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Endogenous frequencies and large shocks: price setting in Greece during the crisis.♣

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ABSTRACT

We utilize a unique micro price data set for Greece that underpins the Greek CPI. It spans more than two decades, during which Greece suffered two large economic shock. We find that during these times there were significant changes in the pricing behavior of Greek firms. We find that macro-economic developments such as annual inflation and output growth are important factors in determining the frequency and size of price changes. This leads to an intertemporal inflation dynamic linking current inflation to future price behavior and inflation. Utilizing the empirical estimates from the data during the first large shock, we combine a Taylor rule and Euler equation with the inflation dynamic resulting from the asymmetric impact of inflation on the frequency of price increases and the frequency of price decreases. The results of the simulations capture the 'out of sample' Greek inflation developments well during the second shock. Finally, we show that during large shocks mispricing increases, which may lead to an overreaction of frequency developments.

JEL classification: E31, E37, C26, C41

Keywords: inflation dynamics, frequencies, prices, microdata.

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1. Introduction

In the period since 2002, Greece has had a unique macroeconomic experience. From the creation of the hard Euro until 2008, Greece enjoyed a period of growth. Like many countries around the world, its output declined, albeit moderately, with the great financial crisis. However, in the wake of the great financial crisis the euro area sovereign debt crisis erupted, which hit Greece strongly. At the peak of the crisis in 2013, real GDP had contracted by around 26 percent from its 2010 level. Up until 2021 it remained about 25 percent below that level. At the same time wages were reduced by more than 20 per cent whilst unemployment increased from a pre-crisis level of around 8 percent to 28 percent. The size of the contraction is similar to that of the Great Depression in the US in the early-1930s.[1] This is the first large aggregate shock of the Greek economy. This negative shock pushed inflation down to an average of 0 percent over a decade. The second large aggregate shock is the energy cost shock starting in 2022 which drove inflation up to levels not seen since mid-1990's in Greece.

We use, for a first time, a product-level data underlying the Greek consumer price index from January 2002 to December 2023. During this time period there are three distinct inflation 'segments'. The first segment is from 2002 to 2010, which is a period of 'normal' inflation. The second period is from 2011 to the end of 2019 which is the period after the sovereign debt crises where inflation was on average 0 per cent. The third period includes the energy cost crisis period where headline inflation increased up to 12 percent.

In this article, we investigate the impact of the first large shock on the price setting behavior of firms in Greece. We utilize the results obtained from the first shock in a small scale DSGE model and investigate whether we can predict, out of sample, inflation developments conditional on the energy cost shock.

We proceed by using the Greek price microdata to construct aggregate statistics, namely the monthly frequency of price increases and decreases, as well as the average sizes of price increases and decreases. These four statistics determine inflation by a simple identity and enable us to gauge the impact of macroeconomic developments on inflation. We utilize the first large shock to obtain empirical estimates for the period 2002 to 2019, while the period

[1] See G. Tavlas (2019) for a description of the Greek crisis.

with the second large shock is used for conditional 'out of sample' inference. We find that for the period 2002 to the end of 2019. 1) The frequency of price increases is primarily determined by and increasing in the level of annual HICP inflation and growth of output. 2) The frequency of price decreases is primarily determined by and decreasing in the level of annual HICP inflation. 3) The size of price increases and decreases are both influenced by the level of annual inflation and output growth. 4) Inflation in Greece is mainly driven by developments in the relative frequencies of price increases and decreases.

These empirical results are interesting for a variety of reasons. Most importantly, the fact that the current behavior of prices depends on past inflation (reflected in the annual HICP) implies an endogenous dynamic of inflation over time. Higher past inflation will lead to a higher frequency of price increases and lower frequency of price decreases, which will tend to increase current inflation. In particular, based on the aforementioned findings, we set up and simulate a small model where inflation dynamics are endogenous. We find that this endogenous inflation dynamic fits with the data we observe in Greece and is in line with stylized facts in the development of the frequency of price changes observed in other countries, during different time-periods. Moreover, the endogenous inflation dynamics setup is able to fit out- of sample inflation developments during the energy crisis period. This is partly because our model is able to match the share of price increases and decreases in the total frequency for the energy cost crisis period. However, it does not match the developments in the frequency of increases and decreases separately. We show that during periods of large shocks, where uncertainty about the total size and duration of the shock is large, mispricing becomes more frequent, leading to an overreaction of frequencies for both price increases and well as decreases.

The remainder of the paper is structured as follows. Section 2 presents the data while Section 3 presents time series evidence on the frequency and size of price changes in Greece. Section 4 investigates key macroeconomic drivers for frequencies and sizes of price changes and section 5 incorporates our regression results into a simple 3 equation New-Keynesian DSGE model. Our adaptation involves replacing the new Keynesian Phillips curve with an empirical Phillips curve based on our estimated equations. The simulations performed are able to replicate key features in the Greek data and capture out of sample developments of inflation. Moreover, the results of the simulation also captures stylized facts of developments seen in other economies and over different time periods. Section 6 presents empirical estimates of

mispricing for the entire period 2002 to 2023 which show an increase in mispricing during periods with large shocks. Finally, section 7 concludes.

2. The Data

In this study, we utilize a unique data set of micro prices obtained by the Hellenic Statistical Authority (ELSTAT), which is used to compute the national index of consumer prices. It consists of 759 products (or items), across unique outlets at the NUTS 2 level, which translates into 47069 unique product identifiers.[2] The data are monthly from January 2002 to December 2023 and unbalanced as the products in the consumer price index change over time. In total, we have almost 10 million price observations, which cover more than 75% of the Greek HICP. Our data does not include most energy prices, prices on fresh fruit and vegetables, seasonal items, centrally collected prices, telecommunication prices and some service-related components, in particular for transport prices. On balance, the data cover most items in the HICP (and CPI) excluding energy and seasonal items. The price data have also been matched to historical VAT rates at the product level. The drawback of the data set is the lack of information concerning product substitution, changes in product metric and information on whether a price observation is a sales-price or not.[3]

A careful examination of the data leads us to the following two 'cleaning' procedures. 1) Very small price changes, of less or equal 0.2%, which are probably due to mistakes or software data approximation differences, are set to 0. This concerns 7,280 observations and changes are mostly at the fourth or fifth decimal of the price. 2) Price changes have been trimmed at the 1st and 99th percentiles given a non-zero price change. This implies that our largest price decrease is 50% while our largest price increase is 100%, which corresponds to a typical seasonal sale of 50% and its subsequent increase back to its 'normal' price.[4] Finally, In order

[2] The data were originally by `product names' which have been matched to COICOP 8 level digits using a list on products researched for the HICP index" for the years 2015 and 2010. Products that have not been included in these two lists have been approximated with a relevant COICOP 8 digit by the researchers.

[3] Product substitution may refer to e.g. the change of the type of outboard motor that is being measured, so we can see a price change from 10000 euros down to 1200 euros between months. Changes in the metric may for example reflect the change in the price collected from a daily full time rate in cleaning services to an hourly rate.

[4] The trimming addresses a majority of price changes due to metric changes and due to product substitutions.

to identify sales in our data we utilize a filter, which builds on Nakamura and Steinsson (2008a) and has been developed further in Gautier et al. (2024).[5]

We can construct an annual inflation time series using our price-quote dataset, both with and without sales. First, we calculate the price changes for each of the 46729 unique product identifiers and the frequency of price changes is measured as the share of prices that change each month. These frequencies are then weighted using relevant weights ($w_{j,t}$) at some aggregate level. For the relevant aggregation level (COICOP level) *j*, the frequency in a given month $f_{j,t}$ is simply the (unweighted) proportion of prices that change each month. Thus the aggregate frequency for a specific month is:

$$f_t = \sum_{j=1}^{n} w_{j,t} . f_{j,t} \tag{1}$$

where n= the relevant number of COICOP levels. Whilst our data is not the full set of price-quotes and excludes some products, in general the aggregate month-on-month inflation is given by:

$$\Pi_t = \sum_{j=1}^{n} w_{j,t} . \Pi_{j,t} \tag{2}$$

Where $\Pi_{j,t}$ is the geometric average of price relatives (ratios of current price to the previous month) over all price-quotes within the product type. However, if we define $\pi_{j,t}$ as the average price relative excluding 1s, i.e. the average conditional on the price changing, we have $\Pi_{j,t} = f_{j,t} . \pi_{j,t}$ and hence:

$$\Pi_t = \sum_{j=1}^{n} w_{j,t} (f_{j,t} . \pi_{j,t}) \tag{3}$$

[5] For details on the sales filter see Nakamura and Steinsson (2008b) and Appendix A3 in Gautier et al. (2024). The filter performs in a satisfactory manner when compared to NSI flags on sales for other European countries. Filtered data, i.e. excluding sales, contains however usual end-point problems. The filter uses the parameters *l, k, j=3*. Where *l* defines the maximum length of the sales period followed by a new regular price. *k* defines *the* maximum number of new regular prices to be considered, and *j* defines maximum length of the sales period where the price returns exactly to the same price as before the sales period. The parameter setting, where all parameters are set to 3 implies that the filter identifies a sale which is followed by a *new regular price* within *j* months.

Both frequencies and price changes can be broken down further into increases (+) and decreases (-) as in Klenow and Kryvtsov (2008):

$$\Pi_t = \sum_{j=1}^{n} w_{j,t}(f_{j,t}^{+}.\pi_{j,t}^{+} - f_{j,t}^{-}.\pi_{j,t}^{-}) \quad (4)$$

There are potentially four different approaches to the data: unweighted with and without sales and weighted with and without sales. The unweighted data is constructed with the special case of n=1 and $w_{1,t} = 1$.

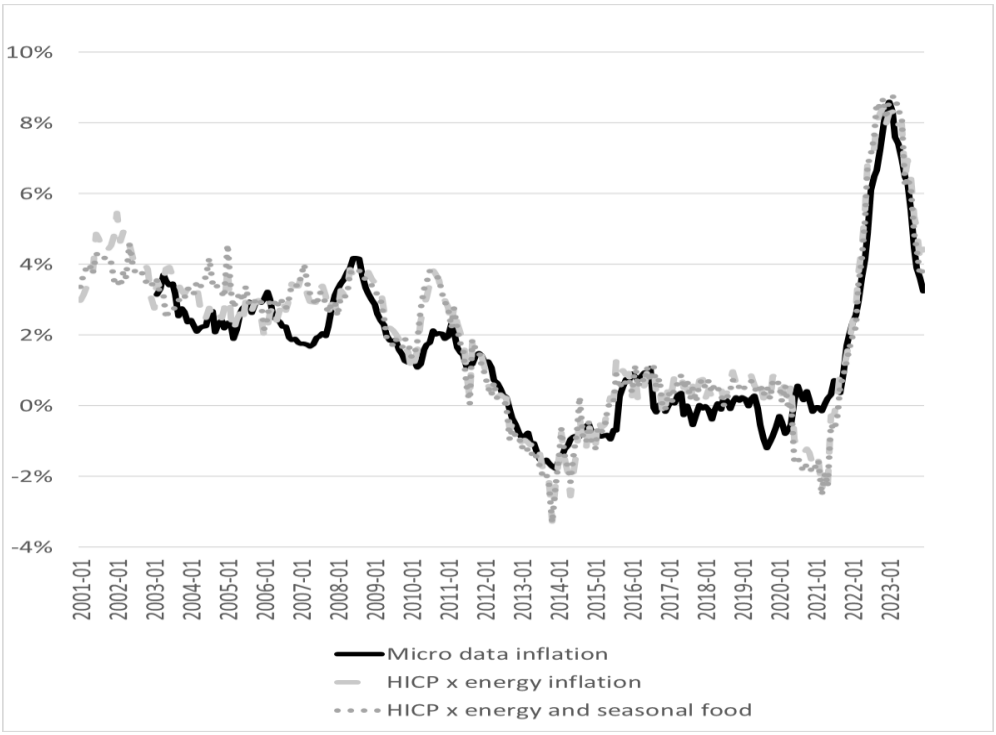


Figure 1: Annual inflation based on unweighted microdata excluding sales, compared to annual inflation of HICP categories

Our data reveals that sales – which are transitory- do not affect aggregate annual inflation. This is in line with Kehoe and Midrigan (2007) who argue that transitory price changes, such as temporary sales, yield much less aggregate price flexibility than an equal number of permanent price changes.[6] In addition both the weighted and unweighted series follow HICP inflation excluding energy closely. In fact, the mean absolute error with inflation excluding energy is smaller for the unweighted series than for the weighted. We will thus proceed our

[6] Even so, Alvarez and Lippi (2020) and Kryvtsov and Vincent (2021) argue, since sales are associated with large volumes of expenditures they can be seen as an integral part of price-flexibility.

analysis using equal weights for our products and with price changes excluding sales.7 Plotting the official HICP inflation rate excluding energy and the annual inflation rate from the micro data they mostly coincide (see Figure 1).

3. A time series analysis of price changes in Greece

3.1. Developments in the frequency

On average over the entire period 2002-2023, the total frequency of price changes excluding sales is 9.3% (see Table 1).[8] Dividing our sample into our three distinct time periods with respect to inflation, i.e. the 'normal period' 2002-2010, the sovereign debt crisis 2011-2019 and the period 2020-2023 which includes the energy crisis, we see that there are important differences. During the sovereign debt crisis the total frequency declines by almost 1 percentage point, from 9.3 percent to 8.4 percent. This masks however significant underlying shift in behaviour. In the case of Greece, the aggregate shock hitting the country during the euro area crisis and its subsequent developments was very large and sustained. Splitting the total frequency of price changes into price increases and price decreases we observe that the frequency of price increases has declined more significantly post crisis by about 2 percentage points while the frequency of price decreases has increased by about 1 percentage point. Hence the modest fall of 1 percentage point in the aggregate frequency reflected a more dramatic fall in price increases and a non-negligible increase in price decreases. During the third period, which includes the energy price shock, we see that the total frequency of price changes increases strongly, by almost three percentage points, with the main contribution coming from the frequency of price increases, which goes up by 2.5 percentage points.[9]

Table 1: Frequencies of price changes excluding sales

Time-period	Total Frequency	Frequency Increases	Frequency Decreases
2002-2023	9.31%	5.80%	3.51%
2002-2010	9.32%	6.40%	2.92%
2011-2019	8.42%	4.60%	3.82%
2020-2023	11.27%	7.15%	4.12%

[7] In order to address potential end-point problems from using the filter we restrict our sample in the empirical analysis to be from May 2002 to September 2023.
[8] Including sales it stands at 13.5%. For comparisons of frequency developments including and excluding sales see Table A1 and Figures A1 and A2 in Appendix A.
[9] See Figure A3 for the developments in the frequency of the main HICP components.

Smoothing out VAT changes which affect the frequency data,[10] and plotting the total frequency of price changes into price increases and price decreases (Figure 2) we observe that the frequency of price increases and decreases during the sovereign debt crisis converged and started to diverge again in 2021 when energy prices started to increase.

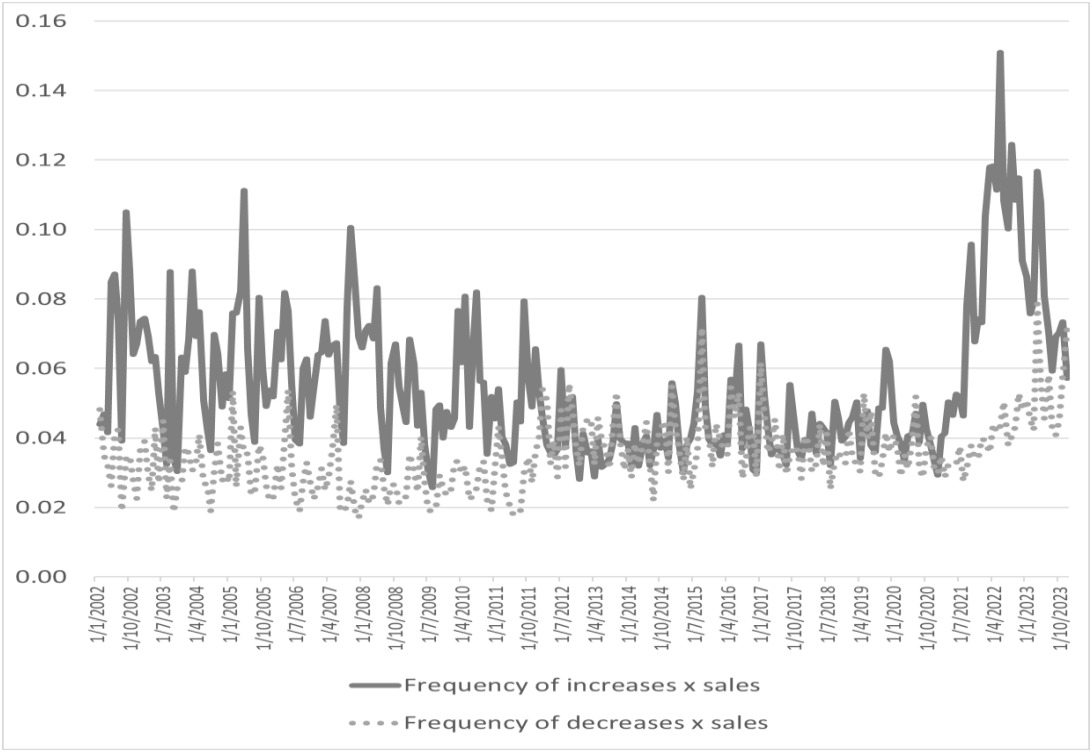


Figure 2: Frequency of price increases and decreases, excluding sales with VAT smoothing.
Source: Calculations by authors

From the relative share of frequencies over the entire period we see that price increases go from being about 2/3 of all price changes -during the 'normal period'- to being about 1/2 of all price changes -during the sovereign debt crises, before starting to diverge again during the energy crisis period (Figure 3).[11] Even so, developments in the relative share of price increases and decreases were gradual. It took around 18 months (2011-2013) to strike a new 'balance' where half of all price changes where price increases. Similarly during the energy crisis it took also almost 18 months for price increases to be about 2/3 of all price changes.

The long period of adjustment in the share of relative frequencies may reflect the fact that that average spell duration is about 9 months and that it takes the average firm about 31

[10] In the raw data we observe large occasional spikes in the frequency of price changes which are related to VAT changes that affect a large share of products included in our sample, see Figure A4.
[11] We exclude the first and last three data points of the series as sales are measured by a filter, which produces the usual endpoint problems for any filtered series.

months to change its price in Greece.[12] As such, it seems that firms responded gradually to the economic shocks.

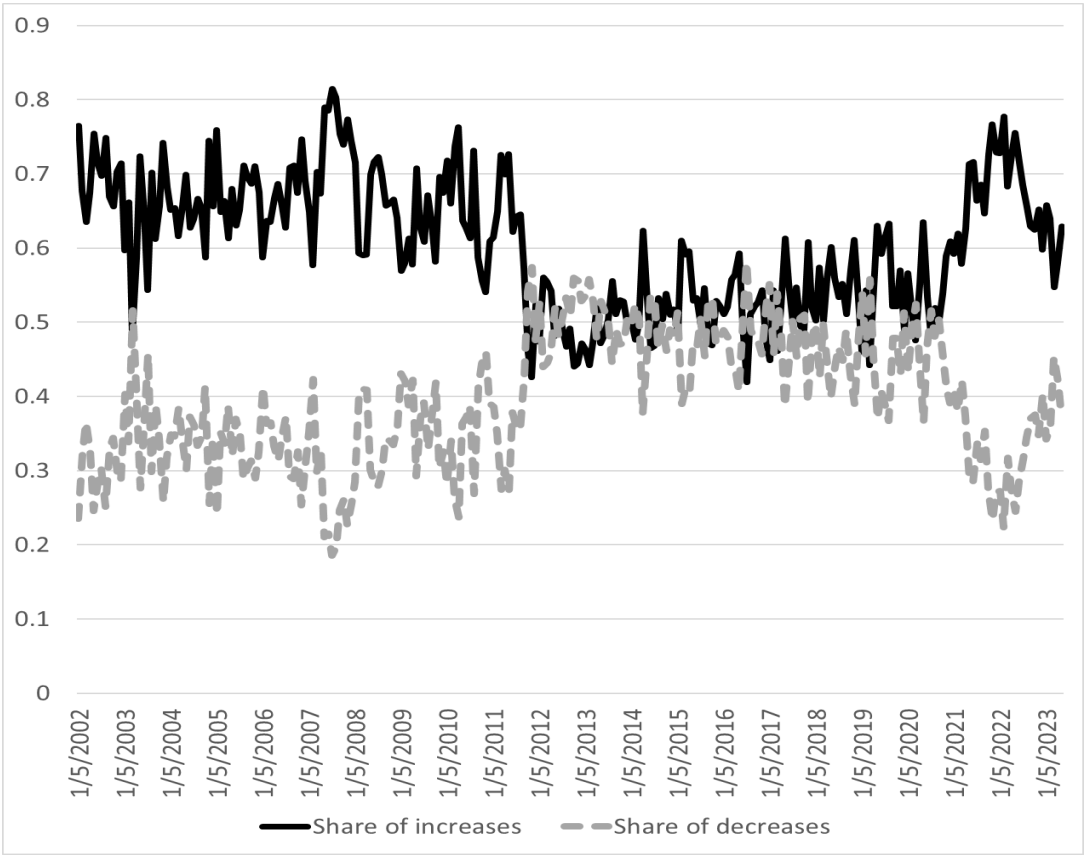


Figure 3: Share of price increases and decreases in total frequency, net of VAT changes
Source: Calculation by authors

3.2. Developments in the size of price changes

Turning our attention to developments in the absolute size of price changes for Greece, we notice an unusual pattern. Namely, that both the average price increase and decrease post the sovereign debt crisis surged significantly, from about 9 to 14 percent for price increases and from 11 to 17 percent for price decreases (Figure 4). Thereafter, during the energy crisis the average price changes remained at elevated levels.

[12] See Appendix B for a cross-sectional analysis of price changes.

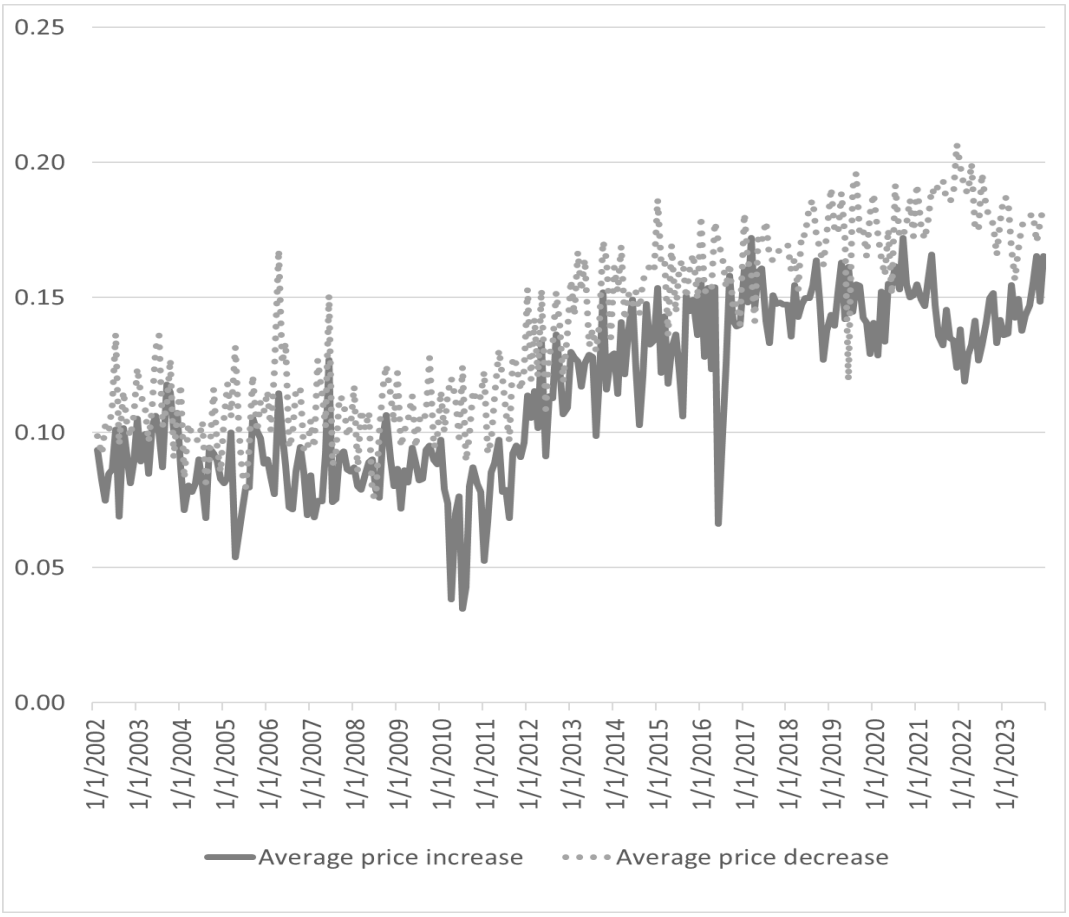


Figure 4: Average size of price increases and decreases.
Source: Calculation by authors

Intuitively one would expect rising price changes to be associated with higher inflation. High inflation would lead the current price to drift away from the optimal price, resulting thus in larger price adjustments when the decision to change prices is taken. However, for Greece we see that average price changes increase during the sovereign debt crisis period which has *lower* inflation.[13]

In order to investigate more closely the underlying reasons for the increase in the average price change we plot the price change distributions for our three time periods of interest (Figure 5). As our price changes are expressed in *dlogs* we create bins, where each bin has a range of 2, which is approximately 2% while the y-axis shows the share of non-zero price changes to all non-zero price changes that are contained in each bin.

[13] This phenomenon is also observed in Norwegian CPI data, see Wulfsberg (2016).

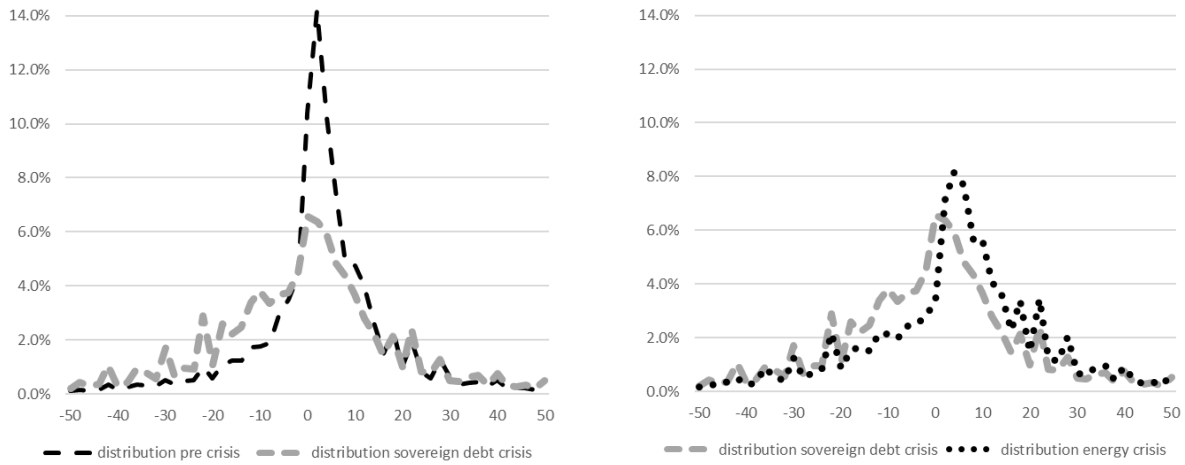


Figure 5: Distribution of Prices changes. Pre crisis is 2002-2011, sovereign debt crisis 2012-2019 and energy crisis 2020-2023.
The X axis is measured in log change terms. Thus -10 implies e^(-10/100)-1≈-9.5%, a price decrease of 9.5%. Similarly +10 implies a price increase of 10.5%.

The left-hand chart compares the distributions of price changes before the sovereign debt crisis with the sovereign debt crisis period. It shows that for price decreases (the bins <0) there is a significant rise in the mass of larger price decreases. This would push up the average price decrease. By contrast, for the price increases we see that there is a large decline in the mass of small price increases. This 'disappearance' of small price increases pushes up the average price increase. The right-hand chart compares the distribution of price changes during the sovereign debt crisis and the energy crisis. We observe that there is almost a parallel shift of the distribution to the right for the bins from -30 to +30 keeping the average price increases and decreases fairly stable.

3.3. What drives inflation

As inflation is the product of the frequency of price changes and the size, we want to investigate which of these two components is the main driver of inflation developments in Greece over the past two decades. In a simple exercise, similar to that of Gautier et al. (2024) we posit the following two counterfactual inflation rates:

$$\Pi_{\bar{f},t} = \sum_{j=1}^{n} w_{j,t}(\bar{f}_{j,t}^{(+)}.\pi_{j,t}^{(+)} - \bar{f}_{j,t}^{(-)}.\pi_{j,t}^{(-)}) \quad (5)$$

$$\Pi_{\bar{\pi},t} = \sum_{j=1}^{n} w_{j,t}(f_{j,t}^{+}.\bar{\pi}_{j,t}^{(+)} - f_{j,t}^{-}.\bar{\pi}_{j,t}^{(-)}) \quad (6)$$

One where we hold the frequencies constant at their average and let the size of price changes vary like in data (eq. 5) and one where the size of price changes is held constant and the frequencies vary as in the data (eq. 6). We can then use the month-on-month inflation rates to construct corresponding counterfactual annual inflation rates and compare them to the actual inflation rate generated by the micro data. Thus, in equation (5) all inflation dynamics come from developments in the size of price changes while in equation (6) all inflation dynamics come from developments in the frequencies. Finally, in Figure 6, we compare these two counterfactuals with the actual inflation calculated from eq. (4), where both the frequencies and sizes vary.

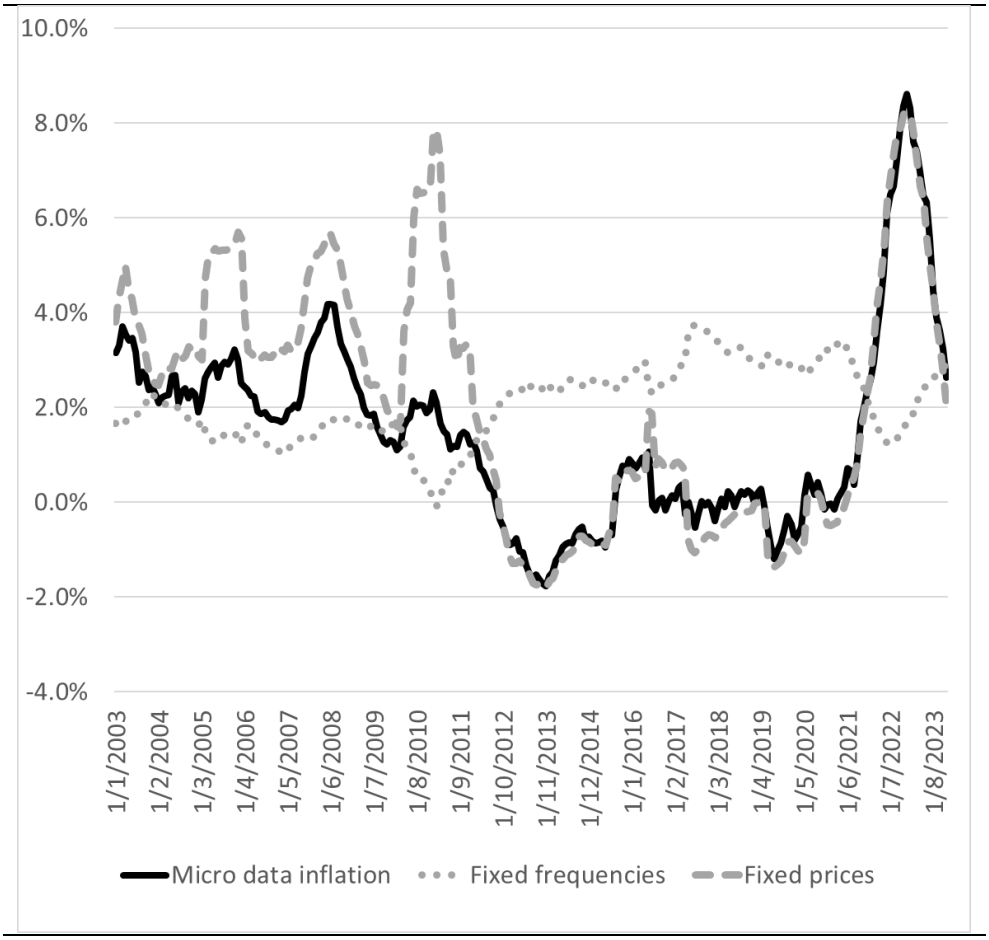


Figure 6: Counterfactual and micro data based inflation.
Source: Calculation by authors

Figure 6 shows that the inflation rate obtained by the micro data co-varies strongly with the inflation rate where prices are fixed and all the inflation dynamics come from changes in the

frequency of increases and decreases. By contrast, the counterfactual, where frequencies are fixed and inflation dynamics come from changes in the size of price increases and decreases shows little connection with actual developments. In terms the correlations, the correlation of inflation obtained from the data and the 'fixed size' counterfactual is around 0.89, while the correlation with the 'fixed frequency' counterfactual is about -0.47 Lastly, this finding holds also if we divide the full sample into the corresponding sub-periods, i.e. pre-crisis, sovereign debt crisis and energy crisis. Within each subperiod inflation developments are driven – almost fully – by developments in the frequency of increases and decreases.[14] Thus, in the coming analysis we will focus on the frequency of price changes, while the analysis on the size of price changes will be included in Appendix C.

4 Drivers of the frequency of price changes

Given the significant changes observed over time in the composition of the frequency of price changes, one important question is what are the economic drivers of the frequency of increases and decreases?

Early studies such as Bils and Klenow (2004), Dhyne et al. (2004), Golosov and Lucas (2007), Mackowiak and Smets (2008) and Klenow and Malin (2011) focus attention on cross-section evidence on the determinants of frequency. Other authors such as Gagnon (2009) and Dhyne et al. (2004) found the effects of inflation on the frequency of price changes to be insignificant as inflation affects price increases positively and price decreases negatively with no overall effect. More recent papers like Vavra (2014) and Nakamura et al. (2018) have found that for the US data, inflation co-varies strongly with frequency over time. Similarly, for the UK, Dixon et al. (2020) find that the annual inflation rate significantly affects the frequency of price changes, but only through the frequency of price increases.

We adopt a time series approach with a single equation estimation methodology similar to Dixon et al. (2020).[15] Our dependent variables are the frequency of price increases and the frequency of price decreases excluding sales while our explanatory variables are HICP

[14] The main role of frequencies as a driver of inflation is also found in Alvarez et al. (2019) for Argentina and Gautier et al (2024) for the euro area.

[15] Porqueddu and Fabiani (2017) also use time series analysis to examine whether the recession that followed the global financial crises affected the price setting mechanism in Italy.

inflation, retail sales growth and consumer sentiment about future developments.[16] All variables are in a monthly frequency. In the estimation we also include monthly dummies in order to capture seasonality and dummies for VAT changes that may affect the frequency of price changes temporarily. Finally, in our estimations, we will utilize our data from the first two periods, namely the pre-crisis period 2002-2011 and the sovereign debt crisis period 2012-2019. The last period, the energy crisis period 2020-2023 is kept for an out-of-sample evaluation of our results.

In order to determine what kind of inflation and output growth, i.e. month-on-month, quarter-on-quarter or annual rates of change, are the most relevant for explaining the frequency of price changes, we follow a general to specific approach. The general to specific results confirm what is ex ante a logical supposition, namely that year on year changes of real and nominal variables – as opposed to month on month or quarter on quarter changes – are an important determinant of price changes. First, as Dixon et al. (2020) put it, "Annual inflation is how inflation is perceived: it is the annual inflation rate that is announced and talked about in the media and what people usually mean by 'inflation'".[17] Second, for many firms output has a clear seasonal pattern. For example, tourist season in the Mediterranean peaks during the summer months, and so do prices. In this respect, the most relevant comparison of prices is the same month of the previous year, i.e. annual inflation.

How would we expect the explanatory variables to affect frequency? In a purely time dependent model, none of these variables would matter as the timing of price changes would be driven by the duration since the previous price change.[18] However, in a state-dependent framework, the decision to change the price this month is driven by the distance of the current price from the optimal flexible price p^*, which is the optimal price to set in the absence of price-setting frictions in all periods. The optimal flexible price is itself a function of the general price and output level, along with an idiosyncratic shock, usually written (in log-linearized form) as:

[16] We have tested a variety of other variables such as the growth of industrial production, the general economic sentiment indicator, current consumer sentiment as well as current and forward-looking sentiment indicators for industry and services.
[17] Yotzov et.al (2026) confirm the attention firms pay on CPI inflation releases covered by the media.
[18] Note however that in a time-dependent model, the size of the price change will be affected by the current and future values of p^*_{t+i} as the reset price is an average of p^*_{t+i} over the lifetime of the price spell.

$$p_t^* = P_t + \gamma y_t + e_t \quad (7)$$

Where P_t is the general price level, y_t the level of output and γ is the sensitivity of the optimal flexible price to output. Importantly, if γ=0 then there might be no relationship of output to the optimal price (this has been called *real price rigidity* by Ball and Romer 1990). However, we would usually expect γ to be strictly positive (even if small) reflecting either an upward sloping marginal cost curve at the firm level or an upward sloping labour supply curve.

With state dependence, the optimal pricing rule is generally of the *(S,s)* form: there is a band of inertia from $p_t^* - s$ to $p_t^* + S$ within which the price is not adjusted.[19] A price change occurs when a change in p^* leads to the current price lying outside this band of inertia. Higher inflation or output growth would both lead to a higher p^* and hence an increase in the proportion of firms increasing price (more firms become too far below the optimal level) and a decrease in the proportion of firms decreasing price (less firms are too far above the optimal price). Similarly for the sentiment indicator capturing beliefs of future developments an increase would imply a higher p^* both now and going into the future. Whilst the current value of p^* relative to the current price might determine whether the price changes or not, the optimal reset price will depend on the path of future p^*. If a firm does decide to reset its price this month, the price it will want to set will be some sort of weighted average over future optimal flexible prices p_{t+i}^* for $i \geq 0$, with the weights depending mostly on the probability of the price to be set lasting for i periods.

We should note that our macro variables, according to eq. 7, imply opposite signs for the frequency of increases and decreases. Thus, it may be the case that for the total frequency of price changes the 'net' effect may be overly small or even non-existent (this was a point made by Gagnon (2008)).

In Table 2 we present the results for our estimates. Our regressions include a lagged dependent variable and our explanatory variables are instrumented by own lags in order to avoid simultaneity. For our two dependent variables: frequency of price increases excluding sales and frequency of price decreases excluding sales, we estimate 5 regressions, all with monthly and VAT dummies. The first three equations are regressions with one of the three

[19] The size of the band is determined optimally and will depend on the exact assumptions made. However, analytical solutions to menu cost models usually rest on the assumption that p* evolves following Brownian motion with drift (e.g. Shesinski and Weiss 1977, Alavarez and Lippi 2020)

explanatory variables on their own (inflation, output growth and sentiment of future developments), the fourth equation is the regression with two 'traditional' variables (inflation and output growth) and the fifth all three explanatory variables.[20]

Turning first to the frequency of increases regressions (1-5) we see that the lagged dependent variable has a non-negligible effect, implying some inertia in the frequency of increases. At the same time annual inflation has a significant and large effect. Specifically, a 1 percentage point increase in inflation leads to an increase in the frequency of price increases by 0.286 percentage points (regression 1). Similarly, a 1 percentage point increase in retail sales volume growth increases the frequency of price increases by almost 0.082 percentage points (regression 2). At first glance this implies that inflation is more important for price increases than output growth. However, we should note that output growth (or retail sales volume growth in our case) is inherently more volatile than inflation. Indeed, for our sample the standard deviation of retail sales growth is 4 times larger than that of inflation while for the pre-crisis period it's 7 times larger. As such, for Greece both inflation and output have affected the frequency of price increases to an almost equal degree. Continuing to the effects of sentiment on the frequency of price increases (regression 3) we obtain a rather small effect both statistically as well as economically. Namely, a 2 standard deviations increase in the sentiment raises the frequency of price increases by only 0.01 percentage points. In regressions 4 and 5 we see that both inflation and retail sales growth retain their significance and are still economically important.

Continuing with the estimations explaining the frequency of price decreases we find that only inflation is significant. The sentiment indicator, while statistically significant, has again a negligible economic significance. As expected, inflation enters with the opposite sign compared to regressions for the frequency of price increases but has less than half the impact (-0.132 vs 0.286).[21] On balance, our estimations indicate that aggregate variables seem to have a better explanatory power in the frequency of price increases regressions than in those of the frequency of price decreases, as reflected in the adjusted R-squared. In this respect, the frequency of decreases is more idiosyncratic.[22]

[20] We have also conducted the same estimations for the size of price changes. The results are presented in Appendix C.

[21] Yotzov et.al (2026) also point to an asymmetric impact of inflation since positive CPI inflation changes have significant effects on own-price expectations, while the effects of negative CPI inflation changes are found to be quantitatively smaller and insignificant.

[22] The results are broadly similar if you use only IV or even simple OLS estimations.

Table 2: Determinants of the frequency of increases and decreases excluding sales. LDV IV estimations

VARIABLES	(1) Frequency of price increase	(2) Frequency of price increase	(3) Frequency of price increase	**(4) Frequency of price increase**	(5) Frequency of price increase	(6) Frequency of price decrease	(7) Frequency of price decrease	(8) Frequency of price increase	**(9) Frequency of price decrease**	(10) Frequency of price decrease
LDV	0.255***	0.307***	0.319***	**0.227*** **	0.226***	0.261***	0.351***	0.345***	**0.261*** **	0.257***
	(0.0335)	(0.0319)	(0.0307)	**(0.0321)**	(0.0312)	(0.0496)	(0.0485)	(0.0476)	**(0.0497)**	(0.0489)
HICP inflation	0.286***			**0.260*** **	0.256***	-0.132***			**-0.130*** **	-0.129***
	(0.0462)			**(0.0444)**	(0.0431)	(0.0275)			**(0.0282)**	(0.0278)
Retail Sales		0.0824***		**0.0706*** **	0.0438**		-0.0111		**-0.00305**	0.00954
		(0.0143)		**(0.0132)**	(0.0178)		(0.00873)		**(0.00845)**	(0.0116)
Consumer Expectations			0.000226***		0.000113**			-0.00006**		-5.30e-05*
			(3.51e-05)		(4.49e-05)			(2.18e-05)		(2.94e-05)
Constant	0.0340***	0.0372***	0.0458***	**0.0364*** **	0.0364***	0.0305***	0.0256***	0.0235***	**0.0305*** **	
	(0.00309)	(0.00326)	(0.00360)	**(0.00297)**	(0.00297)	(0.00232)	(0.00220)	(0.00231)	**(0.00233)**	
Observations	211	211	211	**211**	211	211	211	211	**211**	211
R-sq. Adj	0.839	0.825	0.834	**0.854**	0.854	0.609	0.559	0.574	**0.606**	0.616

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Estimations include monthly and VAT dummies.

The Greek experience stands in somewhat contrast to the UK estimates of Dixon et al (2020), where output was not found significant in explaining the frequency of price increases and decreases. This could be for two main reasons. First, the Greek retail sales measure we use is a better measure of output than the industrial output measure used in the UK study.[23] Second, the changes in Greek output were much more dramatic than in the UK. They were both larger as well as longer lasting, bringing thus out the effect of output on pricing behavior better.

5 Endogenous inflation dynamics.

In this section we will look in more detail as to how past inflation can affect current inflation and hence lead to inflation persistence. We focus on the fact that *annual* inflation seems to be an important determinant of the current frequencies of increases and decreases. Thus, when we are looking at price changes this month, they are going to be affected by the previous behavior of prices over the past year. This links current pricing behavior and past inflation. For simplicity, we will assume that current inflation does not affect the size of price changes. We do this by incorporating our regression results and adapting the simple 3 equation New-Keynesian model. Our adaptation involves replacing the new Keynesian Phillips curve with an empirical Phillips curve based on our estimated equations.

We start with the most basic Euler equation where the output gap at time *t* is defined as:

$$x_t = E_t x_{t+1} - \frac{1}{\sigma}(i_t - E_t \pi_{t+1} - i^*) + \epsilon_{dt} \qquad (8)$$

Where x_t is the output gap at time *t*, E_t are expectations at time *t*, and π_{t+1} is inflation at time *t+1*. In this simple model, there is no investment so that output is equal to consumption.

We include a simple Taylor rule where the nominal interest rate *(i)* at time *t* is:

[23] Industrial output is significant for the frequency of decreases for Greece but with the 'wrong' sign. We believe that retail sales is a more pervasive measure of economic activity as it covers more than half of private consumption, which in turn represents about 60 percent of Greek GDP. By contrast, industry in Greece is around 10 percent of GDP over our sample period.

$$i_t = i_\pi \pi_t + i_x x_t + \varepsilon_{it} \quad (9)$$

The interest rate responds to current inflation and output, with $i_\pi > 1, i_x \geq 0.$

Finally, we include a 'modified' Phillips curve, which is based on our regressions. Specifically, for each month we have the identity:

$$\Delta \Pi_t = f_0^+ \Delta\pi^+ + f_0^- \Delta\pi^- + \pi_0^+ \Delta f^+ + \pi_0^- f^- + \epsilon_{\pi t} \quad (10)$$

Where the difference is from the initial "steady state" values (given by the subscript *0*). We further simplify the model in the light of section 3.3 by taking the counterfactual form where the size of price increases and decreases are fixed. From our regression models (4) and (9) of Table 2, we have, in difference form, the following equations driving changes in frequencies:

$$\Delta f^+ = 0.26 \Delta \Pi^A + 0.23 \Delta f_{-1}^+ + 0.07 x_t \quad (11)$$

$$\Delta f^- = -0.13 \Delta \Pi^A + 0.261 \Delta f_{-1}^- \quad (12)$$

We are giving the output gap the coefficient for retail sales growth. Given the behavior of Greek output in this period, we do not believe the output gap to be well defined in the data.

We also have the annual rate of inflation being given by the sum of the current and previous 11 months month on month inflation:[24]

$$\Pi_t^A = \sum_{i=0}^{11} \Pi_{t-i} \quad (13)$$

Finally, we define our inflationary shock variable:

$$\epsilon_{\pi t} = \rho \epsilon_{\pi, t-1} \quad (14)$$

We will investigate two shocks, a temporary shock where ρ is 0.85, which implies that the initial shock has a half-life of 4 months and dies out after approximately 2 years and a highly persistent shock where ρ is 0.99, with a half-life of almost 6 years, resulting in higher inflation for many years. In all instances, we scale our shock appropriately to 0.3, which implies an increase of month-on-month inflation by 0.3 percentage points on impact. We will compare the outcome of our variables

[24] This is an approximation that ignores the compounding of inflation but works well for inflation rates of 5% or less.

of interest, inflation, output and interest rates with a 'mechanical' approach, where we switch off equations (11) and (12) and simply introduce the shock into equation (10). That is, we will not have a feedback loop between annual inflation and the frequency of increase and decrease, which create further inflation pressures.

The path of the economy in our simple adapted new Keynesian model is the outcome of the interaction between above equations. The initial inflation shock will have a positive feedback generated by the endogenous inflation dynamic as the frequencies respond to the gradual rise in annual inflation.[25] However, there is also negative feedback, as the Taylor rule leads to an increase in the nominal and real interest rate from (9), which leads to a fall in output via (8) and hence a fall in the frequency of price increases via (11). Eventually, the economy will return to its initial steady-state. The Euler equation (8) assumes a unit intertemporal elasticity of substitution which is very standard (albeit stylized), as is the Taylor rule coefficient on inflation and output of 1.5 and 0.5 respectively (which satisfies the Taylor principle). We believe our choice of model in this section is robust and to show this in Appendix C and E we provide some alternative calibrations and scenarios.

The monthly impulse responses of annual inflation are presented in Figure 7 for both a temporary and persistent shock of 0.3 p.p. on month-on-month inflation. We compare the endogenous responses with the 'mechanical' ones, that is, when the feedback loop between annual inflation and the development of frequencies in equations (11) and (12) is switched off and equations (10-12) become more like a regular Phillips curve linking current inflation to output growth. The responses are at a monthly frequency for up to 6 years (72 months) after the shock.

[25] The endogenous dynamics will act as an 'inflation accelerator' in a similar sense as analyzed in Blanco et al. (2025).

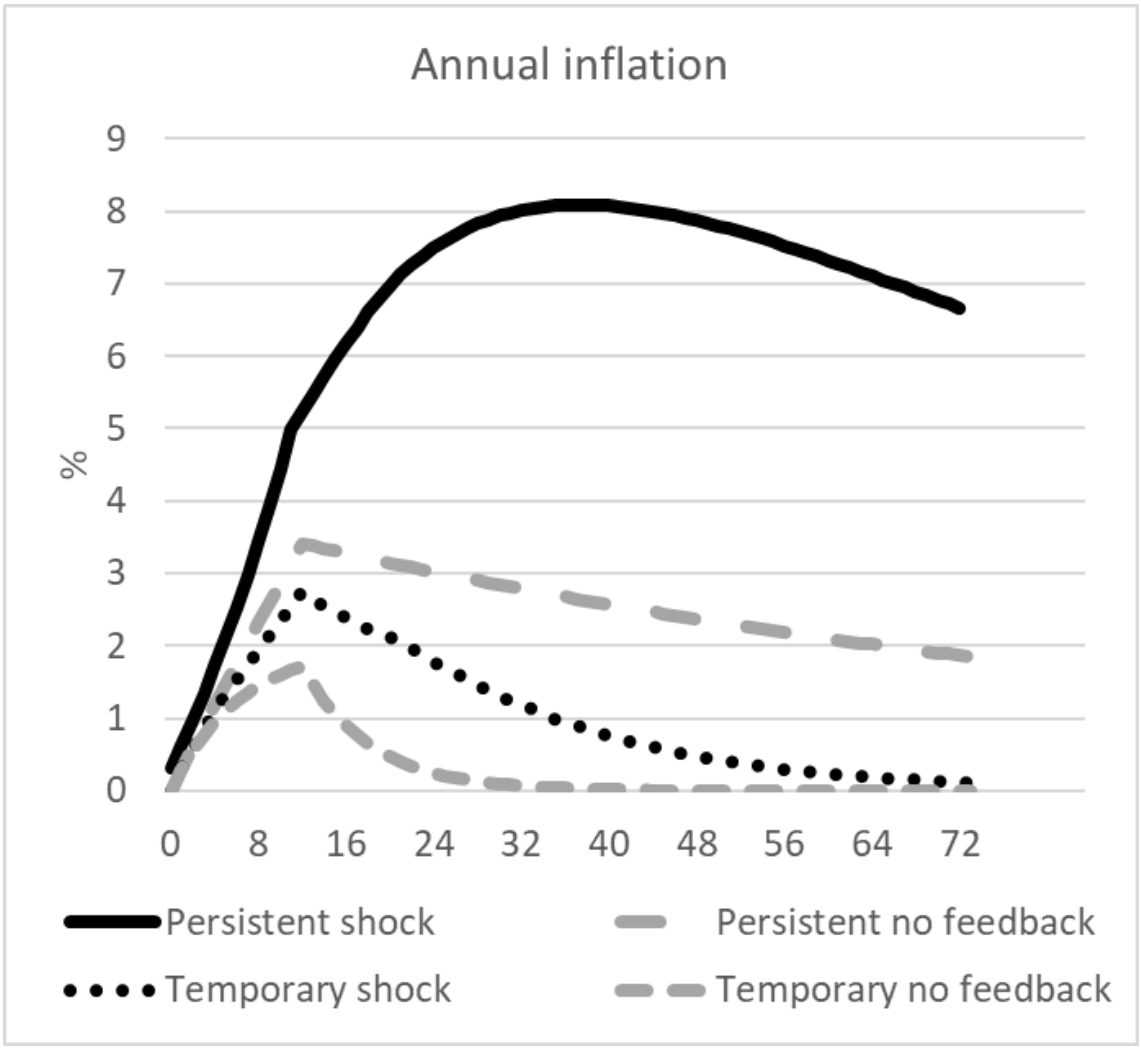


Figure 7: Impulse responses of annual inflation to a 0.3 p.p. shock to month-on-month inflation.

Naturally the mechanical responses die off quickly compared to the response with an endogenous inflation feedback loop. Moreover, the mechanical approaches produce significantly lower headline inflation. The difference between the impulses with and without the inflation feedback loop becomes much bigger with the persistent shock. When the shock is persistent annual inflation accelerates more rapidly during the first year and also continues to increase for another two years reaching its peak after 36 periods (months) at almost 8.1 percent. The peak is higher than in the mechanical response by a factor 2.4. Moreover, the peak is reached two years later when there is an inflation feedback loop. When the shock is temporary we still obtain a higher annual inflation

when we have a positive feedback loop but it's only higher by a factor of 1.6 and they both peak after 12 months. The duration of the shock is thus important in terms of evaluating the importance of the inflation feedback and the main reason is that as inflation keeps increasing we see the frequency of price changes up and down diverging to create additional momentum for annual inflation. This is seen in Figure 8. When the shock is persistent, the frequency of price increases goes up by almost 2.7 percentage points, while the frequency of price decreases declines by almost 1.4 percentage points. The total frequency increases by almost 1.3 percentage points. In the case of a temporary shock the frequency of price increases goes up by about 0.9 percentage points while the frequency of price decreases declines by almost 0.5 percentage points, with the total frequency increasing by about 0.4 percentage points.[26]

This exercise shows clearly that if an aggregate shock is deemed to be temporary, the reaction of the frequencies will be small (more akin to a Calvo model) and produce relatively small differences in annual inflation developments when compared to a world where there is no endogenous inflation feedback loop. By contrast, if a shock is deemed to be persistent the reaction of frequencies will be significantly larger (more akin to a state-dependent model) producing significant differences in annual inflation developments compared to a world where there is no inflation feedback loop.

We can also see that in Figure 8, the effect of a positive inflation shock has a larger impact on the frequency of price increases than on the frequency of price decreases. i.e. it affects the frequencies asymmetrically. All else equal, this implies that in periods of high inflation the total frequency of price changes (the frequency of price increases plus the frequency of decreases) is higher than for low inflation periods. This result is in line with observations in several other countries over different periods of time, including Mexico, in Gagnon (2009), for Norway (see Wolfsburg 2016) as well as for the US and the UK (see Nakamura et al. 2018 and Dixon et al 2020 respectively) and the euro area (see Gautier et al. 2026).

[26] See also Appendix D, Figure D1.

The simulation results are naturally very much in line with the developments in the relative frequencies observed in Greece during the sovereign debt crisis as this is also the period used to estimate the reaction of the frequencies to inflation and output developments in our model.[27]

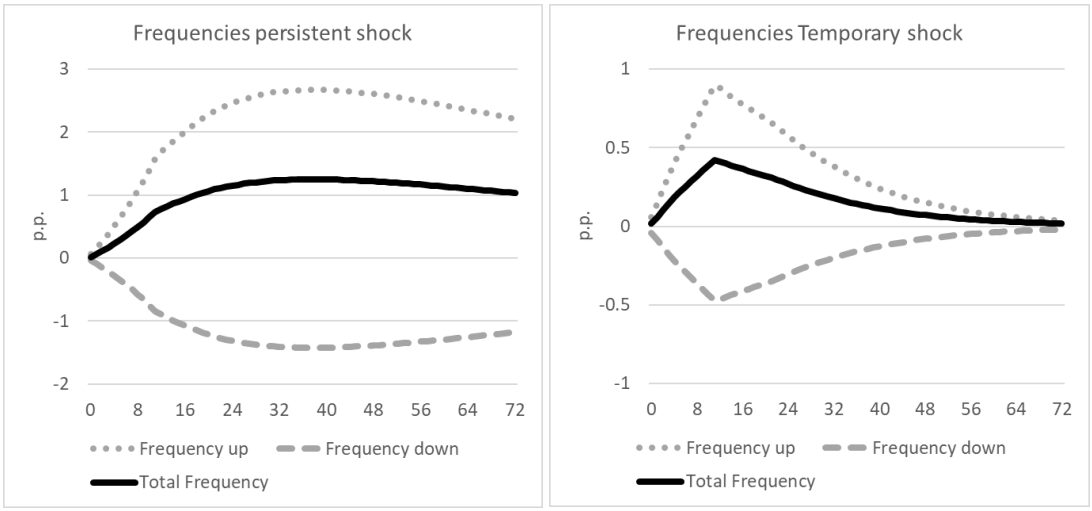


Figure 8: Impulse responses of frequencies to a shock.

How should we interpret the empirical Phillips curve captured in equations (10-14)? We do not claim to have estimated anything more than reduced form relationships in Table 2, and there are thus alternative interpretations that can be made. The simplest is that price setters for consumer goods and services are influenced by the annual rate of inflation, which is what is most prominent in the news. This is a backward-looking measure from one perspective. However, it is also forward looking in the sense that there is a high persistence in the annual rate of inflation and so a higher current rate of inflation would imply a higher rate in the coming months (for example in the 6-9 month horizon), which would also influence a forward looking price-setter.[28]

[27] As shown earlier, Greece was hit by a large negative shock to output whereby the frequency of price increases declined by approximately 2 percentage points, while the frequency of price decreases went up by approximately 1 percentage point. The full impact of the changes in frequencies took about 2 years to materialize.

[28] Furthermore, one can think of the annual rate as an AR(12) process with equal weights on monthly inflation, hence as a simple ARIMA forecasting model for the new monthly inflation that will emerge in the coming months. It is a topic for further research to interpret the reduced form equations structurally, and this would require more detailed firm-level data rather than the HICP price-data used in this paper.

One question of interest is if this simple model can help explain inflation developments out of sample? In particular, how well can this model, which is estimated for a large negative output shock, help explain inflation developments for a large positive cost shock?

5.1 Out of sample projection.

For this exercise we will use the actual increase and subsequent decrease of the energy component of the Greek HICP to obtain the size of the energy price shock. We will enter the size of the shocks into our model, through eq. (14), and investigate whether we can match developments in inflation excluding energy for Greece during the period 2020-2023. We should keep in mind that our micro data, which we have used in our estimations and from which our model of endogenous inflation dynamics is based, exclude energy, thus the results we obtain are to be compared with inflation developments excluding energy.

Energy prices in Greece (and Europe) started to increase dramatically towards the end of 2020 and the increase persisted for about 2 years (see Figure A5). Over this period (end of 2020 to end of 2022) the average month-on-month energy inflation increased by around 3 percent (each month) which corresponds to an impact of about 0.3 percent on total HICP month-on-month inflation.[29] Thereafter (mid to end 2022) energy prices started to decline for a period of about 1 year. The average month-on-month energy inflation decrease over this period was around 2 percent (each month), which corresponds to about 0.2 percent on total HICP month-on-month inflation. We use these developments to calibrate the shocks to month-on-month headline inflation in our modified Phillips curve (eq. (10)), and each shock (+0.3 and -0.2) is modelled as being persistent. Finally, in Figure 9, we combine the annual inflation developments into one timeseries and investigate whether the model presented generates a response in annual inflation which matches the actual developments in HICP inflation excluding energy for Greece. Note that whilst we are simulating a cost shock from energy prices, the calibrated model was based on estimates taken from data from a large (negative) demand shock. Hence we are "out of sample" both in terms of the time period and also the type of shock.

[29] See Figure A5 for the inflation of the energy HICP component in Greece.

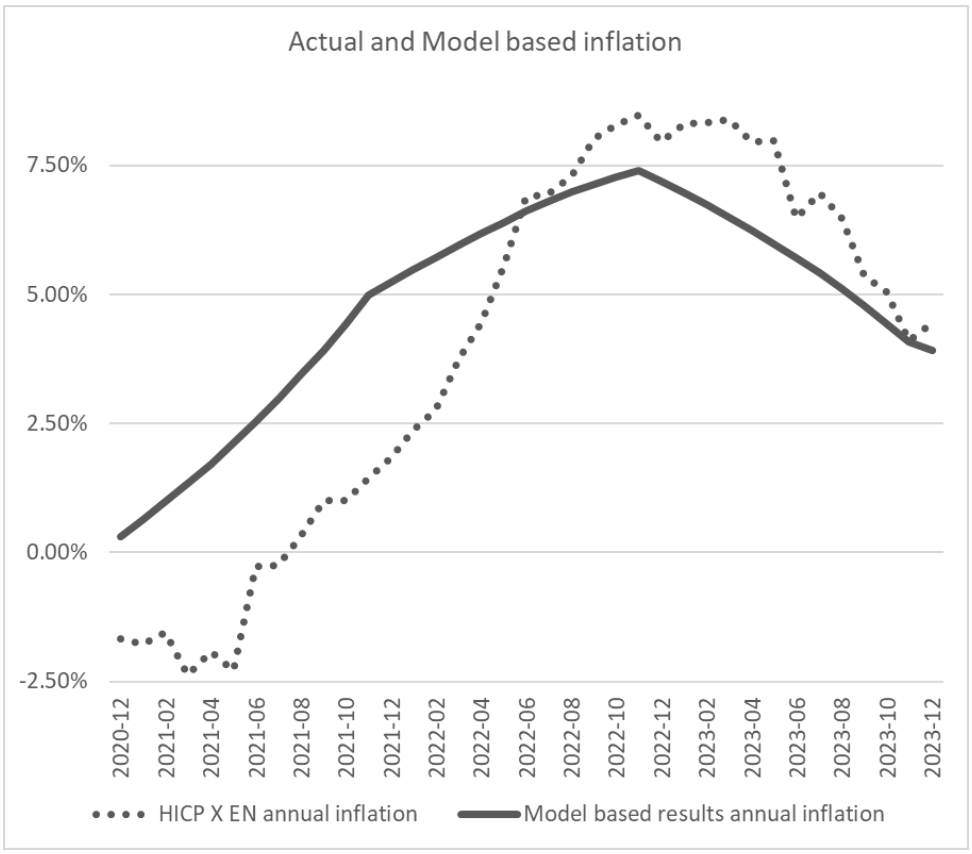


Figure 9: Annual inflation of model-based results based and actual HICP excluding energy.

In Figure 9, we can see that the response simulated from the model is able to capture actual inflation developments very well over a period from December 2020 to December 2023. The fit is good in terms of size and pace of inflation developments during both upward and downward phases of the cycle.[30] This implies that there are significant similarities to inflation developments when shocks are large, irrespective of whether the shock is positive, negative, a demand or a cost shock.

However, we can see that our model underestimates the change in all frequencies (up, down and total) despite having the endogenous loop from inflation to frequencies (see Figure 10). The modelbased frequency of price increases goes up from about 4 percent and peaks at about 6.2 percent while the frequency of price decreases declines from about 4 percent to 2.8 percent.

[30] During 2020 and 2021 there were two additional channels that affected inflation developments to some degree which are not modeled. Namely, the post-Covid supply chain disruptions together with underlying pent-up demand. See for example Giannone and Primiceri (2024).

Correspondingly, the model based total frequency of price changes increases from 7.8 percent to almost 9 percent. This can be contrasted with the larger increases in the data: the frequency of increases went from 4 to 11 percent, the frequency of decreases went from 4 to 5 percent, and the total frequency of price changes increased from 7.8 percent to around 15 percent.

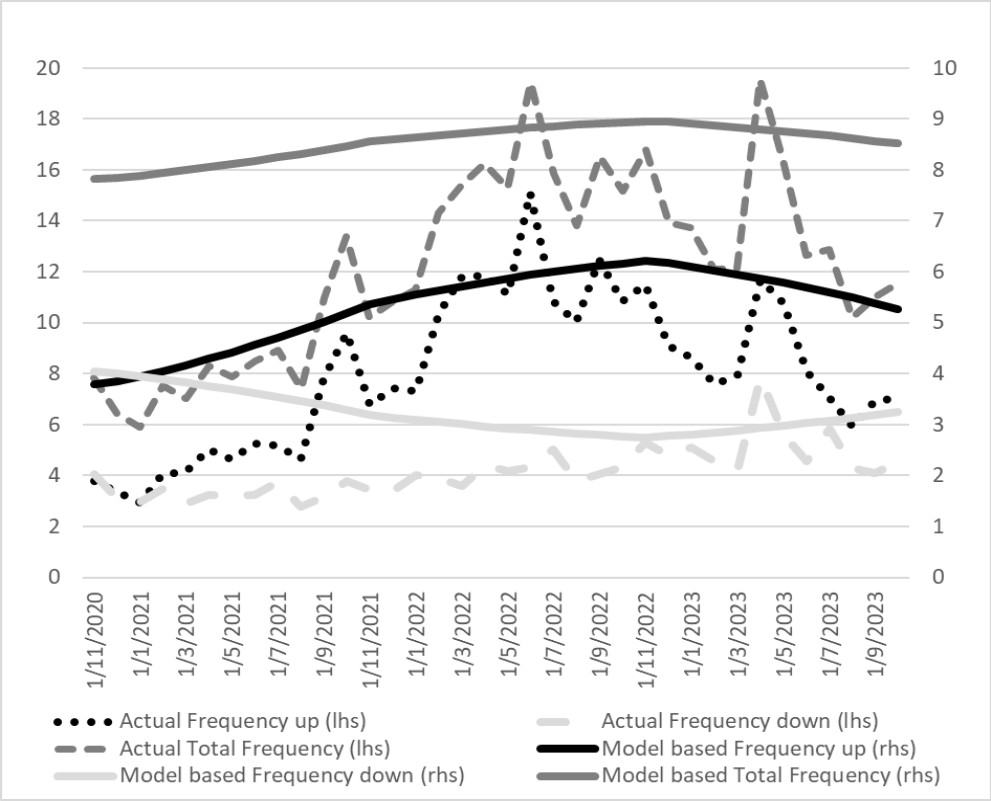


Figure 10: Developments in the Frequencies. Model based and actual

Despite the fact that the model-based frequencies underreact significantly to what is observed, the model is able to match developments in the *relative share* of increases and decreases in the total frequency very well (see Figure 11). This happens due to the asymmetric impact of headline inflation on the frequency of increases and decreases (see eq. 11 and 12) in the endogenous response of frequencies. Evidently matching the relative shares is more important when it comes to matching headline inflation

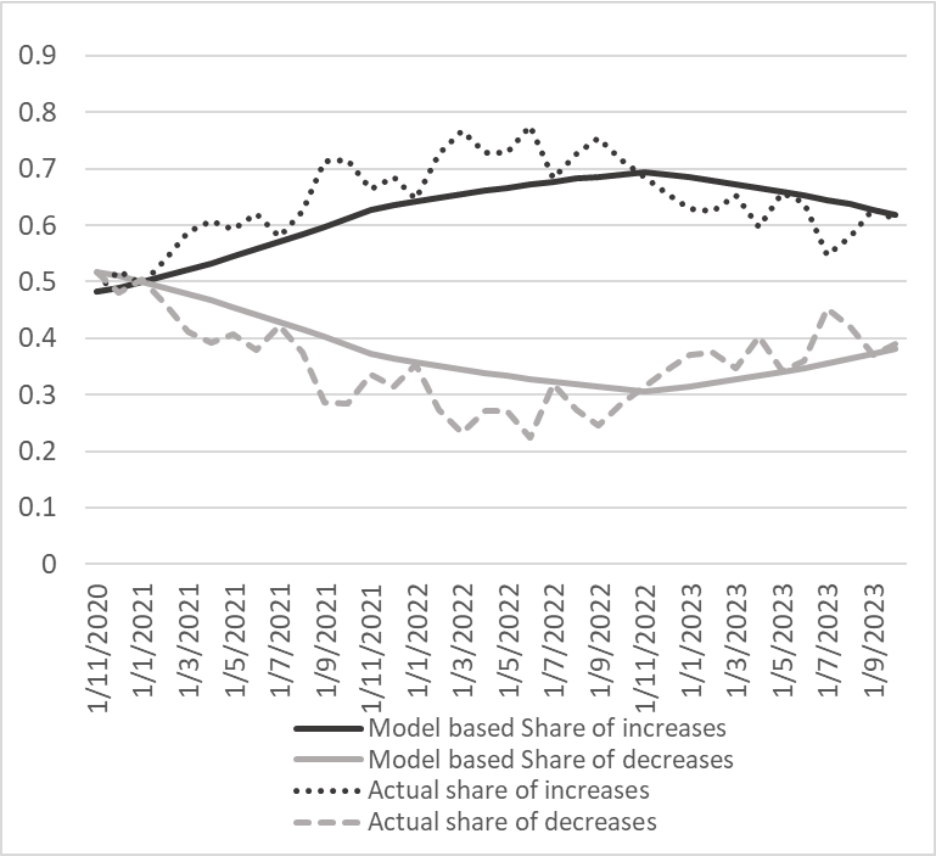


Figure 11: Shares in Total Frequency. Model based and actual.

6 Mispricing and uncertainty

Recent findings show that a large positive cost-shock increases the frequency of price adjustments, more so than a negative shock,[31] with the frequency of price increases reacting much more than the frequency of price decreases. However, when faced with a positive shock, like a cost-shock during the energy crisis, theory predicts that the frequency of price decreases, i.e. the share of products with positive price gap, should decline. By contrast, in the data during the energy cost shock the frequency of price decreases went up. In this section we argue that this "perverse" effect may reflect the increased uncertainty during this period and an element of mispricing (i.e. firms reversing a price change).[32] An increase in mispricing would cause an increase in frequencies of price changes that we observe in the data. In this section we attempt to detect and measure

[31] This is the direct consequence of the asymmetric shape of the hazard function with respect to positive price gaps and negative price gaps as the profit function of firms is asymmetric, see Cavallo et al. (2024).
[32] See for example Baley and Blanco (2019) and Canales and Lopez-Martin (2024).

mispricing in the data. We define mispricing as a price change which is immediately reversed. Specifically, if there is:

- a price decrease in month (t) followed by a price increase at (t+1) or
- a price increase in month (t) followed by a price decrease at (t+1)

then an item/product has been mispriced at time t. Note that our data on price changes are sales filtered, so we are not capturing sales within our definition of mispricing. However, for items with flexible prices which change most months in response to demand and supply, they might naturally follow a pattern that falls under our definition of mispricing. Hence our definition of mispricing will overestimate the level of real mispricing. However, we can think of actual mispricing as a proportion of our measure. In this respect, large changes in our measure reflect large changes in actual mispricing.[33]

We estimate, for each year, a panel probit regression and calculate the marginal probability of each of the two cases of mispricing at the finest product category.[34] Each annual estimate includes between 360 to 490 thousand observations. We plot these conditional probabilities and their standard errors (i.e. the probability of an increase in time (t) given a decrease in (t-1) and the probability of a decrease in time (t) given an increase in (t+1)) in Figures 12 and 13.[35]

Both definitions of mispricing start to increase during the first large shock, the sovereign debt crisis. During the energy crisis period we see that one form of mispricing, namely the probability of an increase in time (t) given a decrease in (t-1), increases greatly over the period 2021-2022 but starts decreasing in 2023. The second form of mispricing, the probability of a decrease in time (t) given an increase in (t-1), remains elevated in 2020 and 2021 and declines strongly in 2022.[36] On balance we see that during large shocks mispricing, as defined here, increases. For the latest period, which includes the energy cost shock, we see that during the inflation peak of 2022 a significant share of price decreases were immediately reversed.

[33] The mispricing merely captures the reversal in terms of sign, not magnitude.
[34] Naturally we estimate the panel probit on price changes excluding sales. The estimations also include dummies for the dates of VAT changes.
[35] The results are robust to alternative lag structures in the definition of mispricing and to alternative period estimation of the panel probit.
[36] Despite this strong decline in 2022 it still remains above the mispricing probability of our 'normal' period 2002-2011.

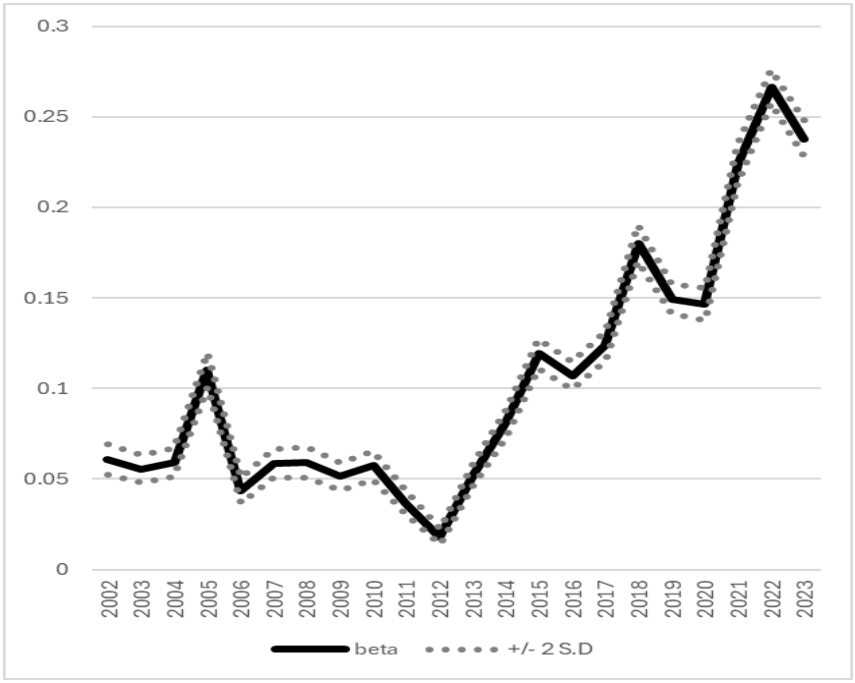


Figure 12: The probability of an increase in time (t) given a decrease in (t-1), marginal effects

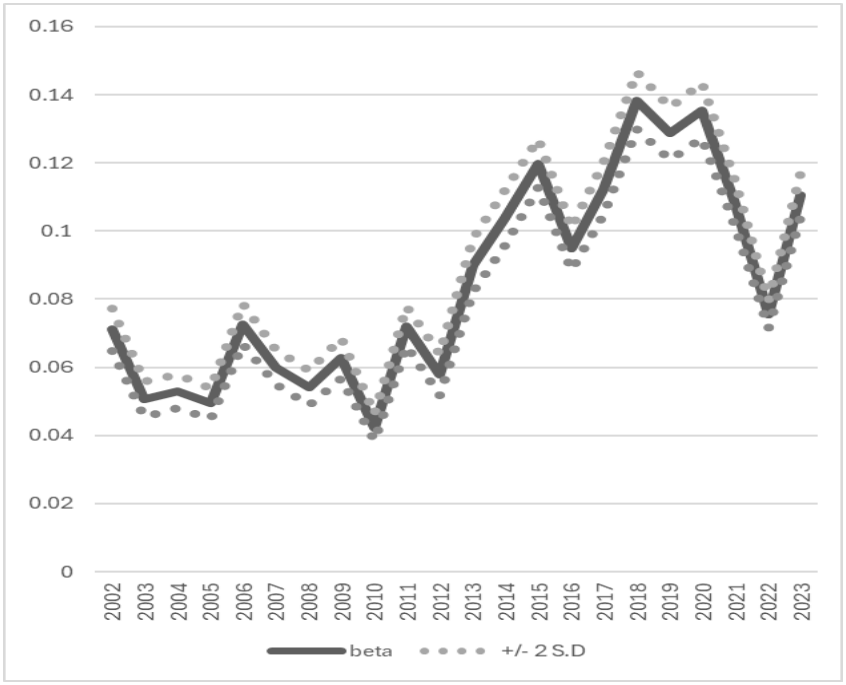
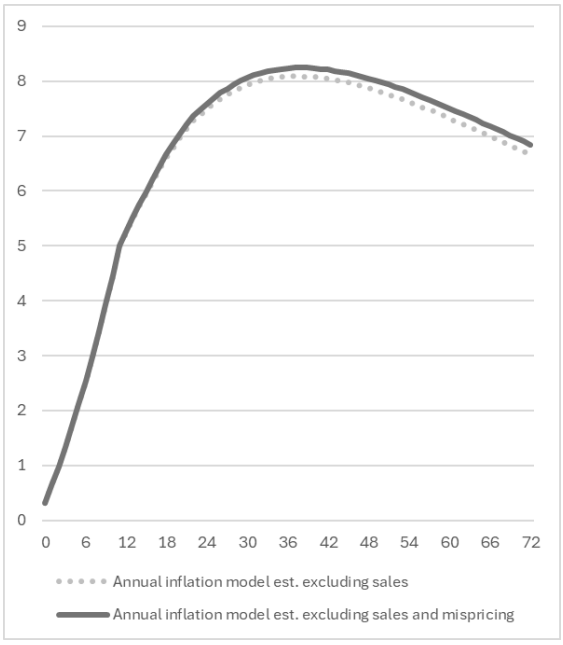
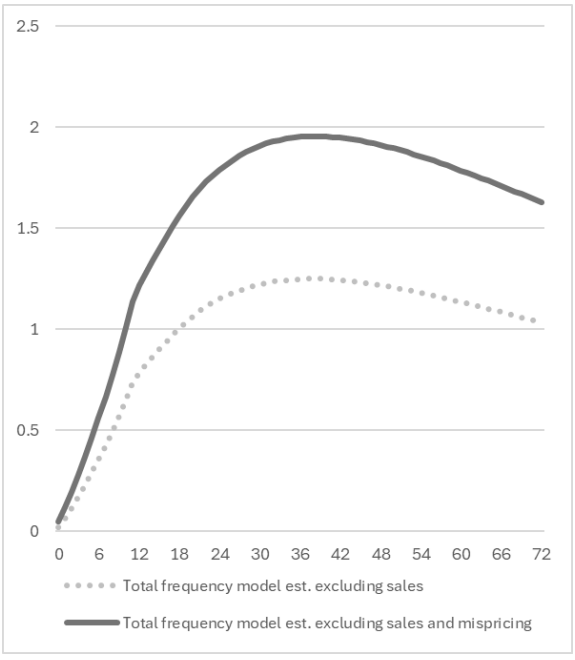


Figure 13: The probability of a decrease in time (t) given an increase in (t-1), marginal effects

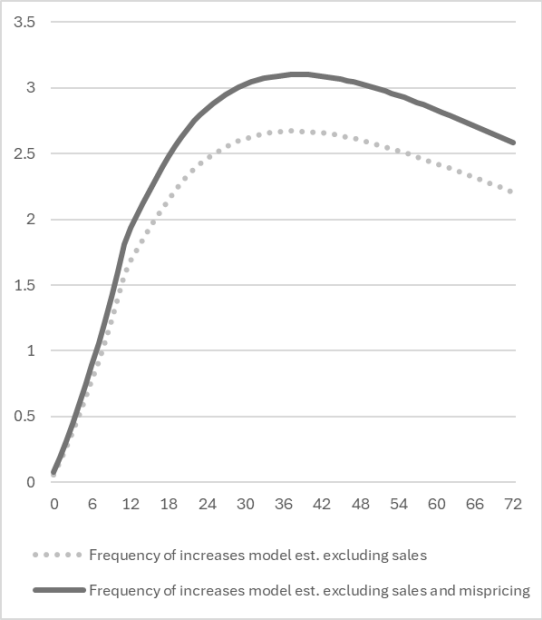
Hence what we observe in the data is a significant increase in mispricing. A mispricing "event" leads to an increase in both the frequency of increases and decreases. Cleaning the data from these events produces thus lower frequency developments in general. However, as with the case of sales, as mispricing is temporary it is neutral to overall inflation. In fact, recomposing inflation from our micro data excluding sales and excluding sales and mispricing produces almost identical year-on-year inflation rates (see Chart E1 in Appendix E). Cleaning our data from mispricing events also produces frequency developments that align with theory. In particular, for the years 2021 and 2022 the frequency of decreases shows a hump shaped decline and starts to increase again in 2023 when inflation is coming down. Lastly, we can note that excluding mispricing does not affect the share of increases and decreases in the total frequency over time (see Charts E2 to E5 in Appendix E).

Despite the fact that mispricing does not affect inflation, the presence of mispricing might have affected our estimates in Table 2. We rerun our main estimations (4) and (9) of Table 2 for frequency developments excluding mispricing and recalibrate our model (see Table E1 in the Appendix E). The results show that annual inflation developments are almost identical. At the same time, the frequency of increases reacts by more to a positive cost shock of the same magnitude as previously, while the frequency of decreases reacts by less, which gives us a larger reaction of the total frequency of price changes for a given cost shock see Figure 14.

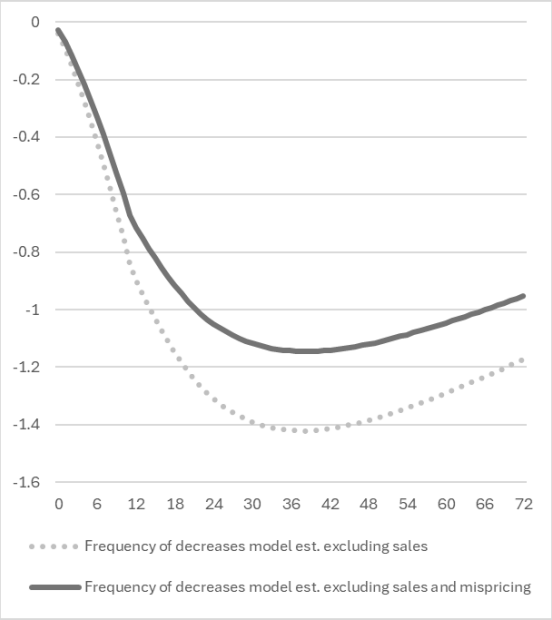




IRF: annual Inflation



IRF: Total frequency



IRF: Frequency of increases

IRF: Frequency of decreases

Figure 14: Impulse responses of alternative calibration, excluding sales and mispricing.

On balance, cleaning the data from mispricing events, seems to bring our results closer to theoretical predictions, in the sense that: a) during the energy cost shock we see that the frequency of price decreases goes down and b) total frequency reacts to a greater degree (see e.g. Cavallo et al. (2024).

7 State vs Time dependent pricing

A final question of interest that our small model with our modified Phillips-curve can shed some light on is how much of the recent inflation surge we observed, in particular during 2022, was state dependent. We can assess this issue indirectly by using the underlying assumption of time-dependent models which is that the total frequency remains constant over time. In our model set up keeping the total frequency constant can be achieved by altering the dynamics of our modified Phillips-curve, in our equations (11) and (12), so that the impact of inflation and the effect from lagged frequencies are equal to each for increases and decreases. This will ensure that the total frequency of price changes remains constant over time as movements in the frequency of

increases is canceled out by movements in the frequency of decreases. Thus, for a time dependent equivalence of our Phillips curve the frequency equations become:[37]

$$\Delta f^{+} = 0.13\Delta\Pi^{A} + 0.261\Delta f^{+}_{-1} + 0.06x_t \quad (15)$$

$$\Delta f^{-} = -0.13\Delta\Pi^{A} + 0.261\Delta f^{-}_{-1} \quad (16)$$

Simulating inflation developments for the same shock (+0.3 on month-on-month inflation) and comparing the outcomes from our original model and our 'time-dependent' version we see that the difference in annual inflation is non-negligible and increases over time (see Figure 15). For the first 12 months the difference in annual inflation is on average 0.3 percentage points, while for the second year (13 to 24 months) the average difference is around 1.5 percentage points.[38] The difference of the two models peaks after 5 years.

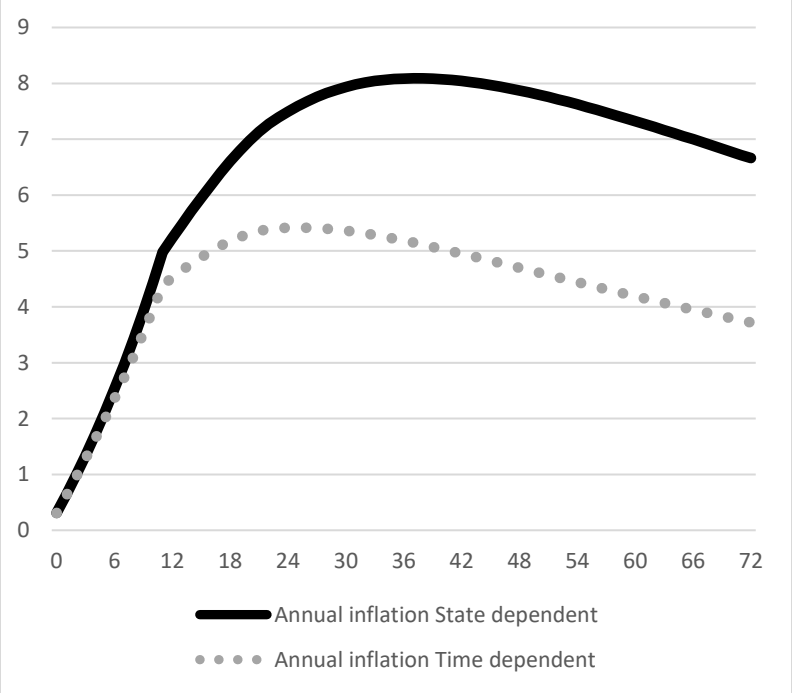


Figure 15: Annual inflation Time-vs-State dependent developments.

[37] One could argue that the difference in the estimated effects of inflation and the autocorrelation components between the frequency of increases and decreases is a measure of the state dependence of an economy.

[38] The size of annual inflation that is due to state dependence during the inflation surge in 2022 is in the same neighborhood as in Gautier et al. (2026), which utilizes a vastly different model. For the evolution of state and time dependent frequencies of this exercise see Figure D2 in Appendix D.

8. Conclusions

In this paper, we analyze price developments in Greece over the period 2002-2023 during which Greece went through two large shocks. The first one was a negative demand shock of similar magnitude of the Great depression and the second a positive cost shock during the energy crisis. We find that during these two shocks there were significant changes in the pricing behavior of firms both as regards developments in frequencies as well as the size of price changes.

We utilize the information gained from the first large shock and investigate whether we can predict developments in inflation excluding energy during the period of the second large shock, i.e. the energy crisis. In particular, we explore the relationship between the macroeconomic variables of inflation and output growth with pricing behavior by regressing these variables on the frequency of price increases and decreases. We find that annual inflation is an important determinant for both raising the frequency of increases and reducing the frequency of decreases. Moreover, the effect of inflation is stronger for the frequency of price increases than the effect on the frequency of decreases. At the same time, output growth affects only the frequency of price increases, but not the frequency of price decreases. These results imply that the inflation response reacts endogenously via an asymmetric impact on the frequency of price increases and the frequency of price decreases. Thus, current inflation affects future pricing behavior and hence future inflation.

Utilizing the results of these estimations, we replace the new Keynesian Philips curve in a simple three equation DSGE model with our estimated endogenous inflation dynamics. That is, we allow for annual inflation to affect the frequency of price changes. The simulations are able to replicate key developments of the Greek economy well and are also in line with stylized facts on the frequency of price changes of other economies and different time periods. The simulations are able to match the 'out of sample' inflation surge during the energy crisis. There are two key points to these results. First, inflation dynamics across time are endogenous, as monthly inflation - through changes in the frequencies- feed into annual HICP inflation which then affects pricing going on into the future. Second, there is an asymmetric effect of macro-economic conditions on the frequency of increases and the frequency of decreases.

While we show that higher inflation is associated with a higher total frequency of price changes the increase is below that observed during the energy crisis. We show that during large shocks, mispricing -defined as immediate price reversals- increases, which inflates the response of frequencies to inflation. Cleaning the data from mispricing events and re-estimating our model results in an increase in total frequency for the same shock while the inflation response remains the same. Finally, we show that for Greece, during the energy crisis period of 2021 and 2022, state dependence increased annual inflation by about 0.3 percentage points in 2021 and 1.5 percentage points in 2022.

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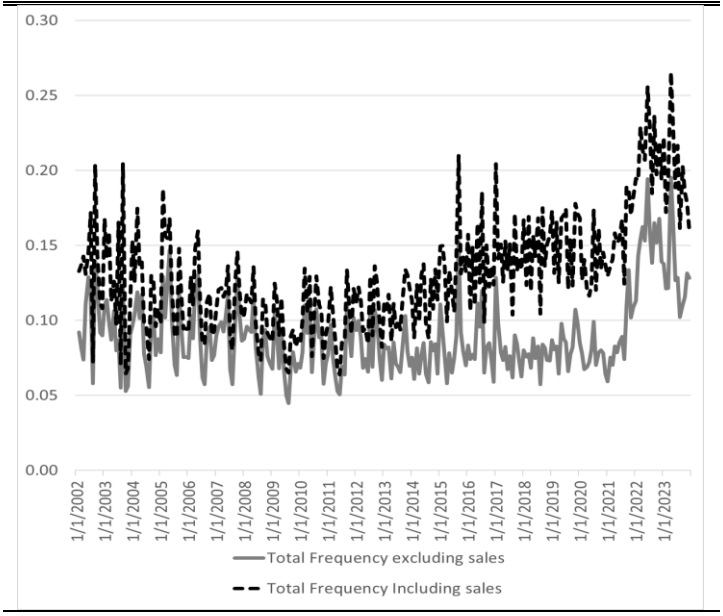
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Appendix A: Figures and Tables referred to in the text

Table A1: Frequencies of price changes including sales

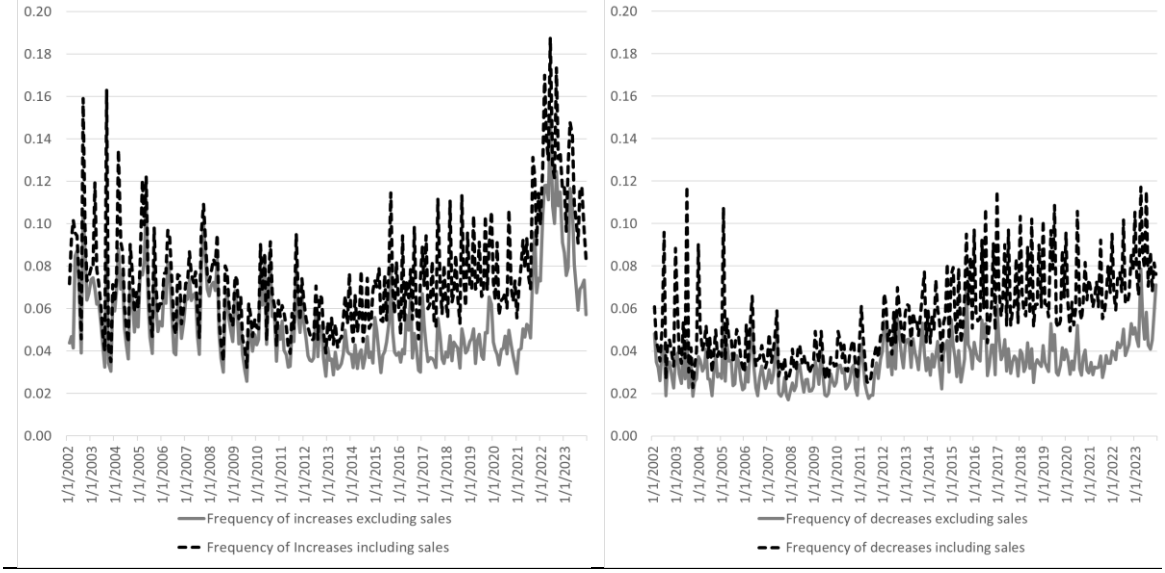
Time-period	Total Frequency	Frequency up	Frequency down
2002-2023	13.46%	7.85%	5.62%
2002-2010	11.89%	7.69%	4.20%
2011-2019	13.16%	6.93%	6.23%
2020-2023	17.67%	10.26%	7.41%

Figure A1: Frequency of price changes, excluding and including sales



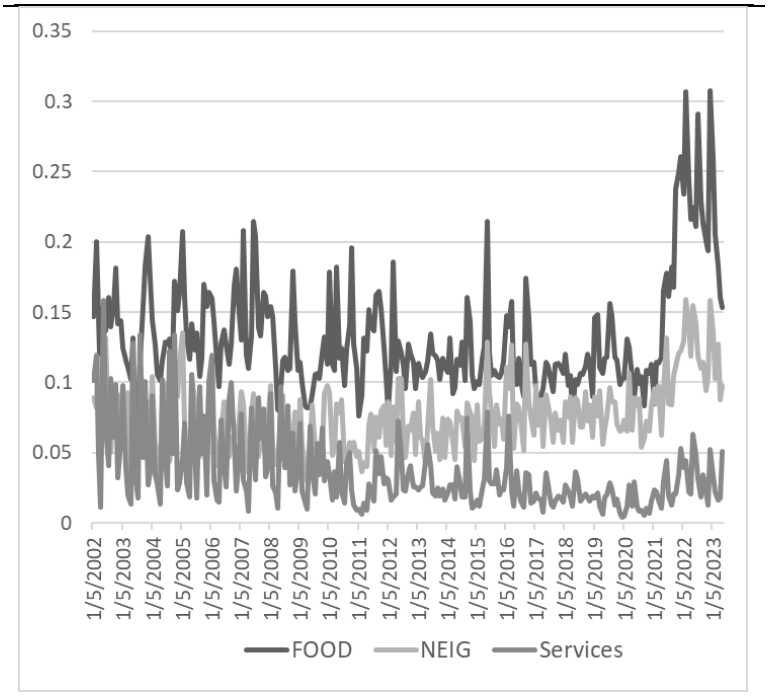
Source: ELSTAT, calculation by authors

Figure A2: Frequency of Increases and Decreases, including and excluding sales



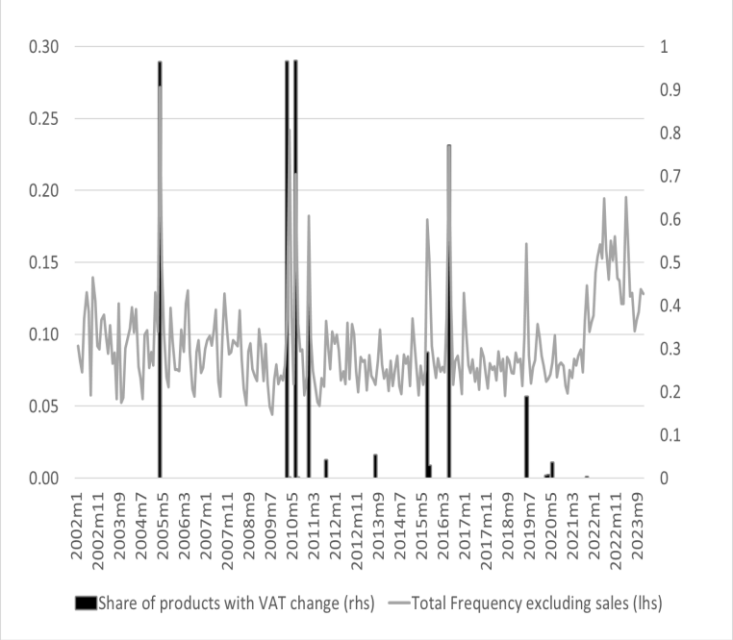
Source: ELSTAT, calculation by authors

Figure A3: Frequency of price changes – Main HICP components



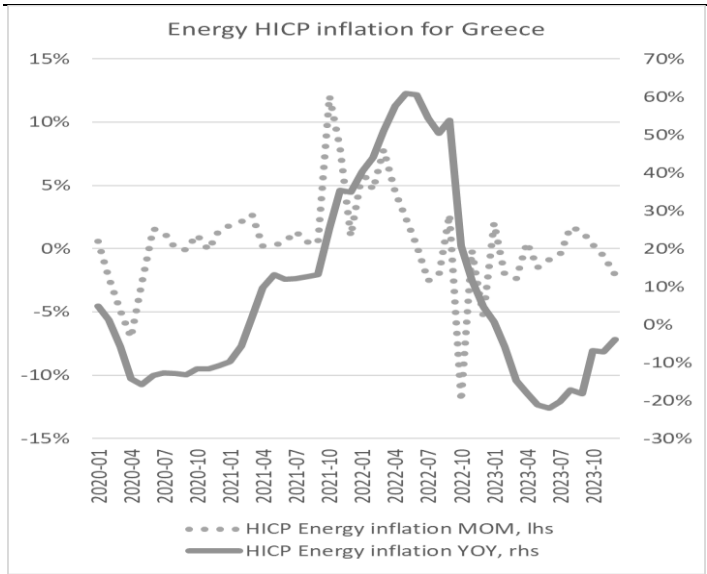
Source: ELSTAT, calculation by authors

Figure A4: Frequency of price changes and share of products with VAT changes



Source: ELSTAT, calculation by authors

Figure A5: Greek energy inflation.



Source: ELSTAT, calculation by authors

Appendix B. A cross-sectional analysis of price changes

When we consider price setting there is often a focus on prices that do change, how many prices change and by how much, as they are the ones 'producing' inflation. However, these prices tend to be a minority of the whole spectrum of prices used to measure inflation. One informative way to look at price setting is to focus on the cross-sectional aspect of price developments through the properties of price spells and the distribution of duration of price changes. In this way, we can represent better the pricing behaviour in micro price data as we take into account both the prices that change as well as the prices that do not change. In particular we can see how long do prices stay fixed on average, how long it takes for the average firm to change its price and how many firms are responsible for a majority of price changes.[39] To do this we need to introduce the concepts of a price-spell and the corresponding distribution of durations (DD) and cross-sectional distribution of durations (CSD).

A *price spell* is a sequence of the same price set by an individual seller for a particular product. The distribution DD gives the share for each duration from 1 month to the maximum F months, with shares summing to one and being non-negative.

$$DD = \left\{ \alpha_i^D \right\}_{i=1}^{F} : \sum_{i=1}^{F} \alpha_i^D = 1, \alpha_i^D \geq 0. \qquad \text{(B.1)}$$

An alternative is to look at the price spell data is to exploit its panel structure and take into account the fact that the spells are being generated by the behavior of the agents setting the prices (which we call firms). We can follow a row of the panel in terms of the price of a product/outlet pairing, following a particular price over time. The behavior of the firms setting prices is better captured by the cross-sectional distribution of durations (CSD). In particular, firms that reset prices frequently generate a lot of short price spells.

The easiest way to understand this is to think of a simple economy consisting of two firms over a year. One resets its price each month generating 12 one-month spells, the other generates one 12 month spell. In DD we observe a distribution of 12/13 one-month and 1/13 twelve-month spells,

[39] Alvarez (2007) provides an informative survey of estimates of price durations for a number of countries and discusses their implications for the assumptions of various theoretical models.

with a mean of 1.85 months. The cross-sectional distribution (CSD) looks at the two firms and averages across them, with ½ one-month spells and ½ 12 month spells. That is, in any one month there will be two spells, one of duration 1 month and the other 12 months. The cross-sectional average across the two firms is thus 6.5 months and more accurately reflects the structure of the economy. Firms which reset prices infrequently are less represented in the DD. On a formal level, the cross-sectional distribution means that spells are "length weighted": longer spells are more important than shorter spells. The CSD is a set of positive coefficients adding up to one.

$$CSD = \{\alpha_i\}_{i=1}^{F} : \sum_{i=1}^{F} \alpha_i = 1, \alpha_i \geq 0. \tag{B.2}$$

There is a simple equation linking the CSD to the DD, where in effect the shares of DD are length weighted. From Dixon and Le Bihan (2012) we have:

$$\alpha_i = \frac{i\alpha_i^D}{\sum_{j=1}^{F} j\alpha_j^D} \tag{B.3}$$

The CSD share α_i is equal to the corresponding α_i^D multiplied by the ratio of the spell length *i* to the mean of DD. This implies that the two distributions "cross-over" as the spell length passes by the mean price spell from DD.

In our data, from 2002 to 2023 there are 895,036 uncensored price spells, with an average duration of 11.1 months (see Table B1). The average cross-sectional duration is 19 months which is significantly longer than the average length of a spell. This indicates that the firms in Greece on average set prices for 19 months. This is longer than in other countries. For example, in the UK , excluding food and energy, we mean CSD is 4.34 quarters (14 months).[40] The difference between the mean of DD and CSD reflects the heterogeneity of pricing behaviour; if all firms set prices for the same length of time (as in the classic Taylor model), then the two distributions would have exactly the same mean. The fact that the mean CSD is longer than the mean DD reflects the fact

[40] See Dixon et al (2021) page 58 and Appendix Table A4.6.

that firms in different sectors generate different spell lengths (and indeed, a single firm might generate a range of spell lengths in the sample). In the Greek data the large difference between the means of CSD and DD reflect a greater heterogeneity of pricing behaviour.[41]

Table B1: Price spells, left and right censored

	Mean spell	Cross-sectional mean	Number of spells
2002-2010	8.9	21	340270
2011-2019	10.2	31	379766
2002-2023	9	31	895088
Food (2002-23)	6.6	19.9	483949
NEIG (2002-23)	10.6	33.6	351283
Serv. (2002-23)	19.6	54.8	52866

We can see that the mean spell increased during the sovereign debt crisis and so did the the cross-sectional mean. This implies that products with short(er) spells declined in their variability (like food prices) while at the same time products with long(er) spells changed prices even more infrequently or even stopped making price changes completely.

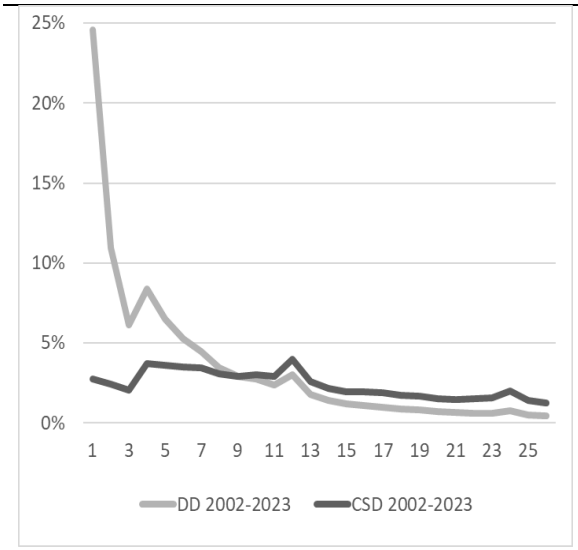
In Figure B.1 we show DD and the CSD for the whole sample and each main subcomponent of the Greek CPI data. The horizontal axis gives the duration of the price spell and the vertical axis the share of all spells. The distribution DD gives the share of each duration in all spells starting from 1 month to the maximum F months, with shares summing to one and being non-negative. The vertical axis for the CSD distribution gives the share of firms responsible for each duration. They cross over at 9 months which is the mean spell duration from DD. For shorter durations the shares for the CSD are much smaller than those of the DD. From the formula, the share of 1 period spells is less than one tenth in CSD as opposed to DD (2.4% vs 24.6%). This implies that the large 24.6% share of one-month spells in our sample is being generated by just 2.4% of firms. The firms generating most of the short spells are in Food and to a lesser extent NEIG which can be seen from their high shares of 1-month spells in their DD. The twelve-month spike is generated mostly by the Service sector and to a lesser extent in NEIG and is almost totally absent in Food. Finally, we can

[41] For a formal analysis of the relation between the means of DD and CSD, see Dixon and Tian (2017) Theorem 1.

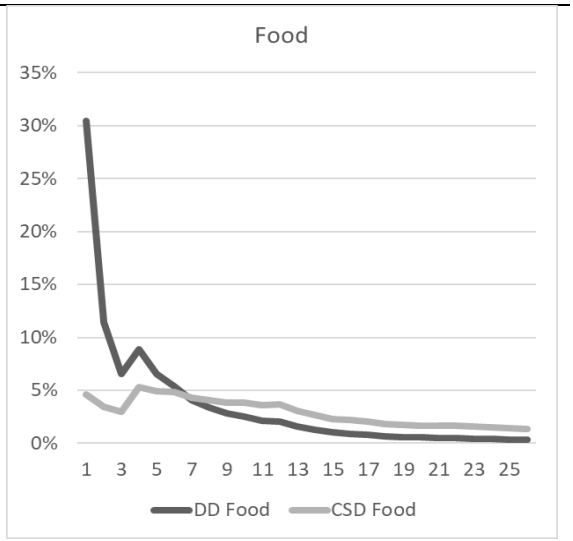
note that the proportion of firms setting prices for 12 months is larger than the share of those firms setting prices for one month (CSD has a long fat tail in contrast to the long thin tail of DD).

Figure B1: The Distribution of Durations (DD) and Cross-Sectional Distribution (CSD) over the whole sample, Total and Subcomponents.

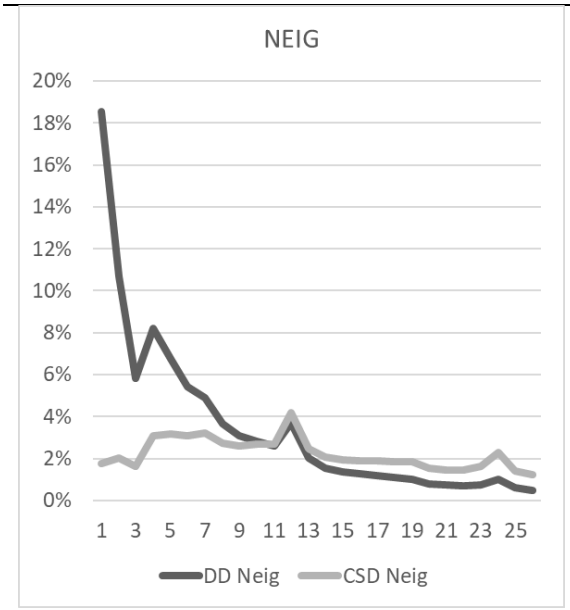
Total



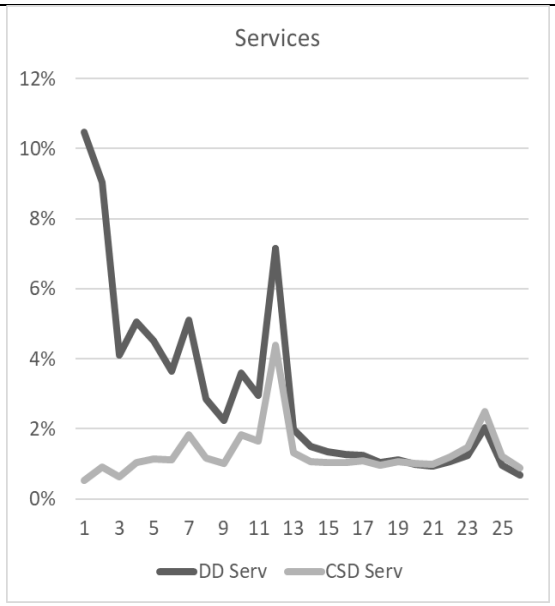
Food



NEIG



Services



Source: calculation by authors

Appendix C: Estimation on the drivers of the size of price changes

Intuitively one would expect rising price changes to be associated with higher inflation. If we consider equation (7) in the main text, high inflation would lead the current price to drift away from the optimal price, resulting thus in larger price adjustments when the decision to change prices is taken. However, in our case higher price changes are observed during a period with *lower* inflation. This phenomenon is also observed in Norwegian CPI data (see Wulfsberg 2016). This relation is confirmed by below estimations (Table C1) where the dependent variables are, the size of price increases and the size of price decreases (as measured by the proportionate growth rates).

We obtain the result whereby higher inflation and improving sentiment lead to smaller price increases (models 1 and 3). Retail sales growth leads to larger price increases only when inflation is included (model 5). By contrast, the size of price decreases seem to be explained only by inflation. What is evident in Table C1is that the magnitude of the lagged dependent variable is about 2-3 larger than in the regressions for frequency, implying that there is significant persistence in the size of price changes.

Table C1: Determinants of the size of price increases and decreases, LDV IV estimations

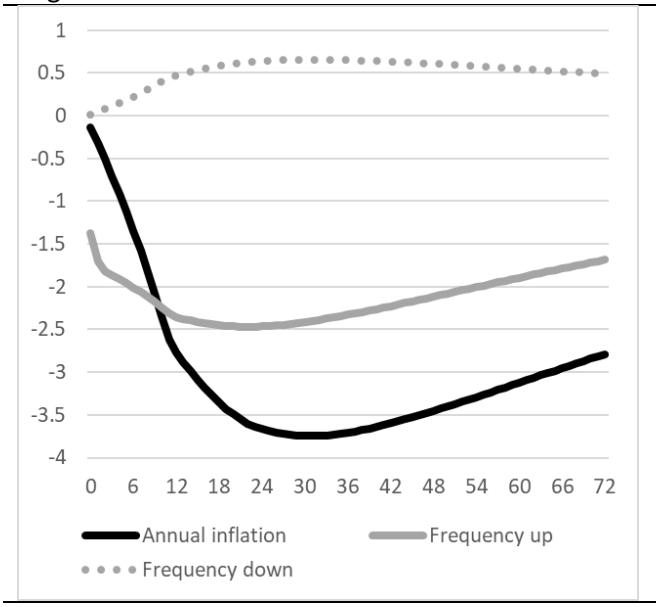
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Size of price increase					Size of price decrease				
LDV	0.691***	0.850***	0.838***	0.678***	0.671***	0.607***	0.842***	0.834***	0.590***	0.583***
	(0.0473)	(0.0301)	(0.0299)	(0.0514)	(0.0508)	(0.0616)	(0.0393)	(0.0398)	(0.0658)	(0.0671)
Annual HICP inflation	-0.327***			-0.353***	-0.330***	-0.497***			-0.535***	-0.526***
	(0.0768)			(0.0867)	(0.0832)	(0.103)			(0.114)	(0.113)
Retail sales growth		-0.0154		0.0106	0.0464**		-0.0187		0.0158	0.0360
		(0.0147)		(0.0160)	(0.0220)		(0.0198)		(0.0208)	(0.0295)
Consumers Future Economic Situation			-0.000103***		-0.000015***			-6.92e-05		-8.3e-05
			(3.68e-05)		(5.37e-05)			(5.06e-05)		(7.2e-05)
Constant	0.0475***	0.0248***	0.0218***	0.0494***	0.0434***	0.0736***	0.0363***	0.0346***	0.0766***	0.0737***
	(0.00671)	(0.00431)	(0.00439)	(0.00737)	(0.00706)	(0.00969)	(0.00614)	(0.00630)	(0.0105)	(0.0103)
Observations	209	209	209	209	209	209	209	209	209	209
R^2-adj	0.825	0.813	0.819	0.823	0.830	0.710	0.682	0.682	0.707	0.705

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Estimations include also monthly dummies and VAT change dummies

Appendix D: Additional simulations

In the simulation below (Figure D1) we shock output growth so that output growth reaches about -20% year on year, which is approximately the largest decline observed in the retail volume sales growth during the sovereign debt crisis. To define the shock as persistent (the volume index on retail sales itself, i.e. the level of output, declined from about 180 to around 100 over the crisis period, cumulatively that is about 44%).

Figure D1: Simulation of inflation developments to a negative demand shock.

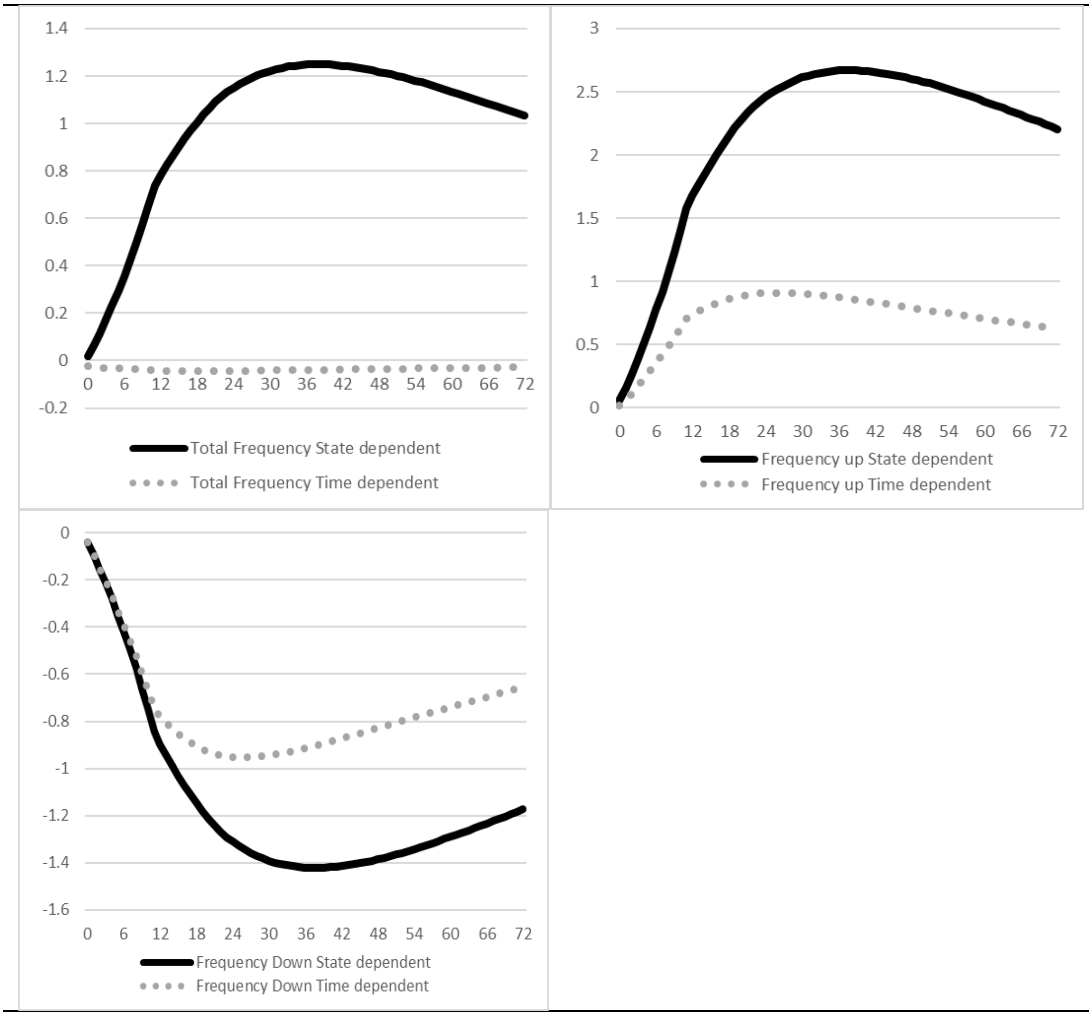


Source: calculation by authors

In this simulation we also switch off the interest rate channel with respect to output. This is in line actual developments for Greece as the country: 1) does not have an independent monetary policy, being part of a monetary union 2) was excluded from most monetary policy operations as it entered the rescue program.

A large and persistent negative shock to output produces results for inflation and frequencies similar to those observed in Greece during the sovereign debt crisis period. The model based annual inflation rates in HICP (excluding energy) as well the frequencies of increases and decreases move by magnitudes similar to those observed in reality.

Figure D2: Simulation of Frequencies in State and Time dependent versions of our small scale model.



Source: calculation by authors

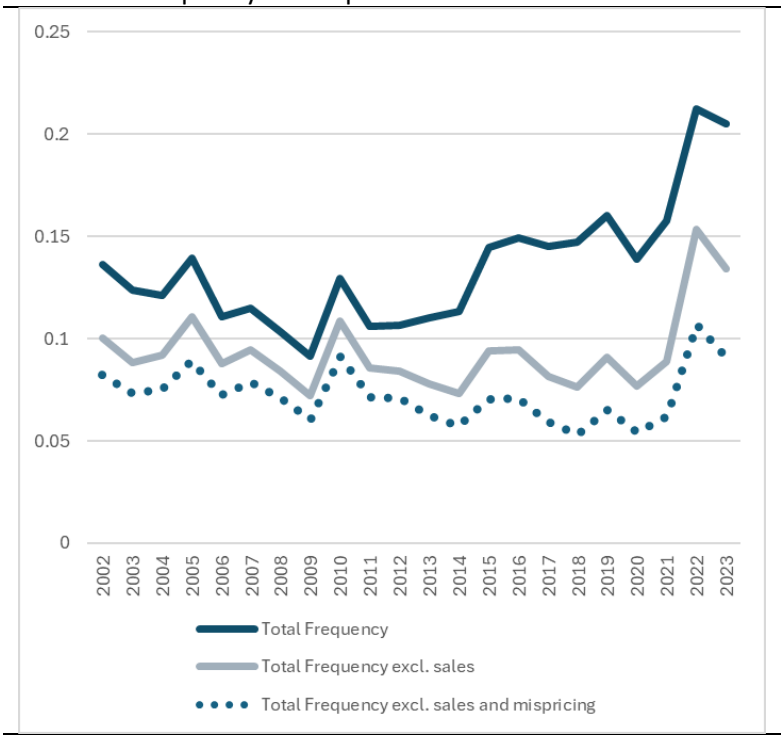
Appendix E: Mispricing analysis

Chart E1: Recomposed inflation based on micro data



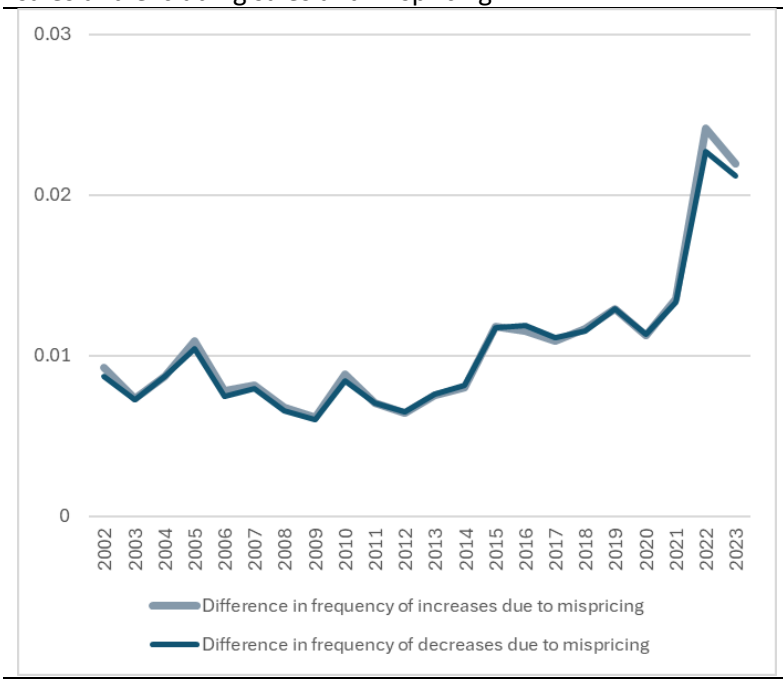
Source: calculation by authors

Chart E2: Frequency developments



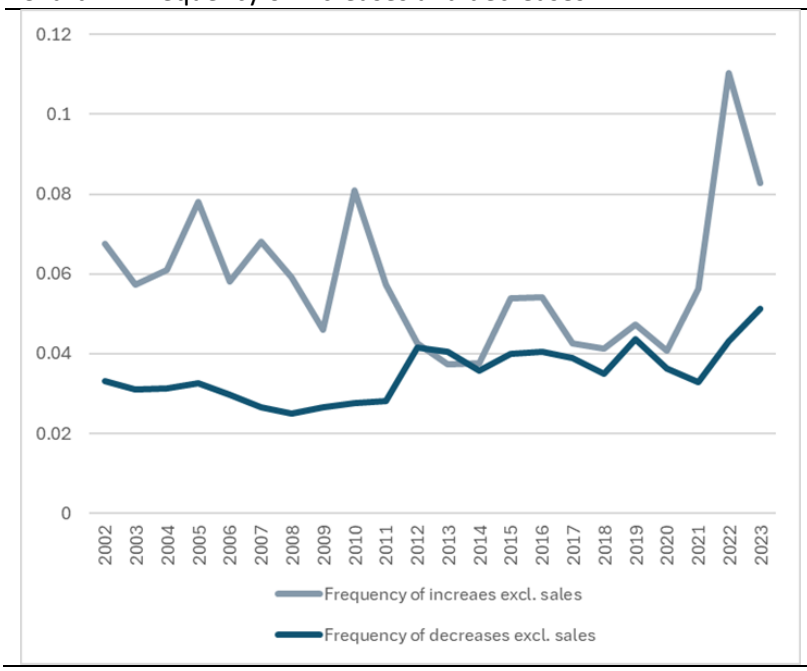
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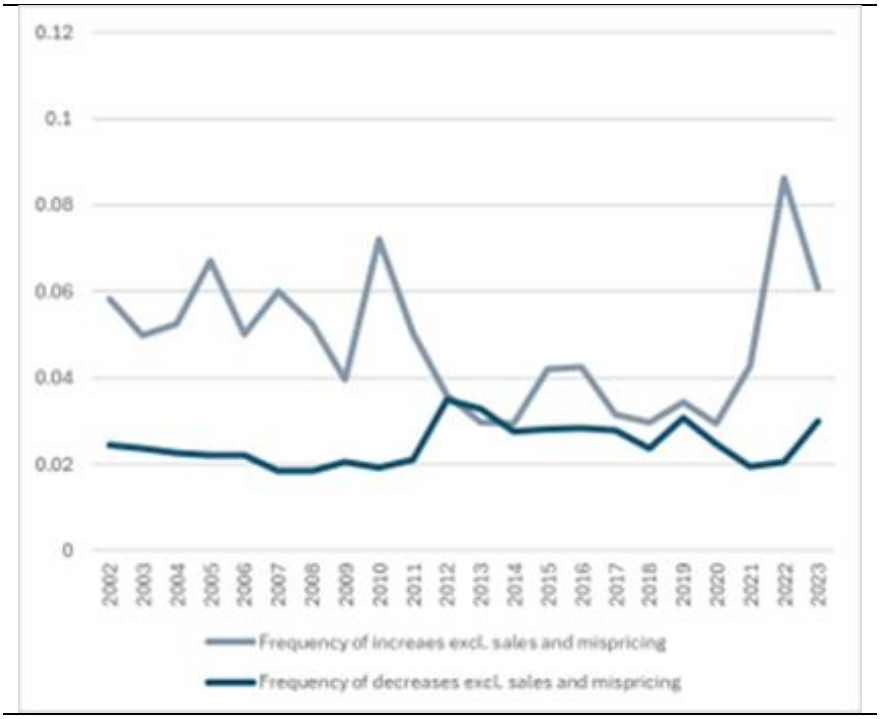
Chart E3: Differences in p.p's between frequencies excluding sales and excluding sales and mispricing



Source: calculation by authors

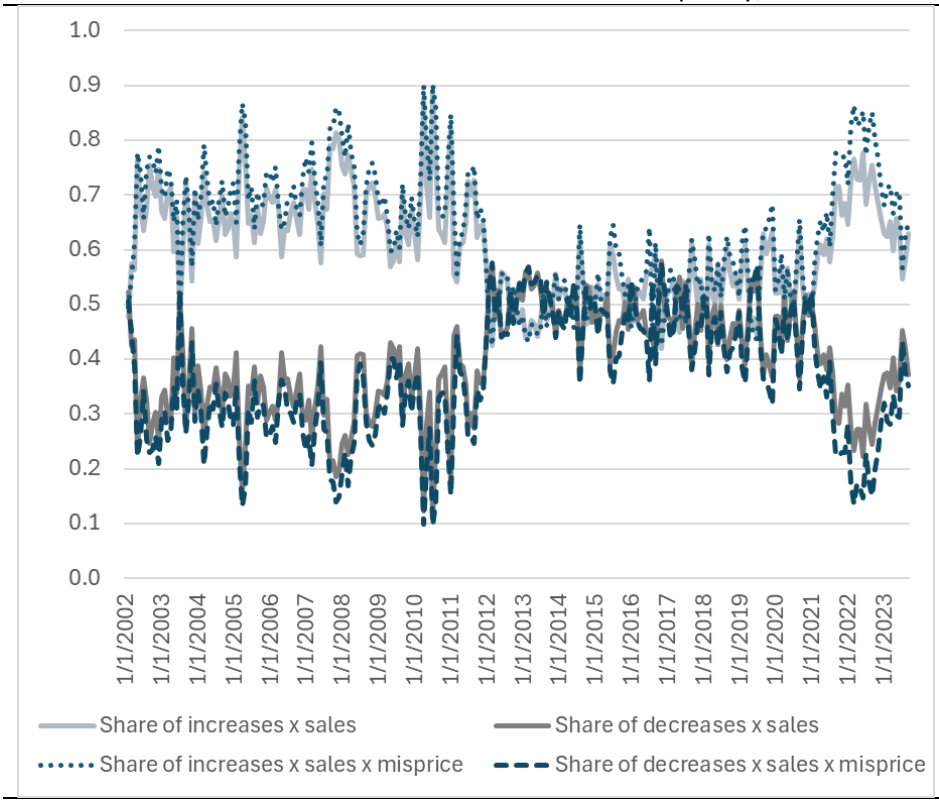
Chart E4: Frequency of increases and decreases





Source: calculation by authors

Chart E5: Shares of increases and decreases in total frequency, with VAT smoothing



Source: calculation by authors

Table E1: Determinants of the frequency of increases and decreases excluding sales and excluding sales and mispricing. LDV IV estimations

	Frequency of price increases		Frequency of price decreases	
	(1)	(2)	(3)	(4)
VARIABLES	Excluding sales	Excluding sales and mispricing	Excluding sales	Excluding sales and mispricing
LDV	0.227***	0.239***	0.261***	0.218***
	(0.0321)	(0.0330)	(0.0497)	(0.0513)
HICP inflation	0.260***	0.292***	-0.130***	-0.109***
	(0.0444)	(0.0441)	(0.0282)	(0.0250)
Retail Sales	0.0706***	0.0544***	-0.00305	-0.0154**
	(0.0132)	(0.0127)	(0.00845)	(0.00756)
Constant	0.0364***	0.0288***	0.0305***	0.0244***
	(0.00297)	(0.00278)	(0.00233)	(0.00195)
Observations	211	211	211	211
R-squared	0.872	0.868	0.653	0.631

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

By recalibrating the model according to above estimations equation (14) and (15) become:

$$\Delta f^{+} = 0.29\Delta \Pi^{A} + 0.24\Delta f_{-1}^{+} + 0.05x_t \quad \text{(E.14)}$$

$$\Delta f^{-} = -0.11\Delta \Pi^{A} + 0.22\Delta f_{-1}^{-} - 0.02x_t \quad \text{(E.15)}$$