	153

Table 18: Drivers of Monetary Non-Neutrality - Cumulated Price Response (FAVAR Approach)

Note: This table replicates Table 2, columns (1)-(3), (9), (11) and (13) in levels. There are only two differences: First, the dependent variable is given by the cumulated impulse price response, $CIR^P_{h,k}$, as defined in Alvarez et al. (2021), over $h = 48$ months, for each six-digit NAICS sector k. Second, our pricing moments are normalized by their cross-sectional means. For example, kurtosis is divided by the cross-sectoral mean of kurtosis. We thus estimate a specification using $(CIR^P_{k,h}) = a + \alpha_{j,h} + \beta' M_k + \epsilon_{k,h}$ where M_k contains the ratio of frequency over kurtosis, or the log of one of our industry-level pricing moments: frequency, kurtosis, average size, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, or standard deviation of price duration.

	Cross-Sectional Determinants of Sectoral Price Response Multivariate Specifications																	
	Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1		Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1		Baseline		Sample 1, IV Sample 2		Sample 2, IV Sample 1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$													-0.132	-0.193	-0.174	-0.094	-0.075	-0.162
													(0.095)	(0.132)	(0.132)	(0.147)	(0.188)	(0.212)
Log Frequency	.446***	.344***	.509***	.424***	.490***	.390**	.576***	.488***	.797***	.555***	.546**	.555***						
	(0.062)	(0.108)	(0.058)	(0.096)	(0.106)	(0.167)	(0.114)	(0.088)	(0.198)	(0.115)	(0.239)	(0.175)						
Log Kurtosis	-0.054	-0.037	-0.059	-0.104	-0.078	-0.055	-0.129	-0.195	-0.377	-0.179	-0.654	-0.603						
	(0.170)	(0.132)	(0.190)	(0.134)	(0.223)	(0.153)	(0.147)	(0.128)	(0.280)	(0.228)	(0.428)	(0.451)						
Log S.D.							-0.031	0.273	-0.230	0.012	1.535	1.816	0.035	0.290	0.160	0.287	0.454	0.859
							(0.204)	(0.207)	(0.743)	(0.644)	(1.322)	(1.471)	(0.198)	(0.304)	(0.466)	(0.475)	(0.768)	(1.001)
Log Avg. Size							0.036	-0.045	0.601	0.231	-2.295*	-2.043	-0.246	-0.287	-0.241	-0.453	-1.182**	-1.49*
							(0.301)	(0.230)	(0.912)	(0.760)	(1.374)	(1.404)	(0.170)	(0.210)	(0.467)	(0.514)	(0.589)	(0.804)
Log Frac. Small							-0.035	0.008	0.150	0.109	-.423**	-0.187	-0.014	-0.001	0.077	0.046	-.279**	-.224*
							(0.098)	(0.104)	(0.184)	(0.126)	(0.208)	(0.160)	(0.090)	(0.092)	(0.121)	(0.110)	(0.137)	(0.135
Log Frac. Pos.							0.990	0.976	1.809*	0.284	-0.234	-0.363	0.743	0.762	0.429	-0.407	-1.162	-1.150
							0.775)	(0.681)	(0.952)	(0.651)	(1.335)	(1.213)	(0.746)	(0.720)	(0.610)	(0.559)	(0.884)	(0.825
Log Kurt/Freq													-0.132	-0.193	-0.174	-0.094	-0.075	-0.162
													(0.095)	(0.132)	(0.132)	(0.147)	(0.188)	(0.212
logprofit													-0.247	-0.078	-.401**	-.316*	-.454***	-.288*
													(0.195)	(0.236)	(0.161)	(0.179)	(0.165)	(0.168
SD(e_k)													18.826**	16.340	9.461	11.565	4.507	10.755
													(9.491)	(10.758)	(8.654)	(10.104)	(9.132)	(10.292
$\rho(e_k)$													.765***	.562***	.663***	.427***	.562***	.459***
													(0.156)	(0.149)	(0.114)	(0.105)	(0.115)	(0.124
constant	2.946***	2.741***	3.155***	2.985***	2.991***	2.813***	3.733***	4.375***	6.626**	4.385***	0.503	2.220	1.519	2.585	1.996	0.985	-1.693	-1.240
	(0.345)	(0.352)	(0.319)	(0.339)	(0.526)	(0.460)	(1.275)	(1.399)	(2.577)	(1.521)	(2.584)	(2.230)	(1.180)	(1.907)	(1.401)	(1.604)	(1.863)	(2.031)
NAICS 3 FE		X		X		X		X		X		X		X		X		X
R^2	0.23	0.44	0.16	0.41	0.27	0.44	0.26	0.47	-0.11	0.53	-0.02	0.32	0.40	0.52	0.48	0.61	0.32	0.49
N	149	149	148	148	148	148	147	147	136	136	136	136	146	146	135	135	135	135
$\frac{\text{Kurtosis}}{\text{Frequency}}$													-.837*	-.908*	-0.327	-0.532	-1.934	-2.497
													(0.476)	(0.470)	(0.892)	(0.765)	(1.402)	(2.102)
Frequency	3.463***	2.624***	3.700***	3.022***	21.836***	16.383***	3.687***	2.974***	3.643***	3.196***	28.048***	24.916**						
	(0.765)	(0.679)	(0.767)	(0.663)	(5.115)	(4.332)	(0.845)	(0.688)	(1.086)	(0.752)	(6.808)	(12.153)						
Kurtosis	-0.965	-0.782	-1.039	-1.138	-0.254	-0.158	-1.511**	-1.450**	-1.327*	-2.388	-.664**	-0.731						
	(0.673)	(0.686)	(0.795)	(0.701)	(0.192)	(0.151)	(0.665)	(0.658)	(0.746)	(1.941)	(0.335)	(1.100)						
S.D.							1.460	2.531	-1.064	6.389	155.343	203.231	-0.318	0.653	-3.130	-2.416	89.592	98.986
							(1.594)	(1.621)	(3.422)	(14.751)	(96.927)	(423.243)	(1.636)	(1.692)	(3.432)	(7.336)	(92.498)	(200.351)
Avg. Size							-3.468*	-3.011*	-0.712	-8.846	-206.300*	-202.782	-1.991	-2.076	0.066	-0.283	-128.788	-88.258
							(1.781)	(1.725)	(5.338)	(18.757)	(111.823)	(419.124)	(1.474)	(1.698)	(3.723)	(8.688)	(79.987)	(164.382)
Frac. Small							-0.278	0.236	-0.308	-0.904	-7.926	0.784	-0.499	-0.253	-0.419	-0.124	-11.258	-2.135
							(0.998)	(0.794)	(1.312)	(2.985)	(12.162)	(14.091)	(0.968)	(0.754)	(1.217)	(1.592)	(10.985)	(9.159)
Frac. Pos.							5.518*	6.336**	2.819	3.993	17.353	22.742	4.462	5.416**	-0.091	1.679	13.017	22.109
							(3.122)	(2.914)	(2.411)	(2.977)	(12.357)	(17.246)	(2.832)	(2.651)	(2.643)	(2.148)	(11.856)	(16.980)
Profit													-2.730*	-1.970	-3.020*	-2.215	-2.603**	-2.159
													(1.407)	(1.528)	(1.629)	(2.115)	(1.135)	(1.378)
SD(e_k)													2.135**	2.203*	2.149**	2.284**	2.359**	1.996*
													(1.016)	(1.134)	(1.045)	(1.048)	(1.044)	(1.168)
$\rho(e_k)$													-.169***	-.119***	-.158***	-.111***	-.137***	-0.088
													(0.030)	(0.032)	(0.033)	(0.031)	(0.035)	(0.055)
constant	5.491***	6.463***	5.326***	6.068***	5.156***	6.100***	2.582	1.199	4.959	6.488	-3.408	-9.223	8.300*	5.035	12.930***	9.036**	5.001	-4.021
	(0.580)	(1.513)	(0.682)	(1.575)	(0.667)	(1.461)	(4.228)	(3.908)	(5.787)	(10.243)	(11.312)	(13.462)	(4.739)	(4.247)	(4.595)	(4.070)	(10.567)	(12.714)
NAICS 3 FE		X		X		X		X		X		X		X		X		X
R^2	0.28	0.53	0.23	0.49	0.32	0.55	0.32	0.56	0.24	0.33	0.17	0.31	0.42	0.58	0.32	0.52	0.38	0.49
N	154	154	153	153	153	153	154	154	153	153	153	153	152	152	151	151	151	151

Table 19: Measurement Error: Instrumental Variables Multivariate Specification II

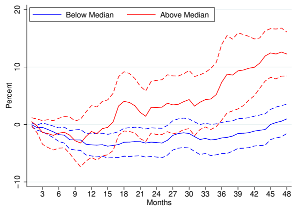
NOTE: This table uses instrumented regression analysis to test the informativeness of pricing moments for monetary non-neutrality. We estimate the following two specifications: First, a specification in logs using $log(CIR^P_{k,h}) = a + \alpha_{j,h} + \beta' M_k + \epsilon_{k,h}$ where CIR^P is the measure of monetary non-neutrality from Alvarez et al. (2021) as dependent variable at a horizon h of 48 months in six-digit NAICS sector k from our FAVAR analysis. $\alpha_{j,h}$ denote three-digit NAICS industry fixed effects and are included in all specifications. M_k contains the log of frequency plus the log of one of our industry-level pricing moments: kurtosis, average size, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, and standard deviation of price duration, or the log ratio of any one moment to frequency. Second, we estimate the specification in levels using the CIR^P measure of monetary non-neutrality as the dependent variable. Pricing moments are calculated over the full sample in columns (1)-(2), (7)-(8), and (13)-(14). In columns (3)-(6), (9)-(12), and (15)-(18), 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

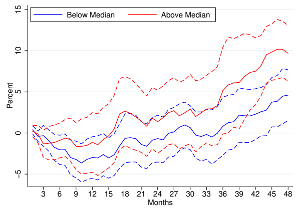
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$	-0.250***											
	(0.074)											
Log $\frac{\text{Avg. Size}}{\text{Frequency}}$		-0.293***										
		(0.051)										
Log $\frac{\text{S.D.}}{\text{Frequency}}$			-0.306***									
			(0.055)									
Log $\frac{\text{Frac. Small}}{\text{Frequency}}$				-0.198***								
				(0.067)								
Log $\frac{\text{Frac. Pos.}}{\text{Frequency}}$					-0.373***							
					(0.068)							
Log $\frac{\text{S.D. Duration}}{\text{Frequency}}$						-0.249***						
						(0.040)						
Log Frequency							0.476***	0.422***	0.418***	0.452***	0.433***	0.332***
							(0.074)	(0.087)	(0.076)	(0.086)	(0.077)	(0.126)
Log Kurtosis							-0.151					
							(0.112)					
Log Avg. Size								-0.004				
								(0.149)				
Log S.D.									-0.045			
									(0.105)			
Log Frac. Small										-0.083		
										(0.073)		
Log Frac. Pos.											0.171	
											(0.355)	
Log S.D. Duration												-0.144
												(0.129)
Constant	-0.854***	-1.960***	-1.918***	-1.764***	-1.262***	-0.796***	-0.652**	-0.974*	-1.084***	-1.115***	-0.844***	-0.852***
	(0.246)	(0.156)	(0.150)	(0.146)	(0.154)	(0.186)	(0.265)	(0.545)	(0.371)	(0.198)	(0.309)	(0.180)
R^2	0.429	0.485	0.482	0.422	0.493	0.503	0.509	0.502	0.502	0.493	0.503	0.505
NAICS 3 FE	X	X	X	X	X	X	X	X	X	X	X	X
N	148	148	148	146	148	148	148	148	148	146	148	148
$\frac{\text{Kurtosis}}{\text{Frequency}}$	-1.494***											
	(0.445)											
$\frac{\text{Avg. Size}}{\text{Frequency}}$		-0.452*										
		0(0.238)										
$\frac{\text{S.D.}}{\text{Frequency}}$			-0.386									
			(0.275)									
$\frac{\text{Frac. Small}}{\text{Frequency}}$				-0.603**								
				(0.245)								
$\frac{\text{Frac. Pos.}}{\text{Frequency}}$					-0.685*							
					(0.357)							
$\frac{\text{S.D. Duration}}{\text{Frequency}}$						-0.420**						
						0(0.196)						
Frequency							2.624***	2.294***	2.370***	2.383***	2.567***	1.963**
							0.679	0.647	0.617	0.628	0.600	0.751
Kurtosis							-0.782					
							0.686					
Avg. Size								-1.141				
								1.559				
S.D.									-0.255			
									1.156			
Frac. Small										0.039		
										0.805		
Frac. Pos.											4.643	
											2.884	
S.D. Duration												-1.521
												1.011
Constant	11.786***	10.678***	10.618***	10.848***	10.891***	10.654***	6.463***	6.964***	6.0367***	5.719***	1.314	7.521***
	(1.299)	(1.243)	(1.256)	(1.272)	(1.261)	(1.226)	(1.513)	(2.171)	(1.796)	(1.651)	(3.035)	(2.165)
R^2	0.462	0.464	0.452	0.461	0.463	0.467	0.529	0.528	0.525	0.524	0.535	0.530
NAICS 3 FE	X	X	X	X	X	X	X	X	X	X	X	X
N	154	154	154	154	154	154	154	154	154	154	154	154

Table 20: Drivers of Monetary Non-Neutrality - Placebo Test (FAVAR Approach)

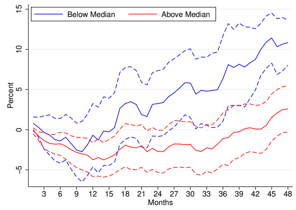
NOTE: This table conducts placebo tests for the ratio of kurtosis over frequency of price changes and its effects on monetary non-neutrality, based on the FAVAR specification. We estimate the following two specifications: First, a specification in logs using $log(IRF_{k,h}) = a + \alpha_{j,h} + \beta' M_k + \epsilon_{k,h}$ where $log(IRF_{k,h})$ denotes the response of prices at a horizon h of 24 months in six-digit NAICS sector k from our FAVAR analysis. M_k contains the log of frequency plus the log of one of our industry-level pricing moments: kurtosis, average size, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, and standard deviation of price duration, or the log ratio of any one moment to frequency. Second, we estimate the specification in levels and use the CIR^P measure of monetary non-neutrality from Alvarez et al. (2021), at a 48-month horizon, as the dependent variable. $\alpha_{j,h}$ denote three-digit NAICS industry j fixed effects and are included in all specifications. Robust standard errors in parentheses. *** denotes significance at the 1 percent level, ** significance at the 5 percent level, * significance at the 10 percent level.



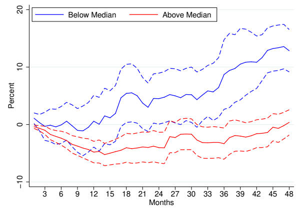
(a) Frequency



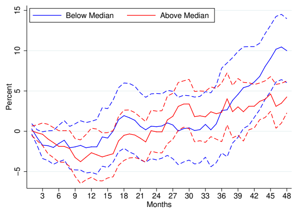
(b) Kurtosis



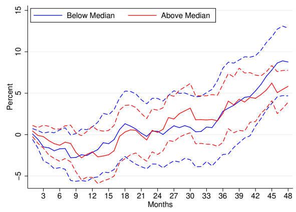
(c) Kurtosis/Frequency



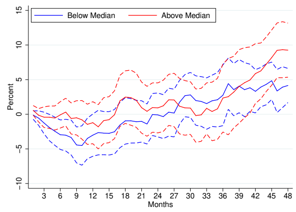
(d) S.D. Duration



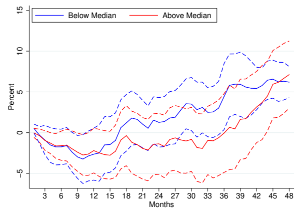
(e) Average Size



(f) Standard Deviation



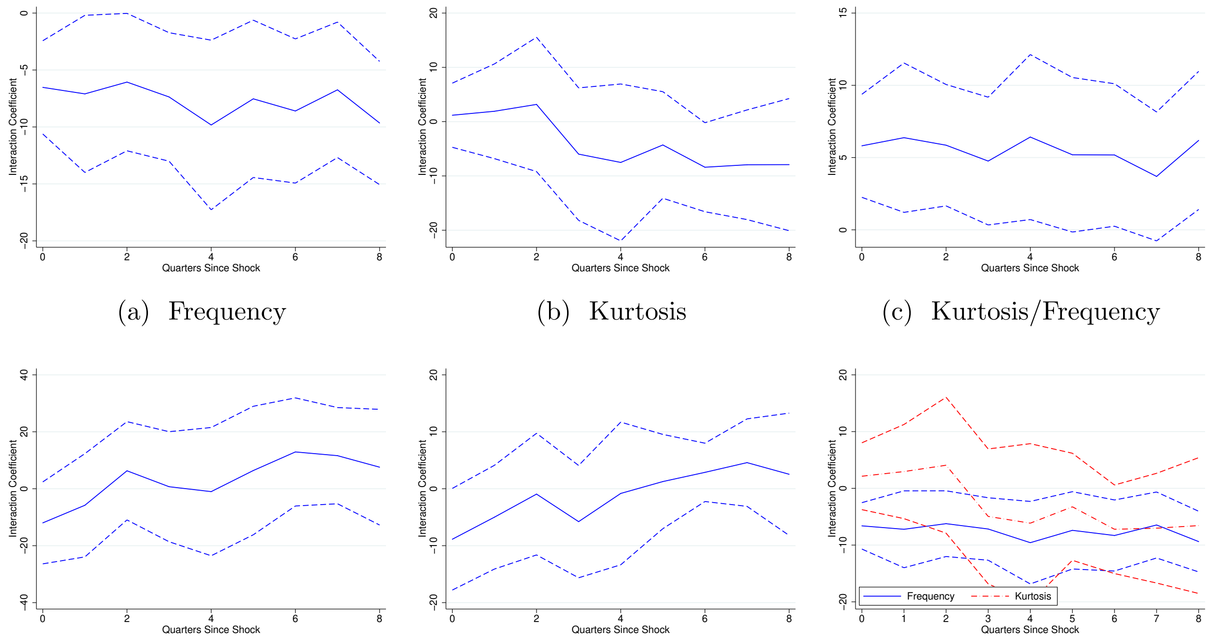
(g) Fraction Small



(h) Fraction Positive

Figure 12: Nakamura-Steinsson HFI Monetary Policy Shock Impulse Responses

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

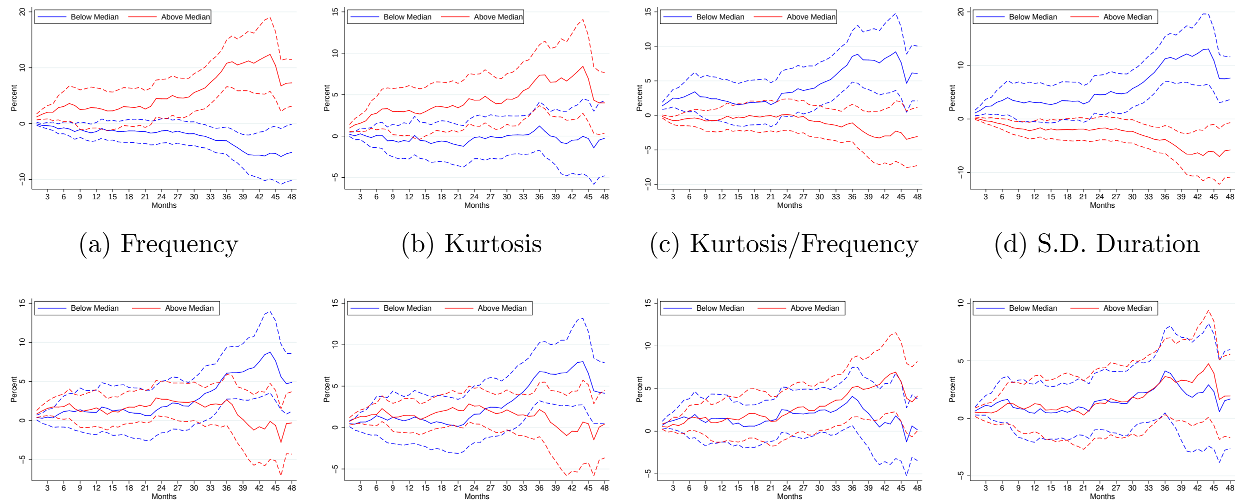


(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency

(d) Average Size (e) Standard Deviation (f) Frequency and Kurtosis

Figure 13: High-Frequency Monetary Policy Shock Firm-Level Impulse Responses

NOTE: In the above panels, we plot the respectively estimated coefficients θ_h from the following specification: $Log(sales_{j,t+h}) = \alpha_{th} + \alpha_{jh} + \theta_h \times M_j \times MP_t + controls_t + \epsilon_{j,t+h}$ 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 four quarters of lagged log real sales. Monetary policy shocks are measured by the Nakamura and Steinsson high-frequency identified series. M_j contains the log of one or more of the firm-level pricing moments: frequency, kurtosis, kurtosis over frequency, average size, or the standard deviation of price change. In panel (f), the solid blue line is the frequency interaction coefficient and the dash-dot red line is the kurtosis interaction coefficient with only those pricing moments included. Standard errors are two-way clustered by firms and month. Dashed lines present 90% standard error bands.

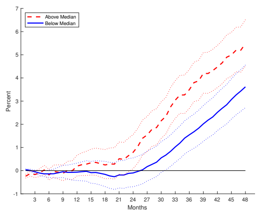


(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency (d) S.D. Duration

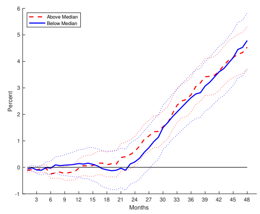
(e) Average Size (f) Standard Deviation (g) Fraction Small (h) Fraction Positive

Figure 14: Gertler and Karadi HFI Monetary Policy Shock IRF

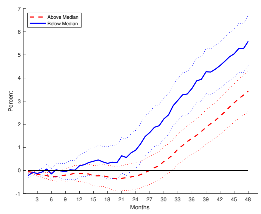
NOTE: In the above figures, we plot the respectively estimated coefficients $\theta_{A,h}$ and $\theta_{B,h}$ from the following specification: $Log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} * MPshock_t + \varphi_{A,h} z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} * MPshock_t + \varphi_{B,h} z_{j,t}] +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



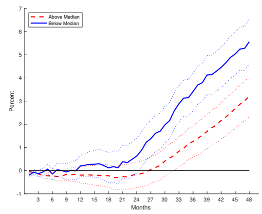
(a) Frequency



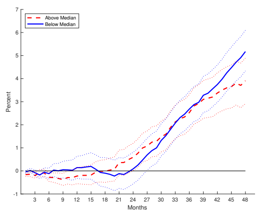
(b) Kurtosis



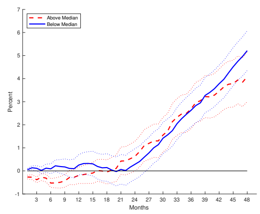
(c) Kurtosis/Frequency



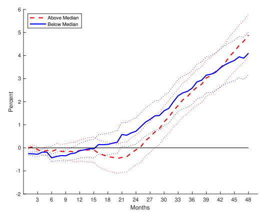
(d) S.D. Duration



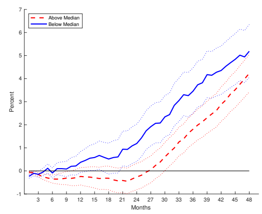
(e) Average Size



(f) Standard Deviation



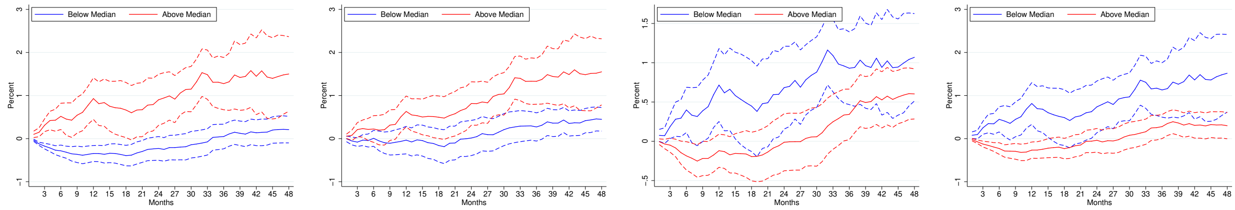
(g) Fraction Small



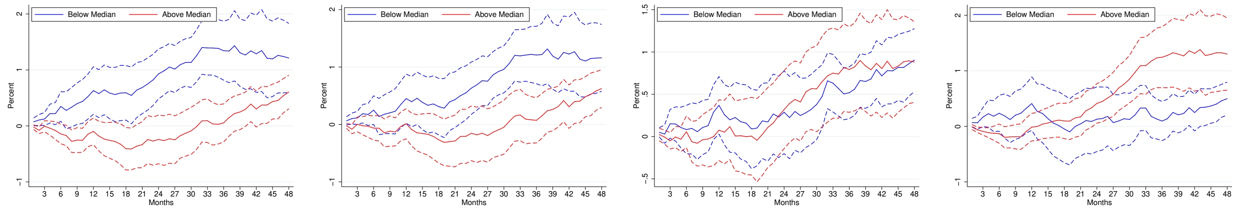
(h) Fraction Positive

Figure 15: Romer and Romer Monetary Policy Shock IRF

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



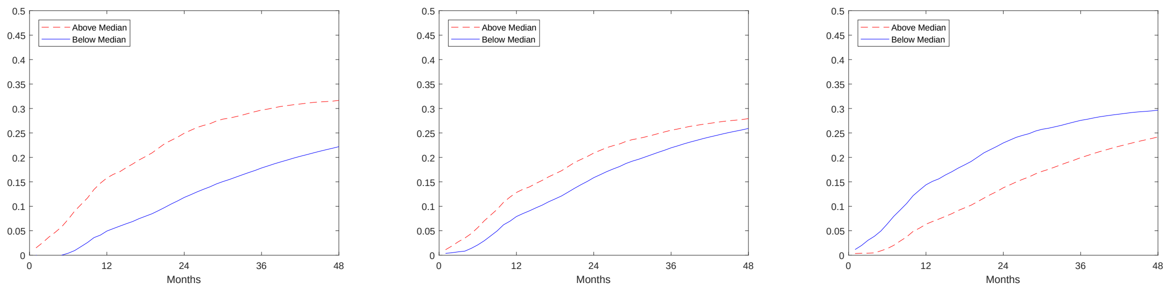
(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency (d) S.D. Duration



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

Figure 16: Romer and Romer Monetary Policy Shock Impulse Responses 1976-2007

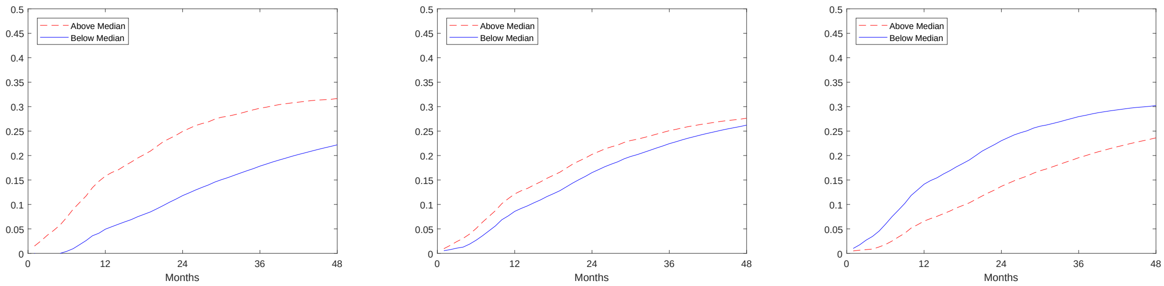
NOTE: In the above figures, we plot the respectively estimated coefficients $\theta_{A,h}$ and $\theta_{B,h}$ from the following specification: $Log(ppi_{j,t+h}) = \beta_h + I_{PS>M}[\theta_{A,h} * MPshock_t + \varphi_{A,h} z_{j,t}] + (1 - I_{PS>M})[\theta_{B,h} * MPshock_t + \varphi_{B,h} z_{j,t}] + \epsilon_{j,t+h}$ where $ppi_{j,t+h}$ is the price level for industries in the "Above Median" or "Below Median" set according to the pricing moment of interest, at time t measured at monthly frequency, h months into the future. Data are from 1976.1 to 2007.12. Controls include two lags of the RR shock, two lags of the fed funds rate, and current and two lags of the unemployment rate, industrial production, and price level. Standard errors are constructed using the Newey-West correction for serial autocorrelation. Dashed lines present 68% standard error bands.



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

Figure 17: FAVAR Monetary Policy Shock IRF - Robustness to Small Price Changes

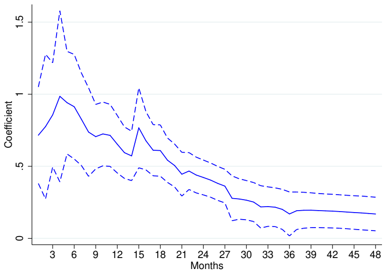
NOTE: In the above panels, "Above Median" and "Below Median" refer to the impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. Data are trimmed as in Case 1 in Table 9. Different from our baseline sample, small price changes are trimmed when they are less than 0.1 percent in absolute value. FAVAR estimated impulse responses of sectoral prices in percent to an identified 25-basis-point unexpected federal funds rate decrease are shown.



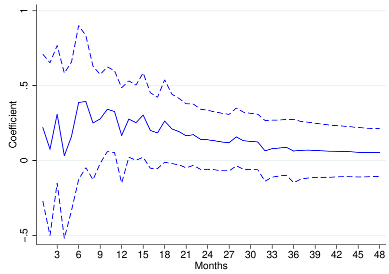
(a) Frequency (b) Kurtosis (c) Kurtosis/Frequency

Figure 18: FAVAR Monetary Policy Shock IRF - Robustness to Large Price Changes

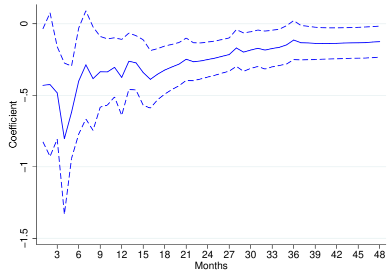
NOTE: In the above panels, "Above Median" and "Below Median" refer to the impulse response function of industries whose pricing moment is above or below the median value of that statistic for all industries. Data are trimmed as in Case 3 in Table 9. Relative to our baseline sample, large price changes 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.



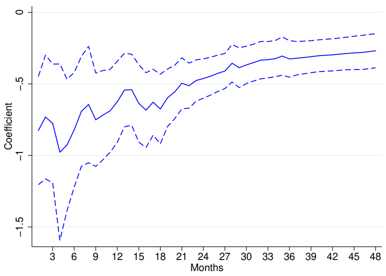
(a) Frequency



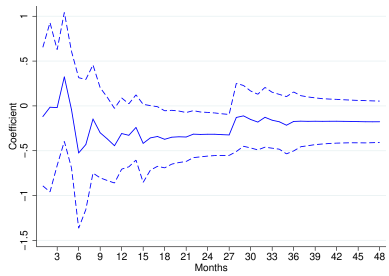
(b) Kurtosis



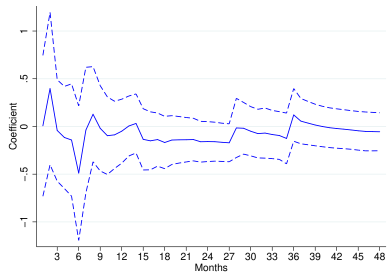
(c) Kurtosis/Frequency



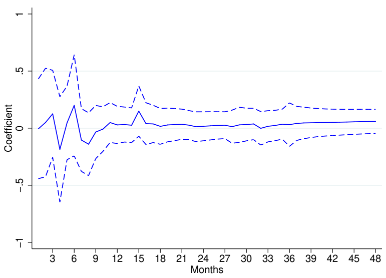
(d) S.D. Duration



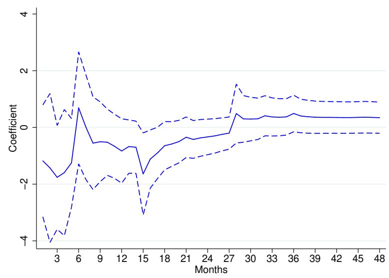
(e) Average Size



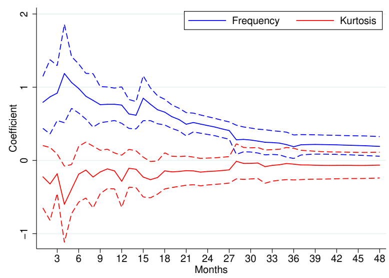
(f) Standard Deviation



(g) Fraction Small



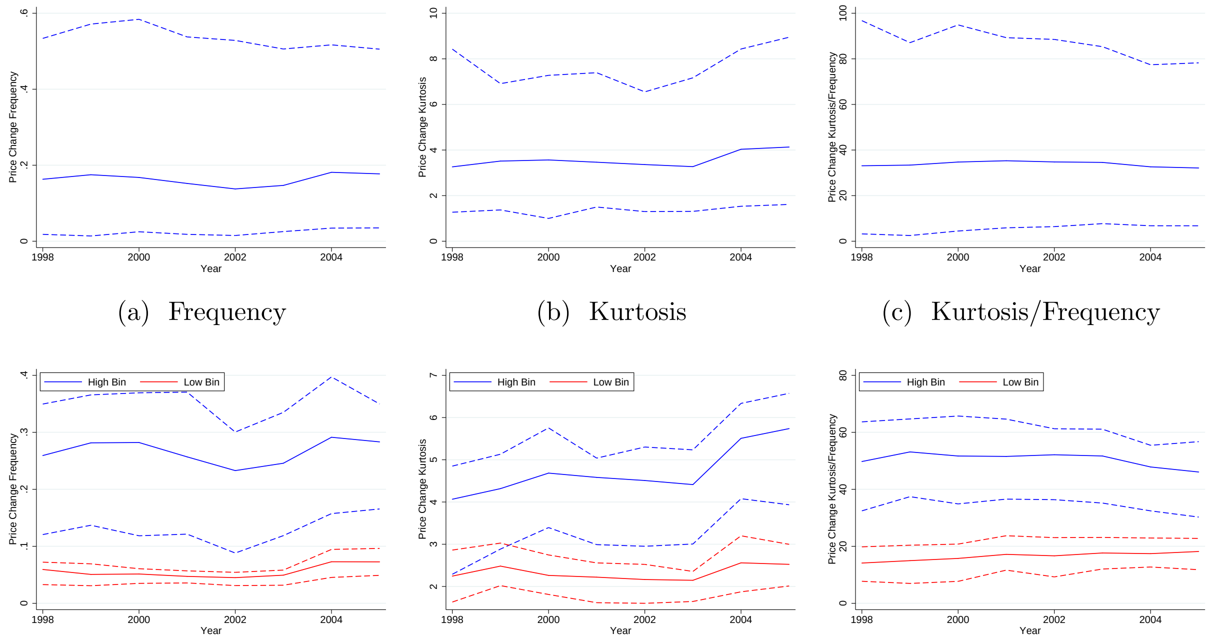
(h) Fraction Positive



(i) Frequency and Kurtosis

Figure 19: FAVAR Cross-Sectional Regression Coefficients

NOTE: In the above panels, we plot the respectively estimated coefficients β_h based on the FAVAR estimated price level response to an expansionary shock from the following specification: $log(IRF_{k,h}) = a_h + \alpha_{j,h} + \beta_h' M_k + \gamma_h' X_k + \epsilon_{k,h}$ where the horizon h is varied from 1 to 48 months after the monetary shock. Panels (a) through (h) show specifications with only one pricing moment included. Panel (i) controls for frequency and kurtosis separately. Three-digit NAICS fixed effects are included in all panels. Dashed lines present 90% standard error bands.



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

(d) Frequency (e) Kurtosis (f) Kurtosis/Frequency

Figure 20: Annual Average Pricing Moments, Aggregate and by 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 either for all moments pooled, or within our above and below median subsets of moments. The dotted lines are the 25th and 75th percentiles of each moment either in the full set of moments or the respective subset.

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