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The real effects of monetary shocks: Evidence from micro pricing moments[☆]

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ABSTRACT

Empirically, what pricing moments are informative about monetary non-neutrality? The frequency of price changes is robustly informative among a set of pricing moments and across specifications: A lower frequency is statistically significantly associated with higher monetary non-neutrality, in line with models of price rigidities. Other moments that describe the price change distribution are not consistently or significantly related to monetary non-neutrality. While the frequency explains the largest share of variation in non-neutrality, no pricing moments individually or jointly explain a majority of the variation in a linear empirical setting. Non-pricing moments explain additional variation, however are not consistently associated with monetary non-neutrality. A multi-sector menu cost model featuring different price adjustment technologies across sectors can rationalize our main findings.

1. 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 in theory models. The use of micro price data, following the pioneering work of

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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 empirically evaluates the informativeness of popular pricing moments for monetary non-neutrality, and rationalizes our key results in a two-sector menu cost model. Our empirical analysis takes two steps: First, we estimate the responsiveness of sectoral prices and firm-level real sales to an identified monetary policy shock.[1] Then, we relate these measures of monetary non-neutrality to observed pricing and non-pricing moments. The main finding is that the frequency of price changes is robustly informative across specifications: A lower frequency is statistically significantly associated with higher monetary non-neutrality, in line with models of price rigidities. Other moments that describe the price change distribution are not consistently or significantly related to monetary non-neutrality. While the frequency of price changes explains the largest share of variation in monetary non-neutrality, no pricing moments individually or jointly explain a majority of the variation in a linear empirical setting. Non-pricing moments explain additional variation, but are not consistently associated with monetary non-neutrality.

A multi-sector menu cost model with idiosyncratic and aggregate shocks can naturally rationalize our main empirical finding. Its critical feature is that sectors may differ in their price adjustment technologies which can induce a composition effect in the aggregate for the relation between pricing moments and monetary non-neutrality. In particular, we consider a fixed menu cost technology in one sector as in Golosov and Lucas (2007) and a CalvoPlus random menu cost technology in another sector as in Nakamura and Steinsson (2010). In such a setup, two results emerge: First, regardless of the price adjustment technology, a lower frequency of price change is associated with higher monetary non-neutrality in both sectors. Second, unlike in the case of the frequency, a composition effect can emerge for the relationship between pricing moments and monetary non-neutrality, in line with our empirical findings. For example, in the case of kurtosis, one sector exhibits a negative relationship and one sector exhibits a positive relationship with monetary non-neutrality. As a result, the aggregate relationship is ambiguous.

Our empirical analysis establishes the following main results. First, we establish that the frequency of price changes is the only one among a set of pricing moments that has a robust, statistically significant relationship with monetary non-neutrality. In this set of moments, we include pricing moments postulated to be relevant for monetary non-neutrality, beyond average size and the frequency of price changes: the ratio of kurtosis over frequency (Alvarez et al., 2016, 2021b); the volatility of price spell durations (Carvalho and Schwartzman, 2015); the dispersion of price changes (Berger and Vavra, 2019); skewness of price changes (Luo and Villar, 2021); synchronization of price changes (Bhattarai and Schoenle, 2014; Bonomo et al., 2020); the fraction of small price changes (Midrigan, 2011); and the fraction of positive price changes (Nakamura and Steinsson, 2008). We establish this first result using a multitude of linear regression specifications. The finding is robust to the use of alternative measures of monetary non-neutrality, fixed effects that account for unobserved heterogeneity, and instruments to account for measurement error.

Second, we find that the frequency of price changes is also the pricing moment that captures most variation (R^2) in the degree of monetary non-neutrality. Frequency univariately explains around 25 to 30 percent of the observed variation in monetary non-neutrality across finely disaggregated sectors. A close second to frequency is the standard deviation of price durations. However, it is highly collinear with frequency and comes out as insignificant in a joint regression with frequency. The other pricing moments exhibit a discrete, significantly lower level of explanatory power: The ratio of kurtosis over frequency is the third most informative moment, but only has an explanatory power of 17 percent. As frequency by itself explains more variation, kurtosis merely adds noise to the information contained in the frequency. Indeed, kurtosis by itself is quite uninformative with an R^2 of 4 percent, with the remaining moments similarly uninformative. All pricing moments together account for 29 to 35 percent of total variation, indicating that frequency brings most of the information to a multivariate setting.

Third, non-pricing moments contain additional information on monetary non-neutrality. In terms of such non-pricing moments, we consider the four-firm concentration measure of market power which affects prices through the degree of competition as recently studied in Mongey (2021) and Wang and Werning (2022); the persistence and standard deviation of sectoral shocks which may affect attention to a monetary shock as in Mackowiak and Wiederholt (2009); the size and centrality of sectors in the production network which may affect the transmission of shocks as in Pasten et al. (2020); and moments related to balance sheet concerns which may affect pricing as shown in Gilchrist et al. (2017) or Kim (2020). These non-pricing moments explain a substantial, additional fraction of variation in monetary non-neutrality. Univariately, the persistence and standard deviation of sectoral shocks rank as the most informative non-pricing moments, explaining between 8 percent and 33 percent in terms of R^2, with a steep decrease in R^2 for other non-pricing moments. Their joint inclusion in our main specification in addition to all pricing moments raises explanatory power (R^2) from 35 percent to 55 percent, with similarly large increases across identification schemes. Their inclusion also influences the statistical significance of some pricing moments, either decreasing or undoing their significance. However, which non-pricing moments are significant varies across specifications and identification schemes. This inconsistency suggests that these non-pricing

[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).

moments do not have clear implications for monetary non-neutrality, unlike the frequency of price changes which has a robustly significant relationship.

Last, our empirical results highlight the fragility associated with any single pricing moment in summarizing the variation of monetary non-neutrality in a complex empirical environment. In theory, given model assumptions, it may be possible to show that pricing moments can serve as sufficient statistics for monetary non-neutrality. Empirically, one cannot show whether there is a sufficient statistic for monetary non-neutrality or not. Our findings delineate in fact some challenges faced by any single pricing moment in summarizing variation of monetary non-neutrality in the data: First, most pricing moments considered – except for frequency – are not even robustly statistically significantly related to monetary non-neutrality in our linear empirical setup. For example, kurtosis is not always statistically significant and the sign of its relationship can switch. Second, our analysis considers a non-exhaustive set of specifications and variables, necessarily leaving room for missing specifications and variables that may contain information or make a particular moment come out significant. In fact, omitted variable bias is present for all individual pricing moments, particularly with respect to non-pricing moments, as we show. To do so, we apply formal tests following Oster (2019) to confirm the general scope for omitted variable bias.[2] These insights highlight the empirical challenges for establishing the importance of single pricing moments for explaining the majority of monetary non-neutrality, even despite comprehensive efforts.

Nonetheless, our theoretical analysis can help provide intuition for our empirical findings and provide guidance how models may be able to make better sense of the complexity of the data. In particular, our theoretical analysis shows that a multi-sector menu cost model with idiosyncratic and aggregate shocks can rationalize a key aspect of our empirical findings: The frequency of price changes is robustly related to monetary non-neutrality while, for example, kurtosis of price changes exhibits an unclear relationship with monetary non-neutrality, taking other moments as given. The main mechanism behind this result lies in differences of price adjustment technologies across sectors which can induce a composition effect in the aggregate for the relation between pricing moments and monetary non-neutrality. We consider a two-sector version of the model where one sector uses a fixed menu cost technology as in Golosov and Lucas (2007), and the other a CalvoPlus random menu cost technology as in Nakamura and Steinsson (2010). As CalvoPlus nests the model of Golosov and Lucas (2007), the model reflects different degrees of state-dependence, with full state-dependence in the Golosov and Lucas (2007) sector.

In such a setup, two results emerge: First, regardless of the price adjustment technology, a lower frequency of price change is always associated with higher monetary non-neutrality. As a result, if we average the relationship between frequency and monetary non-neutrality across sectors, the sign is the same in the aggregate as for each sector. At the same time, we show that these differences in price adjustment technology can give rise to different relationships between other pricing moments and monetary non-neutrality across sectors. When we consider kurtosis, kurtosis has a negative relationship in one sector with monetary non-neutrality and a positive relationship in the other sector. As a result, the aggregate relationship is ambiguous due to a composition effect. When we vary one of the moments at a time by appropriately setting parameters, the theoretical predictions match the data on the relationship between frequency, and kurtosis and monetary non-neutrality.[3]

Arguably, differences in price adjustment technologies across sectors such as the service sector or oil-producing sectors constitute a feature of the empirical environment. By appealing to such differences, our approach relates to the influential work of Coibion and Gorodnichenko (2011) who use aggregate data to estimate the sectoral incidence of price adjustment technologies and implications for the role of monetary policy. We re-emphasize the importance of this approach in the context of relating pricing moments to monetary non-neutrality. Taking into account heterogeneity in price adjustment technologies across sectors can help make sense of a complex empirical environment.

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), Midrigan (2011) or Alvarez et al. (2016, 2021b). 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. By exploiting variation in sectoral and firm-level data, our work provides comprehensive evidence on the extent to which variation in micro pricing moments across sectors relates to monetary non-neutrality in the data.

Another strand of the 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

[2] 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.

[3] While a subordinate result, kurtosis can vary in our Golosov-Lucas sector. Given the result in Alvarez et al. (2016) that kurtosis always equals one in their model, the reason for the difference is that our setup differs, for example, by allowing for aggregate risk. The relative importance of aggregate risk, compared to idiosyncratic shocks, can change the shape of the ergodic steady-state distribution and therefore kurtosis. We present detailed intuition in Appendix C.

this context: First, we provide direct empirical evidence that points to the empirical fragility of any single pricing moment in summarizing the majority of variation in monetary non-neutrality in the empirical environment. Second, in the spirit of Coibion and Gorodnichenko (2011), we show how heterogeneity in price adjustment technologies across sectors in a multi-sector economy can account for robust relations between one pricing moment and measures of monetary non-neutrality, but also an unclear relation for a different moment. In particular, the model replicates the consistent negative relationship between the price change frequency and monetary non-neutrality, and a null result for kurtosis. This analysis emphasizes the challenges that theory faces in light of a complex empirical environment. It suggests that considering heterogeneity of price adjustment technologies in a multi-sector setting may provide a further way to rationalize the relation between pricing moments and measures of monetary non-neutrality.

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, prices for flexible goods actually decrease relative to sticky prices after an expansionary monetary shock. Boivin et al. (2009) present evidence for a positive correlation between the frequency of price changes and price impulse responses following a monetary shock. Our multivariate analysis goes beyond reporting raw correlations by systematically taking into account unobserved heterogeneity through sector fixed effects, and reporting the (relative) explanatory power of a large number of pricing moments vis-a-vis other pricing moments, as well as non-pricing moments. A further important relative contribution of our analysis lies in showing that frequency is robustly the pricing moment with the highest explanatory power.

Finally, we note that our analysis is not designed to assess the role of sectoral or firm-level heterogeneity for aggregate responses to monetary policy shocks. For example, heterogeneity in pricing frictions may create rigidity in the price setting process and can amplify the aggregate real response of the economy to monetary policy shocks. This mechanism is an important theme discussed in the literature since Carvalho (2006), and more recently for example in Carvalho and Kryvtsov (2021) or Gautier and Le Bihan (2022).

The rest of the paper proceeds as follows. Section 2 discusses the data and empirical methodology. Section 3 discusses the empirical results. Section 4 presents the model and model results. Finally, Section 5 concludes.

2. Data and methodology

This section describes our data and methodology. First, we describe the data we use. Second, we outline the empirical approach, including the identification of monetary policy shocks. We also describe how we address potential concerns of heterogeneity in the analysis.

2.1. 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. We transform each series to ensure stationarity, as in Boivin et al. (2009).

For our aggregate analysis, we 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 absolute size of price changes, 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 sector level, each of which corresponds to one of the 154 series. Nakamura and Steinsson (2008) show that sales are not prevalent in the PPI. Therefore, we do not use a sales filter as is typical when using CPI data. Table B.7 in the Appendix contains basic summary statistics. 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.

For our sectoral regressions, we complement the producer price data with several, non-pricing variables that characterize key features of each sector. This information is cross-sectional. It includes the sectoral four-firm concentration ratio from the Annual Survey of Manufactures, averaged over the 1997 to 2001 period; the sectoral consumption share and first-order outdegree from the input-output tables of the Bureau of Economic Analysis as in Pasten et al. (2023). From Compustat, we calculate the liquidity ratio, the ratio of cost of goods sold to sales, and the inventory-to-sales ratio, for the 1976 to 2005 period (consistent with the dates of our Factor-Augmented Vector Auto-Regression (FAVAR) identification explained in the next subsection, that is, from January 1976 to June 2005), and aggregated to sector-level using the average firm sales from 1997 to 2001 as weights. From the FAVAR, we calculate the persistence and volatility of sector-level shocks as in Boivin et al. (2009).

As an important complement to these sector-level series, we use firm-level data on real sales and pricing moments.[4] First, we compute 7 firm-level moments: frequency, kurtosis, the kurtosis over frequency ratio, average absolute size of price changes, standard deviation of price change, and two measures of price change synchronization. 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. We pool all price changes within a firm over time to calculate firm pricing moments. For synchronization, we compute two firm-level measures: One is the firm-specific elasticity $\alpha_{1,j,k}$ of firm j that there is a change in the firm's average price, $I\left(\Delta P_{j,k,t} \neq 0\right)$, to the inflation rate, $\pi_{k,t}$, of it's four-digit NAICS sector k, obtained from the follow probit regression:

$$I\left(\Delta P_{j,k,t} \neq 0\right) = probit\left(\alpha_0 + \alpha_{1,j,k}\pi_{k,t} + \epsilon_{j,k,t}\right) \tag{1}$$

The second measure, $\alpha_{2,j,k}$, comes from an analogous probit specification that relates the probability of a firm's change in its average price to an indicator variable for the first quarter of the year. We take the estimated coefficient on this indicator variable as our second, seasonal measure of synchronization. This is motivated by Olivei and Tenreyro (2007), who show monetary policy is more effective in the first part of the year.

Second, we merge firm-level real sales from Compustat into this dataset to obtain a measure of real output, as well as additional non-pricing moments that may affect the real sales response to a monetary shock. Specifically, we compute the liquidity ratio, ratio of cost of goods sold to sales, and the inventory-to-sales ratio. Whenever we compute pricing moments, we restrict our sample to firms with a minimum of 5 price changes over the full sample period. An additional restriction for the analysis lies in requiring at least 10 years of sales data, which leaves 374 firms in the analysis. Table B.8 in Appendix B contains summary statistics.

Generally, to avoid measurement error in kurtosis as pointed out by Eichenbaum et al. (2014), we follow the approach in Alvarez et al. (2016) in both the sector and the firm exercises. We drop all price changes of less than 1 cent and larger than the 99$^{\text{th}}$ percentile of the absolute price change distribution. We disregard the $25 upper bound on price levels as in Alvarez et al. (2016) since it does not meaningfully apply to PPI micro data. Additionally, our robustness section explores other trimming techniques in both aggregate and sectoral analyses, and other ways of addressing measurement error, including the instrumental variables approach in Gorodnichenko and Weber (2016).

2.2. *Identification of monetary policy shocks and approach*

Our analysis relies on several commonly used schemes of identifying monetary policy shocks. The 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 shows further robustness to using the high-frequency approach as in Nakamura and Steinsson (2018) using data from January 1995 through March 2014.

Given these identification schemes, we relate pricing moments to the price response following an identified monetary shock. Or in the case of our most detailed, firm-level regressions, to the real sales response following the identified monetary shock. Our approach in doing so generically takes two steps. We first outline the specifications used in each step, then discuss the role heterogeneity might play in our approach of identifying the relationship between pricing moments and monetary non-neutrality. As a first step, we simply measure the sector (or firm-level) response to a monetary shock, regardless of sectoral (or firm-level) heterogeneity following Ramey (2016). That is, we estimate impulse response functions of prices to an exogenous, identified monetary shock separately for each unit k and horizon h. In the narrative approach this entails the following specification:

$$P_{k,t+h} = \alpha_{k,h} + \gamma_{k,h}\text{MP shock}_t + \theta_h X_t + \epsilon_{k,t+h} \tag{2}$$

with $P_{k,t+h}$ denoting the log producer price level h periods ahead (and real sales in the firm-level regressions), $\alpha_{k,h}$ denoting a unit and horizon fixed effect, $MPshock_t$ denoting a shock in the narrative measure, and X_t denoting aggregate controls, which in line with Ramey (2016) include six lags of the shock, six lags of the Fed funds rate, the current and six lags of the aggregate unemployment rate, aggregate industrial production, and the aggregate PPI price level. In terms of aggregation levels k, our analysis considers an aggregate view with two very broad sets of sectors, then individual NAICS six-digit sectors as well as firms. In the case with two very broad sectors, $P_{k,t+h}$ represents the average price index in each group while it otherwise represents a sector or firm price index. The estimates of $\gamma_{k,h}$ capture the corresponding impulse responses in all cases.

In the case of the FAVAR, we similarly estimate impulse response functions for each of the k sectors. They are equivalent to the $\gamma_{k,h}$ above, which are then the input into the second step of our approach. As noted, the FAVAR methodology

[4] We have also explored using sector-level industrial production data and found that quantity-based and priced-based impulse responses are consistent, in line with Boivin et al. (2009). However, there is a lot of noise in the industrial production data so we find no significant relation between pricing moments and quantity response.

specifically follows Boivin et al. (2009). As an initial step, this FAVAR setup estimates a set of common but partially unobserved factors C_t, and their evolution. These factors include the federal funds rate which we shock under the standard recursive identification assumption. That is, 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. The evolution of the common factors in response to a Fed funds rate shock is then projected onto PPI inflationary impulse responses $\pi_{k,t}$ for each sector k: $\pi_{k,t} = \lambda_k' C_t + e_{k,t}$. The sectoral inflationary response is given by the loading λ_k' on the VAR evolution of the common components C_t.

In the first step of the approach, some further, minor details differ across identification schemes and levels of aggregation. We provide them below when presenting results for each level of aggregation. However, the second step always takes the same cross-sectional form:

$$\gamma_{k,h} = a_h + \alpha_{j,h} + \beta_h' M_k + \epsilon_{k,h} \tag{3}$$

where $\gamma_{k,h}$ denotes the (log) impulse response for the respective unit k and at horizon h, and M_k denotes our (non-)pricing moments of interest. a_h and $\alpha_{j,h}$ denote horizon and three-digit NAICS-horizon fixed effects which capture any unobserved systematic differences across sectors and horizons that might also relate to monetary non-neutrality. Alternatively, instead of using fixed effects, we also use sector (firm) characteristics as available to us, such as the consumption share, the first-order outdegree, the liquidity ratio, the cost-of-goods-sold to sales ratio, and the inventory-sales ratio. The regression is estimated for each horizon h, from $h = 0$ to 48 months after the shock using industry data, and from $h = 0$ to 8 quarters after the shock using firm-level data. The cross-sectional estimate of β_h from this specification contains the estimate of interest – the extent to which monetary non-neutrality relates to (non-)pricing moments.

A potential concern with the approach described lies in the existence of heterogeneity of nominal sectoral (or firm-level) demand and marginal cost responses to a monetary shock. Such heterogeneity can pose a problem if we do not sufficiently take it into account: It may introduce bias into the estimated relationship between pricing moments and monetary non-neutrality if unaccounted for. For example, if the demand for durables responds to monetary policy more strongly than the demand for nondurables, the marginal cost of producing durables likely responds more as well, as will prices. Thus, even if a pricing moment (e.g. kurtosis of price changes) is higher in the durables sector for which we expect a lower price response, we may well still see prices respond by more due to some sector-specific (or firm-specific) characteristic. If we were to simply take the impulse responses of prices to an identified exogenous shock from the first step (which include any such heterogeneity in the transmission mechanism separate from pricing moments), and regressed these impulse responses on pricing moments, we would not properly control for such sector-specific (or firm-specific) differences in the transmission mechanism of monetary shocks.

Therefore, our second step aims at addressing this concern by directly taking into account both observed sources of potential heterogeneity in sectoral (firm-level) transmission mechanisms of monetary shocks, as well as unobserved sources of heterogeneity through fixed effects. Besides pricing frictions, a well-known source from the New Keynesian literature, sources of heterogeneity that may affect the transmission mechanism following a monetary shock could lie in the context of financial frictions (see for example Gilchrist et al. (2017)). Our non-pricing moments include such information at the level of the sector or the firm, for example with sector (or firm-level) liquidity and inventory to sales ratios.

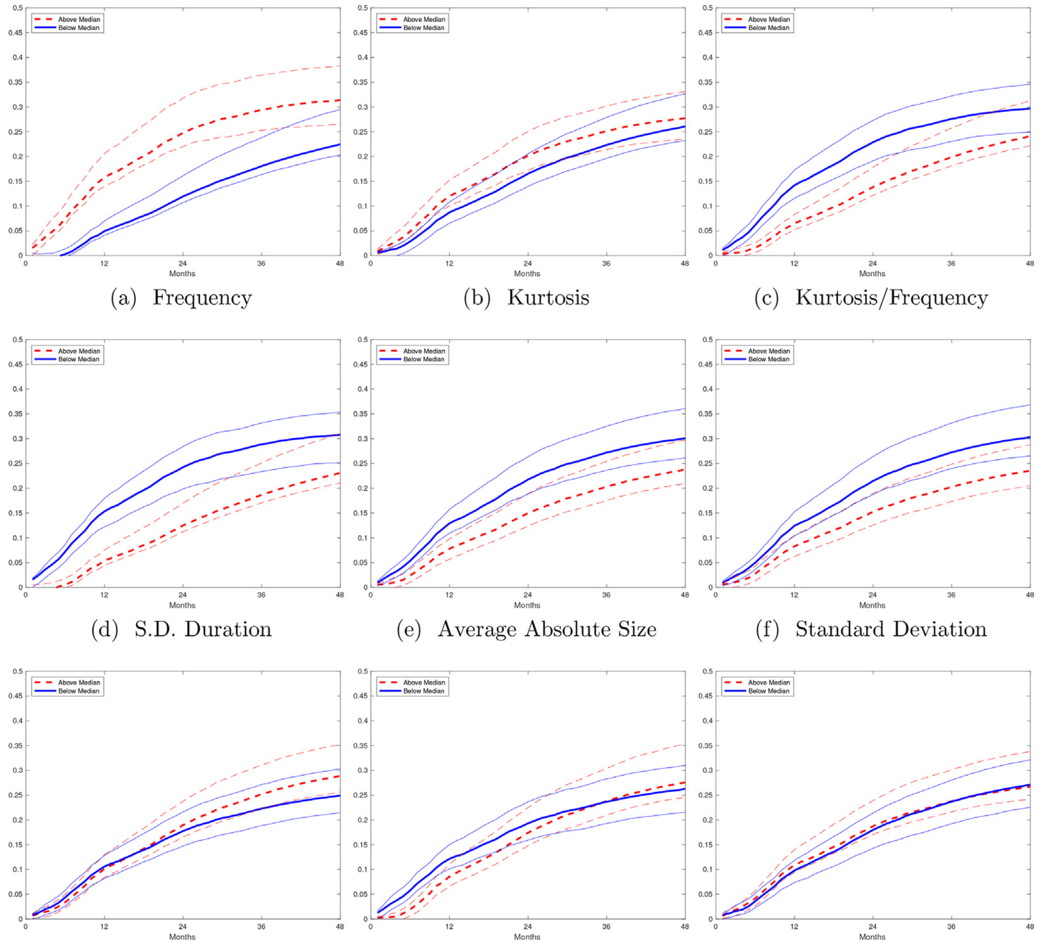
Our analysis complements these observed measures by also including fixed effects at the three-digit NAICS level. These fixed effects capture any unobserved systematic differences across sectors or firms. Such differences may relate for example to differences in the sectoral exposure to oil, market structure, variations in strategic complementarity or any other source of unobserved heterogeneity. We capture these differences at a level of disaggregation such as “Furnitures & Fixtures” or “Fish, fresh/chilled/frozen & other marine products.” While we cannot exhaust our cross-section with a number of fixed effects equal to the number of observations, we also analyze the sensitivity of our results as we go from no fixed effect to fixed effects that are as detailed as possible. As long as no systematic trends emerge regarding the significance and size of the effect of the pricing moments which we are interested in as we increase the level of disaggregation, unobserved heterogeneity in response to a monetary shock should not systematically affect our findings for the role of pricing moments and monetary non-neutrality.

3. Empirical results

This section describes our empirical findings. We present consistent results from an analysis at three levels: at a highly aggregate level where the economy is split into sectors above or below a pricing moment; at the sectoral level; and at the level of the firm. The sectoral and firm-level analyses consist of univariate analysis of pricing moments followed by multivariate analysis of both pricing and non-pricing moments. Finally, we discuss robustness.

3.1. Aggregated approach

Our analysis first gauges the importance of micro pricing moments for monetary non-neutrality at a near-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. In case of the narrative identification scheme, control variables for the narrative approach include two lags of the shock,



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

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

(g) Fraction Small (h) Fraction Positive (i) Skewness

Fig. 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. Standard errors are constructed by bootstrapping. Industries are sampled with replacement, the FAVAR is estimated on the new sample, the average above and below median impulse response are constructed for each sample, and the confidence interval is generated using the percentiles of the IRF distribution. Standard errors are generated using 1000 bootstrap replications. Dashed lines present 68% standard error bands.

two lags of the Fed funds rate, and current and two lags of the unemployment rate, industrial production, and the price level of the respective set.[5]

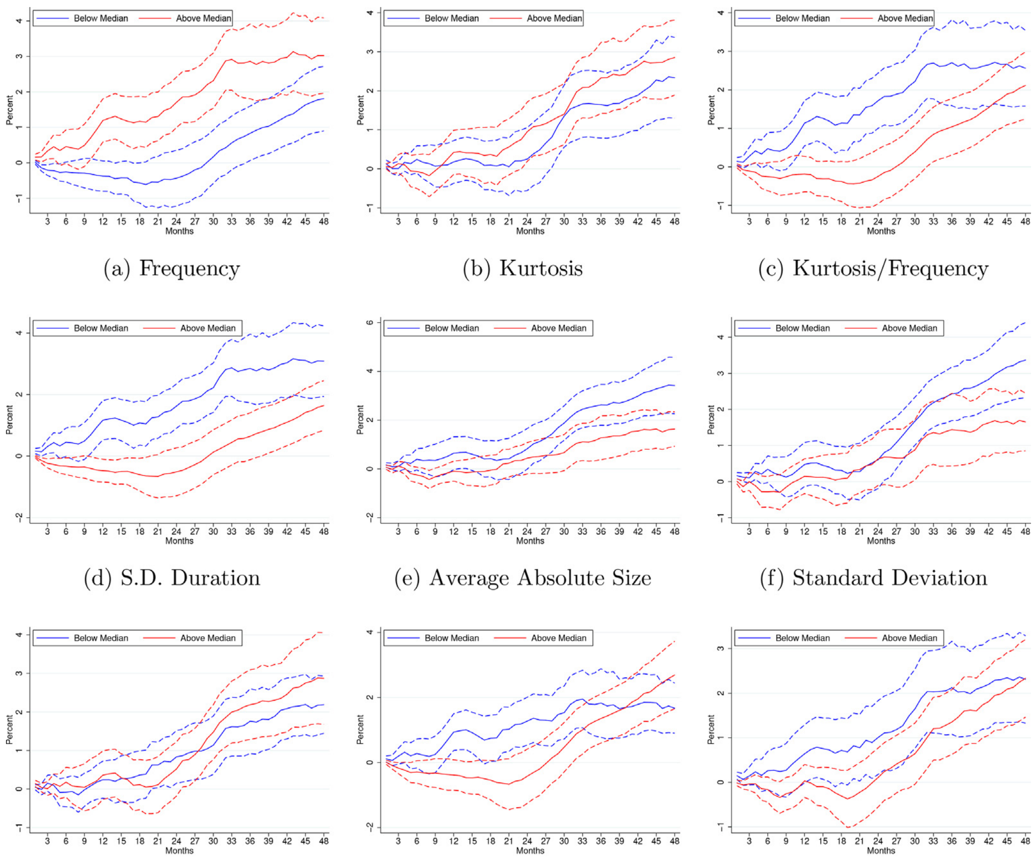
In case of the FAVAR identification scheme, we compute estimated price impulse responses $\gamma_{k,h}$ for each of the k sectors at each monthly horizon h. We then compute the mean of the impulse response at each horizon h in the two subsets of the data characterized as above-median and below-median according to each pricing moment. Because there are only two units of aggregation in the analysis, we plot the two impulse response functions to describe the relative price differences rather than regressing measures of monetary non-neutrality on moments.[6]

Across all identification schemes and specifications, we find that three pricing moments systematically and statistically significantly relate to monetary non-neutrality as Figs. 1 and 2 illustrate:[7] The frequency of price changes, the dispersion of the duration of price spells and the ratio of kurtosis over frequency. First, low-frequency sectors have a smaller price response to the monetary shock than high-frequency sectors. This result suggests that low-frequency sectors have larger

[5] We additionally estimate the OLS specification of Romer and Romer (2004) in Fig. B.7 in Appendix B. The results are consistent using this alternative estimation method. Fig. B.8 in Appendix B shows the impulses estimated using data from 1976 through 2007. Results show the same patterns during this time period.

[6] While sectoral heterogeneity as discussed above may still affect results as we have systematically selected two bins, the near-aggregation to the economy-wide level eliminates much of the underlying sectoral heterogeneity. Our subsequent disaggregated approach, however, takes heterogeneity into account and confirms the near-aggregate findings.

[7] Results using high-frequency shocks show the same patterns and can be found in Fig. B.10 in Appendix B.



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

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

(g) Fraction Small (h) Fraction Positive (i) Skewness

Fig. 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.

cumulative output responses. This finding is in line with most models of price-setting and aligns with the correlational evidence in Boivin et al. (2009).

Second, sectors with a higher dispersion of the duration of price spells show a lower price response, implying low monetary non-neutrality as posited by Carvalho and Schwartzman (2015). However, the reason for this result lies in the negative empirical relationship of the frequency of price adjustment with the dispersion of price durations, with a correlation of -0.74 across industries. Because the dispersion of durations becomes an insignificant predictor when also conditioning on price change frequency, we focus on the frequency of price changes in subsequent regressions.

Third, in terms of the ratio of kurtosis over frequency of price changes, we find that 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 as posited by Alvarez et al. (2016, 2021b). This finding also holds across identification schemes.

This finding is, however, driven by the strong negative relationship of frequency with monetary non-neutrality, not the relationship of kurtosis with monetary non-neutrality: 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. The FAVAR analysis shows that high-kurtosis sectors have an even *stronger*, though not significantly different, price response than low-kurtosis sectors which suggests less monetary non-neutrality. This fragility in the relationship for this pricing moment persists in subsequent exercises — while the relationship of the frequency with monetary non-neutrality also continues to dominate the net effect of the ratio of the two moments. In the model section we show how such fragility can arise naturally in multisector menu cost models.

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

3.2. Detailed regression approach

Exploiting detailed variation in pricing moments at the sector- and firm-level next shows that the same results as above emerge in both univariate and multivariate regression settings with richer sets of controls. We present results in two steps: First, we present univariate regressions, ordering pricing moments as well as non-pricing moments by their univariate explanatory power for monetary non-neutrality. Second, we analyze a multivariate setting. This setting combines all pricing and non-pricing moments, and adds them sequentially up to the most saturated specification. It allows us to learn about the *relative* explanatory power of individual pricing moments and other predictors for monetary non-neutrality.

3.2.1. Sector-Level regression results

As outlined, our regression analysis follows a two-step approach, relating monetary non-neutrality to pricing and non-pricing moments. The sector-level analysis considers not only 8 pricing and 8 non-pricing moments, but also three-digit NAICS fixed effects that capture any common factors across broad industries. While the FAVAR setup already controls for a data-rich environment, the narrative approach additionally includes as control variables for the first-stage regression current and six lags of the unemployment rate, the log of industrial production, a commodity price index, the log of aggregate producer price index, six lags of the Romer and Romer shock, and six lags of the federal funds rate. In what follows, the FAVAR focuses on a 24-month horizon, while the narrative approach known for its delayed response pattern focuses on a 48-month horizon.

In our univariate analysis, we continue to find that the frequency of price changes is significantly related to monetary non-neutrality across our identification schemes of monetary shocks. Among all univariate relationships, the standard deviation of price durations and the ratio of kurtosis over frequency also bear a significant sign. In the case of the FAVAR, the average absolute size of price changes additionally has a statistically significant relationship. Kurtosis of price changes is not statistically significantly related to monetary non-neutrality. The insignificance of the latter relationship suggests that the strength of the relationship of frequency with monetary non-neutrality generates the significant and negative univariate relation of the ratio of kurtosis over frequency with monetary non-neutrality, as we will verify in the multivariate setup. Other moments are univariately not significant or bear an unstable sign. Table 1 and Table 2 summarize the results, the first for the FAVAR and the second for the Romer and Romer shocks.

A further insight from these univariate specifications comes from our measures of informativeness, such as R^2, adjusted R^2, the log likelihood, and the Bayesian information criterion: The frequency of price changes is the most informative pricing moment. Both Tables 1 and 2 present pricing moments in descending order of explanatory power for monetary non-neutrality. Focusing on the FAVAR set up, the explanatory power (R^2) of the frequency of price changes is the highest with 30 percent. A close second to frequency is the standard deviation of price durations. However, it is highly collinear with frequency and comes out as insignificant in a joint regression with frequency, as Column 9 of multivariate Table 3 reports. Subsequently, there is a discrete, significant reduction in informativeness: The ratio of kurtosis over frequency, as the third most informative moment, has an explanatory power of 17 percent suggesting that kurtosis only adds noise to the information contained in the frequency. Indeed, kurtosis by itself is quite uninformative with an R^2 of 4 percent, like other moments. The other measures of fit provide a similar picture. In the Romer and Romer setup, the same results hold, though R^2 is slightly lower across specifications. To model the relationship between price setting and monetary non-neutrality, comparing the informativeness in the various univariate specifications suggests price-setting models to align with frequency or duration based statistics.

We also rank our non-pricing moments by their explanatory power. The most informative non-pricing moments are the persistence and volatility of sectoral shocks, with an R^2 of 33 percent and 13 percent in the FAVAR setup, and 8 percent and 21 percent in the narrative setup. Other non-pricing moments have lower explanatory power. Two complementary tables, Tables B.9 and B.10 in the Appendix, show these rankings. The univariate informativeness of non-pricing moments further suggest a joint, multivariate analysis of pricing and non-pricing moments, our next step.

In such a multivariate setting, our main results emerge. The frequency of price changes bears, consistently with our previous results, a statistically significant relationship with monetary non-neutrality. This result arises both when all pricing moments are included, as well as pricing plus non-pricing moments enter together. Aside from the frequency of price changes, other pricing moments are not significant or consistently significant across the multivariate specifications. In particular, this holds for kurtosis of price changes, which always remains statistically insignificant. Whether we include fixed effects or not does not alter these conclusions about pricing moments and monetary non-neutrality as seen in Table B.12 in the Appendix. Among the non-pricing moments, we find that some bear statistical significance, but not consistently across specifications and identification schemes. For example, the sectoral consumption share or the persistence of sectoral shocks matter in the fully saturated FAVAR specification, but not in the Romer and Romer specification. Table 3 summarizes the results for the FAVAR approach, while Table 4 displays the results for the Romer and Romer approach.

A particular multivariate specification is a bivariate regression setup with the kurtosis and the frequency as the only two explanatory variables, as seen in Column 8 in Table 3 and Column 1 in Table 4. The results from these specifications validate a previously implicit result from the aggregate and univariate analyses: 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

Table 1
Drivers of Monetary Non-Neutrality Univariate (FAVAR Approach).

Cross-Sectional Determinants of Sectoral Price Response									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Frequency	0.422***								
	(0.073)								
Log S.D. Duration		-0.462***							
		(0.084)							
Log $\frac{\text{Kurtosis}}{\text{Frequency}}$			-0.250***						
			(0.074)						
Log Avg. Size				-0.316**					
				(0.148)					
Log S.D.					-0.158				
					(0.127)				
Skewness						0.133			
						(0.305)			
Log Kurtosis							0.138		
							(0.119)		
Log Frac. Pos.								-0.334	
								(0.382)	
Log Frac Small									0.017
									(0.077)
constant	-0.963***	-0.803***	-0.854***	-2.459***	-1.996***	-1.594***	-1.803***	-1.792***	-1.552***
	(0.182)	(0.196)	(0.246)	(0.456)	(0.367)	(0.144)	(0.227)	(0.275)	(0.211)
R^2	0.303	0.295	0.177	0.106	0.067	0.046	0.042	0.031	0.002
adj. R^2	0.298	0.290	0.172	0.100	0.061	0.040	0.035	0.024	-0.005
BIC	270.543	272.308	295.134	307.370	313.682	316.995	317.720	319.420	316.289
Log Likelihood	-130.274	-131.157	-142.570	-148.688	-151.844	-153.500	-153.863	-154.713	-153.161
LR test 1	3.58						50.76		
	(0.0584)						($<$ 0.0001)		
LR test 2	43.53	39.45	52.58	74.42	80.63	84.24	77.01	81.18	86.64
	(0.0001)	(0.0003)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)
δ	0.19736	0.26589	0.27104	0.00041	0.16529	0.40480	-0.18567	0.19497	-0.98756
$\delta(R^2_{\max} = 0.8)$	0.33307	0.44872	0.35987	0.00075	0.29843	0.73325	-0.33231	0.35285	-1.71245
NAICS 3 FE	X	X	X	X	X	X	X	X	X
N	148	148	148	148	148	148	148	148	146

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: $log(\gamma_{k,h}) = a_h + \alpha_{j,h} + \beta_h' M_k + \epsilon_{k,h}$ where $log(\gamma_{k,h})$ is the predicted 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 sector-level pricing moments: frequency, kurtosis, the ratio of the two statistics, average absolute size of price changes, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, skewness, and standard deviation of price duration. $\alpha_{j,h}$ denotes three-digit NAICS-horizon industry j fixed effects, included in all specifications. Two log likelihood ratio tests are computed: LR test 1 compares specifications (1) or respectively (7) against (8) in Table 3, while LR test 2 compares each column against (11) in Table 3 (with the frequency substituted by the standard deviation of price durations in case of (2)). Log likelihood ratio tests and measures of fit are computed excluding sector fixed effects and robust standard errors. 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 δ row comprises a test of each specification against an appropriate specification of all pricing moments, and the second δ row repeats assuming a maximum R^2 of 0.8. Robust standard errors in parentheses. *** denotes significance at the 1 percent level, ** significance at the 5 percent level, * significance at the 10 percent level.

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 1.

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 specification. Hence, frequency is the most informative pricing moment among our set of pricing moments. This insight affirms the conclusion for price-setting models to aim to align with frequency or duration-based statistics when trying to capture monetary non-neutrality.

Second, when we include further, non-pricing moments, the explanatory power of the specifications for the FAVAR and the narrative approaches improves. For example, the simple R^2 measure in the FAVAR approach goes up to 55 percent compared to 30 percent if we only include frequency, or 35 percent if we include all pricing moments. This finding suggests that single or multiple pricing moments are not robust in summarizing variation of monetary non-neutrality. These results can be seen by comparing the univariate, bivariate and multivariate results across Tables 1 and 3, and Tables 2 and 4. This insight from also considering non-pricing moments suggests that pricing moment summary statistics for the non-neutrality of money face a complex empirical environment in practice.

More formally, we show in the context of omitted variable bias that selection on unobservables does not have to be large to explain away our regression results. 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. This approach ties together an

Table 2
Drivers of Monetary Non-Neutrality Univariate (Romer-Romer Approach).

Cross-Sectional Determinants of Sectoral Price Response									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Frequency	9.331***								
	(2.283)								
S.D. Duration		-0.290***							
		(0.061)							
$\frac{\text{Kurtosis}}{\text{Frequency}}$			-0.040***						
			(0.012)						
Kurtosis				0.138					
				(0.106)					
Avg. Size					-6.528				
					(13.812)				
Frac. Pos.						0.263			
						(2.991)			
Skewness							-0.782		
							(1.374)		
S.D.								-1.381	
								(12.426)	
Frac. Small									1.633
									(4.394)
constant	2.506**	7.358***	6.318***	4.557***	5.806***	5.219***	5.382***	5.476***	5.158***
	(1.264)	(1.070)	(1.077)	(1.420)	(1.389)	(1.996)	(1.071)	(1.419)	(1.211)
R^2	0.254	0.225	0.123	0.055	0.028	0.026	0.008	0.007	0.001
adj. R^2	0.249	0.220	0.117	0.049	0.022	0.020	0.002	0.001	-0.006
BIC	812.671	818.519	837.625	849.148	853.436	853.718	856.593	856.706	857.685
Log Likelihood	-401.298	-404.223	-413.776	-419.537	-421.681	-421.822	-423.259	-423.316	-423.806
LR test 1	0.05						36.53		
	(0.8201)						($<$ 0.0001)		
LR test 2	12.00	15.36	53.98	52.70	53.87	54.07	59.02	58.76	58.13
	(0.6062)	(0.3538)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)
δ	0.18479	0.20601	-0.06383	-0.11186	0.00379	-0.08038	-0.04623	$<$ 0.0001	$<$ 0.0001
$\delta(R^2_{\max} = 0.8)$	0.26445	0.29482	-0.09659	-0.16923	0.00575	-0.12187	-0.07020	$<$ 0.0001	$<$ 0.0001
NAICS 3 FE	X	X	X	X	X	X	X	X	X
N	154	154	154	154	154	154	154	154	154

Note: This table uses regression analysis at the sector-level to test the informativeness of pricing moments for monetary non-neutrality based on the Romer and Romer identification. We estimate the following specification: $\gamma_{k,h} = a_h + \alpha_{j,h} + \beta_h' M_k + \epsilon_{k,h}$ where $\gamma_{k,h}$ is the predicted response of the sectoral price level at a horizon h of 48 months after the Romer and Romer monetary shock. M_k contains one of our sector-level pricing: frequency, kurtosis, the ratio of the two statistics, average absolute size of price changes, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, skewness, and standard deviation of price duration. $\alpha_{j,h}$ denotes three-digit NAICS-horizon industry j fixed effects, included in all specifications. Two log likelihood ratio tests are computed: LR test 1 compares specifications (1) or respectively (4) against (1) in Table 4, while LR test 2 compares each column against (10) in Table 4 (with the frequency substituted by the standard deviation of price durations in case of (2)). Log likelihood ratio tests and measures of fit are computed excluding industry fixed effects and robust standard errors. 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 δ row comprises a test of each specification against an appropriate specification of all pricing moments, and the second δ row repeats assuming a maximum R^2 of 0.8. Robust standard errors in parentheses. *** denotes significance at the 1 percent level, ** significance at the 5 percent level, * significance at the 10 percent level.

assessment of coefficient stability and changes in informativeness of various specifications. This connection is important because concern for omitted variable bias should only lessen 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. Hence, when evaluating specifications for omitted variable bias, one should simultaneously normalize any observed coefficient changes by changes in explanatory power.

The results from this approach are summarized in the rows denoted by "δ" in Tables 1. The first row tests each individual moment against the appropriate saturated specifications, indicating scope for omitted variable bias. The second row presents 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 and the fraction of small price changes. Thus, selection on unobservables does not have to be large to explain away our regression results.

We also highlight the fragility associated with using any univariate pricing moment in a linear empirical environment as a summary statistic for monetary non-neutrality, except possibly the frequency of price changes. To do so, we compare the model fit of each univariate specification against our more complex multivariate specifications using likelihood ratio tests for each specification against the most saturated specification in Tables 3 and 4, reported in the row labeled "LR test 2." In the FAVAR-based approach, 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. In the narrative-based approach, we cannot reject the null that a model with only frequency or kurtosis over frequency fits the data equally well as a fully saturated model.

Finally, these multivariate results also address the concerns that unaccounted heterogeneity may raise, as discussed in the methodology section: We find that differential exposure to monetary policy shocks does not noticeably drive our main

Table 3
Drivers of Monetary Non-Neutrality Multivariate (FAVAR Approach).

Cross-Sectional Determinants of Sectoral Price Response											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Log Frequency	0.422***	0.429***	0.471***	0.499***	0.533***	0.535***	0.464**	0.476***	0.332***	0.436***	0.453***
	(0.087)	(0.088)	(0.084)	(0.083)	(0.088)	(0.090)	(0.185)	(0.074)	(0.126)	(0.143)	(0.156)
Log Avg. Size	-0.004	0.061	-0.054	-0.028	-0.067	-0.195	-0.224			0.047	-0.099
	(0.149)	(0.196)	(0.207)	(0.210)	(0.216)	(0.227)	(0.224)			(0.218)	(0.240)
Log S.D.		-0.080	0.033	0.018	0.085	0.072	0.094			-0.218	-0.014
		(0.134)	(0.138)	(0.140)	(0.166)	(0.187)	(0.190)			(0.169)	(0.177)
Skewness			0.348	0.385	0.382	0.373	0.376			0.304	0.058
			(0.279)	(0.263)	(0.266)	(0.259)	(0.267)			(0.206)	(0.219)
Log Kurtosis				-0.182	-0.223	-0.220	-0.205	-0.151		-0.149	-0.239
				(0.126)	(0.135)	(0.139)	(0.146)	(0.112)		(0.127)	(0.147)
Log Frac. Pos.					0.333	0.198	0.143			-0.236	0.131
					(0.411)	(0.415)	(0.427)			(0.311)	(0.369)
Log Frac. Small						-0.106	-0.107			-0.150**	-0.157*
						(0.078)	(0.077)			(0.067)	(0.081)
Log S.D. Duration							-0.097		-0.144		
							(0.190)		(0.129)		
Inverse C4 ratio										1.534	2.920
										(2.615)	(2.389)
S.D.(e_k)										-0.612	3.591
										(10.892)	(12.224)
$\rho(e_k)$										0.462***	0.424***
										(0.115)	(0.114)
Consumption Share										22.484**	21.544*
										(10.991)	(12.867)
First-order Outdegree										-0.135*	-0.152**
										(0.071)	(0.075)
Liquidity Ratio											0.635
											(0.441)
$\frac{\text{COGS}}{\text{Sales}}$											-0.004
											(0.311)
$\frac{\text{Inventory}}{\text{Sales}}$											-0.133
											(0.126)
constant	-0.974*	-0.992*	-0.935*	-0.610	-0.233	-0.950	-0.970	-0.652**	-0.852***	-1.625*	-1.223
	(0.545)	(0.544)	(0.552)	(0.561)	(0.711)	(0.835)	(0.834)	(0.265)	(0.180)	(0.933)	(0.960)
R^2	0.304	0.319	0.337	0.345	0.353	0.347	0.349	0.320	0.320	0.539	0.555
NAICS 3 FE	X	X	X	X	X	X	X	X	X	X	X
N	148	148	148	148	148	146	146	148	148	128	107

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: $log(\gamma_{k,h}) = a_h + \alpha_{j,h} + \beta_h' M_k + \epsilon_{k,h}$ where $log(\gamma_{k,h})$ is the predicted 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 sector-level pricing or non-pricing moments: frequency, kurtosis, the ratio of the two statistics, average absolute size of price changes, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, skewness, and standard deviation of price duration, or the full set of pricing moments. Non-pricing moments include the four-firm concentration ratio, the sectoral consumption share, first-order outdegree, liquidity ratio, ratio of cost of goods sold to sales, inventory-to-sales ratio, volatility of sector-level shocks, and the autocorrelation of sector-level shocks. $\alpha_{j,h}$ denotes three-digit NAICS-horizon industry j fixed effects, 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.

results. On the one hand, inclusion of succesively more detailed fixed effects – which account for systematic unobserved sectoral differences in the transmission of shocks – does not affect our main results as seen in Table B.13. The table shows the robustness of price change frequency as we saturate the regression with more detailed sector fixed effects. As we make fixed effects more granular, from two-digit NAICS to four-digit NAICS, increasing the number from 3 to 42, our main finding continues to hold, price change frequency remains stable and significant. Non-pricing moments tend to not have a consistent significant effect. On the other hand, the inclusion of non-pricing moments also explicitly proxies for other channels of heterogeneous transmission of monetary policy but leaves our main results unchanged.

3.2.2. Firm-Level regression results

Our main findings also emerge robustly from our firm-level regressions. These specifications use Romer and Romer shocks and four-quarter ahead 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.

This firm-level exercise includes as pricing moments the frequency, kurtosis, the ratio of kurtosis over frequency, the standard deviation, and the average absolute size of price changes as moments of interest. It also includes two measures of synchronization of price adjustment: First, the estimated firm-specific elasticity of the probability of a change in the firm producer-price index to its four-digit NAICS inflation rate; second, as a measure of seasonal synchronization, the estimated

Table 4
Drivers of Monetary Non-Neutrality Multivariate (Romer-Romer Approach).

Cross-Sectional Determinants of Sectoral Price Response										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Frequency	9.713***	9.744***	9.956***	9.971***	9.935***	10.942***	7.336**	5.764**	7.830**	10.425***
	(2.540)	(2.570)	(2.570)	(2.546)	(2.576)	(2.836)	(2.993)	(2.599)	(3.040)	(3.371)
Kurtosis	-0.052	-0.048	-0.072	-0.076	-0.075	-0.113	-0.121		-0.140	-0.170
	(0.104)	(0.114)	(0.115)	(0.118)	(0.118)	(0.124)	(0.130)		(0.145)	(0.133)
Avg. Size		1.538	-5.463	-3.966	-4.058	-4.455	-3.307		-12.113	-5.616
		(14.213)	(15.723)	(18.371)	(18.450)	(18.224)	(18.450)		(30.777)	(27.744)
S.D.			8.706	8.691	8.841	14.544	18.575		13.152	5.728
			(13.369)	(13.356)	(13.379)	(15.103)	(15.304)		(22.757)	(20.084)
Frac. Small				0.787	0.820	2.838	2.190		0.950	6.391
				(5.448)	(5.408)	(6.055)	(5.953)		(7.332)	(5.348)
Skewness					-0.216	-0.408	0.283		-1.444	-2.003
					(1.206)	(1.179)	(1.187)		(1.557)	(1.489)
Frac. Pos.						4.970	4.447		3.763	2.132
						(4.063)	(3.973)		(5.270)	(4.952)
S.D. Duration							-0.212***	-0.194***		
							(0.079)	(0.074)		
Inverse C4 ratio									0.474	22.484
									(17.833)	(13.692)
$S.D.(e_k)$									74.052	44.205
									(48.597)	(67.056)
$\rho(e_k)$									1.665**	0.759
									(0.730)	(0.724)
Consumption Share									41.695	63.003
									(57.853)	(63.883)
First-order Outdegree									0.134	-0.137
									(0.330)	(0.312)
Liquidity Ratio										-0.064
										(2.746)
$\frac{COGS}{Sales}$										2.868*
										(1.566)
$\frac{Inventory}{Sales}$										-1.159
										(0.922)
constant	2.693*	2.558	2.403	2.220	2.221	-1.275	1.282	4.928***	-0.929	-2.524
	(1.393)	(1.970)	(2.019)	(2.139)	(2.147)	(4.268)	(4.466)	(1.672)	(5.246)	(4.264)
R^2	0.255	0.255	0.257	0.257	0.258	0.260	0.289	0.277	0.332	0.414
NAICS 3 FE	X	X	X	X	X	X	X	X	X	X
N	154	154	154	154	154	154	154	154	135	112

Note: This table uses regression analysis at the sector-level to test the informativeness of pricing moments and non-pricing moments for monetary non-neutrality based on the Romer and Romer identification. We estimate the following specification: $\gamma_{k,h} = a_h + \alpha_{j,h} + \beta_h' M_k + \epsilon_{k,h}$ where $\gamma_{k,h}$ is the predicted response of the sectoral price level at a horizon h of 48 months after the Romer and Romer monetary shock. M_k contains one of our sector-level pricing or non-pricing moments: frequency, kurtosis, the ratio of the two statistics, average absolute size of price changes, standard deviation of price changes, fraction of small price changes, fraction of positive price changes, skewness, and standard deviation of price duration, or the full set of pricing moments. Non-pricing moments include the four-firm concentration ratio, the sectoral consumption share, first-order outdegree, liquidity ratio, ratio of cost of goods sold to sales, inventory-to-sales ratio, volatility of sector-level shocks, and the autocorrelation of sector-level shocks. α_j denotes three-digit NAICS industry j fixed effects, included in all specifications. Robust standard errors in parentheses. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

elasticity of the probability of a change in the firm producer-price index to a firm-specific first-quarter indicator. Firm-level non-pricing moments include the firm liquidity ratio, the ratio of cost of goods sold to sales and the inventory-sales ratio. Additional controls for the first-stage firm-level regression are the current and two lags of the unemployment rate, the log of industrial production, a commodity price index, the log of aggregate producer price index, two lags of the Romer and Romer shock, and two lags of the federal funds rate. Our specifications include firm-level fixed effects in the first stage, corresponding to Eq. 2 above, and three-digit NAICS fixed effects α_j in the second stage, corresponding to Eq. 3 above, to capture any common factors across broad industries.

Consistent with the results from the previous sector and aggregate analyses, the results from the univariate firm-level regressions show that frequency and the ratio of kurtosis over frequency bear a statistically significant relationship with monetary non-neutrality. None of the other pricing moments do: The relationships associated with the standard deviation of price changes, the average absolute size of price changes and the measures of synchronization are not statistically significantly different from 0. While the ratio of kurtosis over frequency has a positive and significant sign as predicted by theory, a bivariate setting 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. The fully saturated multivariate specification with all pricing and non-pricing moments confirms our main finding: Only frequency again

Table 5
Firm-Level Drivers of Monetary Non-Neutrality (Romer and Romer Approach).

Cross-Sectional Determinants of Firm-Level Sales Responses												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Frequency	-5.601***							-5.948***	-6.081***	-5.762**	-5.833**	-6.195***
	(2.020)							(2.034)	(2.045)	(2.382)	(2.412)	(2.112)
$\frac{\text{Kurtosis}}{\text{Frequency}}$		0.015***										
		(0.005)										
Kurtosis			0.121					0.161	0.124	0.104	0.109	0.127
			(0.121)					(0.120)	(0.125)	(0.138)	(0.137)	(0.126)
Avg. Size				-17.456					-18.552	-19.749	-20.053	-18.233
				(15.995)					(25.249)	(26.517)	(26.388)	(25.322)
S.D.					-6.642				1.184	4.871	5.065	1.544
					(8.561)				(13.115)	(13.426)	(13.288)	(13.080)
Synchronization						-0.004				-0.004		
						(0.008)				(0.008)		
Seasonality Synchronization							-1.337				-1.392	
							(1.283)				(1.283)	
Liquidity Ratio										0.297	0.463	1.030
										(4.598)	(4.631)	(4.105)
$\frac{\text{COGS}}{\text{Sales}}$										2.943	2.681	0.284
										(3.920)	(3.911)	(3.677)
$\frac{\text{Inventory}}{\text{Sales}}$										-1.525	-1.418	-1.035
										(1.683)	(1.692)	(1.547)
constant	7.105***	4.288***	4.026***	5.808***	5.573***	4.404***	3.908***	6.806***	8.287***	5.907	5.519	8.095**
	(0.984)	(0.030)	(0.351)	(1.312)	(1.541)	(0.052)	(0.450)	(1.002)	(1.943)	(3.867)	(3.852)	(3.504)
R^2	0.011	0.010	0.001	0.001	0.000	0.001	0.001	0.012	0.017	0.024	0.024	0.031
adj. R^2	0.008	0.008	-0.002	-0.002	-0.003	-0.003	-0.002	0.007	0.006	-0.002	-0.003	0.012
BIC	2586.495	2586.709	2590.345	2590.203	2590.547	2125.620	2125.501	2591.957	2602.121	2158.467	2158.590	2614.528
Log-Likelihood	-1287.323	-1287.430	-1289.248	-1289.177	-1289.349	-1057.083	-1057.024	-1287.092	-1286.250	-1053.463	-1053.524	-1283.567
LR test 1	0.46		4.31									
	(0.4965)		(0.0378)									
LR test 2	7.51	5.19	11.36	11.22	11.56	7.24	7.00					
	(0.2760)	(0.3934)	(0.0778)	(0.0818)	(0.0724)	(0.4043)	(0.4291)					
δ	-0.10575	0.01352	0.08199	-0.24892	-0.03280	-0.07666	0.15746					
$\delta(R^2_{\max} = 0.8)$	-0.13268	0.01697	0.10329	-0.31334	-0.04128	-0.09638	0.19798					
NAICS 3 FE	X	X	X	X	X	X	X	X	X	X	X	X
N	374	374	374	374	374	307	307	374	374	307	307	374

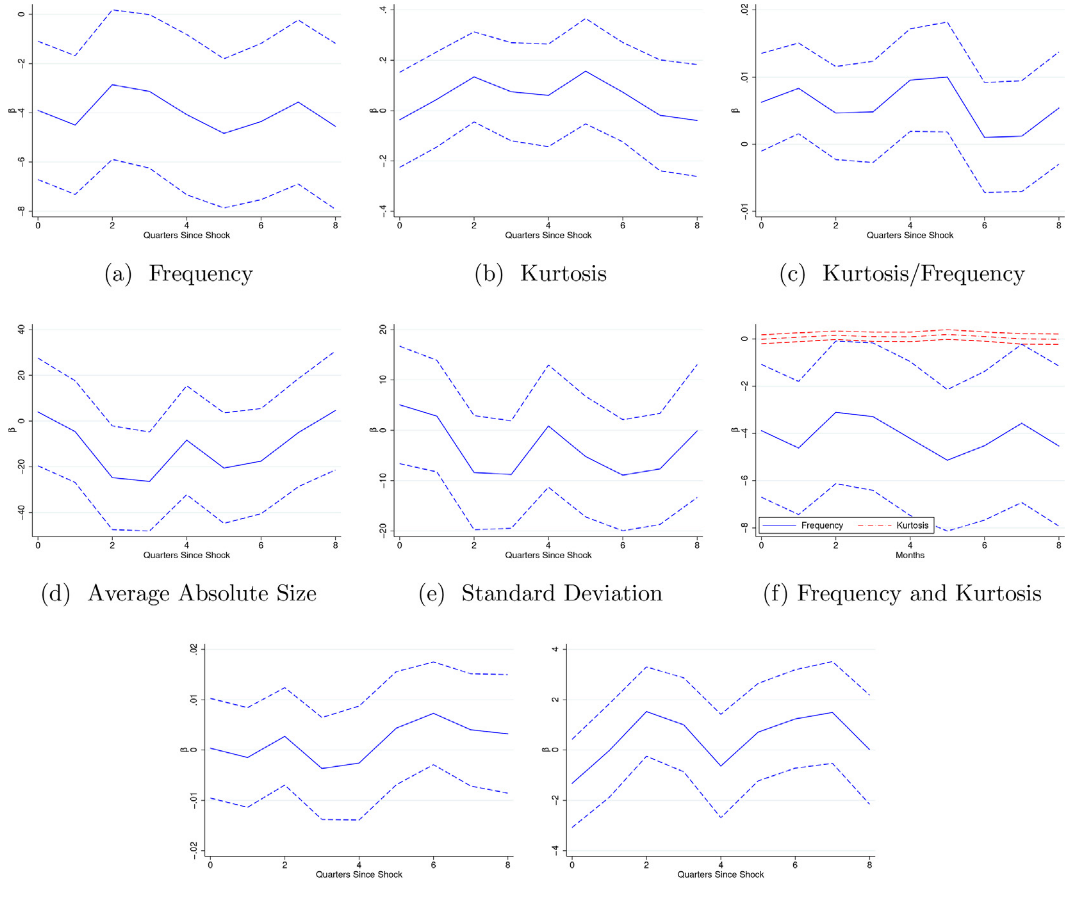
Note: This table uses regression analysis at the firm-level to test the informativeness of pricing moments and non-pricing moments for monetary non-neutrality based on the Romer and Romer identification. We estimate the following specification: $\gamma_{j,h} = a_h + \alpha_{k,h} + \beta_h' M_j + \epsilon_{k,h}$ where $\gamma_{j,h}$ is the predicted response of real sales for firm j at a 4-quarter horizon h after the Romer and Romer shock. M_j contains our firm-level pricing or non-pricing moments: frequency, kurtosis, the ratio of the two statistics, standard deviation of price changes, the average absolute size of price changes, either of two measure of price-change synchronization, or multiple moments. Non-pricing moments include the liquidity ratio, ratio of cost of goods sold to sales, and inventory-to-sales ratio. $\alpha_{k,h}$ denotes three-digit NAICS industry k fixed effects, included in all specifications. Log likelihood ratio tests and measures of fit are computed excluding industry fixed effects and robust standard errors. LR test 1 compares (1) and (3) against (8) while LR test 2 compares (1) through (5) against (12), and (6) and (7) against (10) and (11) for sample size consistency. 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 tests compare (1) through (5) against (12), and (6) and (7) against (10) and (11) for sample size consistency. Robust standard errors in parentheses. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

bears a statistically significant sign. Table 5 summarizes the regression results while Fig. 3 plots the full impulse response for each specification.[8]

In terms of informativeness, we observe the same patterns in the univariate firm-level specifications as in the sectoral regressions. The explanatory power (R^2) of the frequency of price changes is the highest among the pricing moments, though much lower than in the sector-level regressions. The reason for the latter finding lies in the higher level of idiosyncratic noise at the firm-level. Inclusion of three-digit NAICS fixed effects, which partially capture such noise, leads to an R^2 of 18% validating this conclusion. Considering log likelihood and BIC information criteria tells the same story except for the measures of synchronization. There, the criteria come out mechanically more favorable due to a smaller sample size. At the same time, according to the log-likelihood ratio tests, we cannot reject the null hypothesis that frequency-based moments contain the same information as the fully saturated model. This result is in line with the results from the narrative sector-level approach. A new result in the firm-level context is that measures of synchronization, a frequency-related moment, also cannot be rejected to contain as much information as the fully saturated model.

Taken together, these findings suggest for the modeling of price setting and monetary non-neutrality that timing related pricing moments are generally most informative about monetary non-neutrality. The firm-specific results, in addition to the above sector-level results, also suggest that a focus on synchronization may be an empirically relevant modeling direction, such as in Bonomo et al. (2021).

[8] In the Appendix, we show that these results are robust to a horizon of 8 quarters after the shock in Table B.14, and to using the high-frequency identified shocks of Nakamura and Steinsson (2018) as shown in Table B.15 and Fig. B.11. Appendix Fig. B.6 also shows that the unconditional sales response to a expansionary monetary shock is indeed expansionary.



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

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

(g) Synchronization (h) Seasonal Synchronization

Fig. 3. Romer and Romer Monetary Policy Shock Firm-Level Impulse Responses. Note: In the above panels, we plot the respectively estimated coefficients β_h from the following specification: $\gamma_{j,h} = a_h + \alpha_{k,h} + \beta_h' M_j + \epsilon_{k,h}$ where $\gamma_{j,h}$ is the predicted response of real sales for firm j at a h-quarter horizon after the Romer and Romer shock. M_j contains one of our firm-level pricing moments: frequency, kurtosis, the ratio of the two statistics, standard deviation of price changes, the average absolute size of price changes, or one of two measures of price-change synchronization. $\alpha_{k,h}$ denotes three-digit NAICS industry k fixed effects, included in all specifications. Robust standard errors in parentheses. *** Significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Adding non-pricing moments does not change these univariate firm-level conclusions, except that their inclusion more than doubles overall predictive power. This finding reinforces an important lesson of our analysis: Pricing moments individually in our linear empirical setup do not capture the majority of variation in response to a monetary shock. Moreover, they are not the only informative moments that explain the response of key variables of interest to monetary policy shocks.

3.3. Robustness

This section presents additional robustness exercises and 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. The correlation of pricing moments between 1998 to 2003 and 2004 to 2005 at the sectoral level is quite high. It ranges between 0.39 for the average absolute 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. Table B.7 shows these correlations. Moreover, Fig. B.12 in the Appendix illustrates that pricing moments and the ordering across industries are remarkably stable over time.

Second, our aggregate and detailed regression results appear quite robust when we apply different trimming methods for small and large price changes.[9] 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 B.16 in the Appendix presents the aggregate

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

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. Different trimming methods for small and large price changes for kurtosis in the detailed regression approach are shown in Table B.17. The table shows very small differences in the coefficients between different trimming methodologies. Frequency is robustly informative. Moreover, 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 implement such an approach, we follow Gorodnichenko and Weber (2016) in our detailed regression approach and split our sample into an early and a late time period of approximately equal size for each sector. 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: The frequency of price changes is always significant, across univariate, bivariate, and multivariate settings. The ratio of kurtosis over frequency is insignificant in all multivariate specifications. The specific results are shown in Table B.20 for the univariate setting, and in Table B.21 for the multivariate case.

Lastly, we show that the results are robust to an alternative measure of monetary non-neutrality, as well as taking into account product substitution or seasonality. In terms of monetary non-neutrality, we use a specification where the measure of monetary non-neutrality is cumulative, denoted by CIR^P. However, in practice, we find CIR^P and our measure are highly correlated, with a correlation coefficient of 0.9925. This high correlation explains why the baseline result is robust to using CIR^P. A comparison of Table 3 with Table B.22 using CIR^P illustrates this robustness. In terms of taking into account potential product substitution or seasonality effects, we find no difference in terms of our main regression results. Appendix B contains further details while Appendix Tables B.18 and B.19 show these results.

4. Model analysis

One of our main empirical insights lies in the robust relationship between the frequency of prices changes and monetary non-neutrality, but the lack of a clear relationship between other pricing moments such as kurtosis of price changes and monetary non-neutrality. This section draws on a multi-sector menu cost model to illustrate how such a result may readily arise in a theoretical context. The main mechanism is simple: Sectors can differ in their pricing technologies which can induce a composition effect in the relationship between a pricing moment and monetary non-neutrality across sectors.[10] If the associated relationship between a moment and monetary non-neutrality has opposite signs across sectors, then the implied average relationship may be ambiguous, as in the case of kurtosis. If a relationship, such as for the frequency of price changes, bears the same sign across sectors, then the relationship in the aggregate is not affected by a composition effect.

4.1. Model setup and calibration

Our model is given by a multi-sector menu cost model with two sectors that are subject to sector-specific idiosyncratic productivity shocks as well as an aggregate nominal shock. The model is standard, so we relegate the model details to the appendix and instead focus on how the model's main feature – heterogeneity in pricing technologies – affects the relation between pricing moments and monetary non-neutrality. This heterogeneity consists of one sector using a fixed menu cost technology as in Golosov and Lucas (2007), the other a CalvoPlus random menu cost technology as in Nakamura and Steinsson (2010). As we show, each technology implies a different sign for the relationship between the kurtosis and monetary non-neutrality in the sector featuring that technology, but the same sign for the frequency. Our multi-sector model is stylized in the sense of containing only two sectors. However, a multi-sector model with a large number or a continuum of sectors will yield the same results as long as sectors are identical and only differ in the use of one of the two types of price adjustment technology.

The baseline model is calibrated using two complementary sets of parameters. The first set includes parameters that are common across sectors and for brevity their calibration is shown in the Appendix.[11] The second set of parameters is calibrated to match micro pricing moments from the PPI in our two sectors. For the Golosov-Lucas sector, we target the lowest quartiles of frequency and kurtosis in the data, 0.056, and 2.5. These moments pin down the parameters for the menu cost and the variance of idiosyncratic shocks. The Golosov-Lucas model has difficulty generating high values of kurtosis, as Midrigan (2011) and Karadi and Reiff (2019) have shown. For this reason, we choose to calibrate the Golosov-Lucas sector to the set of lowest kurtosis sectors in the data. For the random menu cost sector, we analogously target the highest quartiles of frequency and kurtosis in the data, 0.225 and 4.7, and the average absolute size of price changes in the highest quartile of kurtosis, 0.059. These target values pin down the menu cost, the variance of idiosyncratic shocks, and the probability of a free price change.

[10] In pioneering work, Coibion and Gorodnichenko (2011) use aggregate data to estimate the incidence of 4 different pricing technologies and implications for the role of monetary policy. We re-emphasize the importance of this approach in the context of relating pricing moments and monetary non-neutrality.

[11] These parameters include the discount rate, the elasticity of substitution between differentiated goods, and the trend growth and volatility of the aggregate nominal shock process.

Table 6
Multi-Sector Model Calibration and Parameter Values.

Moment	Data	Baseline	Low Kurtosis	High Frequency
			Golosov-Lucas Sector	
Frequency	0.056	**0.056**	**0.056**	**0.073**
Fraction Positive	0.68	0.50	0.51	0.51
Average Absolute Size	0.10	0.046	0.068	0.037
Fraction Small	0.06	0.00	0.00	0.00
Kurtosis	2.5	**2.5**	**1.7**	**2.5**
			Random Menu Cost Sector	
Frequency	0.225	**0.225**	**0.222**	**0.281**
Fraction Positive	0.62	0.50	0.50	0.50
Average Absolute Size	0.059	**0.059**	**0.059**	**0.058**
Fraction Small	0.14	0.16	0.15	0.16
Kurtosis	4.7	**4.4**	**2.5**	**4.4**
Parameter	**Baseline**	**Low Kurtosis**	**High Frequency**	
		Golosov-Lucas Sector		
χ	0.0195	0.039	0.01	
σ_z	0.0097	0.017	0.0089	
ρ_z	1.0	1.0	1.0	
α	0.0	0.0	0.0	
		Random Menu Cost Sector		
χ	0.4	0.047	0.32	
σ_z	0.055	0.0415	0.058	
ρ_z	1.0	1.0	1.0	
α	0.22	0.16	0.28	
		Common Parameters		
$\beta = (0.96)^{\frac{1}{12}}$; $\theta = 6.8$; μ =0.002; σ =0.0037				

Note: The table shows the model steady-state moments that are internally targeted for each economy, and the corresponding parameter values. In terms of parameter values, χ denotes the menu cost of adjusting prices, σ_z is the standard deviation of log firm productivity following an AR(1) process, ρ_z the persistence of idiosyncratic probability shocks, and α is the probability of a free price change. Common parameters are the discount rate β, the elasticity of substitution θ; and the growth rate and standard deviation of nominal aggregate spending μ and σ. We compute steady-state moments as the long-run ergodic means based on time series simulations over 3000 periods. Data moments are calculated from monthly PPI from 1998 to 2005. The Golosov-Lucas sector is calibrated to the first sectoral quartile of price change frequency and kurtosis, and the average values in the first quartile of price change frequency for the other three moments. The random menu cost sector is calibrated to the fourth sectoral quartile of price change frequency and kurtosis, and the average values in the fourth quartile of kurtosis for the other three moments. The fraction of small price changes is defined as those less than 1 percent in absolute value. Boldface moments are targeted.

We compute the corresponding model moments by simulating one long time series for prices of 3000 periods with a draw of idiosyncratic and monetary shocks every period, and calculate the average moments over time for the ergodic steady state. In the Golosov-Lucas sector we choose a menu cost of 0.0195 and standard deviation of idiosyncratic shocks of 0.0097. In the random menu cost sector we choose a menu cost of 0.4, a standard deviation of idiosyncratic shock of 0.055, and the probability of a free price change 0.22. Table 6 summarizes the key moments in the two sets and sectors as well as corresponding parameter values. For full details of the model, see Appendix A.

4.2. Insights from model simulation

Our main theoretical insight emerges from two simple simulation exercises: First, we lower steady-state kurtosis in both sectors while holding frequency constant. Second, we increase steady-state frequency in both sectors while holding kurtosis constant. In the first case with low kurtosis, this requires that we raise both the menu cost parameter to 0.039 and the volatility of idiosyncratic shocks to 0.055 in the Golosov-Lucas sector, while lowering the menu cost parameter to 0.047, volatility of idiosyncratic shocks to 0.0415, and probability of a free price change to 0.16 in the random menu cost sector. In the second case with high frequency, this requires that we lower the menu cost to 0.01 and volatility of idiosyncratic shocks to 0.0089 in the Golosov-Lucas sector, while decreasing the menu cost parameter to 0.32, and increasing the probability of a free price change to 0.28 and volatility of idiosyncratic shocks to 0.058 in the random menu cost sector. The bottom panel of Table 6 summarizes the corresponding parameter choices.

Given both calibrations, we generate price and consumption impulse responses to an expansionary monetary shock of size 0.002, both at the sector and the aggregate levels as in Bloom (2009). We compare the impulse responses for each variation in the pricing moment to those we obtain from the baseline calibration. This comparison illustrates how pricing moments relate to monetary non-neutrality.

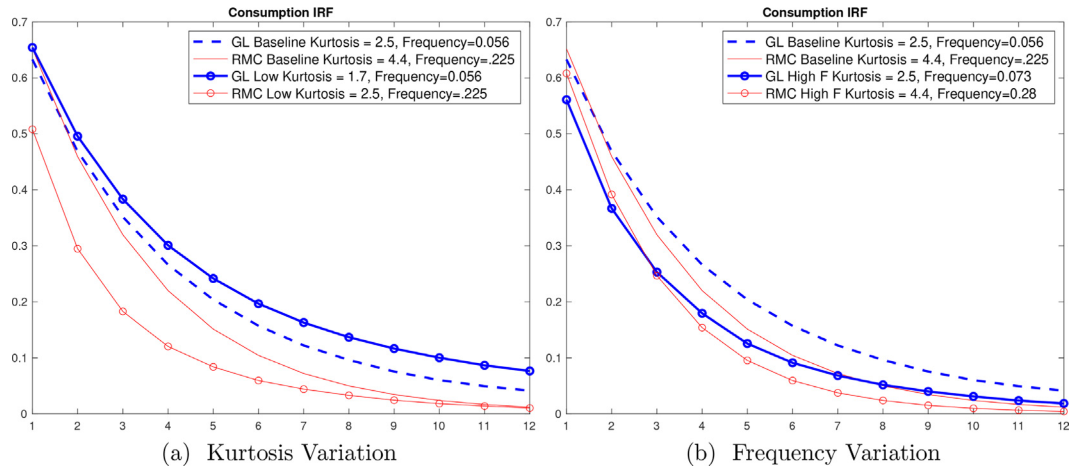


Fig. 4. Consumption Impulse Responses. Note: Impulse responses of consumption to a one-time permanent increase in log nominal output of size 0.002 for different calibrations of our baseline monthly multi-sector model are shown. The left panel shows the sectoral consumption responses when kurtosis is lowered in both the Golosov-Lucas and random menu cost sectors. The right panel shows the sectoral consumption responses when frequency is increased in both the Golosov-Lucas and random menu cost sectors. 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 2500 economies.

A clear result emerges when we make this comparison: The relationship between frequency of price changes and monetary non-neutrality in our multi-sector model is robustly negative, for each sector and at the aggregate level. The relationship between kurtosis of price changes and monetary non-neutrality, by contrast, has opposite signs for the two sectors and as a result, turns out to be effectively zero at the aggregate level: a composition effect is induced.

The composition effect is captured visually in Fig. 4: The left panel shows the consumption responses following a monetary shock when we vary kurtosis rather than the frequency, which is shown in the right panel. The solid red line and dashed blue line represent the impulse responses for our baseline calibration; relative to those, circled lines represent the responses for lower kurtosis (as well as higher frequency). We see that a decrease in kurtosis is associated with higher monetary non-neutrality in the Golosov-Lucas sector (blue lines), but lower monetary non-neutrality in the random menu cost sector (red lines).

As a result of such opposite sectoral responses for variation in kurtosis, a composition effect arises and the model-implied aggregate consumption responses are unchanged for variations in kurtosis: The cumulative aggregate consumption responses are numerically insignificantly different from one another. Variations in frequency (right panel), by contrast, reinforce each other. Now, model-implied aggregate responses of consumption differ markedly from the baseline. In fact, the cumulative aggregate response for consumption falls by 27 percent as frequency increases from 14 to 18 percent. An analogous result holds for prices as shown in Fig. A.5 in Appendix A.

These model insights relate directly to our empirical analysis by showing that differences in sectoral impulse responses can be combined in a multi-sector model to match our empirical results. These differences go back to differences in pricing technologies. At the same time, kurtosis varies in the Golosov-Lucas sector in our model. How is it possible to obtain such variation given the result in Alvarez et al. (2016) that kurtosis is always one in that setup? The reason is that our setup differs from Alvarez et al. (2016), for example by allowing for aggregate risk. By contrast, the theoretical setup in Alvarez et al. (2016) only features idiosyncratic shocks. The relative importance of aggregate risk, compared to idiosyncratic shocks, can change the shape of the ergodic steady-state distribution and therefore kurtosis. Nonetheless, the intuition how deviations in assumptions can come to matter is of interest. We present a detailed explanation and intuition in Appendix C which highlights the relative importance of aggregate risk.

5. 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. Other pricing moments are insignificant, or can become insignificant when non-pricing moments are included. No single pricing moment explains the majority of the variation in monetary non-neutrality in a linear empirical setting. Non-pricing moments contain additional information on monetary non-neutrality, however do not consistently bear significance.

A simple insight from a multi-sector model can rationalize our main finding: Sectoral differences in pricing technologies can lead to a composition effect that “averages” opposite signs in the sectoral relationships between a pricing moment and monetary non-neutrality. As a result, the average relation across sectors may be ambiguous in terms of sign, such as in the case of kurtosis of price changes. Same-signed relations are unaffected by averaging across sectors, such as for the frequency of price changes.

Data availability

The data that has been used is confidential.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2023.06.004.

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