A Study of Belgian Inflation, Relative Prices and Nominal Rigidities using New Robust Measures of Skewness and Tail Weight

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Abstract. This paper studies the distribution of Belgian consumer price changes and its interaction with aggregate inflation over the period June 1976-September 2000. Given the fat-tailed nature of this distribution, both classical and robust measures of location, scale, skewness and tail weight are presented. The chronic right skewness of the distribution, revealed by the robust measures, is cointegrated with aggregate inflation, suggesting that it is largely dependent on the inflationary process itself and would disappear at zero inflation.

1. Introduction

The aim of this paper is to study the cross-sectional properties of Belgian inflation data. The international literature on this issue highlights, broadly speaking, three not mutually exclusive aspects. First, many papers discuss the positive relationship between inflation on the one hand and the dispersion and/or the asymmetry of relative prices on the other. Often these relationships have been interpreted as being symptomatic of nominal rigidities of one form or another. Ball and Mankiw's menu cost model [4] has recently been the focal point of this strand in the literature. Second, in line with the findings of [5], it is often documented that inflation data are fat-tailed and this motivates the stochastic approach to core inflation in which robust estimators of location are proposed. Third, in quite a few countries researchers found not only a considerable degree of frequently switching left and right skewness, but, on average, also a tendency towards right skewness.

This type of analysis often uses the classical characteristics of location, scale, skewness and kurtosis. These measures are, however, very sensitive to outlying values [14]. In this paper we will compare them with robust alternatives, not only for location, as is typically done in the core inflation part of this literature, but

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also for scale, skewness and tail weight. We will address the question whether robust measures are applicable in this context, because inflation is often strongly influenced by outliers which are both correct and important. Overly strong robustness may downweight outliers too much and thus yield little sensitivity. Next, we study the relation between skewness and inflation, and interpret the results in the framework of menu cost models [3].

2. Description of the data

This study is based on Belgian monthly consumer price index (CPI) data for the period June 1976 up to September 2000, yielding a total of 292 months. It was not possible to start at an earlier point in time, for instance during the low inflation regime of the sixties, for data availability reasons. For each month, we have aggregated price indices of 60 different product categories such as meat, clothing, tobacco, electricity, recreational and cultural services, etc. The index of product category i ($i = 1, \ldots, 60$) at month t ($t = 0, \ldots, 291$) is denoted by $I_{i,t}$.

We started by transforming these data into percentage 1-monthly price changes $\Pi_{i,t}$ ($t = 1, \ldots, 291$), defined by $\Pi_{i,t} = (I_{i,t}/I_{i,t-1}) - 1$. For a motivation and more information about selecting $\Pi_{i,t}$ instead of any other transformation of the raw data, we refer to [2].

Summarizing, we can represent our final dataset with a matrix that consists of 291 rows (indicating the different periods) and 60 columns (for the product categories). A cross-section contains the price changes of one particular month, and thus corresponds with one row of the data matrix. Additionally, we have taken account of the fact that each product category has a time-varying weight $w_{i,t}$ which is obtained by multiplying for each period t its fixed Laspeyres-type weight w_i by the change in its relative price between the base period and period t. The Laspeyres-type weights w_i of the CPI reflect the importance of each category in total household consumption expenditure in the base period. The weights satisfy $\sum_{i=1}^{60} w_{i,t} = 1$ for all t. In so doing, the weighted mean of the 60 product-specific price changes $\Pi_{i,t}$ corresponds to aggregate inflation.

3. Detection of outliers

In this section we will mainly show that the Belgian price changes contain a substantial number of outlying values. For this, we will consider the cross-sections and compute robust measures of tail weight for each of them. To show the importance of the tails of univariate data (as the cross-sections are), we can use the classical measure of kurtosis. In general, the kurtosis is said to characterize the fatness of the tails, or equivalently the tail weight, but it also reflects the shape of the density in the centre. Moreover, the classical measure of kurtosis is based on moments of the dataset, and thus it is strongly influenced by outliers. Despite the fact that outliers determine the tail weight, we can construct robust measures to compute it. For this purpose, we first need a robust estimator of location and scale for univariate data. In general, we denote the sample by x_i $(i = 1, \ldots, n)$ and the corresponding weights by w_i. As usual, the weights sum to 1. Time subscripts are omitted to simplify notations.

3.1. Robust measure of location

A measure of location should estimate a value that characterises the central position of the data. The best known measure of location is the weighted mean or average, defined as $\overline{x} = \sum_{i=1}^{n} w_i x_i$. Note that with the dataset we analyse, the weighted mean corresponds to observed inflation.

A typical robust measure of location is the median. Here, we need the weighted variant of the median. In general, all measures based on percentiles can be modified easily to their weighted version by filling in the weighted percentiles. That is the main reason why all robust measures presented in this paper are based on percentiles. Initial work on other robust measures based on couples and triples of observations was abandoned precisely because it was not straightforward to construct them in weighted terms. Indeed, [7] and [8] discuss some unweighted robust skewness measures based on couples and triples. For the p% weighted percentile, denoted by Q_p, we first sort the observations from smallest to largest, and then take the first value with cumulative weight higher than p%. The weighted median equals the 50% weighted percentile, or $Q_{0.50}$.

3.2. Robust measure of scale

Scale characteristics measure how "spread out" the data values are. The classical measure of scale is the standard deviation, which is given by:

$$s = \sqrt{\frac{\sum_{i=1}^{n} w_i (x_i - \overline{x})^2}{1 - \sum_{i=1}^{n} w_i^2}} \tag{3.1}$$

where $\overline{x}$ stands for the mean. This equation is based on the unbiased sample moments of unequally-weighted frequency distributions presented in [12].

The interquartile range or IQR is a robust measure of scale which, like the median, is based on percentiles and is easy to calculate. The (weighted) IQR is the distance between the 75% percentile $Q_{0.75}$ and the 25% percentile $Q_{0.25}$, or

$$IQR = Q_{0.75} - Q_{0.25} \tag{3.2}$$

3.3. Robust measures of tail weight

We propose several tailmass measures as alternative to the classical kurtosis. They simply count the outliers in a data set. To distinguish the outlying values from the regular ones we use the following outlier rules:

1. The *general boxplot rejection rule* defines outliers as points outside the interval:

$$[Q_{0.50} - \frac{3}{2} IQR, Q_{0.50} + \frac{3}{2} IQR] \tag{3.3}$$

This criterion is based on the definition of the whiskers in the univariate boxplot [16]. Note that this interval corresponds approximately to $[\overline{x} - 2s, \overline{x} + 2s]$ in case of the normal distribution.

2. The *asymmetric boxplot rule*. This rule is a special case of the bivariate bagplot [13], which is a bivariate generalisation of the boxplot. Points are considered outlying when they lie outside the interval:

$$[Q_{0.50} - 3(Q_{0.50} - Q_{0.25}), Q_{0.50} + 3(Q_{0.75} - Q_{0.50})] \tag{3.4}$$

For each outlier rule, we define left outliers as those data points which are smaller than the lower bound of the interval defined in (3.3) or (3.4). Analogously the right outliers are larger than the upper bound of this interval. We then obtain the left-tailmass measures as the sum of the weights of the left outliers, i.e.

$$\text{left-tailmass} = \sum_{i=1}^{n} w_i \theta_i \tag{3.5}$$

where θ_i equals 1 if x_i is a left outlier and 0 if not. This leads to left-tailmass(box) and left-tailmass(abp). Considering the right outliers, we obtain right-tailmass(box) and right-tailmass(abp).

3.4. Results for Belgian inflation data

All measures defined above were applied to the cross-sections of the Belgian inflation data. In Figure 1 the resulting time series are plotted, by considering all 291 consecutive cross-sections. On the plots, the scatter points of the different measures are depicted, together with a smoother (solid line). We have chosen to use a lowess smoother, which is a robust scatter plot smoother [9]. Lowess uses robust locally linear fits, by placing a window about each point and weighting the points that are inside the window so that nearby points get the most weight.

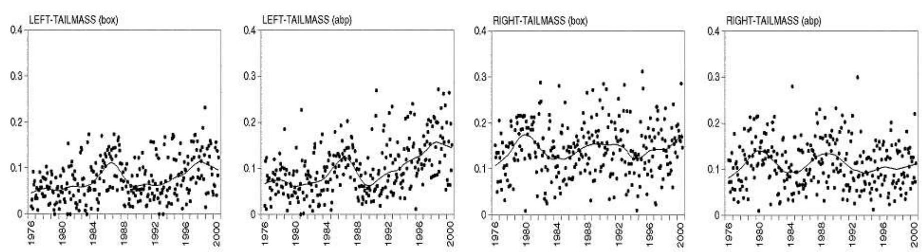

FIGURE 1. Time series of the tail weight measures.

All the tailmass measures show substantial proportions of outliers and these proportions are, moreover, very volatile. This is why we will use robust measures of location, scale and skewness to analyse the data further on. Before doing so, we have a closer look at the tails. On the basis of the smoothed curves, left-tailmass(box) amounted to roughly 5% at the beginning of the sample and increased to approximately 10% at the end of the sample. Right-tailmass(box), in contrast, tends to oscillate around 15% during the whole sample. These observed tail weights are substantially in excess of those for the normal distribution, for which the corresponding tailmass(box) measures amount to 2.15% for each tail. This clearly illustrates the fat-tailed nature of Belgian inflation data, a finding which is in line with the results in the international literature on this issue. It should, however, be stressed that most of the international evidence is based on the classical kurtosis, which may for several reasons underestimate the importance of outliers (see for instance [1] on this so-called masking issue).

The fact that right-tailmass(box) tends to have larger values than the corresponding left alternative is a first indication of the existence of chronic right skewness, albeit apparently decreasing over time. A possible disadvantage of the general boxplot rejection rule is that it takes the left part of the data into account when defining a right outlier and vice versa. Using the asymmetric boxplot rule overcomes this problem. In so doing, we find that left-tailmass(abp) increases and right-tailmass(abp) decreases relative to their symmetrical alternatives, which can be seen as another indication of chronic right skewness. These asymmetrically constructed tailmass measures confirm the tendency for the left-hand tail to increase and the more stationary behaviour of the right-hand tail.

4. Classical and robust measures of location and scale

The classical and robust measures of location and scale are plotted in Figure 2. The robust alternatives were already used in the previous section to construct robust measures of tail weight. In this section we will compare them to their classical counterparts.

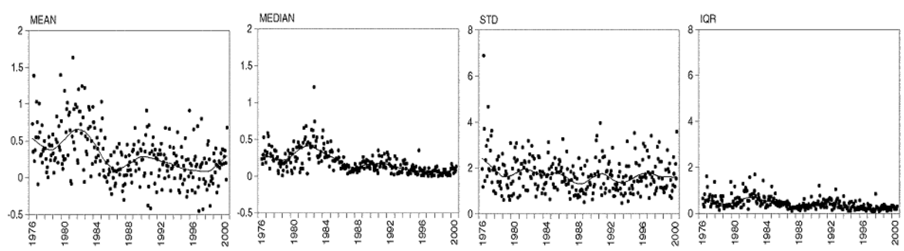

FIGURE 2. Time series of the location and scale measures.

4.1. Location

As the use of robust measures of location for inflation data is well-developed in the core inflation literature (see for instance [1] for references), we only give some brief comments when comparing the mean to the median. In Table 1 the unit root test for the classical and robust measures of location, scale and skewness is given. Given the monthly frequency of the data, for each estimator 11 lags were necessary to produce residuals without autocorrelation. The first column gives the value of the augmented Dickey Fuller test statistic, while the second column reports the significance of the constant in the test equation only if the null hypothesis of a unit root is rejected. The 95% critical value for rejection of the null hypothesis of a unit root is -2.87. Inclusion of a trend in the test equations for those variables for which the null of a unit root was not rejected did not change the results. In other words, they were not trend stationary either.

	ADF statistic	signif		ADF statistic	signif
mean	-1.74		skew(class)	-3.82	0.12
median	-1.58		dskew(class)	-5.80	0.02
			dskew(125)	-2.55	
standard deviation	-3.97	0.00	dskew(250)	-3.44	0.00
IQR	-1.74		meme	-2.59	

TABLE 1. Unit root tests for the classical and robust measures of location, scale and skewness.

As the ADF-tests reported in Table 1 fail to reject the null hypothesis of a unit root for the classical and the robust measures of location, both time series contain a stochastic trend. The smoothed curves in Figure 2 seem to confirm this conclusion. The median is substantially less volatile around its trend than the mean, thus confirming that using a robust estimator of location yields a substantial gain in efficiency in the case of a fat-tailed distribution. This could motivate the use of the median as a measure of core inflation statistically. The first robust core inflation measure was indeed the median [6]. Subsequently, a wide range of alternative robust estimators of core inflation have been proposed.

A cointegration equation of two non-stationary weighted time series X and Y is a linear combination of both time series which is itself stationary [17]. As mean and median both are non-stationary, we can report the normalized cointegration equation (CE) in Table 2. The 95% critical value is 19.96 for rejection of the null hypothesis of no cointegration equation and 9.24 for rejection of the null hypothesis of at most 1 cointegration equation. The cointegration rank and the specification of the deterministic components of the model were determined jointly on the basis of the general test procedure discussed in [11]. However, models having trends in the levels of the variables (constants in the VAR) were not considered. As can be seen from Table 2, the median is cointegrated with the mean, but with a coefficient (0.5934) that is substantially less than one. In Figure 2 it can indeed be verified that the median tends to be lower than the mean. This is another indication of chronic right skewness in the Belgian inflation data. Note that the constant in the cointegration relation is very close to zero, suggesting that the chronic asymmetry would disappear completely at zero inflation.

4.2. Scale

Comparing the classical standard deviation with IQR indicates that relying on a robust alternative dramatically alters the characteristics of the measure of scale. According to the ADF-tests in Table 1, IQR contains a unit root whereas the classical measure appears as a stationary variable. Moreover, Figure 2 shows that

	median	dskew(125)	dskew(250)	skew(class)	dskew(class)
CE:					
Constant	0.0002	0.0412	-0.0533	-0.4711	-11.0449
	(0.0200)	(0.0566)	(0.0209)	(0.3879)	(5.5618)
Mean	-0.5934	-1.5037	-0.2579	-0.2853	6.3588
	(0.0563)	(0.1597)	(0.0589)	(1.0913)	(15.7954)
Trace statistic:					
No CE	35.09	30.86	24.88	28.82	40.62
At most 1 CE	4.70	3.41	3.39	4.37	3.79

Table 2. Cointegration of the robust measure of location (median), of the robust measures of skewness (dskew(125) and dskew(250)) and of the classical skewness measures (skew(class) and dskew(class)) with actual inflation (mean). Between brackets the standard errors are given. Lag number is 11.

the variability of IQR around its smoothed curve is substantially lower than the variability of the classical standard deviation. We owe this to the fact that the classical measure is dominated by the impact of outliers or, in economic terms, by large relative price shocks. In the absence of outliers, IQR would in contrast tend to be larger than the standard deviation (in the case of the normal distribution IQR $\approx 1.35s$). Evidently, the impact of outliers on the classical measure of scale is magnified by squaring their deviations from the mean (see formula (3.1)).

5. Classical and robust measures of skewness

Skewness reflects the shape of the distribution. A symmetric distribution has zero skewness, a distribution which is asymmetric with the largest tail to the right has a positive skewness, and a distribution with a longer left tail has a negative skewness.

5.1. Classical measure of skewness

Normally, the standardized, unitless measures of asymmetry (skewness) are used. The best known measure of skewness is the classical skewness [12]

$$\text{skew(class)} = \frac{\sum_{i=1}^{n} w_i (x_i - \overline{x})^3}{(1 - 3\sum_{i=1}^{n} w_i^2 + 2\sum_{i=1}^{n} w_i^3)\, s^3} \tag{5.1}$$

However, we will consider destandardized measures of asymmetry as well. In this way skewness becomes dependent on scale, but this correlation does not bother us. Indeed, the economic models we rely on suggest that scale and skewness interact. In [4] it is shown that scale magnifies the effect of skewness on inflation, while the asymmetric range of inaction in [3], which is a possible source of right skewness in the data, is also unscaled. All destandardized measures of asymmetry are expressed in some units, and the robust measures have the same units as the data and the measures of location and scale. The destandardized classical skewness is defined as dskew(class) $= s^3$skew(class).

5.2. Robust measures of skewness

A disadvantage of the classical measures of skewness is that they change dramatically when we introduce an outlier. This is clearly shown by the empirical study of [7]. On the other hand, skewness is supposed to measure the asymmetry of the observations, so we may not downweight outliers too heavily. The first robust alternative we propose is dskew(125), which is given by:

$$\text{dskew}(125) = (Q_{0.875} - Q_{0.50}) - (Q_{0.50} - Q_{0.125}) \tag{5.2}$$

with Q_p again the p% (weighted) percentile. The following measure is very similar, but it is based on other percentiles. We compute dskew(250) as:

$$\text{dskew}(250) = (Q_{0.75} - Q_{0.50}) - (Q_{0.50} - Q_{0.25}) \tag{5.3}$$

Note that (5.2) and (5.3) are destandardized versions of the class of skewness measures introduced by Hinkley [10].

Another measure of skewness can be obtained by standardizing the data as $z_i = x_i - Q_{0.50}$ and then taking the first moment of these standardized observations which corresponds to the mean-median difference, yielding meme $= \overline{z}$. This measure is not robust, because it uses the mean. However, we consider it here as an alternative measure of skewness, as it has, compared to the classical measures, the advantage that the influence of what happens in the tails is far less accentuated.

5.3. Chronic right skewness

We have applied both types of measures of skewness on the cross-sections of the Belgian inflation data. The resulting time series are plotted in Figure 3. The classical measures of skewness show a substantial degree of frequently switching left and right skewness, which is a typical result in the literature in regard to the analysis of inflation data. Indeed, this property has been documented for several other countries (see [2] for references). However, they do not show a clear tendency towards positive values. As for scale, the time series properties of the robust measures of skewness are fundamentally different from those of the classical ones. As the ADF tests in Table 1 indicate, the null hypothesis of a unit root in the classical measures was rejected at the 99% significance level. Moreover, the constant term in the test equation was not different from zero at the conventional significance levels for skew(class). For dskew(class) the constant was significant at the 95% level, but not at the 99% level. Also, in this case the estimated value of the constant is small relative to the observed variability. Hence, the classical measures hardly reveal any form of chronic right skewness in a significant way, notwithstanding the fact that we provided evidence of a tendency towards right skewness.

In contrast, the robust measures dskew(125) and dskew(250) show a more pronounced tendency towards positive values. Hence, they better reveal the chronic right skewness of the data. The mean-median difference meme also shows such a tendency, although it takes negative values more frequently than the two other robust measures. We owe the latter to the fact that meme is in fact not robust.

The null hypothesis of a unit root is rejected for dskew(250) at the 95% significance level, suggesting mean reversion around a significant positive constant. In contrast, for dskew(125) and meme, the null of a unit root is not rejected, suggesting a time-varying degree of chronic right skewness. Particularly in the second half of the sample the tendency towards right skewness seems less pronounced, thus confirming the findings of Sections 3 and 4. A chronic tendency towards right skewness is also found in several other countries and some of these studies also mention that this tendency is less pronounced in the most recent period, when inflation is lower (see [2] for references).

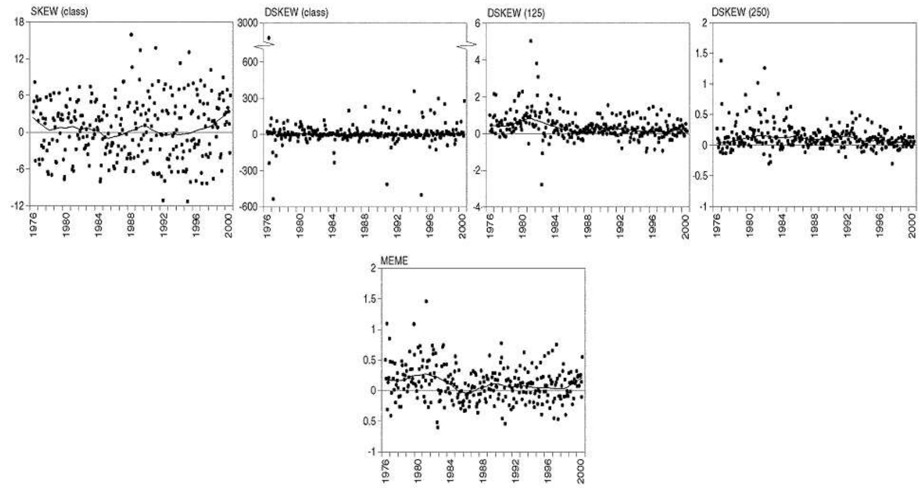

FIGURE 3. Time series of the skewness measures.

6. Inflation affecting relative price changes

In view of the chronic right skewness of the distribution of Belgian consumer price changes revealed in the previous section by the robust measures, it is important to stress that two alternative economic models can generate this phenomenom. The two models have however different, empirically testable implications for the relation between skewness and aggregate inflation.

The first model relies on an exogenous form of downward nominal rigidity of prices of the Tobin-type [15]. This model predicts a negative relation between inflation and skewness: higher aggregate inflation leads to less right skewness (see [18] on this issue). The second model relies on menu costs, i.e. it assumes that changing prices involves a (menu) cost, which is fixed in the sense that it does not depend on the magnitude of the price change. Examples of this type of costs are changes to price lists, catalogues, advertising, etc. This menu cost produces a range of inaction: firms react only to large price shocks, for which the advantage of changing prices outweighs the menu cost. In [3] it is shown that this range of inaction becomes asymmetric in the presence of trend inflation. In other words, (positive) trend inflation reduces the likelihood of observing a downward adjustment of prices relative to the likelihood of an upward adjustment. Therefore, this model implies a positive relation between inflation and skewness: higher aggregate inflation leads to more right skewness.

In view of this, the relation between aggregate inflation and skewness is studied by cointegrating the robust measures of skewness with actual inflation. As is shown in Table 2, using the robust measure dskew(125) reveals a clear positive cointegration relationship between asymmetry and inflation. Each percentage point of additional (monthly) inflation tends to increase deskew(125) by 1.5 percentage points. Moreover, the constant term in the cointegration relation is very small both in statistical and in economic terms, suggesting that the chronic right skewness would disappear completely at zero inflation. As such, the long term behaviour of the chronic right skewness measured by dskew(125) seems to be an integral part of the inflationary process itself. A similar conclusion was obtained on the basis of the cointegration relation between the median and the mean.

Also for dskew(250), the Johansen cointegration test reveals the existence of a positive cointegration relation with inflation, notwithstanding the fact that the ADF-test reported in Table 1 suggests that dskew(250) is stationary. In such conflicting case the Johansen test dominates the ADF-test. This measure of asymmetry tends to increase by 0.26 percentage points for each percentage of (monthly) inflation. The constant in the cointegration relation for dskew(250) suggests the existence of some form of chronic right skewness which is independent of the inflationary process. The impact of this constant is, however, relatively small compared to the impact of inflation. Indeed, each 0.2% of additional monthly inflation (approximately 2.4% on a yearly basis) increases dskew(250) by the same amount as that resulting from the constant. This suggests that a substantial part of the chronic asymmetry measured by dskew(250) disappears at zero inflation.

These findings thus tend to provide evidence in favour of menu cost models, while they strongly contradict the exogenously assumed downward nominal rigidity of Tobin [15]. Distinguishing between these two models is important from a monetary policy perspective, as they have different implications for the optimal rate of inflation. The menu cost model favours a zero inflation rate in order to minimise the disturbing impact of aggregate inflation on the distribution of relative price changes, whereas the Tobin-model model argues in favour of a positive inflation rate, that is sufficiently high to overcome the inefficiencies resulting from the downward rigidity.

A similar analysis which uses the classical measures of skewness did not allow to describe this long-run behaviour of the chronic right skewness. Although with skew(class) the Johansen test suggests the existence of a cointegration relation, we do not interpret this as meaningful because of its coefficients which are estimated very imprecisely (large standard errors for both the coefficient of the mean and the constant). As a matter of fact, in this case the Johansen test exactly confirms the findings of the ADF-test as skew(class) is cointegrated with the constant zero (or, it is stationary around a non-significant constant). Hence this measure does not reveal any form of chronic right skewness in a significant way, nor a systematic long-run impact of the inflation rate on the asymmetry. A similar conclusion can be made with dskew(class), although the constant term is estimated somewhat more precisely. Both tests come to a similar conclusion, namely a stationary behaviour around a positive constant which is (according to the ADF-test) statistically significant at the 95% level, but not at the 99% level. Nevertheless, this constant is small compared to the variability observed in the series of dskew(class), such that we may conclude that dskew(class) hardly reveals any chronic right skewness.

7. Conclusions

In this paper we have studied the properties of the distribution of Belgian consumer price changes, by using both classical and robust measures of location, scale, skewness and tail weight. The robust measures of tail weight showed clearly (i) the fat-tailed nature of the distribution, (ii) the short run volatility of the tail weights, (iii) the tendency for the right-hand tail to dominate the left-hand tail, which points towards chronic right skewness and (iv) the increase over time of the left-hand tail and the more stationary behaviour of the right-hand tail.

It was found that the chronic right skewness was cointegrated with aggregate inflation. Moreover, we found little evidence of chronic right skewness not dependent on the inflationary process, suggesting that the asymmetry would disappear at zero inflation. Overall, these results are in line with the predictions of menu cost models and they are symptomatic of nominal rigidities, in the sense that prices are adjusted infrequently. However, they do not point in the direction of specific downward rigidities, other than those endogenously generated by the prevailing inflation rate. These findings provide arguments in favour of a price stability-oriented monetary policy.

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