An Empirical Test of the Sufficient Statistic Result for Monetary Shocks

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Abstract

We empirically test the sufficient statistic result of Alvarez, Lippi and Oskolkov (2020). This theoretical result predicts that the cumulative effect of a monetary shock is summarized by the ratio of two steady state moments: frequency and kurtosis of price changes. Our strategy consists of three steps. In the first step, we employ a Factor Augmented VAR to estimate the response of different sectors to a monetary shock. In the second step, using microdata, we compute the sectorial frequency and the kurtosis of price changes. In the third step, we relate the measures constructed in the previous two steps and directly test the sufficient statistic result. Our findings show that the sufficient statistic result cannot be rejected, i.e. we find statistical statistical support to the fact that frequency and kurtosis are relevant predictors of the propagation of monetary shocks. Moreover, we find that other moments of the price change distribution, like the mean and skewness, are not statistically significant in explaining the propagation of monetary shocks.

1 Introduction

A central question in macroeconomics is how monetary policy affects the real economy. The literature agrees that monetary policy has a real effect in the short run but not in the long run. A well-known possible explanation for the real effects of the monetary policy is that prices are sticky; stickiness means that firms must pay a cost to adjust prices, which explains why prices do not change immediately after a monetary shock. For example, menu cost models or costly information models formally rationalize price stickiness.

For a large class of sticky-price models, Alvarez *et al.* (2020) analytically show that the cumulative impulse response to a once-and-for-all monetary shock is completely pinned down by two steady state statistics: the frequency and the kurtosis of price adjustments (henceforth, sufficient statistic result). Frequency represents the average time elapsed between price changes, higher frequency implies more price changes in average and, thus, less real monetary effects. Kurtosis, instead represents the so called selection effect of Golosov & Lucas Jr (2007): it is important to take in account which firms adjust their prices. When a firm adjusts its price for the first time right after the shock, it completely internalizes the shock effects and, thus, the shock effects vanishes for that firm. This result is important for two main reasons: **(I)** underlines the importance of the kurtosis of price changes in explaining the propagation of monetary shocks and **(II)** provide a general and clear method to compare the effect of a monetary shocks in different and various sticky-price models.

The sufficient statistic result applies to a large class of sticky-price models such as the Calvo (1983) model, the Golosov & Lucas Jr (2007) model, the calvo-plus model developed by Nakamura & Steinsson (2010), the random menu cost problem of Dotsey & Wolman (2020) and the costly information model by

Reis (2006). More generally, the sufficient statistic result holds for any model where firms' price behavior can be described by a generalized hazard function, which relates the firm's probability to adjust its price to its state, like the markup deviation from the desired level. Indeed, for example, in the canonical Calvo model, the pricing behavior of firms can be described by a constant hazard function with unbounded state or, in the Golosov & Lucas Jr (2007) model, by a bounded state with a zero hazard in the interior and with an "infinite hazard" at the thresholds. However, the notion of the generalized hazard function describes the firms' behavior for a broader class of models respect to the ones listed above. Hence, the Alvarez *et al.* (2020)'s sufficient statistic result holds rather generally in a broad set of models, well-studied and known in the literature of sticky-price models. The sufficient statistic result holds under some other assumptions, for example small inflation, no strategic complementarities and no temporary price changes. The aim of this article is to explore the empirical validity of this result. Our contribution is relevant because, to the best of my knowledge, this is the first empirical test of the above-mentioned results.

Our empirical strategy to test the sufficient statistic result consists of three different steps. In the first step, we exploit a Factor Augmented Vector Autoregression (FAVAR), first developed by Bernanke *et al.* (2005) and by Boivin *et al.* (2009), to estimate the effects of a monetary shock and to construct summary measures of the shock effects. In the second step, using microdata, we compute cross sectional moments, e.g. kurtosis and frequency of the price adjustments. In the third step we relate the summary measures of the shock effects, estimated in the first step, to the cross sectional moments, estimated in the second step. This last step directly tests the sufficient statistic results.

We find evidence for the sufficient statistic result: kurtosis and frequency both have a central role in explaining the propagation of monetary shocks. We find that an increase in the ratio of the kurtosis and the frequency reduces the response of prices, implying that prices are stickier, as predicted by the sufficient statistic result. Moreover, disentangling the effect of frequency and kurtosis, we find that an increase in the frequency or a reduction in the kurtosis implies that prices become more responsive to a monetary shock. Hence, the stickiness of prices decreases in the frequency and increases in the kurtosis, as the sufficient statistic result states. Moreover, in line with the sufficient statistic result, we find that a variation in the kurtosis or in the frequency of price changes has the same effect, in magnitude, in describing the propagation of monetary shocks.

Our empirical strategy is strictly related to two different strands of literature. On one hand, our work is strictly connected with the VAR literature, originally developed by Sims (1980) and Christiano *et al.* (1999) to estimate the effects of a monetary shocks. The FAVAR, estimated in our first step, belongs to this strand of literature: indeed, it is built on the VAR theoretical setup. However, the FAVAR model assumes that some of the variables that drives the underlying economy are not observable, the so called factors. Once the factors are estimated, the FAVAR can be treated as a VAR including observable variables and estimated factors. Moreover, the FAVAR can incorporate any number of time series in his specification, overcoming the problem of sparse information set, and it is able to estimate the impulse response function (IRF) to a monetary shock of any of the time series included in the model. On the other hand, our work is related to the cross sectional analysis literature, that aims to use microdata to infer macro patterns. For example, Klenow & Malin (2010) summarize ten stylized facts for price setting to be incorporate in models with stickiness or Cavallo (2018) compares scraped data and scanner data to discuss important feature of price stickiness.

2 Sufficient Statistic for Monetary Shocks

This section discusses the sufficient statistic result of Alvarez *et al.* (2020), which characterizes the real output effect of a monetary shock with a summary statistic. Indeed, the cumulative output generated by a small and once-and-for-all monetary shock is represented by the output's cumulative impulse response function, the area under the impulse response function. Alvarez *et al.* (2020) analytically show that, for the large class of sticky-price models in which the firm behavior can represented by a generalized hazard function, the output cumulative impulse response, $\mathcal{M}(\delta)$, to a small and once-and-for-all monetary shock, δ, up to a second order approximation, is given by the ratio of the kurtosis of the steady state distribution of price changes, $kurto$, over the frequency of price adjustment, $freq$, times sis, i.e.:

$$\mathcal{M}(\delta) = \frac{1}{6}\frac{kurto}{freq}\delta + o\left(\delta^2\right) \tag{1}$$

Henceforth, we will refer to this as sufficient statistic result or kurtosis result, since this result underlines the importance of the kurtosis in explaining monetary shock effects. The relevance of the frequency of price adjustments has been stressed by the literature since it represents the average time elapsed between price changes. Thus, higher frequency implies more price changes in average and, thus, less effect of monetary shocks. Kurtosis, instead represents the so called selection effect of Golosov & Lucas Jr (2007): it is important to take in account which firms adjust their prices because, for a given firm, the effect of a monetary shock completely vanishes after its first adjustment.

Consider the following setup to understand the mechanism behind the sufficient statistic result. Firms want to minimize the price gap, defined as the deviation of the actual price from to the optimal price, the one that maximize the firms' profits. It is optimal to set the price gap to zero at every point in time. However, the price gap evolves accordingly to a Brownian motion without drift and firms face a cost to change their prices. Therefore, firms do not continuously adjust their prices. In ”equilibrium” the economy is characterized by a distribution of the firms’ price gap; some firms will have a positive price gap, others a negative one. Moreover, in each period of time some firms adjust their price and they return to the optimal price gap, zero. When a monetary shock occurs, the distribution of price gaps is shifted. Hence, if the distribution does not return to the original level immediately, there is a real effect because firms must always satisfy the demand at the given price level. Furthermore, the real effect of the monetary shock depends on the time that it takes for the distribution of price gaps to return to its original level. This depends on how fast, on average, firms change their prices, the frequency, and on which firms have already adjusted their prices, the kurtosis of the distribution of price changes. Precisely, the kurtosis captures the proportion of big and small price changes relatively to medium price changes. A higher kurtosis leads to higher real effects because some firms some firms wait for a long time before adjusting their prices and when they do so, they display a large price change. Notice that the distribution of price changes is a different object with respect to the distribution of price gaps, the former describes how much the firms’ prices change right after an adjustment.

Equation 1 precisely captures the mechanism described above and it generalizes the result of Alvarez *et al.* (2016). Indeed, equation 1 holds in a much more broad class of models, precisely all the models in which firms’ behavior can be characterized by a non-negative, piece-wise continuous symmetric, with at most finitely many discontinuities hazard function. The hazard function is a function relating the firm’s probability to adjust its price to its state, as for example the deviation of the current markup from the optimal markup, i.e. the price-cost margin that maximizes profits.

Equation 1, however, requires some other assumptions. Firstly, the firm’s behavior depends only on its current state, and not on the behavior/state of the other firms. Thus, in the model there are no general equilibrium effects after the monetary shock realization. However, Alvarez & Lippi (2014) show that given a combination of the general equilibrium setup in Golosov & Lucas Jr (2007) and lack of strategic complementarities, these general equilibrium effects are of second order. Another important assumption is that the firms return to their optimal level when they adjust prices, which, for example, happens in random menu cost models. Another important assumption is that the firm's state evolves according to a Brownian motion without drift, this implies that the inflation must be small in the economic environment under study.

Notice that in the Alvarez *et al.* (2020)'s setup there is a one to one mapping to prices and output: this means that the response of prices to a small and once-and-for-all monetary shock is completely pinned down by the ratio of the kurtosis and frequency of price adjustments. Hence, testing equation 1 using prices or output in the left hand side is the same. Moreover, equation 1 implies that the elasticity of output or price to the ratio of kurtosis and frequency must be equal to one.

3 Empirical Strategy

This section discusses the empirical strategy used to test the sufficient statistic result. Our main hypothesis to test the sufficient statistic result, or equivalently to test equation 1, is that each productive sector inside a specific country[1] responds differently to the same shock. In other words, that the agriculture sector reacts differently than the manufacturing sector to the same monetary shock. Under this assumption, we can test the sufficient statistic result in the following three steps.

In the first step, we employ a Factor Augmented VAR (FAVAR) to estimate the impulse response function

[1] In our application, the country under analysis is France.

(IRF) of each sector to a monetary shock. Indeed, the FAVAR model is able to estimate the IRFs for any number of time series to a given shock, which is precisely our aim[2]. Once the FAVAR model is estimated, we construct the cumulative impulse response function (CIRF) of each sector, obtained by summing the IRF of each sector up to a certain time horizon, n, e.g. two years. The CIRF is an important and useful measure because it easily describes with one number the effect of a monetary shock.

In the second step, using microdata, we compute the frequency and kurtosis of price adjustments for each sector of interest. In this step, we notice that there are two potential forces of upward bias for the estimates of the kurtosis: heterogeneity and measurement error. Heterogeneity consists in having different goods in the same category/sector; this could potentially bias the estimates of the kurtosis upwards since a mixture of distributions with different variances and the same kurtosis has a larger kurtosis than each subpopulation. On the other hand, measurement error consists in incorrectly imputing big or small price changes when there were none. To reduce the measurement error bias, we remove price changes below 0.1% in absolute value and the top and bottom 1% of the overall distribution of price changes. Measurement error could also potentially bias the estimates of the frequency upward; this potential bias can be solved in the same way as for the kurtosis.

The third step consists in running two different regressions relating the CIRF to the frequency and the kurtosis of price adjustments. The first regression directly tests the sufficient statistic result and it is the following one:

$$CIRF\_n_j = \alpha + \beta * log\left(\frac{kurt_j}{freq_j}\right) + \epsilon_j \tag{reg1}$$

where j represents each sector, $CIRF\_n_j$ is the cumulative IRF calculated in the first step, n indicates the time horizon considered, and $kurt_j$ and $freq_j$ are the measures constructed in the second step. A positive

[2] Appendix 1 provides a detailed description of the FAVAR model and discusses its theoretical framework.

and statistically significant different from zero coefficient implies that the sufficient statistic result holds. According to the theory, the above regression is imposing that a variation in the frequency and a variation in the kurtosis have the same effect in magnitude on the CIRF. However, this could not be the case in the data, and, to recover these differential responses, we estimate the following specification:

$$CIRF\_n_j = \alpha + \beta^f * log\,(freq_j) + \beta^k * log\,(kurt_j) + \epsilon_j \qquad \text{(reg2)}$$

where all the variables are the same as above. First over all, notice that the first regression, reg1, is the second regression, reg2, under the additional restriction that $-\beta^f = \beta^k$. Moreover, reg2 has two important features. On the one hand, reg2 shows whether frequency and kurtosis are both statistically significant in explaining monetary shock effects. A β^k coefficient positive and statistically different from zero provides evidence for the importance of the kurtosis, and a negative β^f coefficient has an analogous interpretation for the frequency. On the other hand, reg2 separately recovers the effects that changes in the kurtosis and frequency have on real output. Moreover, this allows to test whether these effects are equal in magnitude.

4 Data Description

This section describes the three different datasets used in the empirical analysis, the ”time series” dataset and two ”microdata” datasets. The former dataset contains 601 monthly different time series used to estimate the FAVAR, the other two microdata on consumer and production price changes, respectively, used to estimate kurtosis and frequency of price adjustments. All the data were provided by Banque de France.

The ”time series” dataset contains 601 monthly different time series for the period from January 2005 to April 2019. It contains information regarding the macroeconomic situation of the French economy, as for example data on the level of production, consumption expenditure, the general level of prices, the unemployment rate, the quantity of money in the euro area and exchange rates. Moreover, it contains also information regarding disaggregated time series on production, production prices and consumer prices. Precisely, there are 124 sectorial times series for production prices and 195 sectorial time series for industrial production, both disaggregated at four digit level according to the CPF classification; 253 sectorial time series for consumer prices, disaggregated at 4 digits according to che COICOP classification.

One ”microdata” dataset contains data on production price changes for 184 different sectors classified according to the 4 digits NAVE/CPF product classification. The data were collected during the period 1994-2005. The other ”microdata” dataset contains data on consumer price changes for 331 different sectors classified according to the 5 digits COICOP 2016 classification. The sample period is 1994-2019 for most of the products.

5 Results: Production Prices

This section shows the empirical results of the three step strategy developed in section 3, focusing on production prices. Our baseline specification is using production prices instead of consumer prices because **(I)**, according to the Alvarez *et al.* (2020)'s theory, firms are better represented by producers respect to consumers or retailers and **(II)** microdata and timeseries of production prices are both disaggregated at the same level; instead, for consumer prices, microdata are more disaggregated with respect to the time series data. Time series and microdata of production prices are both disaggregated at 4 digit level; instead, for consumer prices, microdata are classified at 5 digits, time series at 4 digits.

5.1 Step one: measuring responses to monetary shocks

Using the time series described in section 4, we estimate a FAVAR with 12 lags, 5 factors and the 3-month Euribor as the observable variable. The 3-month Euribor is considered as the target interest rate of the monetary policy. All the variables are in log differences, except for the 3-month Euribor for which we apply an HP filter with $\phi = 1600$. We use a Cholesky decomposition, ordering the 3-month Euribor last, to estimate the IRFs to a contractionary monetary shock of 25 basis point. In other words, we estimate the IRFs to an increase of the 3-month Euribor of 25 basis point, imposing that the Euribor can contemporaneously respond to the shock and the factors cannot. The last factor can respond after one period to the shock, the second to last after two periods and so on. Notice that, imposing a Cholesky decomposition in this setup does not imply that the IRFs of production prices cannot respond simultaneously to the monetary shock.

Figure 1 reports the estimated IRFs of production price series; vertical axis is in log deviation from the ”steady state”, the level at which the system would be without any perturbation. The blue line (Aggr PPI) represents the aggregate production price series, our most aggregate variable for PPI. This line shows that price index reduces until a certain point from which it recovers towards the original level, this is completely in line with the theory. Dashed red lines represent the IRFs of different sectors disaggregated at the 2-digit level; recall that our production price time series are at 4-digits, thus the dashed red lines are constructed as an average of estimated IRFs. The thick red line is the average of all the dashed red lines. This line has a very similar shape to the blue line, as we should expect. However, notice that the discrepancy of the blue and the thick red line is due to different weights and missing sectors for disaggregated time series (red lines).

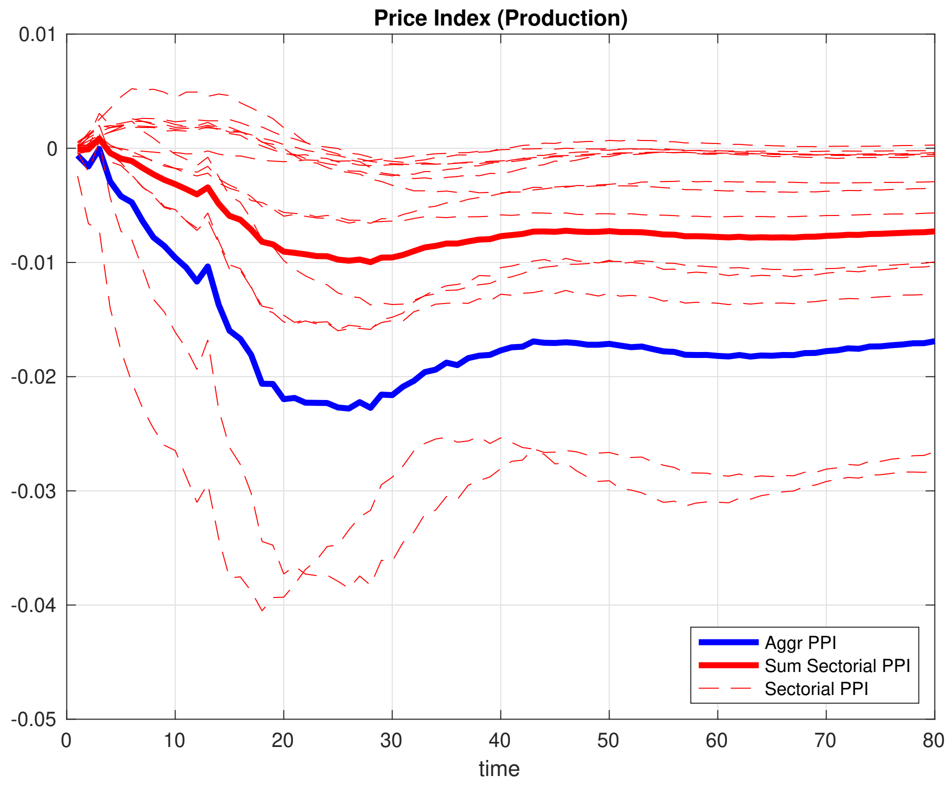

Figure 1: IRFs of PPI to a contractionary monetary shock of 25 bp

Table 1 reports the summary measure of the cumulative impulse response function of production prices (CIRF_PPI_n), constructed as the sum from period zero up to period n of the IRFs, the area under the curve. The CIRF is useful to summary the behavior of the IRF in a concise manner. Indeed, for a given sector, a lower CIRF implies that price reacts more to the shock, thus they are less sticky. We consider different values of n, as for example 24 and 36 months. Table 1 shows the summary statistics of the estimated sectorial CIRF. The mean of the CIRF increases with the time horizon and it is always negative, as predicted by the theory.

Indeed, according to the theory, in aggregate prices must decrease and gradually recover toward they original level after a monetary shock. Table 1 also shows the standard deviation increases with the time horizon, this implies that difference responses in sectors are persistent. According to the sufficient statistic result, the CIRF should be calculated considering an infinite horizon. However, in our case this is not possible since we did not impose any long run restriction in the FAVAR. Moreover, we estimated the FAVAR in difference, thus, our time series are stationary in difference and not in levels. This implies that nothing ensures that the time series return to their original level in the long run after a monetary shock. However, the IRF of each time series must converges to some value, since the time series are stationary in the difference.

Table 1: CIRF of Production prices: Summary measures

	Mean	Std. Dev.	50%	25%	75%	5%	95%
CIRF_PPI_6	-0.00	0.05	0.01	-0.00	0.01	-0.11	0.03
CIRF_PPI_12	-0.03	0.17	0.01	-0.02	0.04	-0.47	0.08
CIRF_PPI_18	-0.07	0.32	0.01	-0.06	0.05	-1.02	0.16
CIRF_PPI_24	-0.13	0.48	0.00	-0.11	0.05	-1.46	0.18
CIRF_PPI_30	-0.20	0.61	-0.03	-0.18	0.04	-1.62	0.24
CIRF_PPI_36	-0.25	0.73	-0.04	-0.26	0.03	-1.73	0.22
Observations	119						

5.2 Step two: measuring cross sectional moments

Using production prices micro data, we calculate the frequency kurtosis, mean and skewness of price changes for each sector. To take into account measurement error, we exclude absolute price changes below 0.1% and the top and bottom 1% of the overall distribution of price changes. Table 2 reports the summary measures of these statistics. The kurtosis and the frequency are interesting because, according to the sufficient statistic result, they are the only two moments that matter in explaining monetary shocks. Instead, the skewness and the mean are helpful in understanding the shape of the distribution of price changes. Frequency has a mean around 19, this means that a given firm in average has a probability of 19% of adjust its price in a given month. On the other hand, kurtosis has a mean of 7.2. Heterogeneity across sectors is captured by the large standard deviation of both frequency and kurtosis. Moreover, the mean of price changes is calculated in log difference and it is positive and around 0.85 with a standard deviation around one. The distribution of price changes in average is symmetric around the mean, given the low value of the skewness.

Table 2: Frequency and kurtosis of Production prices: Summary measures

	Mean	Std. Dev.	50%	25%	75%	5%	95%
freq	18.85	20.91	12.27	8.42	18.69	5.90	90.21
kurto	7.20	3.27	6.56	5.23	8.47	4.04	11.81
mean	0.84	1.01	0.80	0.24	1.50	-0.55	2.33
skewness	0.04	0.64	0.01	-0.34	0.32	-0.90	0.95
Observations	119						

5.3 Step three: testing the sufficient statistic result

In the last step, we relate the measures estimated in the first two steps according to reg1 and reg2. The sufficient statistic result predicts that the ratio of kurtosis and frequency (reg1) should be positive and statistically significant different from zero. Indeed, an higher ratio implies more stickiness, thus prices should react less to the monetary shock. For example, increasing the frequency, and thus reducing the ratio, keeping the kurtosis constant, implies that in average prices change faster and thus they must be less sticky. On the other hand, increasing the kurtosis implies that the selection effect of Golosov & Lucas Jr (2007) is smaller and, thus, prices react less. For these reasons, the sufficient statistic result predicts that the coefficient of the frequency in reg2 should be negative instead the one of kurtosis positive and both statistically significant different from zero.

Table 3 reports the estimates of reg1 and it shows that the coefficient of $log\left(\frac{kurto}{freq}\right)$ increases with the time horizon and it is always positive and statistically significant different from zero. Sectors with an higher ratio are sectors in which prices are more sticky and, thus, they react less to a monetary shock. Table 3 also reports the implied average elasticity, η, of CIRF with respect to $log\left(\frac{kurto}{freq}\right)$, constructed as $\eta = \hat{\beta} * mean\left(log\left(\frac{kurt}{freq}\right)\right)/mean(CIRF\_n)$ where $\hat{\beta}$ is the estimated coefficient of reg1; the elasticity reduces with the time horizon. Equation 1 predicts that the average elasticity must be equal to one, since there is a linear relation between the ratio of the kurtosis and frequency and the cumulative response. For this reason, table 3 reports the results of an F-test under the null that $\eta = 1$. The null cannot be rejected for any time horizon, as shown by the p-value reported in the last row of the table. Hence, this table provides evidence for the sufficient statistic result, given the sign and the significance of the estimated coefficient and given that hypothesis that the elasticity is different from 1 cannot be rejected.

Table 4 shows the estimates of reg2. The coefficient of frequency is always negative and statistically significant, as predicted by the sufficient statistic result. Moreover, it increases in the time horizon. On the other hand, the coefficient of the kurtosis is positive and increases its significance with the time horizon. However, the coefficient of the kurtosis is not statistically significant different from zero for short horizons.

Table 3: Reg1 for Production Prices

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_PPI_6	CIRF_PPI_12	CIRF_PPI_18	CIRF_PPI_24	CIRF_PPI_30	CIRF_PPI_36
$log\left(\frac{kurto}{freq}\right)$	0.0225**	0.0828***	0.173***	0.279***	0.377***	0.460***
	(0.00975)	(0.0301)	(0.0579)	(0.0873)	(0.114)	(0.137)
Constant	0.0126***	0.0335**	0.0553*	0.0680	0.0726	0.0747
	(0.00476)	(0.0149)	(0.0289)	(0.0439)	(0.0575)	(0.0693)
Observations	119	119	119	119	119	119
R^2	0.111	0.156	0.187	0.219	0.242	0.255
η	4.770	2.339	1.831	1.536	1.385	1.308
F-test η	3.328	2.474	1.837	1.241	0.845	0.627
P-val F-test	0.0707	0.118	0.178	0.268	0.360	0.430

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: η is the average elasticity constructed as $\eta = \hat{\beta} * mean\left(log\left(\frac{kurt}{freq}\right)\right)/mean(CIRF\_n)$.

F-test η reports the value of an F-test under the null $\eta = 1$ and P-val F-test the p-value of the test.

According to the sufficient statistic result, frequency and kurtosis should have the same coefficient in absolute value. Hence, Table 4 also shows the results of an F-test under the null that $-\beta^f = \beta^k$, where β^f is the coefficient of the frequency, β^k of the kurtosis. Recall that under this restriction reg2 becomes reg1. The last row of the table reports the p-value of this test and it shows that the null cannot be ever rejected. These results further provides evidence for the sufficient statistic results, since kurtosis and frequency are important in explaining the effects of monetary shocks and it is not possible to reject the null that kurtosis and frequency have the same coefficient but with opposite sign.

5.4 Further test of the sufficient statistic result

This section provides a more ambitious test of the sufficient statistic result: we want to test that only the frequency and the kurtosis of price changes are important in explaining the propagation of monetary shocks and that other moments, instead, are irrelevant. To do so, we regress the CIRF over the ratio of the kurtosis and the frequency, over the mean and the skewness of price changes. Notice that, since the mean and the skewness have both negative values, it is not possible anymore to take logs in the right hand side. Table 5 shows the results of this regression and provides further evidence for the sufficient statistic result. Indeed, Table 5 shows exactly that the ratio is statistically significant different from zero, instead the mean and the skewness are not. Moreover, notice that the estimated coefficient of the ratio is very close to the one estimated without including the mean and the skewness in the specification (not reported), implying that mean and kurtosis do not affect at all our results. Moreover, our findings still hold when we separately regress the CIRF over the ratio and the mean or over the ratio and the skewness of price changes; the ratio is statistically significant different from zero in both specifications, the mean and kurtosis are both not statistically significant (not reported).

Table 4: Reg2 for Production Prices

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_PPI_6	CIRF_PPI_12	CIRF_PPI_18	CIRF_PPI_24	CIRF_PPI_30	CIRF_PPI_36
log_freq	-0.0242**	-0.0884***	-0.184***	-0.296***	-0.401***	-0.490***
	(0.0108)	(0.0330)	(0.0629)	(0.0938)	(0.122)	(0.146)
log_kurto	0.0163	0.0629	0.132*	0.215*	0.291**	0.355**
	(0.0124)	(0.0386)	(0.0746)	(0.112)	(0.145)	(0.174)
Constant	0.0289	0.0861	0.162	0.236	0.298	0.353
	(0.0292)	(0.0872)	(0.162)	(0.234)	(0.295)	(0.346)
Observations	119	119	119	119	119	119
R^2	0.113	0.158	0.189	0.222	0.245	0.259
F-test	0.367	0.420	0.493	0.577	0.651	0.722
P-val F-test	0.546	0.518	0.484	0.449	0.421	0.397

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: F-test reports the value of an F-test under the null $-log\_freq = log\_kurto$ and P-val F-test the p-value of the test.

Table 5: Regression of CIRF over ratio, mean and skewness of price changes

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_PPI_6	CIRF_PPI_12	CIRF_PPI_18	CIRF_PPI_24	CIRF_PPI_30	CIRF_PPI_36
$\frac{kurto}{freq}$	0.0197*	0.0743*	0.156**	0.253**	0.344**	0.421**
	(0.0115)	(0.0390)	(0.0785)	(0.123)	(0.163)	(0.197)
mean	-0.00164	-0.00266	-0.00161	0.00248	0.00763	0.0119
	(0.00363)	(0.0115)	(0.0215)	(0.0321)	(0.0415)	(0.0496)
skewness	-0.00665	-0.0226	-0.0443	-0.0669	-0.0862	-0.102
	(0.00624)	(0.0195)	(0.0373)	(0.0556)	(0.0716)	(0.0851)
Constant	-0.0145	-0.0704**	-0.166**	-0.293***	-0.421***	-0.531***
	(0.0106)	(0.0335)	(0.0644)	(0.0968)	(0.125)	(0.150)
Observations	119	119	119	119	119	119
R^2	0.036	0.055	0.068	0.082	0.092	0.098
η	3.692	1.871	1.474	1.246	1.128	1.067
F-test η	1.564	0.788	0.410	0.165	0.0571	0.0182
P-val F-test	0.214	0.377	0.523	0.685	0.812	0.893

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: η is the average elasticity constructed as $\eta = \hat{\beta} * mean\left(\frac{kurt}{freq}\right)/mean(CIRF\_n)$.

F-test η reports the value of an F-test under the null $\eta = 1$ and P-val F-test the p-value of the test.

6 Robustness Checks

This section provides robustness checks that confirm our findings: it is not possible to reject the sufficient statistic result from the data. Section 6.1 exploits the three step strategy using consumer price instead of production prices. Section 6.2 reports the results of reg1 and reg2 pooling together production and consumer to gain more precision in the estimates. Section 6.3 briefly discusses further robustness checks.

6.1 Consumer Prices

Using consumer prices, we exploit the three step strategy to further test the sufficient statistic result. Consumer prices are considered as a robustness check because consumption price micro data and time series are disaggregated at different levels; microdata are disaggregated at 5 digits, instead time series at 4 digits. Hence, the match between CIRF and micro moments in the third step of the empirical strategy for consumer prices is not as good as for production prices. We consider only the 5-digit category with the biggest weight in the CPI for each 4-digit category available in the time series dataset. Notice that it would be not correct to compute the kurtosis as the average of all the observation inside each 4-digit category because this generates biased estimates.

In the first step, we estimate a FAVAR in the same way as in the previous section, however this time we retrieve the IRFs of consumer prices, instead of production prices and we compute the CIRFs as above. Table 6 reports the summary measures of the cumulative IRFs of consumer prices. Notice that the mean is near zero and it decreases with the time horizon, as for the CIRF of production prices.

Table 6: CIRF of consumer prices: Summary measures

	Mean	Std. Dev.	50%	25%	75%	5%	95%
CIRF_CPI_6	0.00	0.02	0.00	-0.00	0.01	-0.02	0.03
CIRF_CPI_12	0.00	0.07	0.01	-0.01	0.03	-0.07	0.07
CIRF_CPI_18	-0.00	0.15	0.02	-0.02	0.05	-0.13	0.11
CIRF_CPI_24	-0.02	0.23	0.01	-0.03	0.06	-0.19	0.13
CIRF_CPI_30	-0.04	0.30	0.00	-0.05	0.05	-0.25	0.15
CIRF_CPI_36	-0.07	0.36	-0.01	-0.08	0.05	-0.31	0.17
Observations	217						

In the second step, as done for production prices, we compute the frequency and kurtosis of price changes, excluding price changes below 0.1% in absolute value and the top and bottom 1% of the overall distribution of price changes. Table 7 provides the summary statistics of the estimated frequency and kurtosis of price changes. Notice that the mean of the frequency is around 11%, lower respect to the frequency of production prices. Moreover, the standard deviation of the frequency of consumer price is half with respect to the one of production prices. On the other hand, the mean of kurtosis is quite similar, but the standard deviation of the kurtosis is larger for consumer prices.

Table 7: Frequency and kurtosis of consumption prices: summary measure

	Mean	Std. Dev.	50%	25%	75%	5%	95%
freq	10.75	10.51	8.95	4.08	14.58	1.80	24.26
kurto	7.63	5.12	6.78	4.65	8.88	3.00	16.51
Observations	217						

The third step consists in estimating reg1 and reg2 using consumer prices. The results of reg1 and reg2 are reported in tables 8 and 9, respectively. Table 8 shows that as the time horizon increases it is not possible to reject the sufficient statistic results, the coefficient of the ratio is statistically significant different from zero. Moreover, table 8 reports the estimated average elasticity, η, and an F-test under the null $\eta = 1$, as the sufficient statistic result predicts. However, the null can be rejected for any time horizon, the elasticity is lower to one, in contrast to our finding with production prices. Nevertheless, recall that for the sufficient statistic result firms are better represented by producers respect to retailers or consumers. Table 9 reports the results of reg2 and it shows that both the coefficient of frequency and kurtosis increases in absolute value and in significance with the time horizon, in line with the sufficient statistic result and with the results obtained with producer prices. However, for consumer prices frequency is only statistically significant different from zero for long time horizon. On the other hand, kurtosis is always statistically different from zero. These results strengthen the validity of the sufficient statistic result. Moreover, table 9 shows the results of an F-test under the null that the coefficient of kurtosis and frequency are the same in absolute value; the null can only be rejected for time horizons equal to 6 or 12 months.

Table 8: Reg1 Consumer Prices

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_CPI_6	CIRF_CPI_12	CIRF_CPI_18	CIRF_CPI_24	CIRF_CPI_30	CIRF_CPI_36
$log\left(\frac{kurto}{freq}\right)$	0.00427	0.0188*	0.0425*	0.0733**	0.104**	0.130**
	(0.00303)	(0.0106)	(0.0217)	(0.0345)	(0.0465)	(0.0567)
Constant	0.00269**	0.00558	0.00279	-0.00951	-0.0273**	-0.0465***
	(0.00124)	(0.00375)	(0.00701)	(0.0105)	(0.0138)	(0.0165)
Observations	217	217	217	217	217	217
R^2	0.033	0.061	0.082	0.101	0.114	0.121
η	-0.308	-0.998	1.797	0.533	0.360	0.293
F-test η	35.85	12.66	0.757	3.455	15.74	30.61
P-val F-test	8.85e-09	0.000460	0.385	0.0644	9.88e-05	9.14e-08

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: η is the average elasticity constructed as $\eta = \hat{\beta} * mean\left(log\left(\frac{kurt}{freq}\right)\right)/mean(CIRF\_n)$.

F-test η reports the value of an F-test under the null $\eta = 1$ and P-val F-test the p-value of the test.

Table 9: Reg2 Consumer Prices

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_CPI_6	CIRF_CPI_12	CIRF_CPI_18	CIRF_CPI_24	CIRF_CPI_30	CIRF_CPI_36
log_freq	-0.00183	-0.0143	-0.0379	-0.0721*	-0.107**	-0.139**
	(0.00362)	(0.0125)	(0.0255)	(0.0406)	(0.0545)	(0.0664)
log_kurto	0.0110***	0.0312***	0.0552***	0.0768***	0.0928***	0.103**
	(0.00262)	(0.00836)	(0.0162)	(0.0250)	(0.0330)	(0.0399)
Constant	-0.0149***	-0.0271	-0.0307	-0.0187	0.00106	0.0237
	(0.00550)	(0.0172)	(0.0340)	(0.0538)	(0.0729)	(0.0899)
Observations	217	217	217	217	217	217
R^2	0.064	0.071	0.085	0.101	0.114	0.123
F-test	9.051	3.120	0.839	0.0258	0.136	0.551
P-val F-test	0.00294	0.0788	0.361	0.873	0.713	0.459

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: F-test reports the value of an F-test under the null $-log\_freq = log\_kurto$ and P-val F-test the p-value of the test.

6.2 Pooled Data

To increase the number of observation and to obtain more precise estimates, we pooled together producer and consumer price data. We run the two baseline specifications, reg1 and reg2, adding a dummy that takes value one for consumer prices. The results confirms our findings: the ratio, the frequency and the kurtosis are always statistically significant different from zero and with the appropriate sign. Appendix B provides a detailed discussion of these findings.

6.3 Further robustness checks

Using producer prices, we explore other two robustness checks. The first one assume that the measurement error for kurtosis is bigger. Hence, we estimate the kurtosis excluding the top and bottom 5% of distribution of price changes in each category, instead of the 1% of the overall distribution. In the second robust checks, we exclude the top and bottom 1% of the CIRF of producer prices. In both the scenarios, our findings still holds even if they are weaken, since we are reducing the variability in our data. Overall, the sufficient statistic result still holds. Appendix B provides a detailed discussion of these results.

7 Conclusion

Our findings provide evidence on the sufficient statistic result for monetary shocks, namely that the effect of a monetary shock is completely pinned down by the ratio of kurtosis and frequency of price changes. Our empirical analysis shows that the ratio of kurtosis to frequency is positively and statistically significantly correlated with the response of price, the CIRF, as predicted by the sufficient statistic result, implying that a higher ratio leads to more price stickiness. The sufficient statistic result predicts also that the average elasticity of CIRF with respect to the ratio is equal to one; this hypothesis cannot be rejected in our baseline specification. Moreover, the sufficient statistic result predicts that frequency and kurtosis are both important in explaining the propagation of monetary shocks and that they must have the same effect in magnitude. To test this result, we disentangle the effect of kurtosis and frequency of price changes regressing the CIRF over the frequency and the kurtosis. Our findings strengthen the evidence provided for the sufficient statistic result since the coefficients of frequency and kurtosis are statically significant from zero and with the expected sign; moreover, they are not statically different in magnitude. Moreover, we not only find that the kurtosis and the frequency are statistically relevant in explaining the propagation of monetary shocks, but also that other moments, as mean and skewness of price changes, are irrelevant and do not further information in capturing the effects of monetary shocks. Moreover, our findings are robust to different specifications.

References

ALVAREZ, FERNANDO, & LIPPI, FRANCESCO. 2014. Price setting with menu cost for multiproduct firms. *Econometrica*, **82**(1), 89–135.

ALVAREZ, FERNANDO, LE BIHAN, HERVE, & LIPPI, FRANCESCO. 2016. The real effects of monetary shocks in sticky price models: a sufficient statistic approach. *American Economic Review*, **106**(10), 2817–51.

ALVAREZ, FERNANDO, LIPPI, FRANCESCO, & OSKOLKOV, ALEKSEI. 2020. The Macroeconomics of Sticky Prices with Generalized Hazard Functions.

BERNANKE, BEN S, BOIVIN, JEAN, & ELIASZ, PIOTR. 2005. Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly journal of economics*, **120**(1), 387–422.

BOIVIN, JEAN, GIANNONI, MARC P, & MIHOV, ILIAN. 2009. Sticky prices and monetary policy: Evidence from disaggregated US data. *American economic review*, **99**(1), 350–84.

CALVO, GUILLERMO A. 1983. Staggered prices in a utility-maximizing framework. *Journal of monetary Economics*, **12**(3), 383–398.

CAVALLO, ALBERTO. 2018. Scraped data and sticky prices. *Review of Economics and Statistics*, **100**(1), 105–119.

CHRISTIANO, LAWRENCE J, EICHENBAUM, MARTIN, & EVANS, CHARLES L. 1999. Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics*, **1**, 65–148.

DOTSEY, MICHAEL, & WOLMAN, ALEXANDER L. 2020. Investigating Nonneutrality in a State-Dependent Pricing Model with Firm-Level Productivity Shocks. *International Economic Review*, **61**(1), 159–188.

GOLOSOV, MIKHAIL, & LUCAS JR, ROBERT E. 2007. Menu costs and Phillips curves. *Journal of Political Economy*, **115**(2), 171–199.

KLENOW, PETER J, & MALIN, BENJAMIN A. 2010. Microeconomic evidence on price-setting. *Pages 231–284 of: Handbook of monetary economics*, vol. 3. Elsevier.

NAKAMURA, EMI, & STEINSSON, JON. 2010. Monetary non-neutrality in a multisector menu cost model. *The Quarterly journal of economics*, **125**(3), 961–1013.

REIS, RICARDO. 2006. Inattentive producers. *The Review of Economic Studies*, **73**(3), 793–821.

SIMS, CHRISTOPHER A. 1980. Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1–48.

STOCK, JAMES H, & WATSON, MARK W. 1999. Forecasting inflation. *Journal of Monetary Economics*, **44**(2), 293–335.

STOCK, JAMES H, & WATSON, MARK W. 2002. Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, **20**(2), 147–162.

STOCK, JAMES H, & WATSON, MARK W. 2016. Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. *Pages 415–525 of: Handbook of macroeconomics*, vol. 2. Elsevier.

Appendix A: FAVAR Theory

The Factor Augmented Vector Autoregression (FAVAR) was originally developed by Bernanke *et al.* (2005) and by Boivin *et al.* (2009). Stock & Watson (2016) provide also a clear explanation of the model.

Let Y_t be a vector of observable economic variables with dimension M x 1, $M \geq 1$, and let F_t be a vector of unobserved factors with dimension K x 1, $K \geq 1$. Assume that the dynamics of the economy is driven by (Y_t', F_t') which follows the transition equation:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \tag{2}$$

where $\Phi(L)$ is a lag polynomial of finite order and v_t is an error term with zero mean and covariance matrix Q. Equation 2 looks like a VAR, but remind that F_t is unobserved and, thus, we cannot directly estimate equation 2. However, the factors F_t are interpreted as representing forces that potentially affect many economic variables from which we can estimate the factors. Indeed, assume that a large number of time series X_t, called informational time series, are related to the observed variables Y_t and to the unobservable factors F_t by the following equation:

$$X_t = \Lambda F_t^+ + e_t \tag{3}$$

where $F_t^+ \equiv [F_t \ Y_t]'$ and e_t is a vector N x 1 of error terms with zero mean[3]. Notice that the number of informational time series, N, must be large which means N is much greater respect to the number of variables that drives the economy (F_t and Y_t), i.e. $N > K + M$, and potentially N can be bigger than the time period under consideration, T. Moreover, notice that F_t can always capture arbitrary lags of fundamental factors,

[3]If factors are estimated using a principal components analysis, errors can display a small amount of cross-correlation that must vanish as N goes to infinity. See Stock & Watson (2002) for a detailed discussion.

thus it is not restrictive to assume that X_t depends only on the current values of the factors[4].

Under the above assumptions, it is possible to estimate the model, using a two-step approach[5]: in the first step, the common factors are estimated extracting the first K principal components, $\hat{C}^{(0)}$, from the information variables, X_t. Indeed, as shown by Stock & Watson (2002), for N large enough and if the number of principal components used are at least as the true number of factors, the principal components of X_t span the space generated by the factors F_t and the observable variables Y_t; thus, the principal components represent independent but arbitrary linear combinations of F_t and Y_t. However, we want that these combinations do not depend on Y_t and that they are only independent combinations of the factors. For this reason, the factors are precisely estimated as follow. Regress X_t on $\hat{C}^{(0)}$ and Y_t to obtain $\hat{B}_r^{(0)}$, the coefficient of Y_t. After compute $\tilde{X}_t^{(0)} = X_t - \hat{B}_r^{(0)} Y_t$ and estimate $\hat{C}^{(1)}$ as the first K principal components of $\tilde{X}_t^{(0)}$. Iterate until convergence of $\hat{B}_r^{(i)}$ to obtain the desired estimated factors, $\hat{F}_t$. The second step consists in estimating equation 2 as a structural VAR[6], replacing F_t with $\hat{F}_t$. Indeed, we can rewrite equation 2 as

$$\hat{F}_t^{+} = \Phi(L)\hat{F}_{t-1}^{+} + v_t \tag{4}$$

where $\hat{F}_t^{+} \equiv [\hat{F}_t \; Y_t]'$. Assuming $v_t = H\epsilon_t$, it is clear that equation 4 can be treated as a structural VAR.

We are left with only one open question: how is it possible to estimate the IRFs of X_t? Consider again equation 4 and assume that the MA representation exists. Denoting the MA coefficient with $\Psi(L)$, we obtain

$$\hat{F}_t^{+} = \Psi(L)H\epsilon_t \tag{5}$$

Moreover, using $\hat{F_t}^{+}$ instead of F_t^{+} in equation 3 and replacing in this equation equation 5, we get

$$X_t = \Lambda\Psi(L)^{-1}H\epsilon_t + e_t \tag{6}$$

[4]For this reason Stock & Watson (1999) refer to equation 3 as a dynamic factor model.

[5]The model can be estimated also using a single-step Bayesian likelihood approach.

[6]In our application, we estimate the structural VAR using a Cholesky decomposition. However, any other approach can be used.

Equation 6 links the information variables, X_t, to the shocks and provides the theoretical framework to retrieve the IRFs of X_t. However, in practice, the IRFs of X_t are not estimated using the MA representation and, thus, equation 6. Indeed, let $\widehat{IRF(A)}$ be the estimated IRFs of the time series A_t to a given shock. The IRFs of X_t is calculated as

$$\widehat{IRF(X)} = \widehat{\beta} * \widehat{IRF(\hat{F}^{+})} \tag{7}$$

where $\widehat{IRF(\hat{F}^{+})}$ is the VAR estimated IRF of $\hat{F}_t^{+}$ and $\widehat{\beta}$ is the estimated coefficient of the regression of X_t on $\hat{F}_t^{+}$.

Appendix B: Robustness Checks for production prices

In this section, we provide various robustness checks for producer prices to establish the validity of our findings. If not specified, the measures for CIRF, kurtosis and frequency used are the same of section 5.

Table 10 and table 11 report the results of reg1 and reg2, respectively, using a different measure of kurtosis. The kurtosis is estimated excluding the top and bottom 5% of the distribution of price changes in each category and price changes below 0.1% in absolute value. Notice that this alternative measure of kurtosis generates values much lower respect with our baseline specification and reduces the variability of the kurtosis, this attenuates our findings. The results in table 10 are very similar to our baseline specification, table 3, the coefficient of the ratio is positive and statistically significant from zero. However, it is possible to reject the null that the elasticity is equal to one in any specification. Table 11 shows that the frequency is negative and statistically significant from zero, as in table 3. However, the kurtosis is positive and not statistically significant different from zero. Recall that this alternative measure measure of kurtosis reduces a lot the variability of kurtosis in our data and this can lead to a non-significant coefficient. Anyway, it is not possible to reject the null that the frequency and the kurtosis have the same effect in magnitude.

Table 12 and table 13 report the results of reg1 and reg2, respectively, excluding the top and bottom 1% of the production prices CIRFs. Table 12 confirms the findings in table 3, the ratio is positive and statistically significant different from zero and it is not possible to reject the null that the elasticity is equal to one. Table 13 shows that the results for the frequency still hold and that the kurtosis is statistically significant from zero for long horizons. Moreover, it is not possible to reject the null that both coefficient are equal in magnitude.

Table 14 and table 15 report the results of reg1 and reg2, respectively, including together the CIRF of production and consumer prices and adding a dummy for consumer price as dependent variable (dummy_cpi). This specification has the advantage to have an higher number of observations. Both tables confirm exactly our findings, all the coefficient are always statistically significant from zero and with the appropriate sign. Moreover, it is not possible to reject the null that frequency and kurtosis have the same effect in magnitude. However, for some time horizon it is possible to reject the nulla that the elasticity is equal to one.

Table 10: Production prices: Reg1 using a different measure of kurtosis

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_PPI_6	CIRF_PPI_12	CIRF_PPI_18	CIRF_PPI_24	CIRF_PPI_30	CIRF_PPI_36
$log\left(\frac{kurto}{freq}\right)$	0.0196**	0.0729***	0.153***	0.248***	0.336***	0.412***
	(0.00861)	(0.0264)	(0.0503)	(0.0751)	(0.0973)	(0.117)
Constant	0.0237**	0.0753***	0.144***	0.212**	0.269**	0.316**
	(0.00929)	(0.0285)	(0.0543)	(0.0812)	(0.105)	(0.126)
Observations	119	119	119	119	119	119
R^2	0.094	0.135	0.163	0.194	0.215	0.228
η	8.040	3.990	3.142	2.649	2.396	2.268
F-test η	3.964	4.276	4.300	4.217	4.054	3.901
P-val F-test	0.0488	0.0409	0.0403	0.0423	0.0463	0.0506

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: η is the average elasticity constructed as $\eta = \hat{\beta} * mean\left(log\left(\frac{kurt}{freq}\right)\right)/mean(CIRF\_n)$.

F-test η reports the value of an F-test under the null $\eta = 1$ and P-val F-test the p-value of the test.

Table 11: Production prices: Reg2 using a different measure of kurtosis

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_PPI_6	CIRF_PPI_12	CIRF_PPI_18	CIRF_PPI_24	CIRF_PPI_30	CIRF_PPI_36
log_freq	-0.0242**	-0.0860**	-0.178**	-0.283***	-0.380***	-0.464***
	(0.0117)	(0.0362)	(0.0695)	(0.105)	(0.136)	(0.164)
log_kurto	0.00239	0.0239	0.0617	0.116	0.171	0.215
	(0.0111)	(0.0354)	(0.0689)	(0.104)	(0.136)	(0.163)
Constant	0.0569	0.170	0.320	0.466	0.588	0.696
	(0.0363)	(0.114)	(0.220)	(0.334)	(0.437)	(0.527)
Observations	119	119	119	119	119	119
R^2	0.101	0.141	0.169	0.199	0.221	0.234
F-test	1.303	1.056	0.967	0.864	0.792	0.771
P-val F-test	0.256	0.306	0.327	0.355	0.375	0.382

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: F-test reports the value of an F-test under the null $-log\_freq = log\_kurto$ and P-val F-test the p-value of the test.

Table 12: Production prices: Reg1 eliminating top and bottom 1% of CIRFs

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_PPI_6	CIRF_PPI_12	CIRF_PPI_18	CIRF_PPI_24	CIRF_PPI_30	CIRF_PPI_36
$log\left(\frac{kurto}{freq}\right)$	0.0224**	0.0846***	0.136***	0.219***	0.280***	0.342***
	(0.00979)	(0.0302)	(0.0436)	(0.0634)	(0.0812)	(0.0956)
Constant	0.0141***	0.0392***	0.0364*	0.0384	0.0272	0.0190
	(0.00439)	(0.0141)	(0.0219)	(0.0324)	(0.0426)	(0.0506)
Observations	117	117	117	117	117	117
R^2	0.160	0.221	0.145	0.175	0.176	0.190
η	9.382	2.972	1.657	1.359	1.173	1.098
F-test η	4.185	3.450	1.539	0.833	0.259	0.102
P-val F-test	0.0431	0.0658	0.217	0.363	0.611	0.751

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: η is the average elasticity constructed as $\eta = \hat{\beta} * mean\left(log\left(\frac{kurt}{freq}\right)\right)/mean(CIRF\_n)$.

F-test η reports the value of an F-test under the null $\eta = 1$ and P-val F-test the p-value of the test.

Table 13: Production prices: Reg2 eliminating top and bottom 1% of CIRFs

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_PPI_6	CIRF_PPI_12	CIRF_PPI_18	CIRF_PPI_24	CIRF_PPI_30	CIRF_PPI_36
log_freq	-0.0258**	-0.0977***	-0.151***	-0.241***	-0.305***	-0.373***
	(0.0109)	(0.0333)	(0.0498)	(0.0719)	(0.0905)	(0.106)
log_kurto	0.0101	0.0388	0.0852	0.142	0.189*	0.230*
	(0.00970)	(0.0309)	(0.0593)	(0.0871)	(0.112)	(0.132)
Constant	0.0466**	0.161**	0.172	0.242	0.265	0.314
	(0.0223)	(0.0671)	(0.153)	(0.218)	(0.269)	(0.312)
Observations	117	117	117	117	117	117
R^2	0.172	0.238	0.151	0.181	0.181	0.196
F-test	2.434	3.695	0.918	1.001	0.889	1.010
P-val F-test	0.122	0.0571	0.340	0.319	0.348	0.317

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: F-test reports the value of an F-test under the null $-log\_freq = log\_kurto$ and P-val F-test the p-value of the test.

Table 14: Pooled data: Reg1

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_6	CIRF_12	CIRF_18	CIRF_24	CIRF_30	CIRF_36
$log\left(\frac{kurto}{freq}\right)$	0.00917***	0.0360***	0.0775***	0.128***	0.177***	0.218***
	(0.00353)	(0.0115)	(0.0228)	(0.0353)	(0.0468)	(0.0567)
dummy_cpi	0.000304	0.00803	0.0208	0.0378	0.0535	0.0646
	(0.00447)	(0.0140)	(0.0269)	(0.0404)	(0.0524)	(0.0626)
Constant	0.00311	9.45e-05	-0.0129	-0.0392	-0.0700	-0.0979*
	(0.00379)	(0.0118)	(0.0224)	(0.0333)	(0.0428)	(0.0508)
Observations	336	336	336	336	336	336
R^2	0.056	0.093	0.119	0.144	0.162	0.172
η	-28.71	1.727	1.023	0.752	0.635	0.575
F-test η	7.223	1.731	0.00571	1.433	4.713	8.072
P-val F-test	0.00756	0.189	0.940	0.232	0.0306	0.00477

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: η is the average elasticity constructed as $\eta = \hat{\beta} * mean\left(log\left(\frac{kurt}{freq}\right)\right)/mean(CIRF\_n)$.

F-test η reports the value of an F-test under the null $\eta = 1$ and P-val F-test the p-value of the test.

Table 15: Pooled data: Reg2

	(1)	(2)	(3)	(4)	(5)	(6)
	CIRF_6	CIRF_12	CIRF_18	CIRF_24	CIRF_30	CIRF_36
log_freq	-0.00804**	-0.0349***	-0.0787***	-0.135***	-0.189***	-0.237***
	(0.00406)	(0.0131)	(0.0257)	(0.0395)	(0.0522)	(0.0631)
log_kurto	0.0125***	0.0392***	0.0742***	0.110***	0.140***	0.163***
	(0.00353)	(0.0113)	(0.0220)	(0.0336)	(0.0442)	(0.0532)
dummy_cpi	0.00101	0.00872	0.0201	0.0339	0.0458	0.0527
	(0.00466)	(0.0146)	(0.0279)	(0.0418)	(0.0540)	(0.0643)
Constant	-0.00614	-0.00892	-0.00351	0.0120	0.0325	0.0576
	(0.00961)	(0.0293)	(0.0560)	(0.0837)	(0.109)	(0.130)
Observations	336	336	336	336	336	336
R^2	0.059	0.093	0.119	0.145	0.164	0.175
F-test	1.347	0.137	0.0405	0.540	1.286	2.060
P-val F-test	0.247	0.712	0.841	0.463	0.258	0.152

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: F-test reports the value of an F-test under the null $-log\_freq = log\_kurto$ and P-val F-test the p-value of the test.