Essays on Price Setting Mechanisms

by

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Hereby I testify that this thesis contains no material accepted for any other degree in any other institution and that it contains no material previously written and/or published by another person except where appropriate acknowledgement is made.

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Abstract

Prices have been documented not to respond instantly to changes in the economic environment. This phenomenon has inspired numerous articles which study its causes and implications. The research in this area has particular relevance for monetary policy practices and is therefore a very dynamic field. This thesis contributes to the literature in this area in three parts. The first part documents the rigidity of prices in Slovakia. While most of the research focuses on the U.S. and Europe economies, studies on transition countries are more scarce. During the period examined Slovakia was preparing for integration into European Union and for the introduction of Euro as the national currency which makes this study a valuable exercise as impacts of these factors can be examined. In the second part, the general behavioral patterns of price adjustments as identified in the first part are examined using a novel estimation approach. The third part builds on the results of the second part in that it evaluates the welfare implications of the price-modeling structure and highlights the importance of correct assumptions in the standard macroeconomic models which are the crucial tool in hands of the central optimizer.

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Introduction

> The large amount of theoretical research on the micro foundations of macroeconomic behavior has made clear that a thorough understanding of the extent and causes of the sluggish adjustment of nominal prices is crucial to the design and conduct of monetary policy. In this respect, empirical work aimed at an improved characterization of the price-setting behavior of firms is of major interest for monetary policy making.
>
> *Fabiani et al. (2006) (WP)*

Prices do not adjust instantly in response to changes in the economic conditions that price-setters are exposed to, such as the size of demand, size of supply, production costs etc. In recent decades a large number of papers have documented the rigidity of prices and modeled its implications. In these models monetary policy is of main interest and impact of the extent of price rigidities is examined on the dynamic behavior of some macroeconomic variables, such as consumption and inflation.

This thesis consists of three parts which are strongly interlinked. The first part documents the rigidity of prices in Slovakia to contribute to the large pool of related research by analyzing one of the less-documented countries. While most of the research focuses on the U.S. and Europe economies, studies on transition countries are more scarce. During the period examined Slovakia was preparing for integration into European Union (EU) and for the introduction of Euro as the national currency. Therefore, analyzing this country makes this study a valuable exercise as impacts of these factors can be examined and some lessons can be learned.

Findings from the first part of this thesis directly motivate the second part. The general behavior of price adjustments turns out to follow a special distribution; prices seem to adjust upwards more often than downwards; inflation seems to affect how price-setters adjust their prices both in the timing of adjustment as well as in the size etc. These and other factors are examined in the second part of this thesis to establish on the causal relationship between these and the price setting.

The third chapter builds on the results of the second part in that it evaluates the implications of the pricing structure used in a macroeconomic model on the resulting welfare. More importantly, though, it shows that if an economy is modeled assuming pricing structure very different from the true one, the estimated welfare losses can be significantly under- or over-estimated. This highlights how important role the right assumptions play in the standard macroeconomic models which are the crucial tool in hands of the central optimizer.

Chapter 1

Facts on Price-setting Patterns in Slovakia

1.1 Introduction

This chapter documents price-setting patterns in Slovakia before and after integration into EU. The analysis method is very simplistic, as it uses simple descriptive statistics, which makes the results easy to understand and provides a good insight into the basic price-setting patterns.

Throughout the thesis a large database is used on price quotes in Slovakia that final consumers face in, what is referred to as, a typical store. The database covers the whole consumer basket which makes it possible to analyze the behavior of price-setters that matter most to the final consumers. The types of questions that this chapter attempts to answer are: How often does an average consumer face a change in a price; is this a price increase or a price decrease; is this price change sizable (compared to the prevailing inflation); when is a price change most likely; are sales common; is a consumer in underdeveloped regions exposed to different pricing mechanisms than a consumer from economically stronger regions etc.

The nature of the database makes it possible to compare results with similar analyses for Euro-area by Dhyne et al. (2006) (EA hereafter) and U.S. by Klenow and Kryvtsov (2008) (KK hereafter) and by Bils and Klenow

(2004) (BK hereafter). It turns out that, qualitatively, all these countries show similar patterns in price-setting. In quantitative terms differences occur and Slovakia turns out to be more close to the U.S. and somewhat further away from the Euro-area. This can most readily be attributed to the higher inflation rates in the U.S. and Slovakia as compared to the Euro-area in the time periods examined but other factors can contribute as well.

The chapter starts with sample description in Section 1.2. The descriptive statistics are presented as frequency of price changes in Section 1.3 and their sizes in Section 1.4. Particular shapes of distributions of price changes are examined in Section 1.5. More specific types of analyses include asymmetry, synchronization, seasonality, inflation and regional analysis in Sections 1.6, 1.7, 1.8, 1.9 and 1.10, respectively. The final section concludes.

1.2 Sample Description

The raw data comes from the Slovak Statistical Office and covers years 2002 to 2007 on monthly frequency. It is described in detail in Appendix A. For the purposes of this analysis regulated products are removed altogether from the dataset together with products taxed with a special, very high tax such as alcohol and tobacco. Also, products that are subject to some sort of regulation or their prices are in other way not fully determined on the free market are also removed. These are products related to education, postal services, public transportation etc.

Unlike some related studies, this study also omits energy products. The primary reason is that their prices are not freely determined on the market. The secondary reason is that the results of the analysis could not be readily compared with those of related studies as all reported statistics are weighed with very different product weights for each country. In Slovakia, the energy products have the largest weight in the consumer basket and larger than the weights in other Euro-area countries or the U.S. This is documented in Table 1.1. This also means that the overall results would be strongly driven by energy products, hence when comparing the overall results, one must bear this in mind. Most reasonable comparisons can be made on a product-category level.

Country	CPI weight of Energy	Country	CPI weight of Energy
Austria	81‰	Luxembourg	77‰
Belgium	96‰	Mexico	79‰
Canada	93‰	Netherlands	72‰
Czech Republic	121‰	New Zealand	66‰
Denmark	92‰	Norway	79‰
Finland	63‰	Poland	144‰
France	80‰	Portugal	95‰
Germany	96‰	Slovak Republic	154‰
Greece	77‰	Slovenia	135‰
Hungary	132‰	Spain	94‰
Iceland	71‰	Sweden	91‰
Ireland	64‰	Switzerland	74‰
Italy	63‰	United Kingdom	67‰
Japan	73‰	United States	91‰

Table 1.1: CPI Weights of *Energy* in various countries as of 2005 (OECD).

The analysis also treats temporary price reductions specially. As there is no sales indicator in the database used in this study, these have to be approximated. This is generally done is such a way that those price drops which are followed by price increases of the same size are marked as temporary sales. This is referred to as *V-shape* in the literature and KK find that 60% of sales exhibit this pattern. If sales are identified or can be proxied by such V-shapes, there is a tendency in the literature to exclude them from the analysis. One way of excluding them is to omit them which creates missing observations. Another approach, and it is used in this study, is to replace the temporary price reductions by the best proxy of the regular price which is the price surrounding it. This way the imputed price changes become zero.

As KK highlights, focusing on prices cleaned off sales is not unambiguously the right approach as sales may have macro content and can be sensitive to inflation or shocks. KK report statistics using both posted prices and prices cleaned off sales and show some differences in the results stemming therefrom. In the present study, the statistics were calculated both with and without sales and for most of the statistics both results are presented for comparison purposes[1].

BK and KK both use data from the U.S. Bureau of Labor Statistics but cover different time periods. BK covers 1995-2001 while KK covers 1988-2004. Both BK and KK use a large portion of the database covering majority of the consumer goods and services. Sales indicators exist and results can be compared with and without using them. Euro-area as documented in EA is a mixture of country-level analyses and covers different time periods ranging between 1994 to 2004. The samples also vary on the country-level but are standardized in EA by using almost identical 50 products and unified time period starting in January 1996. Sales indicators exist in some countries and do not in other so in this aspect the overall analysis may be inconsistent. Also, as mentioned above, energy products are not included in the present analysis while BK, KK and EA use them. However, as they highlight, these products drive some of the results due to their high weights, low frequencies of price changes and their prices going up much more often than going down.

In the present study, out of the total of 4,013,179 price changes in the final sample, there were 34,450 temporary sales. The dataset's basic statistics are presented in Table 1.2.

1.3 Frequency of Price Changes

As can be seen from the samples composition, several products are grouped in each of the six product categories. Frequency of price changes is calculated on the product level, i.e. for each product separately. These are then aggregated for each product category using weighed averages where product-level weights correspond to their 2006 consumer basket weights.

To calculate frequency of price changes for a given product, various approaches can be used. One is to calculate the frequency on the store-level and then aggregate up weighing the stores equally (i.e. not using store weights).

[1]It can be argued that temporary price reductions could possibly drive autocorrelation detected in the data, hence these are removed from the data in later sections.

	CPI category	Sample category	Weight in ‰	Product Count	Store Count	Observation Count	Sales Count
1.	Food and non-Alcoholic Beverages	A. Unprocessed Food	46	40	521	457,378	7,476
		B. Processed Food	112	97	579	1,277,958	22,361
3.	Clothing and Footwear	C. Clothing and Footwear	44	92	2,062	973,122	2,292
5.	Furniture, House Equipment	D. Furniture, House Equipment	54	85	2,527	856,739	1,985
11.	Hotels and Restaurants	E. Hotels and Restaurants	16	31	966	302,613	173
9.	Recreation and Culture	F. Other Services	15	23	1,506	145,369	163
12.	Other Goods and Services						
		Total	287	368	7,262	4,013,179	34,450
		US^{BK}	689	350	22,000	-	-
		US^{KK}	~700	300	20,000	13,500p.m.	~11%
		EA	-	50	-	-	-

Table 1.2: Samples composition and statistics.

Another approach is to use store weights where these are derived from the number of time periods available for each store (stores with fewer time periods would get larger weights and vice versa, the relationship could be linear, quadratic etc.). The third approach is to calculate the frequency directly on the aggregate level, i.e. as if the whole country was one large store.

Mathematically, these three approaches are equal if the panel is balanced; the latter two are equal if the store weights are linear inverse of the number of periods available therein. With unbalanced panel, however, they are not equal. With store-level approach, it is implicitly assumed that the missing observations are price changes with a probability equal to the probability corresponding to that specific store (calculated from the available observations of price changes for that store). With aggregate approach, the missing observations are implicitly assumed to be price changes with a probability equal the overall probability (calculated from all the available price changes altogether). Because these are highly unlikely to be equal and because the number of missing periods varies per store, the two approaches are different. One might argue that most reasonable is to use the aggregate approach as it implies the safest latent assumption, but for comparison reasons, for most of the statistics, results are reported using store-level approach with no store-weighing and also using the aggregate approach.

Let us denote p as product, r as region and s as store. Let $pc_{p,r,s,t}$ denote log-difference of price (hence "pc" for price change) of product p in location $\{rs\}$ between periods t and $t-1$.[2] Let denote $T_{p,r,s}$ number of periods in which $pc_{p,r,s,t}$ can be defined, i.e. price quote exists in both t and $t-1$. With total number of periods being 72 it holds that $1 \leq T_{p,r,s} \leq 71$. With $I(.)$ an indicator function, frequency of price changes for product p in location $\{rs\}$ is then defined as

$$f_{p,r,s} = \frac{\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} <> 0)}{T_{p,r,s}} \tag{1.1}$$

[2] Apparently, the first time period falls out when taking differences but note that some additional periods may also fall out if there are missing observations.

Now define S_r^p as the number of stores available in region r for product p and let R be the number of regions. Aggregate frequency of price changes on the store level is then an unweighed average of store-level frequencies across all stores in all regions[3]:

$$f_p = \frac{\sum_{r=1}^{R} \sum_{s=1}^{S_r^p} f_{p,r,s}}{\sum_{r=1}^{R} S_r^p} \tag{1.2}$$

To use the aggregate approach, find the total number of region-store-period tuples for product p where price change $pc_{p,r,s,t}$ can be defined, which equals $\sum_{r=1}^{R} \sum_{s=1}^{S_r^p} T_{p,r,s}$. The overall frequency of price changes is then

$$f_p = \frac{\sum_{r=1}^{R} \sum_{s=1}^{S_r^p} \sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} <> 0)}{\sum_{r=1}^{R} \sum_{s=1}^{S_r^p} T_{p,r,s}} \tag{1.3}$$

This gives us two distinct definitions of frequency of price changes for a given product. The product category frequencies f_c, i.e. frequencies aggregated over a sample of similar products as defined above, are calculated from f_p using the corresponding consumer basket weights w_p of all products p that are in product category c:

$$f_c = \frac{\sum\{w_p f_p\}_{p \in c}}{\sum\{w_p\}_{p \in c}} \tag{1.4}$$

This gives us two distinct values of f_c and they are both presented in Table 1.3, the former under *Store-level* columns and the latter under *Agg.* columns[4].

The results for Slovakia can be roughly compared to results for Euro-area from EA who report 15.1% frequency of price changes and for the US from KK who report 29.9% and BK who report 24.8%. This places Slovakia closer to the US which can be most easily explained by higher inflation rates in

[3]The reason to break down the definitions into regions is to later enable applying the definitions on regional analysis seamlessly.

[4]Note that the overall frequency values are not equal to simple averages over the six product categories. This is because the product-category frequencies are calculated as weighted averages over the products therein.

	All price changes		Without sales			
Product category	Store-level	Agg.	Store-level	Agg.	EA	BK
A. Unprocessed Food	53.4%	53.8%	49.7%	50.1%	28.3%	47.7%
B. Processed Food	32.3%	32.5%	28.5%	28.7%	13.7%	27.1%
C. Clothing and Footwear	19.1%	19.7%	18.6%	19.1%	∼ 9.2%	∼ 22.4%
D. Furniture, House Equipment	16.6%	17.0%	15.9%	16.4%	∼ 9.2%	∼ 22.4%
E. Hotels and Restaurants	7.9%	8.3%	7.7%	8.1%	∼ 5.6%	∼ 15.0%
F. Other Services	8.0%	8.2%	7.8%	7.9%	∼ 5.6%	∼ 15.0%
Total	28.0%	28.4%	25.7%	26.1%	15.1%	24.8%
KK	-	36.2%	-	29.9%		

Table 1.3: Frequency of price changes.

Slovakia and US as compared to the Euro-area. More analysis on inflation is presented in Section 1.9. However, one must bear in mind that energy products were excluded which have high weights and low frequencies. However, results per product category can be compared and the pattern described above prevails.

EA list other possible factors behind higher frequencies in the U.S. besides inflation, for example the structure and degree of competition in the sectors, price collection methods and the composition of the consumption basket. The latest can bring the estimated frequencies to any direction, especially given that the product weights differ across countries. The price collection methods can also result in differences in any direction. With higher market share of large supermarkets as opposed to corner shops in the U.S. the highest frequency in the U.S. is intuitive. However, in Slovakia, especially during the period examined, the share of large supermarkets was not larger than the share of small corner shops. Some differences in this respect may be present on a regional basis, more analysis by regions is in Section 1.10. Also, the price-collection guidelines dictate that the stores have to be selected as typical and supermarkets were not necessarily typical in Slovakia at the time examined; more on the price collection methodology can be found in Appendix A. Therefore, the driving mechanism behind the similarities and differences cannot be determined unambiguously.

The qualitative pattern, however, is the same across all the countries. The frequency of price changes of unprocessed products is found largest in the U.S., Euro-area and also in Slovakia while services are the stickier components. EA find that this can be attributed to differences in costs and market competition. BK suggest that the lower frequency of price changes for services could reflect the lower volatility of consumer demand for them. To understand the forces behind the price-setting mechanisms a very complex analysis would be necessary. In as much as data allows, deeper analysis of the factors determining the particular price-setting patterns in Slovakia are examined in Chapter 2.

Decomposing frequency of price changes into frequency of price increases and price decreases makes it possible to see if prices increased more often than they decreased or vice versa. Denoting frequency of price increases with a "$^+$" superscript and frequency of price decreases with a "$^-$" superscript their store-level definitions are as follows:

$$f^{+}_{p,r,s} = \frac{\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} > 0)}{T_{p,r,s}} \qquad f^{-}_{p,r,s} = \frac{\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} < 0)}{T_{p,r,s}} \tag{1.5}$$

Because the same $T_{p,r,s}$ appears in these two definitions as in the definition of the overall frequency, the decomposed frequencies sum up to the overall frequency on the store-level. Aggregation over stores for a given product p is done according to the following formulas:

$$f^{+}_{p} = \frac{\sum_{r=1}^{R}\sum_{s=1}^{S_r^p} f^{+}_{p,r,s}}{\sum_{r=1}^{R} S_r^p} \qquad f^{-}_{p} = \frac{\sum_{r=1}^{R}\sum_{s=1}^{S_r^p} f^{-}_{p,r,s}}{\sum_{r=1}^{R} S_r^p} \tag{1.6}$$

Because R and S_r^p are the same for the product p for both f_p^+ and f_p^- it is straightforward that they sum up on the aggregate level, too. Similarly, when using direct aggregation, because f_p^+ and f_p^- are defined for the same locations, the two sum up to f_p.

To calculate the product-category frequencies f_c^+ and f_c^-, the product level frequencies are averaged over all products in the category c using their corresponding weights w_p, just like in case of the overall frequencies.

The results on the decomposed frequencies are presented in Table 1.4. It can be seen that price decreases are not uncommon, although price increases always dominate over price decreases. Because in Slovakia average year-on-year inflation was 4.87% during the period examined and average month-on-month inflation was .41%, higher frequency of price increases than frequency of price decreases is intuitive. However, this is only the intensive margin. Although many studies only focus on examining price-setting patterns through the intensive margin (KK show that intensive margin plays a much stronger role), extensive margin also contributes to the size of inflation and is examined in later sections.

		All price changes		Without sales		
Product category		Store-level	Agg.	Store-level	Agg.	EA
A. Unprocessed Food	PI	27.2%	27.3%	25.4%	25.5%	14.8%
	PD	26.2%	26.4%	24.4%	24.6%	13.3%
B. Processed Food	PI	18.5%	18.6%	16.6%	16.7%	7.1%
	PD	13.8%	13.9%	11.9%	12.0%	5.9%
C. Clothing and Footwear	PI	10.3%	10.7%	10.0%	10.4%	~ 4.2%
	PD	8.8%	9.0%	8.5%	8.7%	~ 3.2%
D. Furniture, House Equipment	PI	8.4%	8.7%	8.1%	8.3%	~ 4.2%
	PD	8.1%	8.3%	7.8%	8.0%	~ 3.2%
E. Hotels and Restaurants	PI	5.9%	6.2%	5.8%	6.1%	~ 4.2%
	PD	2.0%	2.1%	1.9%	2.0%	~ 1.0%
F. Other Services	PI	5.7%	5.8%	5.6%	5.7%	~ 4.2%
	PD	2.3%	2.4%	2.2%	2.2%	~ 1.0%
Total	PI	15.3%	15.5%	14.2%	14.4%	8.3%
	PD	12.7%	12.8%	11.5%	11.7%	5.9%

Table 1.4: Frequency of price increases (PI) and decreases (PD).

Another interesting pattern seen from the results is that where frequency of price increases is high, frequency of price decreases is high, too and vice versa. To better determine this relationship, correlation of frequency of price increases and of price decreases is plotted in Figure 1.1. It can be seen that the two are almost perfectly correlated (slope is estimated to equal .9436) and that the frequency of price increases is always slightly larger (intercept is estimated to equal .0307). These findings are very similar to those of EA. This strong correlation between the frequency of positive and negative price adjustments suggests that the idiosyncratic shocks play an important role and justifies the models which enrich the standard set-up by this type of shocks.

Figure 1.1: Correlation between frequencies of price increases and decreases by product.

To better determine the relative share of price increases among the price changes one can compare the frequencies of price increases and price decreases against each other. The results are demonstrated in Figure 1.2. It is clear from the figure that price increases most strongly dominate for services and least so for industrial goods and unprocessed foodstuff. Very similar results were found in EA and they underline the prevailing pattern across product categories which is robust across countries.

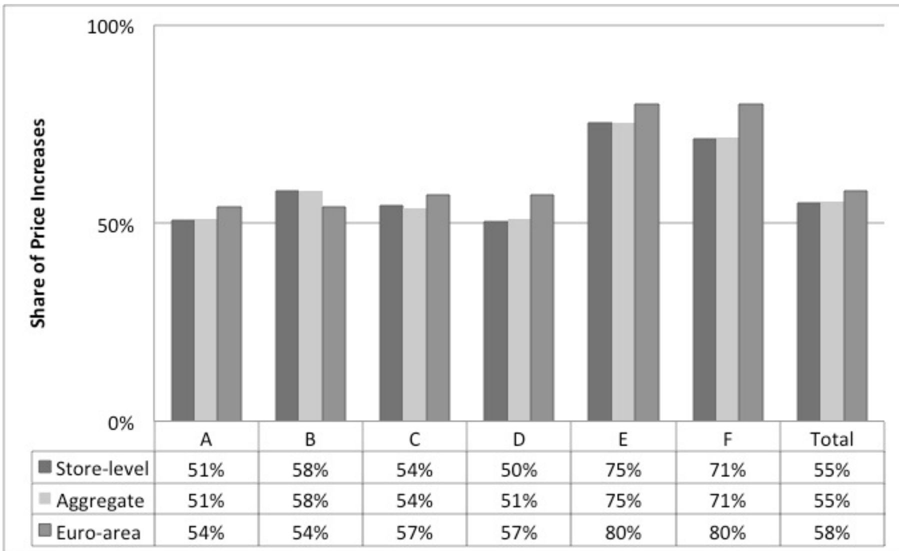


Figure 1.2: Shares of price increases by product category.

1.4 Size of Price Changes

The sizes of price changes are calculated as log-differences conditional on the existence of the price change. As with frequencies, two approaches are used. On the store level, the sizes of product-level positive and negative price adjustments are calculated as store-level time averages which are then averaged over stores:

$$size^{+}_{p,r,s} = \frac{\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} > 0) pc_{p,r,s,t}}{\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} > 0)} \qquad size^{-}_{p,r,s} = \frac{\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} < 0) pc_{p,r,s,t}}{\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} < 0)} \tag{1.7}$$

$$size^{+}_{p} = \frac{\sum_{r=1}^{R} \sum_{s=1}^{S^p_r} size^{+}_{p,r,s}}{\sum_{r=1}^{R} S^p_r} \qquad size^{-}_{p} = \frac{\sum_{r=1}^{R} \sum_{s=1}^{S^p_r} size^{-}_{p,r,s}}{\sum_{r=1}^{R} S^p_r} \tag{1.8}$$

On the aggregate level, the sizes of adjustments are calculated as pooled time averages:

$$size_p^+ = \frac{\sum_{r=1}^{R}\sum_{s=1}^{S_r^p}\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} > 0)pc_{p,r,s,t}}{\sum_{r=1}^{R}\sum_{s=1}^{S_r^p}\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} > 0)} \tag{1.9}$$

$$size_p^- = \frac{\sum_{r=1}^{R}\sum_{s=1}^{S_r^p}\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} < 0)pc_{p,r,s,t}}{\sum_{r=1}^{R}\sum_{s=1}^{S_r^p}\sum_{t=1}^{T_{p,r,s}} I(pc_{p,r,s,t} < 0)} \tag{1.10}$$

The product category sizes $size_c^+$ and $size_c^-$ are calculated from $size_p^+$ and $size_p^-$ using the weights w_p of all products p that are in their corresponding product category c:

$$size_c^+ = \frac{\sum\{w_p size_p^+\}_{p\in c}}{\sum\{w_p\}_{p\in c}} \qquad size_c^- = \frac{\sum\{w_p size_p^-\}_{p\in c}}{\sum\{w_p\}_{p\in c}} \tag{1.11}$$

The results are presented in Table 1.5. Interesting finding is that price decreases are more sizable than price increases which is also documented in EA[5]. Together with the results on frequency this means that while prices more often increase than decrease, opposite is true for their magnitude. Surprisingly, though, this only holds on the aggregate – when correlations between the sizes and frequencies are plotted in Figure 1.3 on the product level, the relationship is not visible. This means that frequencies and sizes do not necessarily move hand in hand or against each other and do not determine one another. This finding is important in that it shows that studies which focus on the intensive margin and disregard the extensive margin can only derive limited conclusions. It is argued here, that both margins must be considered when modeling the price-setting patterns.

The magnitude of price changes is not sizable when compared to the prevailing inflation. The documented values cannot be literally interpreted as percentages as they are logarithmic values, but in the ranges documented they can be roughly interpreted as percentage values.

[5] One exception is the category of services which suggests prices were increasing very vehemently there during the period in question, especially given that the same pattern holds for frequencies for this category.

Product category		All price changes Store-level	Aggregate	Without sales Store-level	Aggregate	EA
A. Unprocessed Food	PI	.133	.130	.133	.130	.147
	PD	-.142	-.139	-.143	-.140	.163
B. Processed Food	PI	.098	.096	.095	.093	.069
	PD	-.112	-.109	-.110	-.106	.081
C. Clothing and Footwear	PI	.120	.107	.120	.107	$\sim$ .094
	PD	-.127	-.119	-.128	-.119	$\sim$ .114
D. Furniture, House Equipment	PI	.108	.095	.108	.094	$\sim$ .094
	PD	-.115	-.104	-.115	-.103	$\sim$ .114
E. Hotels and Restaurants	PI	.142	.122	.142	.122	$\sim$ .073
	PD	-.154	-.139	-.154	-.140	$\sim$ .097
F. Other Services	PI	.163	.139	.163	.140	$\sim$ .073
	PD	-.151	-.134	-.152	-.138	$\sim$ .097
Total	PI	.115	.107	.114	.105	$\sim$ .082
	PD	-.124	-.117	-.124	-.117	$\sim$ .100
KK	abs	-	.140	-	.113	

Table 1.5: Size of price increases (PI) and decreases (PD).

Prices adjust upward with probability 14.4% every month by .105 and downward with probability 11.7% every month by -.117. This means that, roughly, prices adjust by .15% on average each month. The average month-on-month CPI inflation reported for Slovakia during the period equaled .41%. This inflation includes the energy products which have very high frequency of price changes, large share of price increases and on the top of that high(est) share in the consumer basket so are weighed by highest factor in the CPI inflation.

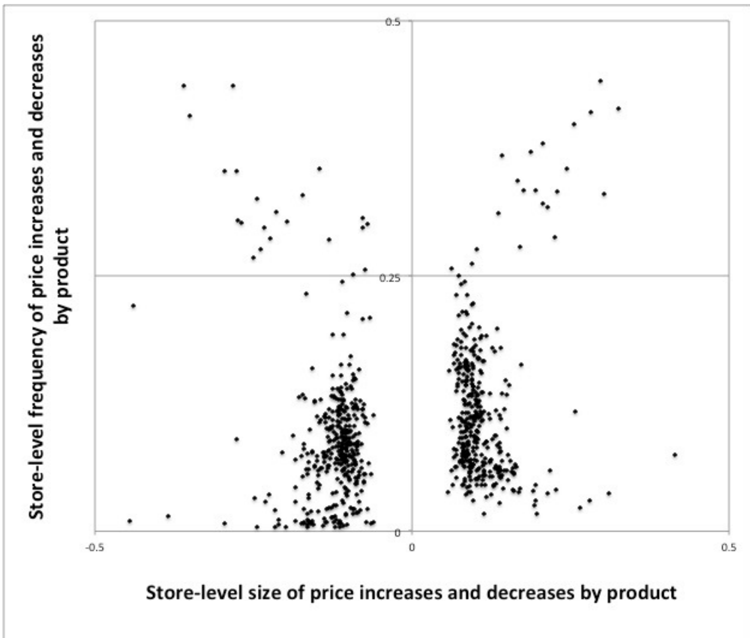


Figure 1.3: Correlation between sizes of price increases and decreases and their frequencies by product.

Similarly as with frequencies, magnitudes of positive and negative adjustments seem to go hand in hand – where price increases are sizable also price decreases are and vice versa. Figure 1.4 documents weaker relationship than with frequencies (the data is more dispersed) and price decreases dominate price increases (slope is estimated to equal .7197 which is well below 1).

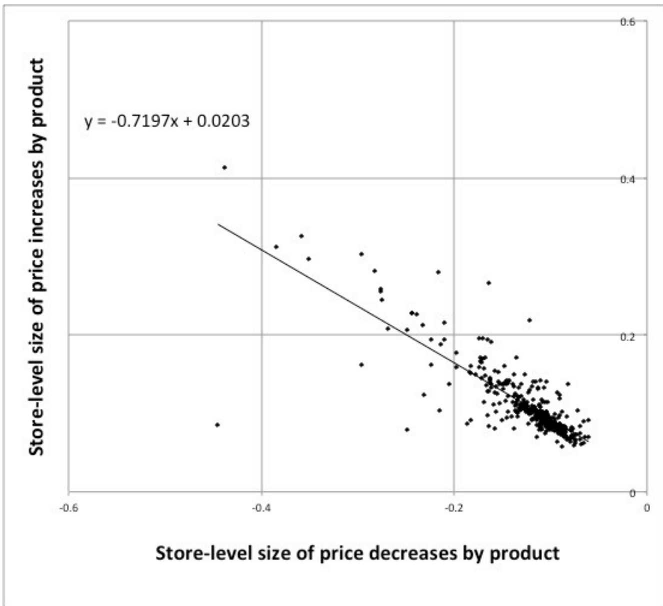


Figure 1.4: Correlation between sizes of price increases and decreases by product.

1.5 Distribution of Price Changes

Histograms of price changes are a good means of examining the price-setting behaviour. With results on frequency of price changes it is apparent that the distributions of price changes are largely dominated by zero price changes. Distributions of non-zero price changes are presented in Figure 1.5 for each product category separately.

In relation to all the descriptive statistics it is necessary to highlight here that the distributions depict unweighed pooled data so do not fully correspond to the results from above. As a result, for comparison reasons Table 1.6 documents unweighed statistics. Some additional statistics are introduced which formally describe some properties of the histograms. Specifically, kurtosis and skewness are the third and fourth moment of a distribution and describe the peakedness and the tail-length of a graph, respectively.

The distributions look different for all six categories which is underlined by differing descriptive statistics. However, some common patterns emerge.

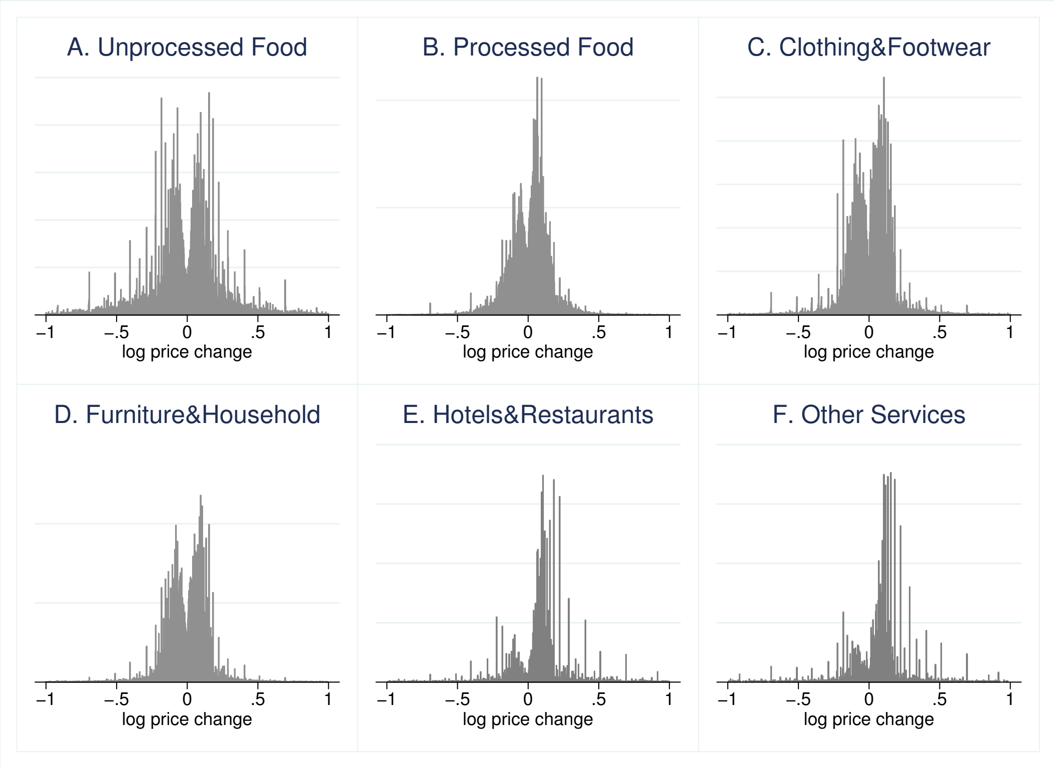


Figure 1.5: Distributions of price changes in log differences by product category.

Product category	freq.	mean	c.s.d.	u.s.d.	kurtosis	skewness
A. Unprocessed Food	47.3%	-.008	.259	.178	6.432	-.431
B. Processed Food	27.7%	.008	.138	.073	6.669	-.216
C. Clothing and Footwear	16.4%	.006	.161	.065	8.859	-.103
D. Furniture, House Equipment	14.7%	-.003	.145	.056	9.650	-.269
E. Hotels and Restaurants	8.0%	.066	.195	.058	8.992	-.041
F. Other Services	7.6%	.053	.052	.182	10.163	-.232

Table 1.6: Unweighted statistics, *c.s.d.* stands for conditional s.d., *u.s.d.* stands for unconditional s.d.

The graphs look peaky by eyeballing which is documented by high values of kurtosis (for Normal distributions this equals 3). Skewness is negative in all categories which means the negative adjustments stretch further away from the mean than the positive ones do, hence it documents a sort of asymmetry in the adjustment (this statistic equals 0 for a Normal distribution because it is perfectly symmetric). Means are of very small values. This means that with the intensive margins smaller for negative adjustments, the extensive margins must be larger so they offset each other.

Perhaps the most interesting pattern, though, is the bimodal behavior of the distributions. EA also document such pattern in the working version of their paper. KK find that around 44% of regular price changes are smaller than 5% in absolute value, 25% are smaller than 2.5%, and 12% are smaller than 1% which is not a direct evidence of bimodality but shows that the density graphs are populated less evenly than would be dictated by some standard distributions. This kind of behavior was documented also in Hoffmann and Kurz-Kim (2005) and Mizon et al. (1990) with more strongly pronounced bimodality in case of foodstuff and more asymmetric distributions in case of industrial goods and services. Bimodal distributions of price changes suggest that purely time-dependent price setting is not prevalent, as that dictates random selection in adjustment sizes, hence small price changes are not avoided. At the same time, though, menu-costs state-dependent price setting cannot be the case either. Menu costs do not generate any small price changes and these *are* present in the data, so roughly a mixture of the two must be the applied strategy by the price-setters.

1.6 Asymmetry in the "small"

In this section small price changes are examined, both relative and absolute. In relative terms any non-zero price changes smaller than log(1.01) are considered which roughly corresponds to 1% change in either direction. In absolute terms prices smaller than 1 SKK (1/30.126 EUR) are considered. The reason for the latter lies in the fixed-costs pricing theory for which absolute small price changes must be analyzed as in Chen et al. (2008). But because average price levels are very different across product categories, it is informative to also present statistics on small *relative* price changes. Shares of both types of small price changes among all price changes are reported in Table 1.7.

Positive small adjustments are more frequent than negative adjustments, whether considering relative or absolute changes. The most intuitive reason for this pattern is inflation but, as suggested by Chen et al. (2008), it can be partially due to rational inattention on the consumer side. If consumers are inattentive to small differences in prices, price-setters can better afford to increase prices by small amounts as they incur no costs which they would from perfectly attentive consumers. Because of this, more small price increases can be observed than small price decreases.

The results also show that small price adjustments are not being avoided by the price-setters; small price adjustments exist which undermines fixed-costs models which dictate that due to fixed costs incurred by the act of price adjusting, price-setters avoid any small price changes and thus none can be observed.

	relative price adj.		absolute price adj.		average
Product category	positive	negative	positive	negative	price level
A. Unprocessed Food	1.04%	0.91%	4.92%	3.87%	62.22
B. Processed Food	2.87%	2.04%	15.69%	9.87%	52.88
C. Clothing and Footwear	2.64%	1.64%	0.79%	0.33%	1020.3
D. Furniture, House Equipment	3.34%	2.26%	2.73%	1.95%	2686.03
E. Hotels and Restaurants	2.75%	1.05%	13.05%	4.73%	77.42
F. Other Services	2.28%	1.49%	2.65%	2.92%	896.99
Total	2.44%	1.69%	8.34%	5.36%	610.59

Table 1.7: Share of small price changes.

The results also document the average price level for each product category. Intuition would dictate that product categories with low price level will have larger proportion of small absolute price changes and product categories with expensive products will have smaller share of small absolute price changes (remember, "small absolute" is defined as smaller than 1 SKK).

Roughly, that is the pattern that is observed but with food products the results diverge slightly from this intuition. Unprocessed food products seem to adjust rarely by small amounts while processed food products experience small adjustments very often even though both categories have low price levels. This might be because of the seasonal nature of the unprocessed foodstuff which causes its prices to jump by higher magnitudes. Compared to that processed foodstuff is less sensitive to seasonality.

Related to this BK considered whether a good's frequency of price change is related to the absolute size of the good's price in such a way that they categorized goods into groups by price level and then analyzed the frequencies of price changes within each group. They found that the cheapest products had the highest frequencies and that these were followed by the most expensive products. Their findings were strongly significant which shows that the price level for a product has a strong effect on the frequency of price changes.

Another way to analyze small price adjustments is described in Chen et al. (2008) and is based on *asymmetry thresholds*. For a given product asymmetry threshold is defined as the smallest absolute size of price change at which the frequency of price decreases equals or exceeds the frequency of price increases. As an example take an imaginary sequence of prices in which price changes of absolute size of 0.1 SKK happen in 9 cases for positive change and in 7 cases for negative change. For size 0.2 SKK the corresponding values are 8 and 4 and continue to be higher for the positive changes till price changes of absolute size 0.8 SKK. At size 0.9 SKK the corresponding values are 4 and 4 hence value 0.9 SKK is reported as the asymmetry threshold for this product in this store during the time-span. Apparently, this definition of the asymmetry threshold builds on the fact that price increases are more common than price decreases and could be altered if necessary. This definition of asymmetry threshold also means that this metrics is not a qualitative but rather a quantitative measurement of the extent of asymmetry in price adjustments.

Chen et al. (2008) find that small price increases occur more frequently than small price decreases for changes of up to 10¢. This serves as evidence that price adjustments are very asymmetric in small magnitudes. Similar

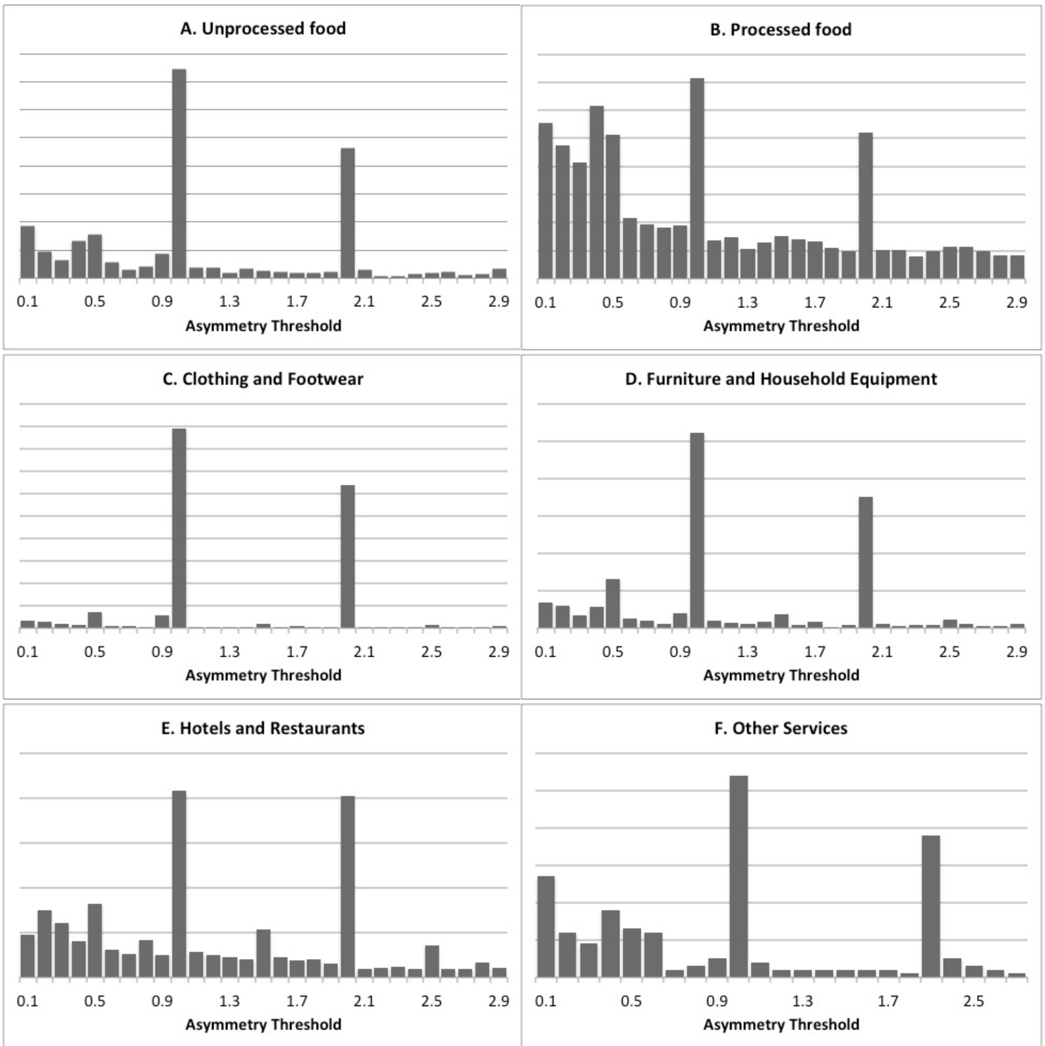


Figure 1.6: Asymmetry threshold distributions.

analysis is conducted on the present dataset using 3 SKK as the threshold value which is an approximate equivalent of 10¢. Although all the statistics before were conducted on aggregate and also on the store level, with this statistics, only the store level is reasonable to analyze.

The results are presented in Figure 1.6 as distributions of asymmetry thresholds for each product category over all products available therein and over all stores available therefor. It can be seen from the results that round values of 1 SKK and 2 SKK are most often the threshold values. This suggests that when price-setters decrease their prices, they tend to do so by round amounts and that is when price decreases overtake price increases in terms of frequency. For smaller magnitudes it is price increases that price-setters prefer. Another finding is that although the distributions are concentrated around smaller values, the thresholds are not always small values and products and stores can be found where the thresholds are larger. This points to an asymmetry in price adjustment "in the small" which Chen et al. (2008) readily explain partially by inflation and partially by consumer rational inattention. This phenomenon dictates that if consumers are ignorant to small price changes, price-setters use this fact to increase their prices by small amounts but refrain from decreasing them when otherwise this would be optimal. More on asymmetric behavior of price adjustments due to inflation is in Section 1.9.

1.7 Synchronization

Synchronization measures the extent to which price-setters act in a synchronized manner over time. With macroeconomic shocks price-setters might be prone to react similarly, with idiosyncratic shocks their actions may become more scattered or there can be any other reason for them to be or not to be synchronized. Also, price-setters in close mutual proximity might be more synchronized while isolated stores will behave more independently. In what follows Fisher and Konieczny index as introduced in Fisher and Konieczny (2000) is used to measure the extent of synchronization among firms.

However, synchronization can also be understood as the extent to which a given store synchronizes its action across products, i.e. on the store level. In that sense bigger synchronization would mean more products adjusting their prices at once so fixed costs of adjustment can be minimized. In the second part of this section within-store synchronization is measured as the share of products adjusting prices in a given period and distributions across firms are reported as in Lach and Tsiddon (1996).

1.7.1 Synchronization Across Stores

Let denote the Fisher and Konieczny index as SI and for product p let it be defined as

$$SI_p = \sqrt{\frac{1}{T-1} \frac{\sum_{t=2}^{T} \left(f_{pt} - \bar{f}_p\right)^2}{\bar{f}_p(1-\bar{f}_p)}} = \frac{\sqrt{s^2_{f_{pt}}}}{\sqrt{\bar{f}_p(1-\bar{f}_p)}} \tag{1.12}$$

where f_{pt} is the proportion of stores that changed the price of the product p between periods $t-1$ and t and $\bar{f}_p = \frac{1}{T-1}\sum_{t=2}^{T} f_{pt}$ and $s^2_{f_{pt}}$ are the sample mean and variance of f_{pt} over time, respectively.

This index is constructed from two orthogonal factors - the numerator and the denominator. They are orthogonal because the numerator is standard deviation and the denominator is constructed from averages and these are independent of each other. The denominator is constructed in such a way that it has the largest value if $\bar{f}_p = 0.5$. Because $0 \leq \bar{f}_p \leq 1$, the numerator attains values from interval $[0, \bar{f}_p(1-\bar{f}_p)]$ and so the index is between 0 and 1. Essentially, the numerator captures how much the share of the adjusting firms diverges from the time-average in each point of time. The more diversion, the larger the index and vice versa. Joint dependence of the index on different values of the numerator and the denominator is plotted in Figure 1.7.

It can be seen that for the index to attain certain value (where the dark plane cuts the gray surface) the standard deviation must be larger or smaller depending on whether the average (or its complement) is larger or smaller because the index captures relative distance of standard deviation from the average (or its complement).

The results on synchronization across stores are documented in Table 1.8

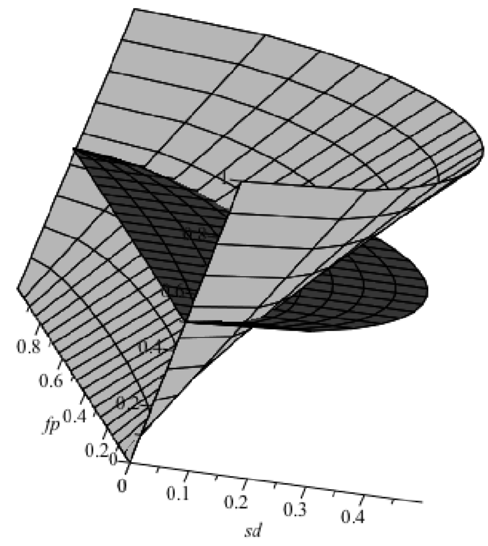


Figure 1.7: Fisher and Konieczny index for different values of its parameters.

by both weighing and not weighing the product-level results by product weights. It can be seen that synchronization reaches its maximum for *E. Hotels and Restaurants* and minimum for *D. Furniture and House Equipment.* The values vary from .162 to .339 by product categories. In EA they vary between .060 and 1.00 on the country level and between .080 and .62 as Euro-area averages. This means synchronization in Slovakia is relatively small to moderate. Given that Euro-area is very diverse in terms of size of countries and hence the market composition on which the index is calculated (for example Germany vs. Luxembourg), the results seem intuitive. This reasoning is also consistent with the finding of highest synchronization index in the largest city of Slovakia, capital Bratislava, as presented in later sections. At the same time, small synchronization can suggest relative importance of idiosyncratic shocks on the firm level by which the actions of firms are more scattered to offset the effects of the shocks.

Product category	unweighed SI_c	weighed SI_c
A. Unprocessed Food	.277	.267
B. Processed Food	.217	.240
C. Clothing and Footwear	.252	.251
D. Furniture, House Equipment	.162	.165
E. Hotels and Restaurants	.339	.301
F. Other Services	.273	.249
Total	.233	.236
EA	median:	.180

Table 1.8: Synchronization across stores.

1.7.2 Synchronization Within Stores

The statistical office provides no description of the methodology on how the price collectors code the stores. In this section it is assumed that if more products can be collected in one store, the code for this store is the same across all these products. To verify this assumption it is examined if there are stores with infeasible combinations of products such as e.g. unprocessed food products together with services. The findings are that stores typically only sell products from one single product category. In other cases they sell products from related product categories such as from A and B, from C and D or from E and F. As a result it can be safely assumed that stores are coded with same codes if more products are collected in them. This makes it possible to conduct analysis of within-store synchronization similar to Lach and Tsiddon (1996) on meat and wine products.

Out of $7,262$ stores it is $1,299$ that sell more than 10 products in each period. Although Lach and Tsiddon (1996) use 3 and 5 products as the threshold value, the size of the present sample allows to relax this restriction and move this threshold to number 10. As can be seen from the histogram in Figure 1.8, no products get their prices adjusted in 27% of the cases (*"cases"* means store-time combinations). With average inflation in Slovakia during the period examined being 4.87% on a year-on-year basis and 0.41% on a month-on-month basis, it is very unlikely that a price-setter would want *not* *to* adjust prices in a given month. In that light, 27% of no adjustments points to high level of synchronization (price-setters are waiting for the shocks to accumulate and then adjust more products' prices at once to decrease the fixed costs). Once determined to adjust prices, it is more common for a price-setter that less than half of the products sold in a given store get their prices adjusted meaning that price-setters do not wait too long for the shocks to accumulate.

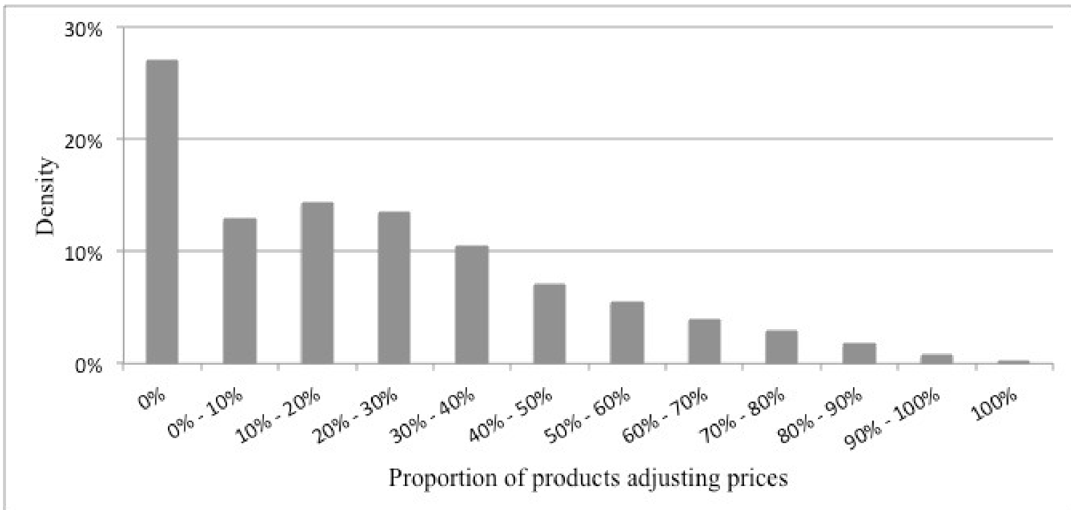


Figure 1.8: Synchronization within large stores by deciles.

1.8 Seasonality

Price adjustments are affected by seasonal forces. Costs of producing certain fruits and vegetables decrease rapidly in certain months, demand for hotel and restaurant services peaks in summer and/or winter months, demand for certain types of clothes and footwear depends on weather etc. Price-setters react to these forces differently and as documented in Table 1.9, generally, prices get adjusted immediately in the new year (January). Similarly, December is the month in the year when price-setters are least likely to adjust prices, most probably because they postpone the adjustments for the post-Christmas periods. Only with unprocessed foodstuff least likely month of adjustment is March which marks the peak season for this type of goods. Same findings were documented in EA.

Product category	Most adjustments	Least adjustments
A. Unprocessed Food	January	March
B. Processed Food	January	December
C. Clothing and Footwear	October	December
D. Furniture, House Equipment	February	December
E. Hotels and Restaurants	January	December
F. Other Services	January	December
Total	January	December

Table 1.9: Seasonality by months.

A different approach to examining seasonality is to analyze the proportion of products that undergo a price change in a given month in an average store (which sells more than 10 products). Results are presented in Table 1.10 and January and December again come out as the most and the least probable months for adjustment, respectively.

Month	Share of adjusting products	Month	Share of adjusting products	Month	Share of adjusting products
January	**28.25%**	May	22.23%	September	21.90%
February	24.28%	June	21.53%	October	24.62%
March	20.80%	July	22.34%	November	21.84%
April	23.55%	August	21.87%	December	**18.44%**

Table 1.10: Share of products adjusted in multi-product stores by months.

1.9 Inflation

Inflation is most closely related to price adjustments. It is measured from CPI so price-setting patterns directly influence it but at the same time price-setters adjust their prices in light of the prevailing and/or expected inflation rates. As documented in Table 1.11 year-on-year inflation rates averaged to

4.87% during the years 2002 – 2007 in Slovakia. For comparison, inflation was much lower in Euro-area during years 1994 – 2004 and was also not very volatile as compared to Slovakia. On the other hand, U.S. inflation was also high and relatively volatile during 1988 – 2004, as documented by KK. Trajectories of inflation in Slovakia and U.S. are plotted in Figure 1.9 and Figure 1.10.

	Year-on-year				Month-on-month			
Country	Average	Min	Max	s.d.	Average	Min	Max	s.d.
Slovakia	4.87%	1.96%	9.80%	2.47%	.41%	-.37%	5.27%	.86%
Slovakia – High	8.05%	6.00%	9.80%	1.03%	.62%	-.16%	5.27%	1.34%
Slovakia – Low	3.32%	1.96%	5.15%	.95%	.31%	-.29%	2.05%	.48%
Euro-area	1.9%	na	na	na	.12%	na	na	.20%
U.S	3.3%	$\sim$ 0%	$\sim$ 7.5%	na	.27%	na	na	.36%

Table 1.11: Year-on-year and month-on-month CPI inflation rate statistics for Slovakia during 2002 – 2007, Euro-area 1994 – 2004 and U.S. 1988 – 2004.

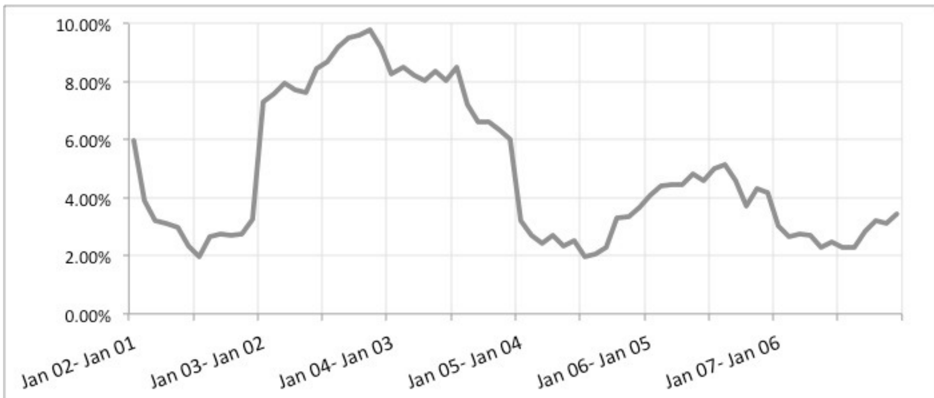
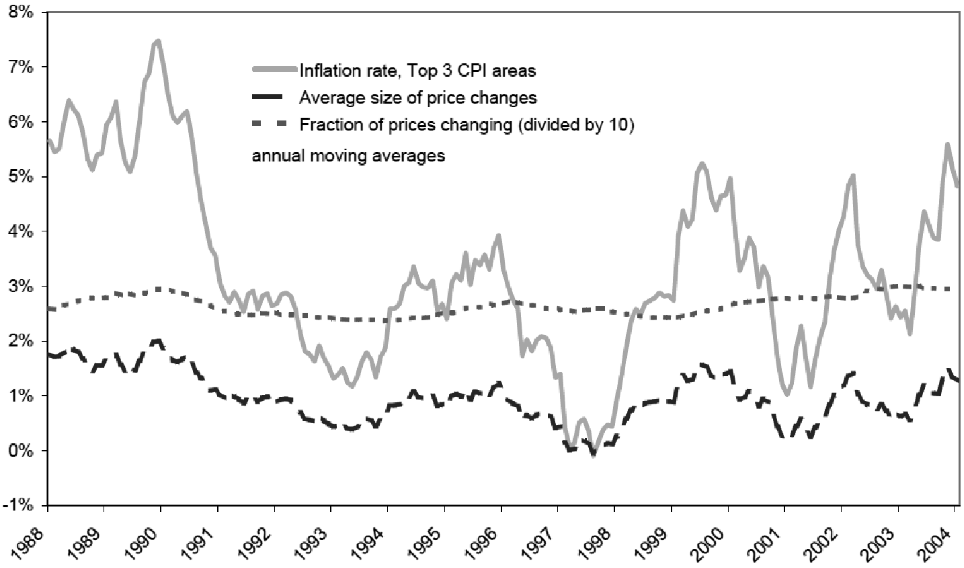


Figure 1.9: Year-on-year CPI inflation rates in Slovakia during 01/2002 – 12/2007.

To better determine on the role of inflation in price-setting the main descriptive statistics are calculated separately for periods when inflation was high (01/2003 – 12/2004) and for periods when inflation was low (01/2005 – 12/2007). Average inflation during the former was 8.05% and during the



source: Klenow and Kryvtsov (2008)

Figure 1.10: Year-on-year CPI inflation rates in the U.S. during 1988 – 2004.

latter it was 3.32%. The results are presented in Table 1.12.

The results show that the intensive margin is very sensitive to inflation rates and frequencies are higher under higher inflation. It also holds for decomposed frequencies so price-setters seem to adjust more often both upwards and downwards during high-inflation periods. Extensive margin reacts in the opposite way and price adjustments are more sizable under low-inflation periods. This suggests that inflation has positive effects on the intensive margin and negative on the extensive margins which is an interesting finding in light of the earlier finding according to which the correlation between frequencies and sizes shows no clear relationship between the two. This means that a more sophisticated estimation methods must be applied to determine on the role of inflation on the price-setting mechanisms.

Chen et al. (2008) compared the results on asymmetry thresholds for high-inflation periods with results for low-inflation periods and found that only part of the asymmetry could be explained by inflation; some proportion remained unexplained. For the present database the distributions of

Product category		Frequency	PI freq.	PD freq.	PI size	PD size
A. Unprocessed Food	H	54.87%	28.00%	26.87%	.126	-.138
	L	45.82%	24.08%	21.74%	.134	-.140
B. Processed Food	H	34.07%	20.72%	13.34%	.085	-.098
	L	25.43%	14.28%	11.15%	.105	-.117
C. Clothing and Footwear	H	20.44%	11.09%	9.34%	.098	-.113
	L	18.24%	9.60%	8.65%	.117	-.127
D. Furniture, House Equipment	H	17.69%	8.63%	9.07%	.077	-.099
	L	15.68%	7.89%	7.80%	.113	-.110
E. Hotels and Restaurants	H	11.03%	9.01%	2.02%	.116	-.114
	L	7.19%	5.20%	1.99%	.139	-.156
F. Other Services	H	9.81%	7.51%	2.30%	.143	-.120
	L	7.09%	4.77%	2.31%	.137	-.152
Total	H	29.90%	16.89%	13.01%	.097	-.109
	L	23.76%	12.92%	10.85%	.116	-.125

Table 1.12: Descriptive statistics under high (H) and low (L) inflation.

asymmetry thresholds by product categories are presented in Figure 1.11 for high and low inflation periods. It can be seen that, largely, the nature of the distributions is unchanged and no specific reshuffling of densities can be marked. When looking at average threshold values, it is found that they increase under low-inflation periods. This is in contrary with findings in Chen et al. (2008) who report lower thresholds under low-inflation periods and even lower thresholds under deflation periods. This means that inflation cannot explain any of the asymmetry in Slovakia and a more reasonable driving mechanism behind this phenomenon is the rational inattention on the consumer side. In periods with low inflation, price-setters have smaller incentives to increase prices but because they are aware of the rational inattention region on the consumer side, they exploit it. Under high-inflation periods, the necessary price adjustments must be large to overcome the inflation and thus are too large to affect results of analysis "in the small".

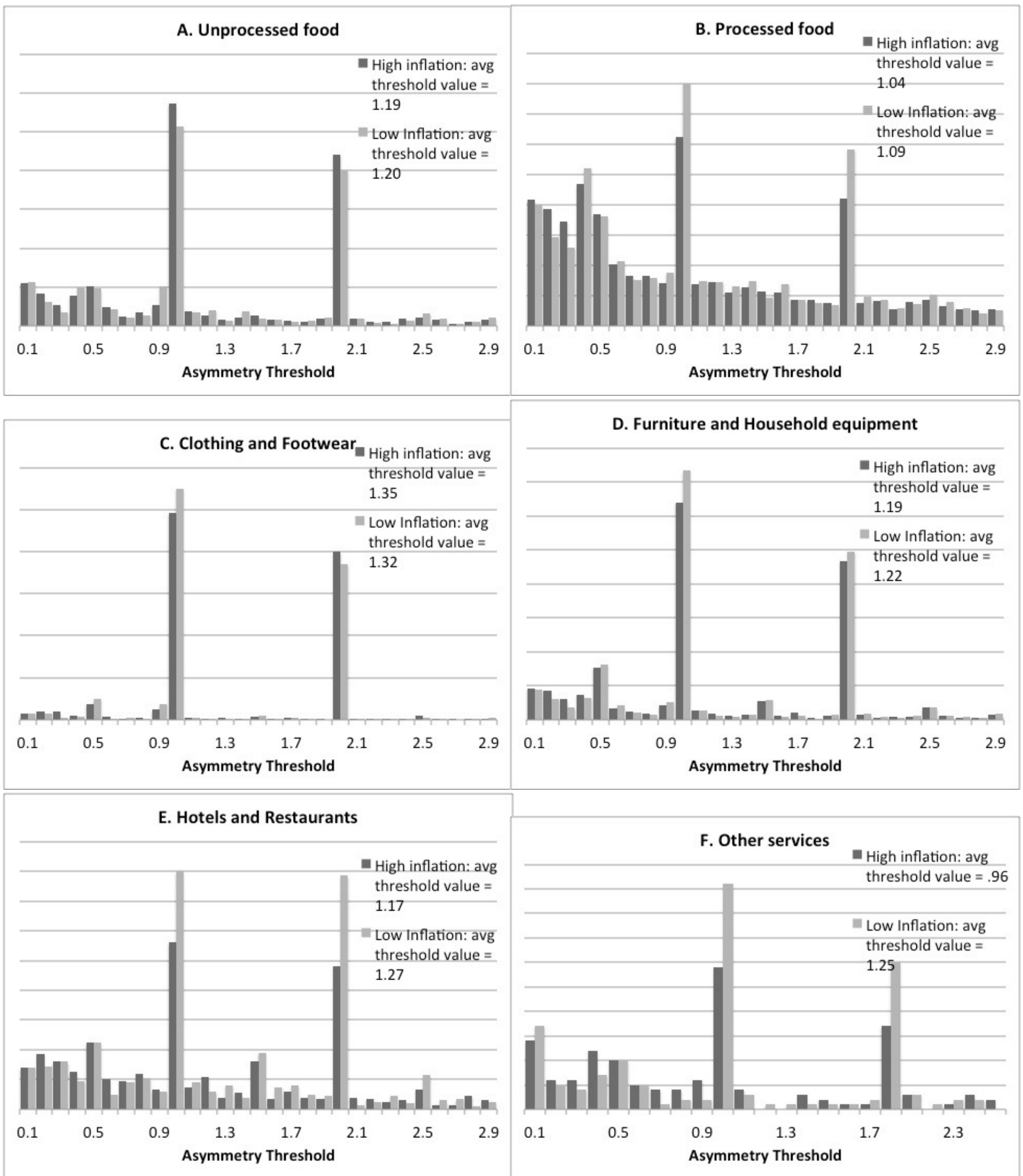


Figure 1.11: Asymmetry threshold distributions under high and low inflation.

1.10 Analysis across Regions

Slovakia is a very heterogenous country from economical and demographical point of view. In Table 1.13 some general statistics are documented which show the extent to which 8 main geographical regions of Slovakia differ. Generally, eastern regions are considered least developed regions and western regions, particularly the capital of Bratislava, are considered comparable to EU levels[6].

	region	urban. index	small retail	GDP share	avg salary index	unempl. rate	store count all	store count large	sales count
1	Bratislava	83.15	35.9%	27.21%	134.4	5.2%	952	85	1,337
2	Trnava	49.35	9.0%	11.11%	93.1	10.4%	538	181	2,303
3	Trenčín	57.26	6.8%	9.85%	87.5	8.1%	999	121	2,358
4	Nitra	47.34	9.4%	11.68%	82.5	17.8%	510	167	4,213
5	Žilina	50.72	14.2%	10.62%	87.8	15.2%	461	139	4,770
6	Banská Bystrica	53.84	10.2%	8.76%	84.2	23.8%	584	188	5,632
7	Prešov	49.13	7.8%	8.71%	76.3	21.5%	982	225	7,326
8	Košice	56.17	6.7%	12.08%	97.1	24.7%	537	193	6,511
	Total	55.42	100%	100%	100	16.2%	13,915	1,299	34,450

Table 1.13: General characteristics of regions as of 2005 (Slovak Statistics Office).

Regions of *Prešov* and *Košice* are selected to represent the under-developed regions and *Bratislava* to represent the developed regions. The main descriptive statistics of price adjustments are calculated separately for these regions for comparison reasons in Table 1.14. The differences are very big and show that price-setters adjust prices differently as they are exposed to different macroeconomic and demographic conditions in different regions. The frequencies of price changes are larger in the underdeveloped regions. The magnitudes are much more sizable in *Bratislava* in both directions, hence the distributions are more dispersed. When comparing the regional results on sizes of price increases and decreases with the overall results, it can be

[6]Urbanization index is share of the population living in the cities to the total population.This index has been decreasing in most of the regions for most of the time between 2002 and 2007 suggesting there is a tendency of people moving to the rural areas (which is typically in close proximity of a big city). All reported values are for year 2005. Small retail is the share of all profits in small retailing by regions.

seen that the country values are between those of *Bratislava* and *Košice* and/or *Prešov*. These three regions are indeed on the two extreme ends and apparently drive the country's heterogeneity. These findings suggest that the distribution of price changes can also be driven by this kind of heterogeneities on the top of the idiosyncratic firm-level shocks.

Synchronization index is presented in Table 1.15 for all the 8 geographical areas for comparison reasons. Synchronization is larger within regions than on the overall. This could be interpreted as evidence that close proximity of stores matters in their synchronization. However, it can also be some specific store characteristics that drive these results in which case it would not be evidence for synchronization but rather something exogenous behind the results. Another interesting finding is that synchronization is larger in *Bratislava* which might most probably be because the concentration of price-setters on the market, and hence the intensity of competition, is larger and price-setters are more prone to act in synchronization. These findings underline the suggestion that the distributions of price changes might be driven by regional heterogeneity as well besides the idiosyncratic firm-level shocks.

Synchronization within stores is analyzed in histogram in Figure 1.12. With positive (and not exactly low) inflation rates during the time periods examined, price-setters are likely to desire changing their prices so seeing at least 15% of cases to exhibit no price changes of any products within a store means price setters are probably waiting for shocks to accumulate which means they are synchronizing price adjustments within their stores. This seems more so in *Bratislava* and three more western regions (first four columns from left within first cluster) where the share of periods with no adjusting products is above 30%. The rest of the distribution has largely the same shape for every region as the overall distribution discussed earlier and the conclusion is that price-setters do not wait for so many shocks to accumulate that would allow them to adjust more than 50% of products at once, but typically keep the fraction of products below 50%.

	Frequency of price changes			Share of price increases			Size of price increases			Size of price decreases		
Product category	BA	KE	PO	BA	KE	PO	BA	KE	PO	BA	KE	PO
A. Unprocessed Food	46.1%	52.6%	51.7%	51.0%	50.8%	50.1%	.137	.121	.128	-.151	-.130	-.135
B. Processed Food	25.8%	34.8%	31.9%	57.1%	57.7%	56.7%	.106	.079	.086	-.124	-.091	-.095
C. Clothing&Footwear	17.4%	29.0%	21.1%	53.2%	54.4%	52.4%	.141	.076	.117	-.137	-.089	-.121
D. Furniture&Household	15.9%	22.5%	19.1%	51.0%	49.9%	48.0%	.115	.075	.098	-.113	-.079	-102
E. Hotels and Restaurants	6.0%	12.4%	7.3%	79.6%	72.0%	77.3%	.142	.090	.138	-.152	-.107	-.147
F. Other Services	11.4%	11.1%	8.4%	62.5%	68.7%	72.9%	.157	.114	.157	-.119	-.090	-.138
Total	24.1%	31.9%	28.4%	54.5%	54.9%	53.7%	.123	.087	.106	-.129	-.095	-.112

Table 1.14: Analysis across regions (BA - Bratislava (west), KE, PO - Košice, Prešov (east)).

region	city	across
1	Bratislava	.442
2	Trnava	.354
3	Trenčín	.379
4	Nitra	.340
5	Žilina	.342
6	Banská Bystrica	.317
7	Prešov	.319
8	Košice	.330
	Total	.233

Table 1.15: Synchronization of price setters by regions.

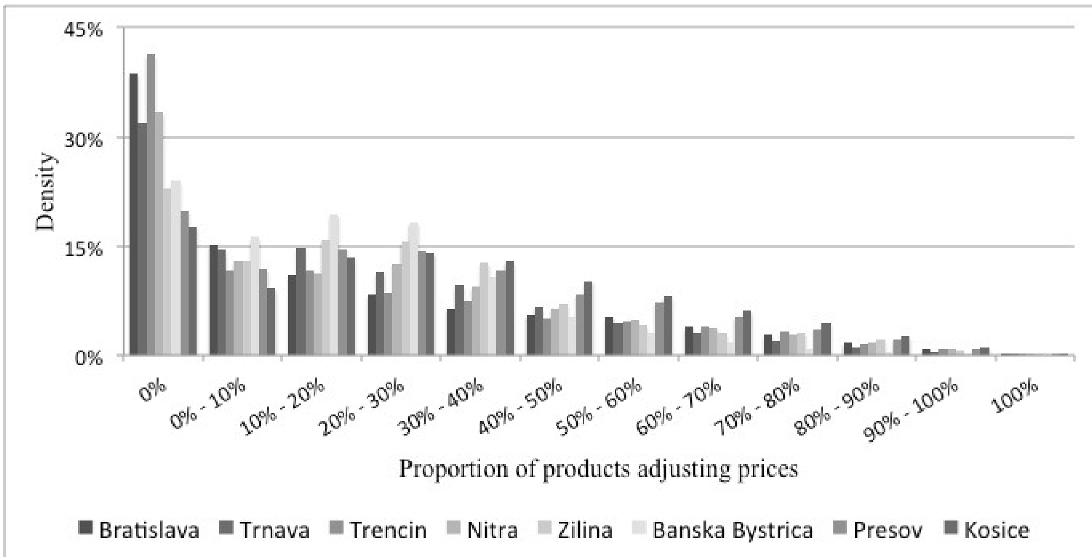


Figure 1.12: Synchronization within large stores by deciles by region.

1.11 Conclusion

This analysis documented price-setting patterns in Slovakia using descriptive statistics on a large database of price quotes during 2002 – 2007. Evidence was found for prices to be relatively sticky and inflation was found to be responsible for increasing the intensive margin but decreasing the extensive margin. High correlation between frequencies of price increases and price decreases is attributed to idiosyncratic shocks on firm level; no clear correlation is found between frequencies and sizes of price adjustments so focusing only on either in analyzing price-setting behavior is concluded to be possibly erroneous.

Results in this analysis can be related to similar results for studies for Euro-area and U.S. although reliable comparisons can be only done on product category level as energy products are so different in case of Slovakia. Still, though, on the qualitative side Slovakia exhibits very similar patters as are documented in the related studies. On the quantitative side, differences occur, which are partially explainable by inflation but much remains an issue of data collection methods, market, cultural and/or country specific differences etc.

All in all, the present analysis aims to provide basic insights into price-setting patterns in Slovakia and offers the necessary data for calibration exercises or macroeconomic model building.

Chapter 2

State-dependency in an empirical price-setting model

2.1 Introduction

This chapter is mainly motivated by the results from Chapter 1. The distributions of price changes were documented to be bimodal; the dispersion of distributions varied by product categories; frequency of negative and positive adjustments exhibited different extent of asymmetry, relationship between sizes and frequencies was not unambiguous etc. In this chapter these properties are modeled via parameters of the distributions of price changes.

The modeling approach is motivated by Costain and Nakov (2011) (CN hereafter). While the authors develop and simulate a DSGE model minimizing an ad-hoc criterion, in the present analysis censored maximum likelihood approach is applied motivated by the Tobit model which enables it to fit both the frequency and sizes of price changes. The ability of the model to match both the extensive and the intensive margin makes it very accurate and suitable for macroeconomic modeling.

Other twists are also made in the assumptions of the model in the present approach. While CN use productivity shocks with mean-zero normal distribution, the present chapter alters this assumption to Laplace distribution with estimable mean. The reason to allow for mean to vary is the asymmetry in the distributions which suggests the mean may not be zero. The reason to opt for Laplace distribution is its steeper center and fatter tails which the normal distribution is reported to fail to match. The goodness-of-fit is compared between the Normal and Laplace specification and implications of this altered assumption are examined in a dynamics exercise via impulse response functions to monetary shocks.

The hazard function used in CN is shown to be over-identified in its original specification and it is estimated in the present analysis with one of its parameters fixed. Last but not least, the present chapter estimates the parameters of the distributions unconditionally for comparison purposes, but adds conditional estimates using some macroeconomic variables as explanatory variables in an attempt to better explain forces behind the price-setting mechanisms.

The structure of this chapter is as follows. Section 2.2 places the present chapter in context within the literature on price setting. Section 2.3 describes the model and methodology used. Section 2.4 presents the results of estimation and Section 2.5 studies some of the dynamics properties of the sticky-price general equilibrium model under the present specification. The last section concludes.

2.2 Literature Review

Frequency of price changes has been more deeply examined than their sizes. For example Carvalho (2006), Caballero and Engel (1993b), Cecchetti (1986), Kashyap (1995), Genesove (2003), Campbell and Eden (2005), Peltzman (2000), Toolsema and Jacobs (2007) etc. focus on frequency analysis, while Lach and Tsiddon (1992), Chen et al. (2008), Buckle and Carlson (1998), Ball and Mankiw (1994) look at sizes of price adjustments. As documented by Klenow and Kryvtsov (2008), size is relatively more important than frequency in explaining inflation volatility. Also, Friedman and Woodford (1987) argue that as there is substantial heterogeneity in the micro data, it is useful to characterize the distribution of the size of price changes as opposed to focusing primarily on frequencies. Also, theoretical models can be better calibrated if they fit the empirical distributions of sizes of price changes (see for example CN and Caballero and Engel (1993b)) as opposed to merely fitting the documented frequency of price adjustments.

If the link between frequency and sizes of price changes was unambiguous, one could argue that analysis of frequencies would suffice. Some studies have identified positive link between the frequency and sizes of price changes while others argue negative sign is to be expected and find empirical support for it, such as Carlton (1986) and Dhyne et al. (2006). Therefore, when identifying factors behind the price-setting patterns, frequency and size are not interchangeable. Correlations between frequencies and sizes of price changes documented in Chapter 1 indicated towards the same conclusion, too. Because of this, this chapter places particular importance on modeling price adjustments in such a way that both the empirical frequency and sizes of price adjustments are matched.

The present analysis builds on the fact that price-setters are reluctant to adjust prices. As shown in Amirault et al. (2006), survey evidence shows that one of the main reasons why firms keep prices stable is that they are concerned about losing customers or market share. They also argue that the existence of long-term relationship with customers might delay the adjustment of prices in the face of a shock. They find that on average 86% of the companies report that most of their customers are regular and argue that this is the reason why firms might prefer to smooth price changes to keep their customers. Similarly, Blinder (1991) find that firms tend to adjust prices with delays to shocks. Among other reasons behind such behavior are implicit contracts, quality signals, pricing points, temporary shocks and coordination failure.

This price-staggering can be modeled through censoring mechanisms of various forms. Calvo (1983) assumes exogenous and fixed probability of adjusting where a randomly selected but fixed-size subsample of price-setters get a green light to adjust prices while all the rest wait for the next draw in the next period. This adjustment fashion is often referred to as time-dependent.

In other studies this hazard rate is allowed to be endogenous depending on a state variable of the model. This branch of modeling is often referred to as state-dependent price setting. In Rotemberg (1982), Caballero and Engel (1993b), Lombardo and Vestin (2008) the hazard rate is assumed of quadratic form and dependent on the underlying desired price change. This way the increasing relationship between the desired price change and the probability of actually adjusting to this price is captured[1].

A special type of state-dependent price-setting model is menu cost model as in Mankiw (1985). In this case the price-setter incurs fixed costs due to the act of adjusting prices and hence avoids price changes smaller than this cost. The motivation behind this type of model lies in the attempt to explain why price-setters avoid small price changes.

In their recent paper, CN proposed a model in which price-staggering is modeled using an inverse hyperbole specification for the hazard rate. There are three main arguments why this function is suitable in this kind of analysis: i) it maps real values into values between 0 and 1 making it possible to interpret it as a probability function ii) it nests purely time-dependent (Calvo) and purely state-dependent (menu-cost) price setting in its two extremes iii) continuous range of state-dependent pricing strategies lies between the two extremes which is controlled with one of the parameters of the probability function. This way this parameter can be interpreted as the extent of state-dependency in the model.

Using US data, authors are able to estimate the extent of state-dependency in the economy using this probability function as the hazard rate in the model. The present model exploits this specification of hazard rate for its valuable properties as outlined above but some of the assumptions as well as the estimation approach are altered for better accuracy.

2.3 Model

The same samples are used in this chapter which were analyzed in Chapter 1. They include two samples from foodstuff, two samples from non-energy industrial goods and two samples from services.

[1] CN alter this approach and use gain in firm's value as the state variable. In this study, the standard approach is taken.

A bimodal distribution most commonly arises as a mixture of two different uni-modal distributions, e.g. the combined distribution of heights of men and women is sometimes used as an example of a bimodal distribution of the heights of the human population. In the present analysis a special censoring mechanism is suggested by which a single uni-modal distribution can be transformed into a bimodal distribution with the steepness and curvature controlled by the parameters of the censoring function.

The censoring mechanism builds on the intuition that the costs incurred by the firms due to price adjustments vary across individual firms. Due to these costs price-setters are reluctant to adjust their prices unless the benefits from the adjustment compensate the incurred costs. Each price-setter has their *desired price change* which is distributed according to some distribution function $f(\mu, \sigma)$ where μ is the location parameter and σ is the scale parameter. Applying the censoring mechanism, this latent distribution of desired price changes is transformed to the distribution of the *actual price changes* which are observed in the data.

The location parameter reveals whether prices were generally increasing or decreasing so is strongly related to inflation. Note that although the positive (negative) mode of the distribution can be larger than the negative (positive) one, the μ parameter can still be estimated negative (positive). This is because in this analysis both frequency and sizes of price changes are accounted for jointly so while one may drive inflation upward, the other may drive it downward and vice versa. This way both intensive and extensive margins are allowed to determine this parameter. As shown in Klenow and Kryvtsov (2008), inflation can be decomposed into size and frequency element and they jointly influence the size of inflation, so it is not sufficient to conclude on the inflation focusing only on either. This parameter is not estimated in CN but is assumed equal zero. As can be seen from the Figure 2.1, such a simplification can be afforded in case of the AC Nielsen data which behave in a symmetric manner but must be relaxed in case of the Slovak data where larger extent of asymmetry was observed.

Hazard rate is constructed using a probability function p which takes on values between 0 and 1 and which is a function of the desired price change.

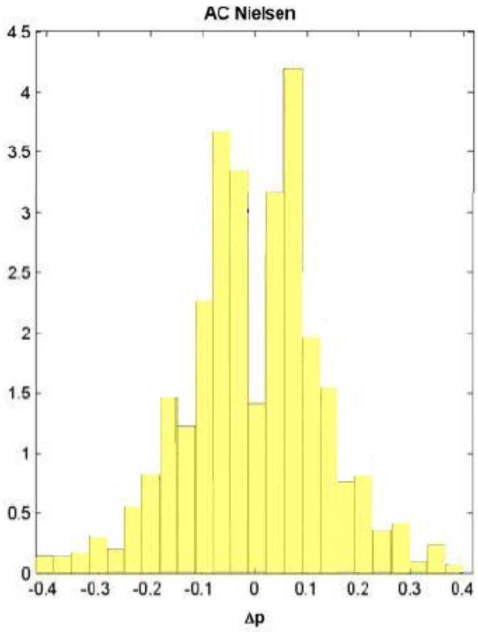


Figure 2.1: Histogram of price changes from US data (AC Nielsen).

The larger the desired price change (in absolute terms) the larger the probability of adjustment as larger price changes more easily compensate the incurred costs, which builds on the increasing hazard property from Caballero and Engel (1993a). There are various functional forms that the function p can take on which map the real numbers into $[0, 1]$ interval. In the working version of their paper CN propose a family of S-shaped functions and find the best fit with an inverse hyperbole which then remains in the focus of the final version of the paper. The properties of this function are discussed in the following section and it is proposed how the over-identification of this function can be resolved.

2.3.1 Hazard rate

$$\Lambda(x; \alpha, \bar{\lambda}, \xi) = \frac{\bar{\lambda}}{\bar{\lambda} + (1 - \bar{\lambda})(\frac{\alpha}{|x|})^{\xi}} \tag{2.1}$$

The hazard rate function in its original form as presented in (2.1) has three parameters: $\bar{\lambda}$, α and ξ, which determine its steepness, curvature and vertical shift. Parameter ξ can be best described as determining the steepness of the probability function - for large values the function is very steep (becomes a step function in the limiting case $\xi \to \infty$) and is flat for the minimum value when $\xi = 0$ when the function equals $\bar{\lambda}$. This is also the reason why this function is so suitable in the context of price-setting modeling. It can be interpreted as probability because it attains values between 0 and 1; its two limiting cases can be interpreted as Calvo-type price setting (when $\xi = 0$) and as menu-costs model (when $\xi \to \infty$); for values of $\xi > 0$ it can be interpreted as a mixture of time- and state-dependent price-setting hazard. This allows for parameter ξ to be interpreted as the extent of state-dependency in price setting. Parameter $\bar{\lambda}$ can be interpreted as the Calvo constant as the function equals $\bar{\lambda}$ when there is no state-dependency and all existing price rigidity can be attributed to time-dependency. Parameter α cannot be given a special interpretation in the context of price setting but it holds that the saddle point of the function (in case that it has one, which is when $\xi > 1$, which is when the function has an S-shape) lies between 0 and α and converges to α when $\xi \to \infty$, so the function becomes a step function in α.

There is one major problem with this function, though. It is over-identified because out of its two parameters α and $\bar{\lambda}$, one is abundant. This can be shown both graphically and analytically. Figures 2.2, 2.3, 2.4 demonstrate graphically how the shape of the function depends on α parameter and on $\bar{\lambda}$ parameter under varying values of ξ parameter. It can be seen that for a given value ξ parameter α magnifies the steepness of the function as determined by ξ. Parameter $\bar{\lambda}$ also magnifies the steepness of the function as determined by ξ so the two parameters can be interchanged.

This can be verified analytically. Take a pair of parameter combinations $\{\bar{\lambda}_1, \alpha_1, \xi_1\}$ and $\{\bar{\lambda}_2, \alpha_2, \xi_2\}$ such that $\bar{\lambda}_1 \neq \bar{\lambda}_2$, $\alpha_1 \neq \alpha_2$ and $\xi_1 = \xi_2 = \xi$ for which it also holds that $\alpha_2 = \alpha_1 \left(\frac{\lambda_2(1-\lambda_1)}{\lambda_1(1-\lambda_2)}\right)^{1/\xi}$. It is straightforward to show that the hazard function attains same values for all x with these two parameter combinations.

A straightforward solution to this issue is to fix one of the two parameters

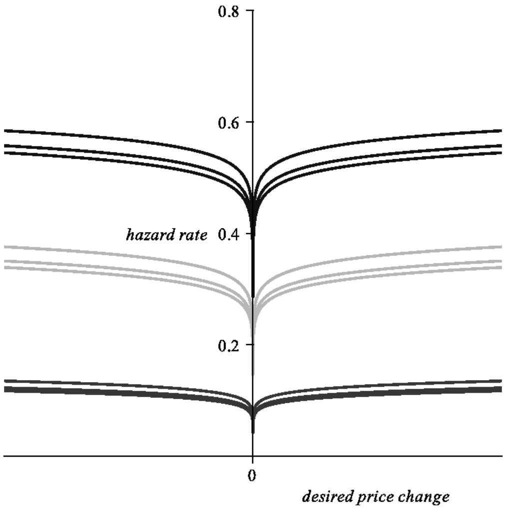


Figure 2.2: $\xi = .1$, $\alpha \in \{.1, .3, .5\}$, $\bar{\lambda} \in \{.1, .3, .5\}$

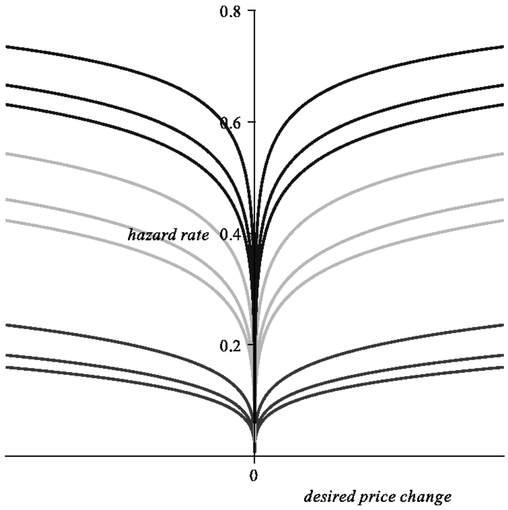


Figure 2.3: $\xi = .3$, $\alpha \in \{.1, .3, .5\}$, $\bar{\lambda} \in \{.1, .3, .5\}$

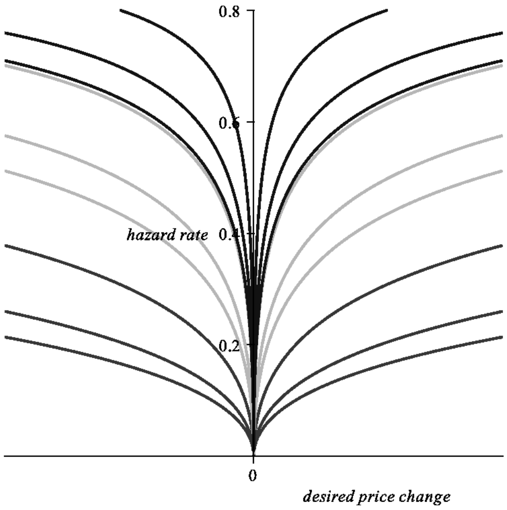


Figure 2.4: $\xi = .5$, $\alpha \in \{.1, .3, .5\}$, $\bar{\lambda} \in \{.1, .3, .5\}$

which can be interchanged, i.e. α or $\bar{\lambda}$. However, this specific inverse hyperbole has such property, that for value $\xi = 0$ the parameter α can take on any value (so it can be fixed to anything) and it will be $\bar{\lambda}$ that will determine the particular shape of the hazard function but for value $\xi \to \infty$ it is $\bar{\lambda}$ that can take on any value and it will be α that will determine the particular shape of the hazard function. For all values of ξ between these two extreme values, the two parameters α and $\bar{\lambda}$ are interchangeable and their effects cannot be determined separately, but their relative strength in the function depends on the size of ξ.

As $\bar{\lambda}$ has a better interpretation property in the context of price-setting modeling, α would be the natural choice of the parameter to fix. However, if the interpretation property of $\bar{\lambda}$ is to be pertained, this is not so trivial anymore because as is clear from the formula, the value of $\bar{\lambda}$ depends on what α is fixed to and what the value of ξ is. More precisely, for small values of ξ the function $p(.)$ is very different if $\bar{\lambda}_1 \neq \bar{\lambda}_2$ and $\alpha_1 \neq \alpha_2$ but is less different for large values of ξ.

In context of estimation this means that if α is fixed and $\bar{\lambda}$ and ξ are estimated, their estimated values will depend on what α is fixed to to a larger extent if ξ is large than if ξ is small; with small ξ the estimates of $\bar{\lambda}$ will be more robust. In practical terms this means that $\bar{\lambda}$ can still be interpreted as indicating the extent of time-dependency in price-setting but should not be considered equal to the Calvo constant unless ξ is estimated to equal 0. If ξ is estimated large, values of $\bar{\lambda}$ are very non-robust and can be estimated to equal a relatively large range of values for the estimation to be equally accurate. That means that unless the significance criteria (or the matching-moments criteria) are very strict, estimates of $\bar{\lambda}$ are not very robust for large values of ξ.

2.4 Estimation

The latent distribution $f(\mu, \sigma)$ is assumed Normal with mean zero in CN. As the authors emphasize, though, the fit is poor at the tails due to relatively fat tails of the empirical distribution as opposed to the Normal distribution used in the model. Also, the central area is more peaked in the actual data than the Normal distribution can deliver. The fit they achieve is plotted in Figure 2.5.

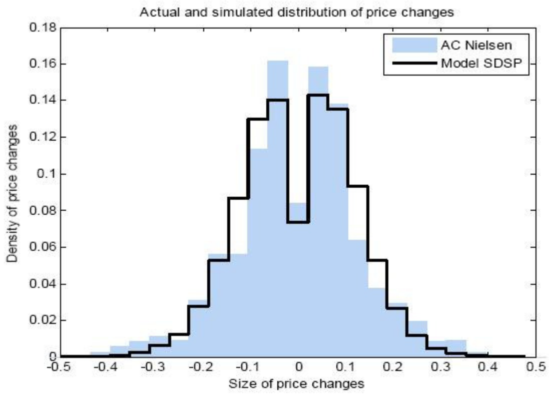


Figure 2.5: U.S. data fitted with Normal distribution of desired price changes.

As a remedy for this shortcoming the Laplace distribution is proposed in the present analysis which is a steeper distribution with fatter tails and so is more appropriate to match the empirical distribution.

This distribution belongs to the family of exponential distributions and differs from the Normal distribution in that its argument is in its level as opposed to the second power. Symmetry is assured using absolute values:

$$L(x|\mu, s) = \frac{1}{2s}\exp\left(-\frac{|x-\mu|}{s}\right) \tag{2.2}$$

The mean of this distribution is equal μ and standard deviation and variance are equal $\sqrt{2}s$ and $2s^2$, respectively. As Laplace function is steeper than Normal, it produces larger density around the mean value and a fatter tails at both ends.

This property of Laplace distribution places it among the so-called leptocurtic functions. Leptocurtic functions display high values of kurtosis, i.e. the fourth moment, which as mentioned above captures the high peakedness of the function. Some other studies have considered distributions with higher kurtosis, e.g. Gertler and Leahy (2008) and Karadi and Reiff (2011) opt for standard distribution functions (uniform and normal, respectively) but apply fixed hazard rates on them which capture probability of a shock happening. The smaller the probability of a shock happening, the steeper the pile of zero shocks and the higher the kurtosis of the resulting distribution function. Although neat in its nature, this kind of solution does not allow for bimodality in the resulting distribution and is rather restrictive in that it models the hazard rate as a constant. Also, the fatter tails of the empirical distributions of price changes failed to be matched under normal distribution so in this regard Laplace specification promises to be a better option.

A similar approach was taken by Midrigan (2011) who also applies fixed hazard rate on a latent distribution function. Here the choice is a Beta distribution which has a limited support and only yields the desired shape if parameter values are restricted. This in itself is not a serious hindrance but a big drawback of this specification is that it is always symmetric around zero. While the U.S. data shows a relative symmetric behavior, it is not the case in general and it is desirable to allow for the fitted distribution to be asymmetric. Equally importantly, this function has a complicated functional form which makes it unattractive for maximum likelihood approach. The three above mentioned leptocurtic distributions are presented in Figures 2.6, 2.7 and 2.8[2].

The estimation is approached in several steps. The first estimation is the most simple in which price changes are estimated unconditionally and with no autocorrelation. For comparison purposes, the error term is once estimated Normally distributed and once by Laplace distribution. Denote p^*_{ct} desired price change and p_{ct} actual price change in product category c at time t. Then formally:

$$p^*_{ct} = \varepsilon_{ct}, \quad \varepsilon_{ct} \sim N(\mu_c, \sigma^2_c) \quad or \quad L(\mu_c, s_c) \tag{2.3}$$

$$p_{ct} = \begin{cases} p^*_{ct} & \text{with probability } \Lambda(p^*_{ct}; \alpha_c, \bar{\lambda}_c, \xi_c) \\ 0 & \text{with probability } 1 - \Lambda(p^*_{ct}; \alpha_c, \bar{\lambda}_c, \xi_c) \end{cases} \tag{2.4}$$

[2] In the first two figures red curves are the latent distributions from which the actual distributions (blue curves) are derived using constant hazard rates.

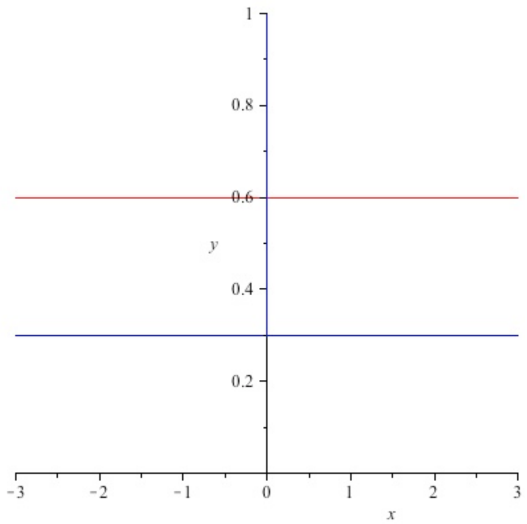


Figure 2.6: Uniform distribution with fixed probability.

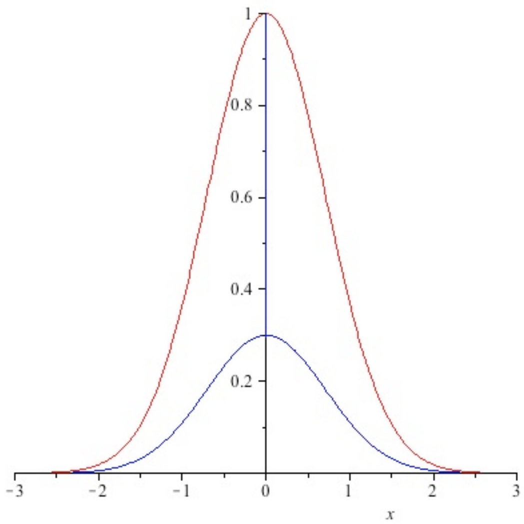


Figure 2.7: Normal distribution with fixed probability.

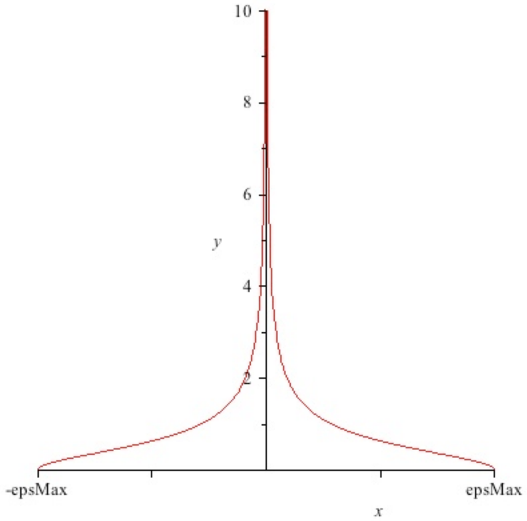


Figure 2.8: Beta distribution with restricted parameter values.

The latent equation of desired price changes can be formulated in this way because in a structural model (as e.g. in CN or Dorich (2007)) this can be derived from the idiosyncratic productivity innovations. To estimate the model, maximum likelihood method is applied. Parameters to estimate are μ_c, σ_c or s_c as parameters of the latent distribution and $\bar{\lambda}_c$ and ξ_c as free parameters of the hazard function. Parameter α_c is fixed to equal 0.0320 for all c as reported in CN for comparison purposes. Important distinction is that μ_c is not assumed equal zero but is a free parameter, which allows for the distributions to be estimated asymmetric for a better fit.

The log-likelihood function is constructed as in censored models in which the zero and the non-zero observations contribute differently to the overall likelihood. Denote $g(x; \mu_c, \sigma_c^2, \alpha_c, \bar{\lambda}_c, \xi_c)$ as a product of $N(x; \mu_c, \sigma_c^2)$ and $\Lambda(x; \alpha_c, \bar{\lambda}_c, \xi_c)$ (or alternatively, replace N(.) with L(.) and σ_c^2 with s_c for Laplace specification) and denote $G(x; \mu_c, \sigma_c^2, \alpha_c, \bar{\lambda}_c, \xi_c)$ its primitive. Then $G(\infty; \mu_c, \sigma_c^2, \alpha_c, \bar{\lambda}_c, \xi_c)$ is the definite integral over the whole support of $G(.)$ and represents the area below $g(.)$. Then formally:

$$lnL = \sum_{p_{ct} \neq 0} ln[g(p_{ct}; \mu_c, \sigma_c^2, \alpha_c, \bar{\lambda}_c, \xi_c)] + \sum_{p_{ct}=0} ln[1 - G(\propto, \mu_c, \sigma_c^2, \alpha_c, \bar{\lambda}_c, \xi_c)]$$

The results from this specification are presented in Table 2.1 under Laplace specification and in Tables 2.2 under Normal[3]. The results are plotted in Figure 2.9 under Laplace specification and in Figure 2.10 under Normal.

All the estimated parameters are significant. As can be seen from the results, μ_c is always estimated non-zero and the fitted distributions are asymmetric. Also, the central area of the histograms, which is relatively steep, is well-fitted under Laplace specification, less so under Normal. As a goodness-of-fit measurement method and for comparison purposes, Euclidean distance is reported over 25 equally-spaced bins on the interval of -0.5 to 0.5.[4]

[3]The estimation was run on observations between -0.5 and 0.5 so the results can be readily compared to those of CN who also only consider this interval.

[4]This metrics is also reported over 250 equally-spaced bins. This is only done for comparison purposes; narrower bins do not necessarily increase the precision of the metrics as the histograms do not necessarily become smoother upon increasing the bin number.

Product category	A.	B.	C.	D.	E.	F.	CN
Parameters:							
μ	0.0056	0.0129	0.0116	0.0038	0.0445	0.0328	0 (fixed)
s	0.1540	0.0797	0.0932	0.0836	0.0748	0.0734	-
σ^2	0.0474	0.0127	0.0174	0.0140	0.0112	0.0108	0.0677
$\bar{\lambda}$	0.3901	0.2424	0.1468	0.1350	0.0649	0.0634	0.1101
α	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320
ξ	0.3351	0.3678	0.2104	0.2157	0.2237	0.2431	0.2346
Matching moments:							
Frequency	44.97	27.66	16.28	14.77	7.41	7.18	10.0
Data	45.43	27.60	16.11	14.55	7.63	7.34	10.0
Conditional s.d.	0.1930	0.1291	0.1410	0.1302	0.1139	0.1149	0.122
Data	0.1788	0.1280	0.1313	0.1234	0.1349	0.1298	0.104
Unconditional s.d.	0.1301	0.0678	0.0566	0.0497	0.0315	0.0311	-
Data	0.1205	0.0674	0.0527	0.0471	0.0404	0.0375	-
Euclid. distance (25)	0.0313	0.0464	0.0531	0.0548	0.0608	0.0605	0.056
Euclid. distance (250)	0.00339	0.00478	0.00549	0.00563	0.00692	0.00690	-

Table 2.1: Estimation results under Laplace distribution.

The main parameter of interest ξ as the main indicator of state-dependency extent, is estimated very similar to what CN report and is relatively low. In relative terms, it is larger for foodstuff and smaller for non-services goods such as clothes, footwear and household equipment. With the state variable being the desired price change, this means that price-setters of foodstuff are more aware of their desired price changes and reflect their magnitude in their price-setting actions to a larger extent than price-setters of non-food products and services. A different pattern is found under the Normal distribution specification. Because the latent distribution, which in this case is Normal, is not peaky enough, the estimated hazard rate is close to a constant for the two services categories to ensure the resulting actual distribution function is as peaky as possible. Because the histograms do exhibit a bimodal behavior, this result is seen as a drawback of this latent distribution specification and is interpreted as justification for altering the distribution with Laplace.

The dispersion of price changes is estimated largest for unprocessed foodstuff and could most readily be attributed to the seasonal character of these products. The mean is estimated largest for services in general which goes in line with the findings of the related literature including Chapter 1 of this thesis which documents that for services prices more often rise than fall.

The results on μ parameter are very similar under Normal and Laplace specification. In case of σ^2 parameter, since two different distributions are in question, the absolute differences in this parameter are not of interest. It is the pattern that matters and it is the case under both specifications that largest dispersion of price changes is found for unprocessed foodstuff and smallest for services. Parameter $\bar{\lambda}$ cannot be readily interpreted as a time-dependency measure, but it is a good indicator of the probability that price-setters will be actually able to adjust their prices. This probability is highest for unprocessed foodstuff and lowest for services.

It is worth noting two major distinctions when comparing the results under Laplace and Normal distribution. First, for furniture and household products the state of dependency parameter ξ was estimated negative under the Normal specification which is a value out of the desired range. However, this result points to an important fact. For negative values of ξ the

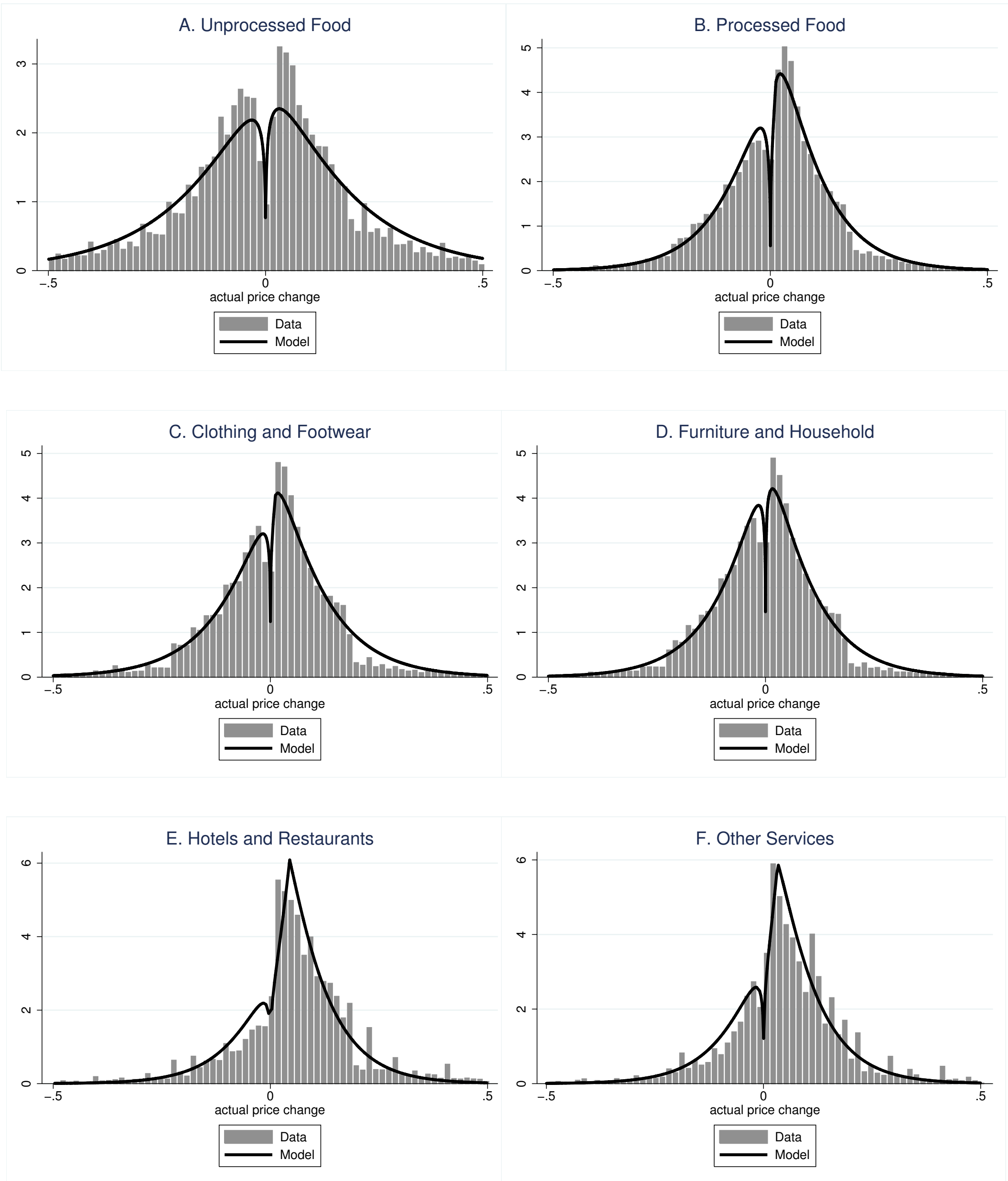


Figure 2.9: Fitted distributions under Laplace specification.

Parameter	A.	B.	C.	D.	E.	F.	CN
μ	0.0142	0.0299	0.0103	0.0074	0.0603	0.0440	0 (fixed)
σ^2	0.0240	0.0118	0.0097	0.0149	0.0096	0.0084	0.0046
$\bar{\lambda}$	0.4064	0.2518	0.1443	0.1641	0.0718	0.0655	0.1101
α	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320
ξ	0.1770	0.1400	0.1284	-0.1406	0.0040	0.0756	0.2346
Frequency	44.73	32.79	15.33	15.20	7.20	6.81	10.0
Data	45.43	27.60	16.11	14.55	7.63	7.34	10.0
Conditional s.d.	0.1596	0.1502	0.1013	0.1171	0.0951	0.0910	0.122
Data	0.1788	0.1280	0.1313	0.1234	0.1349	0.1298	0.104
Unconditional s.d.	0.1075	0.0789	0.0407	0.0447	0.0263	0.0247	-
Data	0.1205	0.0673	0.0527	0.0471	0.0404	0.0375	-
Euclid. distance (25)	0.0300	0.0473	0.0528	0.0544	0.0612	0.0607	0.056
Euclid. distance (250)	0.00327	0.00488	0.00548	0.00560	0.00695	0.00692	-

Table 2.2: Estimation results under Normal distribution.

hazard function is decreasing in its argument (as opposed to increasing for positive values) so in this context, it points to the fact that the latent distribution (Normal) was not peaky enough to match the empirical distribution and needed to be multiplied by a large factor to match the peaky central area. No such thing happened under the Laplace distribution because it is a distribution peaky enough. This was the primary reason to opt for the replacement of Normal by Laplace distribution and so this finding justifies this alteration. It could be argued that this conclusion is only applicable on the Slovak data. Opposite is true. Because the results from the Normal specification are very similar to those for the U.S. data (particularly graphical representation of the fitted and empirical distributions) the conclusion that Laplace distribution offers a better fit at fat tails and peaky central area holds for the U.S. data, too.

To accurately measure and compare the goodness-of-fit, Euclidean distance measure is used which measures the discrepancy between empirical and matched distribution. At first sight it does not seem to point too strongly in favor of the Laplace distribution although the graphical representation of the results suggests better fits in case of Laplace specification. The most intuitive explanation for this is that as Laplace was meant to ensure a better fit at tails and in the central (peaky) area, even if this is met, it does not necessarily mirror into the Euclidean distance, as the tail and central bins do not constitute majority of the overall number of bins.

The presented results come from the simplest model specification. A more sophisticated specification follows Costain and Nakov (2011) who allow for the error term to be autocorrelated and estimate the parameter ρ. In Table 2.3 are documented the findings when errors are assumed autocorrelated. Unlike the reference article, the Slovak data exhibit low levels of autocorrelation[5], but similarity arises in that they are estimated positive for almost all product categories. When this exercise was run on the same samples with sales not omitted from the sample, the correlations were estimated negative which could have been driving the results. With no sales in the sample, the autocorrelation seems to disappear.

[5]Autocorrelation could not be estimated for services.

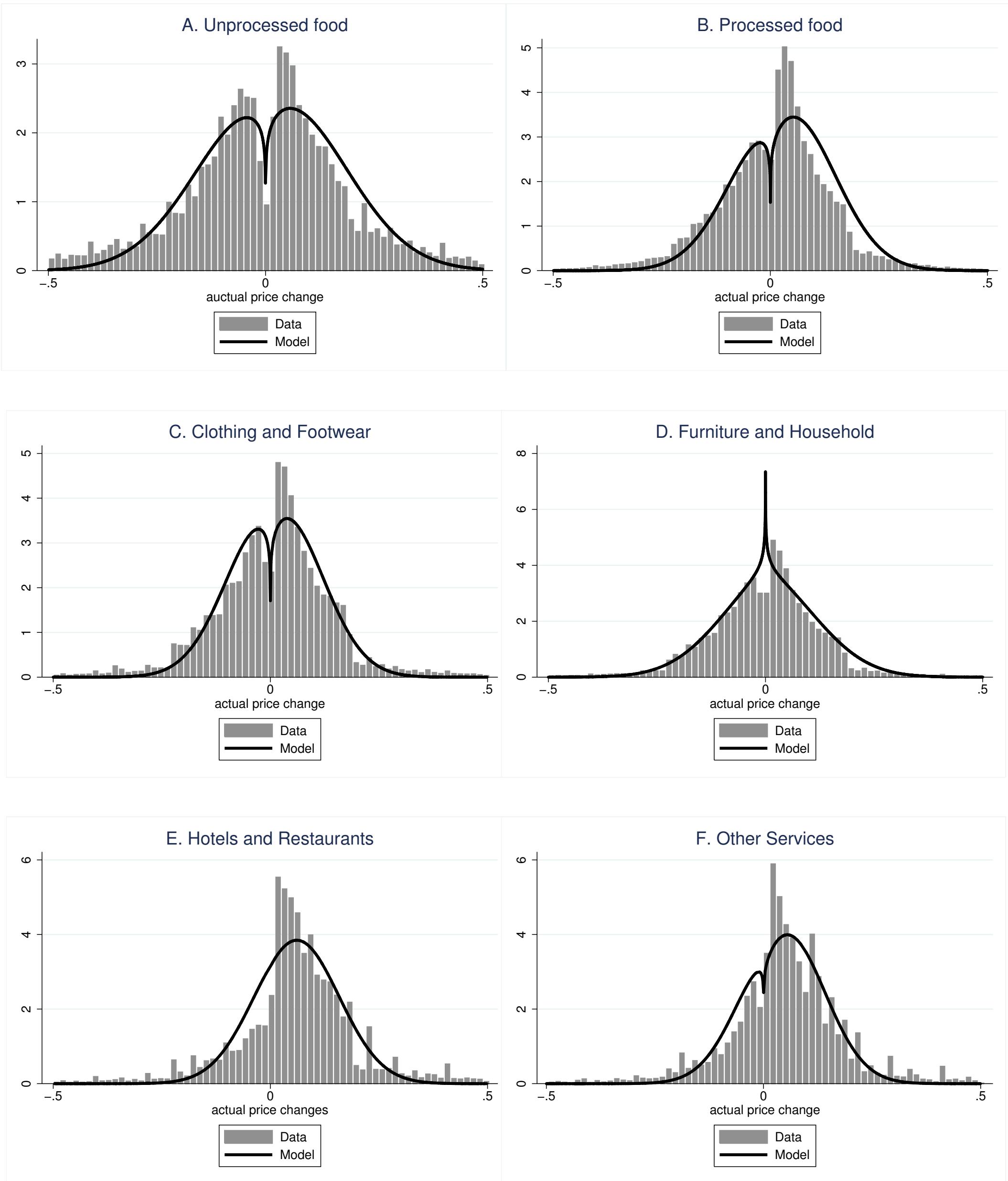


Figure 2.10: Fitted distributions under Normal specification.

Parameter	A.	B.	C.	D.	E.	F.	CN
μ	0.0054	0.0107	0.0126	0.0048	0.0640	-	0 (fixed)
s	0.1560	0.0800	0.0941	0.0855	0.1212	-	-
σ^2	0.0486	0.0128	0.0177	0.0146	0.0294	-	0.0677
$\bar{\lambda}$	0.3953	0.2444	0.1481	0.1341	0.0796	-	0.1101
α	0.0320	0.0320	0.0320	0.0320	0.0320	-	0.0320
ξ	0.3082	0.3385	0.1936	0.2056	-0.0047	-	0.2346
ρ	0.0301	-0.2002	0.0533	0.0531	0.0625	-	0.9002

Table 2.3: Estimation results under Laplace distribution with ρ parameter.

The two model specifications presented above were estimated to allow for a comparison between the Slovak data and the Dominick's database: to establish on the contribution of the altered assumption of the latent distribution (Laplace) to the model's fit; on the altered assumption of non-fixed mean of the error term and to examine the results when one parameter of the hazard function is fixed.

This benchmark model can also be referred to as unconditional as no explanatory variables are included in the model. In what follows, inflation and interest rates are allowed to contribute to explaining the price-setting patterns. Inflation was discussed in detail in Chapter 1. It is assumed that last month's year-on-year inflation enters the decision process of a price-setter hence lagged inflation rates are included. Interest rates are also assumed to influence the price-setters in their first lag. These are the base interest rates as reported by the national central bank on monthly basis. Structural break is also allowed to be estimated by including an EU dummy which marks the periods after integration to the European union.

The results are documented in Table 2.4. The structural break is significant for both parameters of the latent distribution and also for the ξ parameter. Integration of Slovakia to the EU increased the mean of price

	Product category					
	A.	B.	C.	D.	E.	F.
Parameters:						
μ**:**						
cons	0.0892	-0.0316	-0.0351	0.0484	-0.6064	0.0157
EU dummy	-0.0407	0.0451	-0.0763	-0.0029	0.4507	0.1021
inflation	-0.0034	0.0012	0.0016	0.0020	0.0939	-0.0197
interest rate	-0.0085	0.0021	0.0176	-0.0107	-0.0177	0.0103
E[μ]	0.0056	0.0129	0.0116	0.0038	0.0445	0.0328
s:						
cons	0.2375	0.0573	0.0549	0.0842	-0.2337	0.1235
EU dummy	0.0851	-0.0123	0.0860	0.0100	0.0881	0.0425
inflation	-0.0089	-0.0026	-0.0039	0.0080	0.0006	-0.0027
interest rate	-0.0189	0.0087	0.0009	-0.0093	0.0512	-0.0128
E[s]	0.1540	0.0797	0.0932	0.0836	0.0748	0.0734
E[σ^2]	0.0474	0.0127	0.0174	0.0140	0.0112	0.0108
$\bar{\lambda}$	0.3901	0.2424	0.1468	0.1350	0.0649	0.0634
α	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320
ξ						
cons	1.3751	0.7089	0.3242	-1.0077	2.8887	-2.0573
EU dummy	-1.6829	-0.5520	-0.1842	1.9797	-4.3126	1.5145
E[ξ]	0.3351	0.3678	0.2104	0.2157	0.2237	0.2431

Table 2.4: Estimation results under Laplace distribution with structural break and explanatory variables.

adjustments and also their dispersion for services, for the rest of the product categories, the effects are mixed. Inflation has mostly positive effect on the mean parameter which shows the intuitive relationship between the inflation and price adjustments and negative on the variance which goes in line with the findings in Chapter 1 where sizes of price changes where found to be smaller in periods of higher inflation. Interest rates are found to have mixed effects on both the mean and the variance parameter. With the ξ parameter it is found that state dependency increased after integration to the EU in case of furniture and household goods and services but decreased otherwise. The increased values show that price-setters had to become more aware of their desired adjustments and avoid incurring fixed costs. The decreased values show that price-setters became more passive and whereonly able to adjust prices at random intervals after the integration.

2.5 Dynamics Analysis

If firms are fully rational, fully informed and capable of frictionless adjustment in response to large idiosyncratic shocks, they will adjust their prices every time such a shock is realized. This chapter used a scenario in which firms suffer costs from adjustments due to which the probability of adjustment depends on a state variable. CN present a model which begins with standard New Keynesian general equilibrium model enriched with price stickiness to study the dynamics implied by money supply shocks.

In this section this dynamics exercise is performed under the altered specification of the underlying distribution, i.e. replacing the Normal distribution by Laplace[6]. This exercise is performed under different values of ξ to capture the Calvo case, moderate state-dependency case and menu-costs. In Figures 2.11, 2.12 and 2.13 this is demonstrated by green lines vs. black lines (for large shocks) and by red lines vs. blue lines (for small shocks).

Under Calvo specification, no difference can be seen in the impulse responses between the Laplace and Normal specification. This is because under

[6]MatLab codes used for this exercise were made available by CN.

Calvo, the difference between Laplace and Normal distribution lies effectively in the tails and the central area, which constitute a small fraction of the overall area and hence do not get pronounced in the dynamic response. As one moves across figures, more differences can be seen because with increased state dependency, the difference between how the censored Normal and censored Laplace distribution looks becomes more pronounced which translates into different set of price-setters affected by the impulse[7].

When comparing the effects of Laplace specification to those of Normal specification, curves within each figure were compared. To compare the impulse responses under different state-dependency extent, curves across figures must be compared. Under Calvo weak effects exist on Inflation because some of the firms get a green light to adjust although they do not desire to. At the same time, strong effects exist on Consumption because not everybody gets to adjust their prices who desires to. Under moderate and full state-dependency (menu-costs) strong effects exist on Inflation due to "selection effect" which dictates that all adjusting firms have genuine reason to adjust and for the same reason weak effects exist on consumption. Yet another comparison can be done which is examining the effects of shock on dynamics when the shock is small and large. This can be done comparing blue vs. green curves (for Normal specification) or alternatively red vs. black lines (for Laplace specification). The responses under small and large shocks are just scaled and no twists can be identified.

As pointed out in earlier sections, CN allow productivity process to be an AR(1) process and estimate parameter ρ. In this section, it is examined how the dynamics is affected by different values of this parameter as it was estimated quite high for the US data but relatively low for the Slovak data. In Figure 2.14 the impulse responses are recorded under Calvo specification for $\rho = 0$ (blue curves), $\rho = 0.3$ (green curves), $\rho = 0.6$ (red curves) and $\rho = 0.97$ (black curves). It is visible that the AR(1) parameter of the productivity process has a strong effect on the dynamics of the model. Price dispersion is most strongly affected by it because the productivity process directly affects

[7]Real money holdings are not of of special interest in this exercise, but are reported because the differences are most strongly pronounced there.

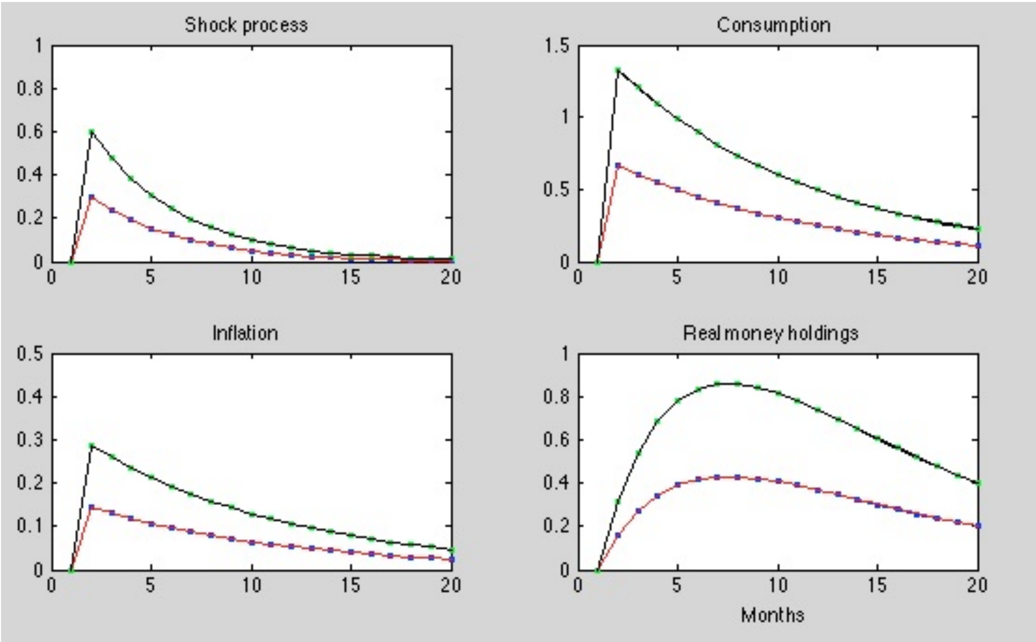


Figure 2.11: Normal vs. Laplace distribution under Calvo.

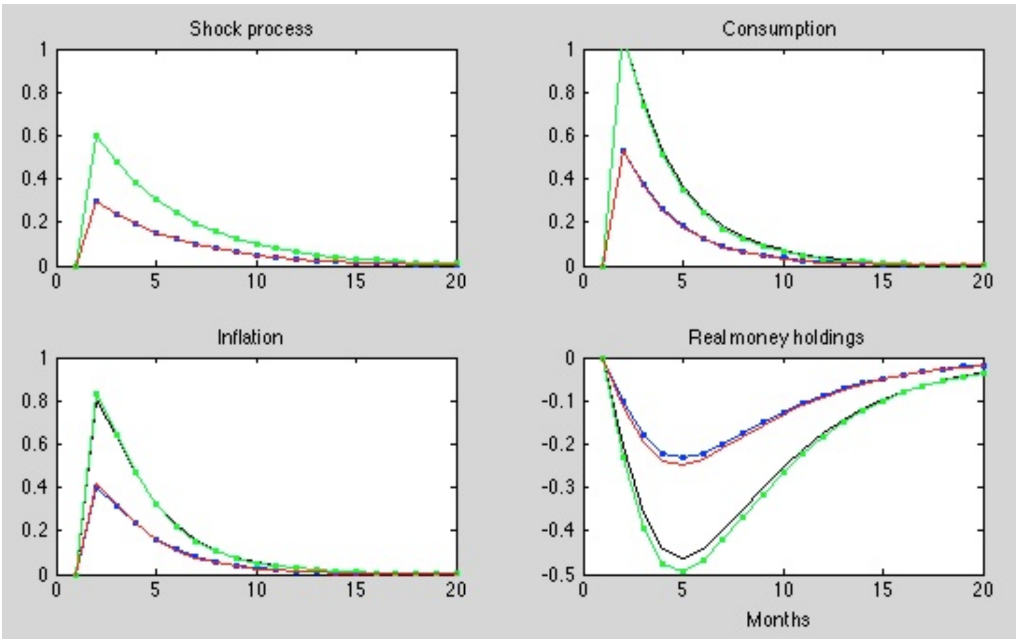


Figure 2.12: Normal vs. Laplace distribution under moderate state-dependency.

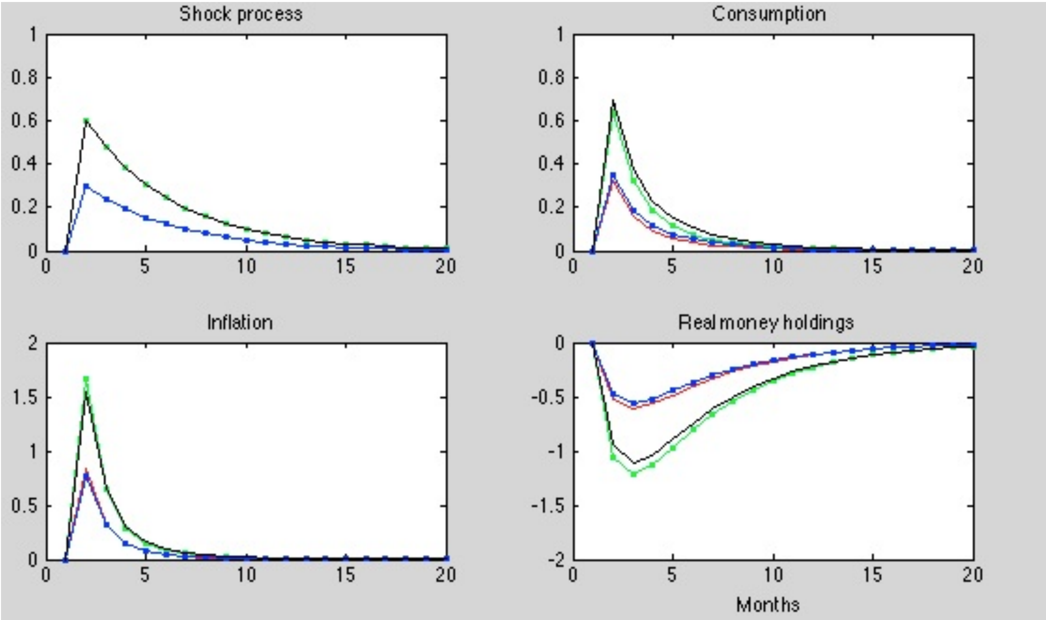


Figure 2.13: Normal vs. Laplace distribution under menu-costs.

the resulting distribution of price adjustments. With higher persistency of the shock (larger ρ) inflation reacts more strongly, but dies out faster. On the other hand, consumption effect dies out slower under lower persistency.

2.6 Conclusion

This analysis focused on explaining some of the patterns identified in the descriptive statistics from Chapter 1. The special bimodal behavior of distributions of price adjustments was modeled deploying a sophisticated hazard function with latent distribution of idiosyncratic shocks following Laplace distribution as opposed to more standard Normal distribution, which was criticized for failing to match rather fat tails and peaky central area. Although the improvement of goodness-of-fit was not significantly larger, some fitted parameters as well as the graphical analysis favored the new specification. Also, allowing for the mean of the distributions to be estimable made it possible for the fitted distributions to be asymmetric which increased the

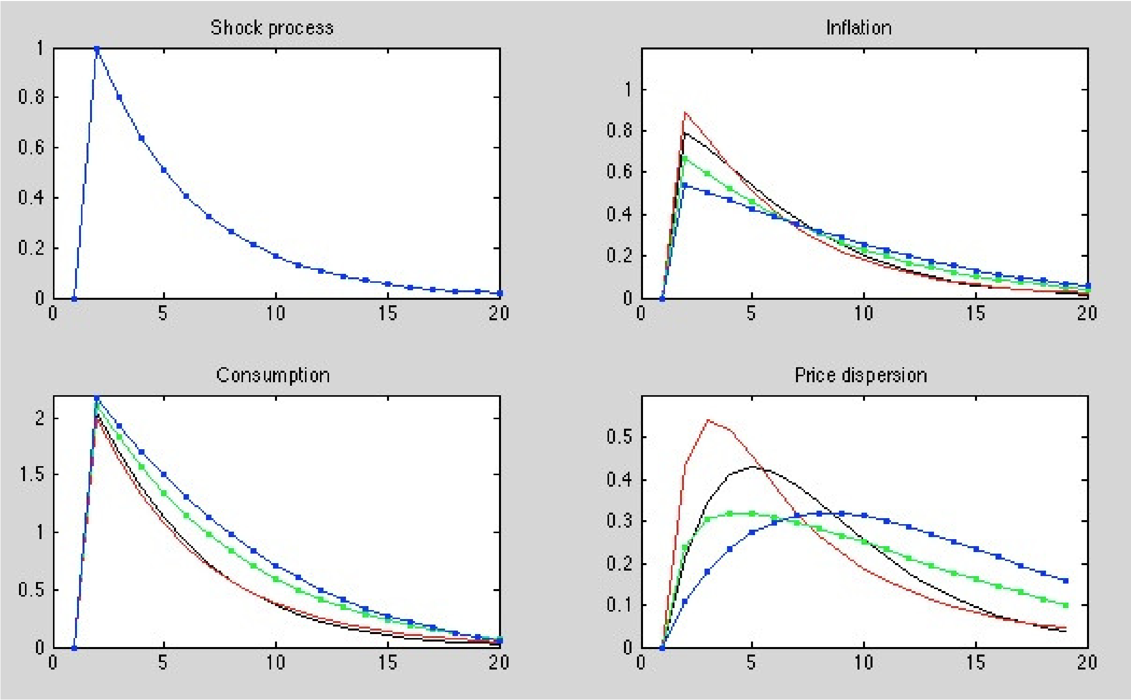


Figure 2.14: Dynamics-ρ. Blue ($\rho = 0$), Green ($\rho = 0.3$), Red ($\rho = 0.6$), Black ($\rho = 0.97$) under Calvo specification.

goodness-of-fit as the data exhibited asymmetry.

When the model was enriched with some explanatory variables it was found that the structural break due to integration of Slovakia into European union was significant. Inflation was found to have mostly positive effect on the mean parameter which shows the intuitive relationship between the inflation and price adjustments and negative on the variance which goes in line with the findings in Chapter 1 where sizes of price changes where found to be smaller in periods of higher inflation. Interest rates are found to have mixed effects on both the mean and the variance parameter.

Last but not least, dynamics implications of the altered assumptions were also examined together with impulse responses under different values of the model parameters. The Laplace specification in place of Normal was shown to have small effects, but larger under menu-costs specification as opposed to Calvo. The extent of state-dependency had very strong effects on the dynamics after shock but the shock size was shown to play irrelevant role besides scaling the impulse response.

Chapter 3

Welfare Losses Under Different Price-setting Structures

3.1 Introduction

Using relationships derived from a dynamic stochastic general equilibrium model (DSGE) this chapter quantifies welfare losses defined as lost consumption when price rigidities are present. It contributes to the existing literature by modeling price rigidity in a way that allows to generalize the implications of different pricing models on welfare losses. In particular, it shows that Calvo type time-dependent price adjustments generate the largest welfare losses and as the extent of state dependency in the pricing strategies increases welfare losses monotonically decrease and reach minimum when menu-cost model is assumed. This way it is concluded that misspecification of the type of price adjustment mechanism can possibly generate significant under- or over-estimation of welfare losses that arise due to price rigidity.

Over the decades, three main approaches have been developed in modeling the price rigidities in which firms were assumed to change their prices with: i) exogenous and constant probability independent of the state of the economy as in Calvo (1983) ii) endogenous and non-constant probability often referred to as state-dependency as in Rotemberg (1982) or Caballero and Engel (1993a) iii) endogenous and constant probablity often referred to as menu costs as introduced by Mankiw (1985) due to which no small price changes were possible. Costain and Nakov (2011) introduced an S-shape hazard rate to model a mixture of time- and state-dependent models which has a special property that it nests the time-dependent Calvo-type pricing and the menu-cost model in its two extremes.

Welfare losses are normally measured in terms of lost consumption. The losses are measured as the difference between equilibrium consumption under flexible prices and staggered prices using various methods of modeling the staggering mechanism. Unlike these approaches this paper measures the welfare losses using one specific method of modeling the pricing behavior but still encompasses practically all the three most common pricing models as mentioned above. Based on this approach the paper shows that welfare losses decrease as state-dependency increases. This finding is shown to be very robust.

The present study is not the first to address the welfare implications of different pricing models. Lombardo and Vestin (2008) express the utility function under flexible prices and under staggering prices using first order approximation and second order approximation to show that Calvo-type pricing and Rotemberg-like pricing are only the same to the first order of approximation, but a higher order of approximation proves them different and the welfare maximizing central bank faces a different problem depending on which pricing mechanism is in place. Dorich (2007) evaluates the welfare losses separately for Calvo-type pricing and for state-dependent pricing using quadratic hazard function and shows them larger for the former and lower for the latter.

The present paper compares the welfare losses across different types of pricing mechanisms using a universal hazard function as proposed in Costain and Nakov (2011) which nests several pricing models. Due to the fact that it incorporates the full continuum of state-dependent cases of pricing strategies, starting with the Calvo-like behavior all the way to the menu-costss model, its potential in comparing implications of various pricing methods is large.

The present analysis builds on the standard DSGE model enriched by idiosyncratic firm-level shocks as presented in Dorich (2007). The introduction of idiosyncratic shocks is justified by findings in the first chapter which documented that frequency of price increases and decreases was strongly positively correlated. Simulating this model, the author compared the welfare losses under Calvo-type and Rotember-like pricing method in such a way that some selected moments were matched of an empirical distribution of price changes. In this chapter this model is simulated exploiting the S-shaped hazard function as described above which allows to evaluate the welfare losses for a continuum of state-dependent economies.

The relationship between welfare losses and pricing mechanism can be expected, given the results in the related literature and the fact that with increased state dependency, more firms get to adjust their prices if it is optimal for them. In case of low levels of state dependency, e.g. under Calvo specification, it is purely random, who are those who adjust and who are those who do not, so the welfare losses are intuitively largest. The main added value of the present analysis is the higher accuracy in modeling the price setting mechanism via the sophisticated hazard rate function by means of which a whole continuum of state dependency extents can be modeled and thus it can be more precisely calibrated how large the implied welfare losses are at each state. Such findings underline how important the assumptions about underlying pricing mechanisms are for the central banker whose policy decisions are centered around the welfare estimation.

The structure of this chapter is as follows. Section 3.2 presents the model and the derivations of the formula for the welfare losses. Section 3.3 presents how the simulation exercise is approached and the findings. In Section 3.4 robustness checks are presented. Finally, Section 3.5 concludes.

3.2 The Model

The model builds on the model as presented in Dorich (2007) which is a simple closed-economy dynamic stochastic general equilibrium model (DSGE) enriched with idiosyncratic shocks in which the probability of changing prices is an increasing function of the target price which builds on the increasing hazard property from Caballero and Engel (1993a). It is presented here as it was presented in the above mentioned study up to the point where the pricing mechanism is discussed. This mechanism is modeled deploying the hazard function from the previous chapter which is discussed in detail in Section 2.3.1 of the previous chapter. This function enables a whole continuum of state dependency to be calibrated by the model which remarkably increases the potential of the model to calibrate the welfare losses under more scenarios using one single model, thus increasing the credibility of the results. The main aim of the model is to validate the intuitive relationship between the welfare losses and the state dependency assumed arguing that the consequences of infeasible assumptions regarding the pricing mechanisms could be potentially large.

3.2.1 Households

Assume the economy is composed of continuum of households of unit mass. The households derive utility from a consumption basket and disutility from hours worked. Stochastic discount factor and initial wealth are given to them. They face a budget constraint. Formally, a representative household maximizes the following objective function:

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, H_t) \tag{3.1}$$

subject to:

$$C_t = \left(\int_0^1 C_t(i)^{(\epsilon-1)/\epsilon} di \right)^{\epsilon/(\epsilon-1)} \tag{3.2}$$

$$P_t = \left(\int_0^1 P_t(i)^{(1-\epsilon)} di \right)^{1/(1-\epsilon)} \tag{3.3}$$

$$\sum_{t=0}^{\infty} E_0 Q_{0,t} P_t C_t \leq B_0 + \sum_{t=0}^{\infty} E_0 Q_{0,t}[(1+\eta) W_t H_t + \Pi_t + T_t] \tag{3.4}$$

where $0 < \beta < 1$ is the discount factor, C_t is aggregate consumption and H_t is hours worked. Parameter ϵ is the constant elasticity of substitution among differentiated goods $C_t(i)$. The first condition states that the consumption basket is a CES function in the Dixit-Stiglitz fashion of different consumption goods. The second condition shows the price index associated with the consumption basket - the price level. The last condition is intertemporal budget constraint where B_0 is the initial level of wealth, W_t is the nominal wage per hour worked, Π_t is profit and T_t represents a lump sum transfer. Consumers supply homogenous labor in a competitive labor market where wage rigidity is not assumed. Parameter η denotes a constant rate of employment subsidy that is funded by negative lump sum transfer (tax), $Q_{0,t}$ is a stochastic discount factor that satisfies $Q_{0,0} = 1$ and $E_0 Q_{0,t} = \prod_{s=0}^{t-1}(1+i_s)^{-1}$ where i_t denotes the interest rate.

Solving the expenditure minimization problem we get the standard demand function for each good:

$$C_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} C_t \tag{3.5}$$

3.2.2 Firms

There is a continuum of monopolistically competitive firms of unit mass. Individual consumption goods are produced using only labor services according to the following production function

$$Y_t(i) = A_t(i) H_t(i)^{\gamma} \tag{3.6}$$

where $Y_t(i)$ is the level of output for firm i, $A_t(i)$ is the firm i's idiosyncratic productivity level and $H_t(i)$ is the total hours hired by firm i. Uncertainty is introduced via random fluctuations in labor productivity - the idiosyncratic productivity level is assumed to follow an AR(1) process of the form:

$$\log A_t(i) = \rho \log A_{t-1}(i) + \varepsilon_t(i) \tag{3.7}$$

where $\varepsilon_t(i)$ follows an i.i.d. process with zero mean and constant variance σ_ε^2.

Firms maximize the expected present value of profits. While wages are flexible, prices are assumed rigid and are modeled using an endogenous probability function as discussed in what follows.

3.2.3 The pricing mechanism

Modeling the state-dependent pricing mechanism is done in the following way. Start with the *desired price* of a firm i at time t under no price rigidities $P_t^*(i)$ and the *actual price* $P_t(i)$. The desired price is not observed and constitutes the firm's target price which would be applied if the firm faced no frictions. The actual price is observed and constitutes the price a firm can charge after accounting for the frictions. Using logarithms the relative price deviation is defined as

$$x_t(i) = p_t(i) - p_t^*(i) \tag{3.8}$$

With very persistent productivity (i.e. unit root in the limit) the expectation of the future frictionless prices is approximately the current price (apart from some constant), so that $\Delta p_t^*(i) \approx \Delta p_t^f(i)$ where

$$p_t^f(i) = \Theta\left[-\log\gamma + \omega_t + \frac{1-\gamma}{\gamma}(\epsilon p_t + c_t) - \frac{1}{\gamma}a_t(i)\right] \tag{3.9}$$

Introducing idiosyncratic firm-level productivity shocks that follow an AR(1) process with zero mean, σ_ε^2 variance and ρ coefficient, with no aggregate shocks for simplification and inflation equal to zero it holds that $\omega_t = \bar{\omega}$, $p_t = \bar{p}$ and $c_t = \bar{c}$. The desired prices then follow the process

$$\Delta p_t^*(i) \approx \Delta p_t^f(i) = -\frac{\Theta}{\gamma}\Delta a_t(i) \tag{3.10}$$

where $\Theta = \frac{\gamma}{\gamma+(1-\gamma)\epsilon}$. With ρ very close to 1 it holds that $\Delta a_t(i) \approx \varepsilon_t(i)$ hence

$$\Delta p_t^*(i) \approx= -\frac{\Theta}{\gamma}\varepsilon_t(i) \tag{3.11}$$

The desired price changes every period due to idiosyncratic productivity shocks which in turn results in changes in actual price. The adjustment hazard which affects the firms' decision on whether to adjust to the desired level or remain with unchanged price is equal to $\Lambda(.)$. This function takes on $x_t(i)$ as its parameter, hence state-dependency is allowed for. As a specific functional form of $\Lambda(.)$ we assume the inverse hyperbole from Chapter 2:

$$\Lambda(x_t(i)|\bar{\lambda}, \alpha, \xi) = \frac{\bar{\lambda}}{\bar{\lambda} + (1 - \bar{\lambda})(\frac{\alpha}{|x_t(i)|})^{\xi}} \tag{3.12}$$

The timing in the model starts at the beginning of period t in which firm i has a price imbalance of $x_{t-1}(i)$. Then the idiosyncratic shock hits the firm and $x_{t-1}(i)$ moves to $x_{t-1}(i) + \Delta p_t^*(i)$. Whether this price deviation is then applied to eliminate the price imbalance or not depends on $\Lambda(x_{t-1}(i)+\Delta p_t^*(i))$ in the following way:

$$x_t(i) = I_t(i)(x_{t-1}(i) + \Delta p_t^*(i)) \tag{3.13}$$

where

$$I_t(i) = \begin{cases} 1 & \text{with Probability } 1 - \Lambda(x_{t-1}(i) + \Delta p_t^*(i)) \\ 0 & \text{with Probability } \Lambda(x_{t-1}(i) + \Delta p_t^*(i)) \end{cases}$$

If there were no idiosyncratic shocks the firms would have the same desired price over time. In the first period, this desired price would determine the discrepancy which in turn would determine the probability of adjustment. Based on this probability the next period's discrepancy would remain the same as the current one (no price change happens) or would change to zero (i.e. such price change would be applied which eliminates the discrepancy). Because there are no idiosyncratic shocks, sooner or later the discrepancy gets eliminated so the desired price equals the charged price. The probability equals zero at zero, hence the discrepancy will remain zero forever thereafter. In sum, the frictions get taken care of once and for all if the idiosyncratic shocks are absent.

Under the idiosyncratic shocks the price setting process goes as follows. Without idiosyncratic shock it would be $x_t(i)$ in $t+1$, too but instead becomes different by whatever the shock means to its desired price (it does not affect the actual price directly but via some parameters – the difference this shock generates to the desired price can be shown to equal $-\frac{\Theta}{\gamma}\Delta a_{t+1}(i)$) so the new discrepancy $x_{t+1}(i)$ is the old one $x_t(i)$ plus this difference.

If the firm was allowed to eliminate this stochastically determined discrepancy in each period, no inefficiencies would arise due to frictions as prices would always be optimal (the shocks in t would be counter-acted in the same period). But firms are not allowed to adjust their prices any time they encounter a shock. Under Calvo specification, they face a fixed probability of a green light to adjust and have to keep their old charging price if they receive a red light. Under menu-costs models, firms get the green light endogenously - if their desired price is large enough they can adjust, otherwise not. With the mixture of the two as modeled here, this probability is increasing with the desired price change.

3.2.4 Equilibrium

Market clearing in the goods market requires that $C_t(i) = Y_t(i)$ which implies that

$$Y_t = \left(\int_0^1 Y_t(i)^{(\epsilon-1)/\epsilon} di \right)^{\epsilon/(\epsilon-1)} \tag{3.14}$$

Also, labor supply and demand must clear, hence $H_t = \int_0^1 H_t(i)di$. Combining these conditions we get market clearing condition in the labor market

$$H_t = Y_t^{\frac{1}{\gamma}} \int_0^1 \left(\frac{Y_t(i)/Y_t}{A_t(i)} \right)^{\frac{1}{\gamma}} di \tag{3.15}$$

Define $d_t = \gamma \log \int_0^1 \left(\frac{Y_t(i)/Y_t}{A_t(i)} \right)^{\frac{1}{\gamma}} di$ a measure of output dispersion across goods adjusted by idiosyncratic shocks. This term captures how the composition of output among firms affects total output. Alternatively, it can be expressed as $d_t = \gamma \log \int_0^1 \left(\frac{1}{A_t(i)} \right)^{\frac{1}{\gamma}} \left(\frac{P_t(i)}{P_t} \right)^{\frac{-\epsilon}{\gamma}} di$ in which case it would be interpreted as a measure of how distorted the relative prices are. Using the former we can express the market clearing condition in logs in the following way:

$$\gamma h_t = y_t + d_t \tag{3.16}$$

3.2.5 The Welfare Losses

The welfare losses due to price rigidities are given by the difference between the households' utility under sticky prices and flexible prices. Using second order approximation of the utility function around a zero inflation steady state we get

$$U_t - U \approx U_C C\left(\widehat{y}_t + \frac{1-\sigma}{2}\widehat{y}_t^2\right) + U_H H\left(\widehat{h}_t + \frac{1+\chi}{2}\widehat{h}_t^2\right) \tag{3.17}$$

where hat variables represent log deviations from steady state, market clearing condition $\hat{y}_t = \hat{c}_t$ was used and $\sigma = -\frac{U_{CC}}{U_C}C$ and $\chi = \frac{U_{HH}}{U_H}H$. Rewrite $\hat{h}_t$ in terms of $\hat{y}_t$ and exploit d_t, then

$$U_t - U \approx U_C C\left(\widehat{y}_t + \frac{1-\sigma}{2}\widehat{y}_t^2\right) + \frac{U_H H}{\gamma}(\hat{y}_t + d_t) + U_H H\frac{1+\chi}{2\gamma^2}\hat{y}_t^2 \tag{3.18}$$

It holds that $-\frac{U_H}{U_C} = \gamma\frac{Y}{H}$ because government grants subsidy to labor under efficiency in the zero inflation steady state, hence the following holds for period t

$$\frac{U_t - U}{U_C C} \approx \frac{1-\sigma}{2}\hat{y}_t^2 - d_t - \frac{1+\chi}{2\gamma^2}\hat{y}_t^2 \tag{3.19}$$

which measures the deviation of period utility from its steady state. It is expressed as a fraction of steady state consumption.

Define U_t and U_t^F as utilities under sticky prices and flexible prices, respectively. Then if welfare losses of price stickiness are expressed as fraction of steady state consumption, we can write

$$L_t = \frac{U_t - U_t^F}{U_C C} \tag{3.20}$$

To find formula for L_t we need to express formula (3.19) under flexible prices and under sticky prices. If $\hat{y_t^n}$ and d_t^n denote the natural output and the adjusted output dispersion without price rigidities respectively, then the following formula finds the deviation of utility from the steady state under flexible prices:

$$\frac{U_t^F - U}{U_C C} \approx \frac{1-\sigma}{2}(\hat{y_t^n})^2 - d_t^n - \frac{1+\chi}{2\gamma^2}(\hat{y_t^n})^2 \tag{3.21}$$

and the deviation under sticky prices comes from (3.19). Subtracting the two welfare losses can then be expressed as

$$L_t = -\left[\frac{\gamma\sigma + 1 - \gamma + \chi}{\gamma}\right](\hat{y}_t - \hat{y_t^n})^2 - (d_t - d_t^n) \tag{3.22}$$

The first term is the output gap and measures how close total output is from the natural output, the second element measures, as mentioned above, how distorted relative prices are or alternatively, how inefficient the sectoral allocation of goods is. It can be shown that the dispersion of the price gaps across goods is related to $d_t - d_t^n$ so that[1]:

$$d_t - d_t^n = \frac{\epsilon}{2\Theta}\mathrm{Var}_i\left\{p_t(i) - p_t^f(i)\right\} \tag{3.23}$$

where $\Theta = \frac{\gamma}{\gamma+(1-\gamma)\epsilon}$, $p_t(i)$ is the log of actual price of good i and $p_t^f(i)$ is the log of a properly flexible price of that good. Hence higher relative price distortions due to price stickiness imply more welfare losses and welfare losses always exist in this model unless flexible price allocation is reached.

Using these formulas we can write the welfare losses as:

$$L_t = -\frac{\epsilon}{2\Theta}\mathrm{Var}_i\left\{p_t(i) - p_t^f(i)\right\} - \left[\frac{\gamma\sigma + 1 - \gamma + \chi}{\gamma}\right](\hat{y}_t - \hat{y_t^n}) \tag{3.24}$$

Under zero inflation policy zero output gap results up to a first order approximation. Assuming that the New Keynesian Philips Curve is a good approximation to relate output gap and inflation the welfare losses can be

[1]Full derivation can be found in Dorich (2007)

expressed by

$$L_t = -\frac{\epsilon}{2\Theta} Var_i\{p_t(i) - p_t^f(i)\} \tag{3.25}$$

which implies that the only source of welfare losses is the dispersion of price gaps across products. Define $x_t(i)$ as the price deviation from the desired price, we can then express the welfare losses as follows:

$$L_t = -\frac{\epsilon}{2\Theta} Var_i\{x_t(i)\} \tag{3.26}$$

3.3 Simulation of the Model

In this section the relationship is analyzed between the extent of the state-dependency and the corresponding welfare losses in a simulation exercise deploying the model as described in the previous section. The cross-sectional variance $Var_i\{x_t(i)\}$ is estimated from simulation of process x_t for firm i.

The parameters to calibrate are ϵ, γ and ρ. It is assumed that $\epsilon = 3$ in line with Rossi et al. (2002) where price elasticities are estimated to range between 2 and 4. Parameter γ equals the average labor income share (0.66) times the mark-up implied by $\epsilon = 3$, i.e. $\gamma = \frac{\epsilon}{\epsilon-1}.66 = 0.99$. The productivity process AR(1) persistency parameter is assumed very high by setting $\rho = .97$.

Parameters to estimate are $\bar{\lambda}, \alpha$ and σ_ε^2. However, as discussed in Section 2.3.1 of the previous chapter, of the two parameters $\bar{\lambda}$ and α one is abundant, therefore the exercise is performed once fixing the former and once fixing the latter. This can be viewed as a form of robustness exercise. In the baseline analysis the US price data is used from the Dominick's store-chain for comparison reasons with the reference article. Two empirical moments of the distribution are being matched: the frequency and the standard deviation. Frequency in this dataset equals 20%; standard deviation conditional on price change is 10.4%, unconditional standard deviation is 4.6%. The simulation is done for a number of values of ξ ranging from 0 to 100 capturing different extents of state-dependency starting from Calvo pricing mechanism all the way to menu-costs.

The estimated values are presented in Table 3.1 under fixed $\bar{\lambda}$ parameter and in Table 3.2 under fixed α parameter. As can be seen, the time-dependent pricing strategy yields the largest welfare losses and they monotonically decrease as state-dependency increases. Welfare losses are found to reach their minimum in case of menu-costs pricing in which small price changes are not allowed to happen. The relationship is depicted in Figure 3.1.

The results under Calvo parameters ($\xi = 0$) can be readily related to the results of Dorich (2007) who also reports 1.33% welfare losses. The state-dependent welfare losses are estimated using quadratic hazard rate so cannot be related to any specific value of ξ but the value 0.28% is comparable to the values reported in the present analysis for moderate and higher state-dependency extent values.

The reason why the relationship is decreasing from Calvo to menu-costs is that under the former the selection of the firms allowed to adjust prices is random and there are firms left out who would need to adjust but are not allowed to. On the contrary, when state-dependency is allowed, the selection becomes less random and all such firms adjust for whom it is optimal. As a result, larger welfare losses are incurred under Calvo and smaller under state-dependency and menu-costs. Still, though, that the relationship is monotonic, not linear and decreasing faster for lower values is not trivial. This finding shows that making a mistake in the assumption about the price-setting mechanism close in the Calvo region can have larger implications on the estimated welfare losses which are an important tool of the central optimizer.

Pricing Model		ξ	Matching moments Freq.	Cond. s.d.	Uncond. s.d.	Parameters σ_ε	$\bar{\lambda}$	α	Welfare losses
		0	19.97%	10.43%	4.66%	0.0472	0.2	0.0500	1.33%
	Calvo	0.1	19.85%	10.34%	4.61%	0.0471	0.2	0.0500	1.17%
		0.2	19.89%	10.42%	4.65%	0.0469	0.2	0.0500	1.03%
		0.3	19.68%	10.46%	4.64%	0.0470	0.2	0.0520	0.95%
		0.4	19.80%	10.35%	4.60%	0.0466	0.2	0.0500	0.84%
	Low	0.5	19.70%	10.45%	4.64%	0.0468	0.2	0.0510	0.78%
		0.6	19.58%	10.46%	4.63%	0.0468	0.2	0.0517	0.73%
		0.7	19.64%	10.44%	4.63%	0.0468	0.2	0.0517	0.67%
		0.8	19.62%	10.44%	4.62%	0.0469	0.2	0.0520	0.63%
		0.9	19.69%	10.44%	4.63%	0.0470	0.2	0.0520	0.59%
State-dependency	Medium	1.0	19.78%	10.43%	4.64%	0.0470	0.2	0.0520	0.56%
		1.3	19.83%	10.41%	4.64%	0.0470	0.2	0.0530	0.48%
		1.5	20.00%	10.35%	4.63%	0.0470	0.2	0.0530	0.43%
		2	19.86%	10.35%	4.61%	0.0470	0.2	0.0550	0.37%
		2.5	20.00%	10.32%	4.62%	0.0470	0.2	0.0560	0.32%
		3	19.80%	10.38%	4.62%	0.0470	0.2	0.0580	0.30%
	High	5	19.70%	10.40%	4.62%	0.0470	0.2	0.0620	0.24%
		7	19.70%	10.39%	4.61%	0.0470	0.2	0.0643	0.21%
		10	19.84%	10.34%	4.61%	0.0470	0.2	0.0662	0.20%
		20	19.66%	10.38%	4.60%	0.0470	0.2	0.0700	0.19%
	Menu-costs	50	19.60%	10.39%	4.60%	0.0470	0.2	0.0727	0.19%
		100	19.77%	10.35%	4.60%	0.0470	0.2	0.0735	0.18%

Table 3.1: Welfare losses, fixed $\bar{\lambda}$ parameter.

Pricing Model		ξ	Matching moments: Freq.	Cond. s.d.	Uncond. s.d.	Parameters: σ_ε	$\bar{\lambda}$	α	Welfare losses
		0	19.97%	10.43%	4.66%	0.0472	0.2000	0.05	1.33%
	Calvo	0.1	19.85%	10.34%	4.61%	0.0471	0.2000	0.05	1.17%
		0.2	19.71%	10.37%	4.60%	0.0470	0.1995	0.05	1.04%
		0.3	19.67%	10.39%	4.61%	0.0470	0.1993	0.05	0.95%
		0.4	19.59%	10.38%	4.59%	0.0468	0.1990	0.05	0.86%
	Low	0.5	19.60%	10.39%	4.60%	0.0469	0.1989	0.05	0.79%
		0.6	19.62%	10.38%	4.60%	0.0469	0.1988	0.05	0.73%
		0.7	19.69%	10.38%	4.61%	0.0469	0.1987	0.05	0.67%
		0.8	19.76%	10.38%	4.62%	0.0471	0.1985	0.05	0.63%
		0.9	19.44%	10.46%	4.61%	0.0470	0.1930	0.05	0.60%
State-dependency	Medium	1.0	19.57%	10.44%	4.62%	0.0470	0.1930	0.05	0.56%
		1.3	19.84%	10.39%	4.63%	0.0472	0.1900	0.05	0.48%
		1.5	19.92%	10.38%	4.63%	0.0472	0.1860	0.05	0.44%
		2	19.75%	10.37%	4.61%	0.0470	0.1700	0.05	0.37%
		2.5	20.07%	10.29%	4.61%	0.0470	0.1600	0.05	0.32%
		3	19.87%	10.32%	4.60%	0.0470	0.1400	0.05	0.29%
	High	5	20.04%	10.28%	4.60%	0.0470	0.0850	0.05	0.23%
		7	19.84%	10.34%	4.61%	0.0470	0.0430	0.05	0.21%
		10	20.17%	10.25%	4.60%	0.0470	0.0170	0.05	0.19%
		20	19.63%	10.38%	4.60%	0.0470	0.0003	0.05	0.19%
	Menu-costs	50	19.65%	10.38%	4.60%	0.0470	2e-09	0.05	0.18%
		100	19.94%	10.31%	4.60%	0.0470	9e-18	0.05	0.18%

Table 3.2: Welfare losses, fixed α parameter.

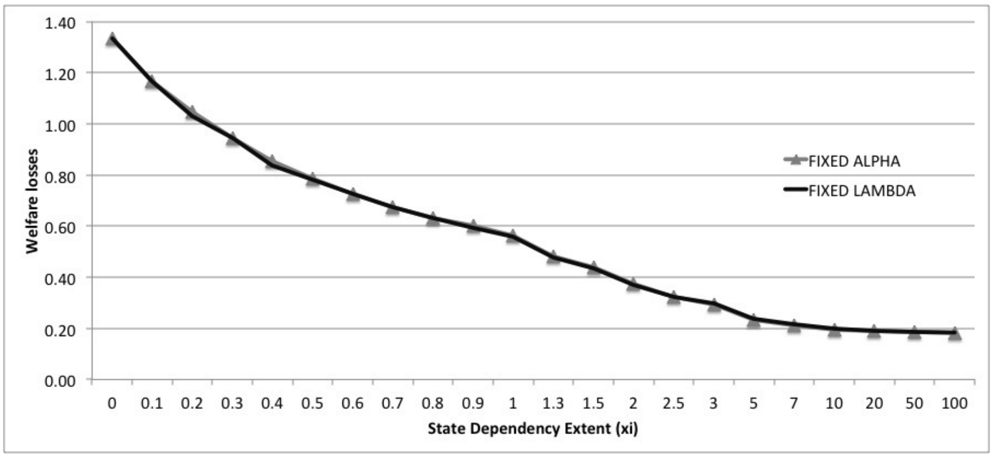


Figure 3.1: Welfare losses.

3.4 Robustness Checks

3.4.1 Parameter ρ

Parameter ρ is assumed close to 1 so that $\Delta p_t^*(i) \approx \Delta p_t^f(i)$ and (3.10) can be approximated with (3.11). In general $\Delta a_t(i)$ can be expressed as follows:

$$\begin{aligned}
a_t(i) &= \rho a_{t-1}(i) + \varepsilon_t(i) \qquad (3.27)\\
&= \rho(\rho a_{t-2}(i) + \varepsilon_{t-1}(i)) + \varepsilon_t(i)\\
&= \rho^3 a_{t-3}(i) + \rho^2 \varepsilon_{t-2}(i) + \rho\varepsilon_{t-1}(i) + \varepsilon_t(i)\\
&= \rho^t a_0(i) + \cdots + \rho^2 \varepsilon_{t-2}(i) + \rho\varepsilon_{t-1}(i) + \varepsilon_t(i)\\
a_{t-1}(i) &= \rho a_{t-2}(i) + \varepsilon_{t-1}(i)\\
&= \rho(\rho a_{t-3}(i) + \varepsilon_{t-2}(i)) + \varepsilon_{t-1}(i)\\
&= \rho^3 a_{t-4}(i) + \rho^2 \varepsilon_{t-3}(i) + \rho\varepsilon_{t-2}(i) + \varepsilon_{t-1}(i)\\
&= \rho^{t-1} a_0(i) + \cdots + \rho^2 \varepsilon_{t-3}(i) + \rho\varepsilon_{t-2}(i) + \varepsilon_{t-1}(i)\\
\Delta a_t(i) &= a_t(i) - a_{t-1}(i)\\
&= \rho^{t-1}(\rho - 1)a_0(i) + \dots\\
&+ \rho^2(\rho-1)\varepsilon_{t-3}(i) + \rho(\rho-1)\varepsilon_{t-2}(i) + (\rho-1)\varepsilon_{t-1}(i) + \varepsilon_t(i)
\end{aligned}$$

Whether $\rho = 1$ or $\rho \neq 1$, with $t \to \infty$ it holds that $\Delta a_t(i)$ is distributed Normally as it inherits the distribution from $\varepsilon_t(i)$. To find the parameters of its distribution μ and σ^2, the respective weights need to be applied on the parameters of the distribution of ε, which are 0 and σ_ε^2:

$$\begin{aligned}\mu &= \cdots + \rho^2(\rho-1)0 + \rho(\rho-1)0 + (\rho-1)0 + 0 \\ \sigma^2 &= \cdots + [\rho^2(\rho-1)]^2\sigma_\varepsilon^2 + [\rho(\rho-1)]^2\sigma_\varepsilon^2 + [(\rho-1)]^2\sigma_\varepsilon^2 + \sigma_\varepsilon^2\end{aligned} \tag{3.28}$$

In the context of calibration as in this analysis, where we search for such σ_ε^2 that certain moments are matched as generated by the resulting $\Delta a_t(i)$, it holds that for any value of ρ such parameter σ_ε^2 can be found that these moments are matched (provided it can be found in the benchmark case of $\rho = 1$ which was done in the previous section). This essentially means, that parameter σ^2 is matched by searching for the right σ_ε^2 to the given ρ. As a result, the parameters of the distribution of $\Delta a_t(i)$ are the same regardless of ρ and the calibrated welfare losses remain unchanged. However, it must not be forgotten, that the assumption of ρ being close to 1 was necessary for the model derivation and therefore as such, values further away from 1 are not reasonable.

3.4.2 Parameter ϵ

In the benchmark case it is assumed that $\epsilon = 3$. In this section ϵ is allowed to take on values 2 and 4 to examine the robustness of the benchmark results in line with Rossi et al. (2002) where price elasticities are estimated to range between 2 and 4. The values of the estimated welfare losses are plotted in Figure 3.2.

The findings validate the standard results that elasticity of substitution is relatively important in order to determine the size of welfare losses and that with higher elasticity of substitution even small price change results in large changes in the consumption of the goods and hence larger welfare losses for firms who fail to accommodate the price changes. The more important finding in this case is that the monotonicity of the relationship between the welfare losses and the extent of the state-dependency is found robust.

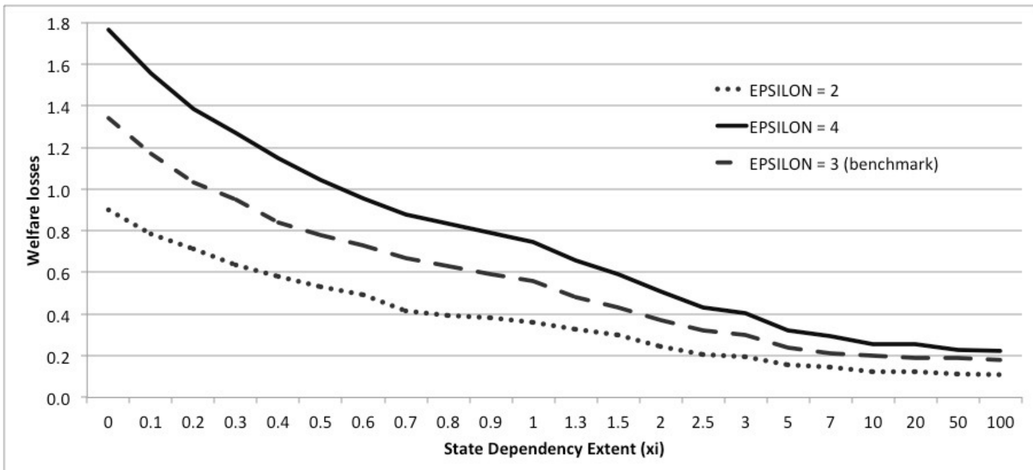


Figure 3.2: Welfare losses under varying ϵ (fixed $\bar{\lambda}$).

3.4.3 Data choice

In the benchmark model the distribution moments of the Dominick's dataset as documented by Dorich (2007) were used to match - the frequency of price changes (20.00%) and the standard deviation of price changes (unconditional (4.6%) and conditional (10.4%)). In this section different values of these moments are examined to determine the strength of their role in the benchmark calibration exercise. In Table 3.3 are listed frequencies of price changes for the EU countries and U.S. as documented in EA, KK, BK, Dorich (2007) (Do) and Nakamura and Steinsson (2008) (NS).

It is clear that the frequency used in the benchmark calibration (20%) can be both smaller and greater in the empirical data. On the top of the documented values for other European countries and the U.S., results from Chapter 1 show that the frequencies can vary a lot also depending on the composition of the sample. Although the data on standard deviation is more scarce, for the sake of the robustness exercise it is simply assumed that also this moment can be both smaller and greater than the benchmark value

country	freq.	country	freq.	country	freq.
Austria	15.4%	France	20.9%	Euro-Area	15.1%
Belgium	17.6%	Italy	10.0%	US (BK)	24.8%
Germany	13.5%	Luxembourg	23.0%	US (KK)	29.9%
Spain	13.3%	Netherlands	16.2%	US (Do)	20.0%
Finland	20.3%	Portugal	21.1%	US (NS)	10.0%

Table 3.3: Frequency of price changes by country.

(conditional (10.4%)). In this exercise, new values to match are 25% and 15% for frequency (f) and 12% and 8% for the conditional standard deviation (c.s.d.).

Figure 3.3 plots the welfare losses when calibrated to these varying values. For better visualization, the graphs are edited in such a way that color is specific for a given value of standard deviation and line-pattern is specific for a given value of frequency. It is apparent that the colors created three clusters which means that the standard deviation drives the welfare losses more than frequency. More importantly, though, the monotonic nature of the relationship remains unchanged under all scenarios.

It is intuitive that the role of standard deviation in determining the welfare losses is strong. Under Calvo set-up the rigidity mechanism (constant probability of adjustment) affects a random subset of price-setters hence price-setters with large desired price changes appear in this subset as well as price-setters with small desired price change. Hence if the desired price changes are spread far due to large standard deviation, the inefficiencies in terms of non-adjustments are larger resulting in larger welfare losses. Analogically, if the desired price changes are rather concentrated around the mean and take on smaller values, the inefficiencies due to non-adjustments are smaller resulting in smaller welfare costs. This does not hold when the rigidity mechanism is modeled in terms of menu-costs. In that case the rigidity mechanism is focused on the small values of price changes and does not really affect the larger values of the desired price changes - those get to happen regardless of whether they are spread far apart or concentrated closer to mean. Hence all the inefficiencies are generated by the small price adjustments, so only small differences can be marked between the resulting welfare losses under the menu-cost model.

The role of frequency is also intuitive. With small fraction of price adjustments actually happening there are more firms who do not get to adjust although they may desire to and vice versa, when the probability of getting a green light is large, smaller inefficiencies arise due to those firms who do not get to adjust although they would need to.

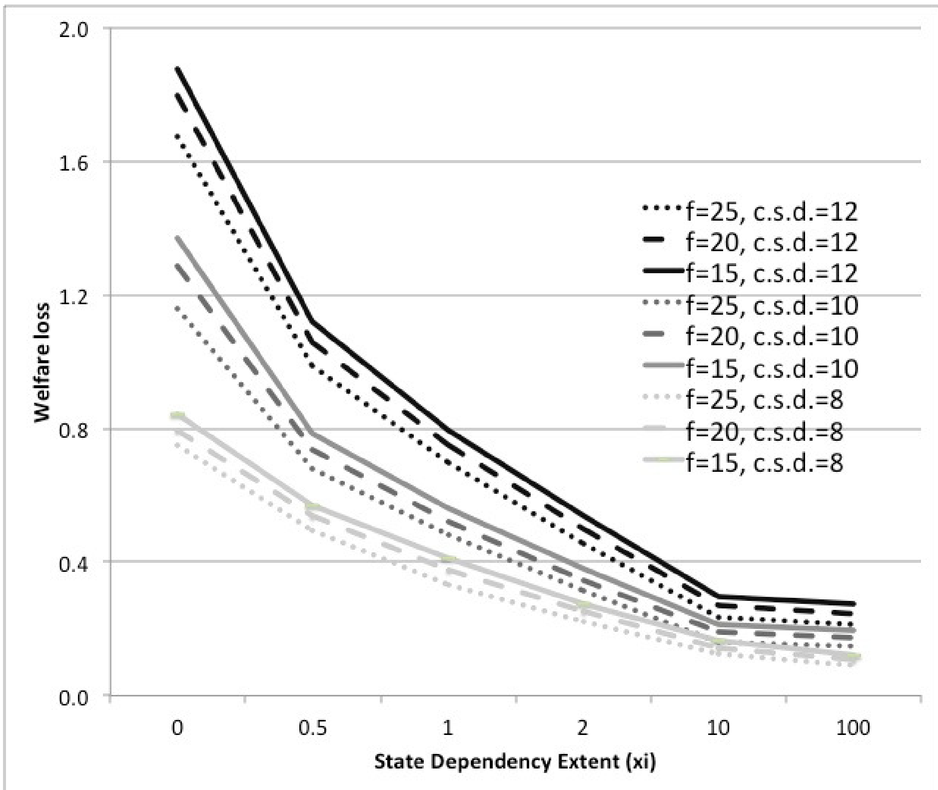


Figure 3.3: Welfare losses under varying values of the matching moments.

3.5 Conclusion

The present analysis focused on quantifying welfare losses based on the standard New Keynesian model enriched with idiosyncratic firm-level shocks and deploying a special price-setting mechanism. The pricing structure was modeled in such a way that state-dependency could be introduced in a different extent nesting the Calvo-type pricing on the one extreme and menu-costs model on the other. The model was calibrated so that some statistical properties of the empirical price changes' distributions could be matched.

The results verified a healthy economic intuition which dictates that the time-dependent pricing strategies, as represented by Calvo-type pricing, generate largest welfare losses in terms of lost consumption and decrease monotonically as the extent of state-dependency increases. The welfare losses reach their minimum in case of the menu-costs model.

This findings show that if certain extent of state-dependency in the data is assumed when modeling price rigidities, welfare losses generated by this data can be remarkably under- or over-estimated. Although this finding does not explicitly give a directive to the policy maker on how to manage the macro variables it does underline the importance of certain assumptions in the macroeconomic models that policy makers use.

To sum up, this analysis shows that welfare losses depend monotonically on the extent of state-dependency in the pricing strategies of the firms and that wrong assumptions about the character of the pricing mechanism in the economy can significantly under- or overestimate the estimated welfare losses in the data and thus influence the central bankers optimization processes.

Conclusion

This thesis focused on analyzing price-setting mechanisms from the statistical, econometrical and theoretical viewpoint.

Chapter 1 documented price-setting patterns in Slovakia using descriptive statistics on a large database of price quotes during 2002 – 2007. Evidence was found for prices to be relatively sticky and inflation was found to be responsible for increasing the intensive margin but decreasing the extensive margin. High correlation between frequencies of price increases and price decreases was attributed to idiosyncratic shocks on firm level and no clear correlation was found between frequencies and sizes of price adjustments so focusing only on either in analyzing price-setting behavior was concluded to be possibly erroneous.

Results from this analysis were related to similar results from studies for Euro-area and U.S. On the qualitative side Slovakia exhibits very similar patters as are documented in these studies; on the quantitative side, differences occur, which are partially explainable by inflation but partially remain an issue of data collection methods, market, cultural and/or country specific differences etc. All in all, this chapter aimed to provide basic insights into price-setting patterns in Slovakia and offered the necessary data for calibration exercises or macroeconomic model building.

Chapter 2 focused on explaining some of the patterns identified in the descriptive statistics from Chapter 1. The special bimodal behavior of distributions of price adjustments was modeled deploying a sophisticated hazard function with latent distribution of idiosyncratic shocks following Laplace distribution as opposed to more standard Normal distribution, which had been reported to fail to match rather fat tails and peaky central area of the empirical distributions. Although the improvement of goodness-of-fit was not significantly larger, some fitted parameters as well as the graphical analysis favored the new specification.

When the model was enriched with some explanatory variables it was found that the structural break due to integration of Slovakia into European union was significant. Inflation was found to have mostly positive effect on the mean parameter which shows the intuitive relationship between the inflation and price adjustments and negative on the variance which goes in line with the findings in Chapter 1 where sizes of price changes where found to be smaller in periods of higher inflation. Interest rates were found to have mixed effects on both the mean and the variance parameter.

The analysis also analyzed some dynamics implications of the altered assumptions. The Laplace specification in place of Normal was shown to have small effects, but larger under menu-costs specification as opposed to Calvo. The extent of state-dependency had very strong effects on the dynamics after shock but the shock size was shown to play irrelevant role besides scaling the impulse response.

Chapter 3 focused on quantifying welfare losses based on the standard New Keynesian model enriched with idiosyncratic firm-level shocks and deploying a special price-setting mechanism. The pricing structure was modeled in such a way that state-dependency could be introduced in a different extent nesting the Calvo-type pricing on the one extreme and menu-costs model on the other. The model was calibrated so that some statistical properties of the empirical price changes' distributions could be matched.

The results verified a healthy economic intuition which dictates that the time-dependent pricing strategies, as represented by Calvo-type pricing, generate largest welfare losses in terms of lost consumption and decrease monotonically as the extent of state-dependency increases. The welfare losses reach their minimum in case of the menu-costs model.

This findings show that if certain extent of state-dependency in the data is assumed when modeling price rigidities, welfare losses generated by this data can be remarkably under- or over-estimated. Although this finding does not explicitly give a directive to the policy maker on how to manage the macro variables it does underline the importance of certain assumptions in the macroeconomic models that policy makers use.

To sum up, this paper shows that welfare losses depend monotonically on the extent of state-dependency in the pricing strategies of the firms and that wrong assumptions about the character of the pricing mechanism in the economy can significantly under- or overestimate the estimated welfare losses in the data and thus influence the central bankers optimization processes.

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Appendix A

Raw Data Description

A.1 Price Collection Methodology

The raw database was provided by the Slovak Statistical Office and is used for computing the consumer price index. According to the methodology guidelines for year 2011 available on the main webpage of the office the price collectors are instructed to collect prices for a "typical representative " of each product. This means there is no obligation to follow the same brand over time as long as the choice of the brand falls into the category of "typical" to mirror what products an average consumer faces. Replacement of products happens in accordance with quality, product characteristics and price of the product to be replaced to ensure consistency of the data.

The price collectors are instructed to collect prices in a "typical" store to mirror what kind of store an average consumer faces. In a given locality more stores are visited to collect price quotes for a given product depending on availability of the stores, size of the locality and availability of the product. The price collectors are instructed to visit the same store over time unless the store closes down. In that case the collector finds the best possible substitute for that store. No indicator exists for this change in the database available for this analysis.

A.2 Raw Data Basic Statistics

The database covers years 2002 - 2007 on a monthly basis amounting to 72 periods. Altogether 736 products are included. Data was collected in 38 geographical areas, the regulated products are marked with an additional geographical area which represents the central regulator. There are 14,014 distinct stores available.

During the years 2002 – 2007 some changes happened in the consumer basket products. Particularly, the number of products available per year is presented in Table A.1.

year	non-regulated	regulated	total
2002	623	0	623
2003	631	0	631
2004	631	67	698
2005	638	65	703
2006	637	64	701
2007	627	66	693

Table A.1: Number of products in CPI per year.

There are altogether 79 products coming from a special region which will be referred to as "central" region hereafter. This region marks centrally determined price, a regulated price. Out of these products 9 have data coming from both a "regular" region as well as the "central" region. This is an ambiguity which makes it hard to treat these products and are thus removed from the analysis (these products are the following: 02200101, 02200102, 04505101, 07202101, 07302101, 07302102, 07302103, 07302106, 07302107 and they reduce the number of stores by 99).

However, according to documents of the Slovak Statistical Office there are altogether 113 regulated products. The reason why prices of some regulated products are observed in "regular" regions as opposed to "central" regions is that for these products the regulator only sets the ceiling price and the price-setters are free to charge a lower price.

Not all products are always available in all geographical areas. In every region at least 605 products are available altogether, in a given month at least 561 products. Maximum number of available products altogether in a region is 656 (in the region of the capital) and if we look on a monthly basis it is 638 (also in the capital).

Many products are collected in the same stores within a region so the store count is smaller than the product count in most regions. The smallest number of stores necessary to visit to collect all prices in one specific month was in region 808-Roznava and it was 172 stores. The most stores that needed to be visited in one specific month was 655 and it was in region 707-Presov. On average 3-5 stores are visited in each region for each product.

Examining the number of products covered and the number of stores visited per region it can be concluded that no clear pattern exists across regions. This means that it is not the case that for example many small stores had to be visited in say eastern regions because large multi-product stores were not existent there or vice versa – it was not the case that few large stores were enough to visit in the capital.

The panel of the data is very unbalanced. Out of 105,204 product-region-store tuples only 70,047 provided price quotes in all 72 months. The remaining 35,157 provided price quotes in fewer periods where fewer means any number between 1 and 71. Multiples of 12 are the most frequent values which suggests that changes in products and/or stores in the database were mostly happening at the breaks of the years.

To ensure that these kinds of replacements do not bias the analyses, "big" changes are filtered out. This means that every time a store or a product seems to be the same in period t and $t + 1$ according to the database, but the log price change is too large or too small (defined as larger than 1) and the new price level pertains, it is assumed that the product or the store were changed and these are then treated as separate.

A.3 CPI categories and weights

The raw database only consists of numerical values. To understand the meaning of its content one needs to match the product codes with product names and region codes with region names. Consumer basket definition from year 2006 is used to interpret the product codes. There are 701 products listed in this basket out of which 700 can be matched with the data (product 10300101 with weight 3.282‰ is unmatched). As all the analysis uses weights, only these 700 products can be used. This results in 13,697 stores visited and altogether 6,112,668 price quote observations.

The products can be grouped into 12 categories as they appear in the consumer basket. Table A.2 lists the categories with their corresponding product counts, store counts and weights.

CPI category:	Weight in ‰	All Product Count	Regulated Product Count: Documented	Regulated Product Count: Centralized	Regulated Product Count: Altogether	Store Count
1. Food and non-Alcoholic Beverages	158	137	0	0	0	721
2. Alcohol Beverages and Tobacco	45	12	0	1	1	352
3. Clothing and Footwear	44	92	0	0	0	2,062
4. Housing, Water, Fuels	283	45	19	8	19	1,635
5. Furniture, House Equipment	54	85	0	0	0	2,527
6. Health Services	26	39	39	0	39	658
7. Transportation Services	95	73	19	22	29	1,478
8. Postal Service and Telecom.	37	21	12	20	20	146
9. Recreation and Culture	80	75	2	8	8	3,000
10. Education	12	6	4	0	4	437
11. Hotels and Restaurant	69	44	5	0	5	1,553
12. Other Goods and Services	94	71	13	7	14	2,912
Total	997	700	113	66	139	13,697

Table A.2: Basic statistics on the raw database.

Appendix B

Codes

B.1 Chapter 1 Codes

B.1.1 Descriptive statistics (MySQL)

Import RawData from text file

```
create table FullDatabase (
year year(4),
month tinyint,
region varchar (3),
store varchar (10),
product varchar (10),
price float(10,2),
index using btree (year),
index using btree (month),
index using btree (region),
index using btree (store),
index using btree (product)  );
load data local infile
"/path/.../path/file.txt"
  into table FullDatabase
fields terminated by ','
```

```
optionally enclosed by '"'
lines terminated by '\r\n'
ignore 1 lines
     (@yearmonth, region, store, product, price, @temp)
                set year=left(@yearmonth,4),
                month=right(@yearmonth,2) ;
show warnings; #no warnings should appear
```

Raw Data statistics

```
#basic stats:
select  count(distinct product) DistinctProducts,
        count(distinct region) DistinctRegions,
        count(distinct region, store) DistinctStores,
        count(distinct year, month) DistinctPeriods
from FullDatabase;

#stats on store and product counts:
select  x.region,
        max(x.DistinctStoreCount) max_dsc,
        min(x.DistinctStoreCount) min_dsc,
        max(x.DistinctProductCount) max_dpc,
        min(x.DistinctProductCount) min_dpc
from
     (select region, year, month,
             count(distinct store) DistinctStoreCount,
             count(distinct product) DistinctProductCount
      from FullDatabase
      group by region, year, month) as x
group by x.region
order by max_dsc;

#ambiguous products:
```

```
select product, group_concat(distinct region) c
from FullDatabase
group by product
having c like '%999%'
and length(c)>3;
```

Assigning weights

```
create table WeightedDB
select fd.*,w.weight
from FullDatabase fd
right join RawData.Weights w
on w.product=fd.product;
```

Constructing samples

```
set @price=null, @product=null, @region=null, ...
      @store=null, @month=null, @year=null;

create table Sample
select *,
   if((@product=product and @region=region and @store=store),
      if((@year=year and month=@month+1) or
         (year=@year+1 and month=1 and @month=12),
            @price,null), null) as lag_price,
   if((@product=product and @region=region and @store=store),
      if((@year=year and month=@month+1) or
         (year=@year+1 and month=1 and @month=12),
            price - @price,null), null) as abs_pc,
   if((@product=product and @region=region and @store=store),
      if((@year=year and month=@month+1) or
         (year=@year+1 and month=1 and @month=12),
            log(price) - log(@price),null), null) as log_pc,
   @price:=price delete_me1,
```

```
   @product:=product delete_me2,
   @region:=region delete_me3,
   @store:=store delete_me4,
   @year:=year delete_me5,
   @month:=month delete_me6
from WeightedDB
where product not in (...regulated...)
   and region!=999
   and left(product,2) not in (2,4,6,7,8,10)
order by product, region, store, year asc, month asc;
```

Sales indicator

```
set @prev_abs_pc=null, @product=null, @region=null, ...
    @store=null, @month=null, @year=null;
create table Sample2
select *,
   if((@product=product and @region=region and @store=store and
      ((@year=year and month=@month-1)
         or (year=@year-1 and month=12 and @month=1))
         and @prev_abs_pc=-abs_pc and abs_pc<0), 1,0) as sales,
            @prev_abs_pc:=abs_pc as delete_me,
            @product:=product delete_me2,
            @region:=region delete_me3,
            @store:=store delete_me4,
            @year:=year delete_me5,
            @month:=month delete_me6
from Sample
order by product, region, store, year desc, month desc;
```

Frequency of price changes

```
#store level
select y.sample, sum(y.wf)/sum(y.weight) f
```

```
from (
   select x.sample, x.product, weight, weight*avg(f) wf
   from (
      select sample, product, weight, region, store,
              sum(if(log_pc!=0,1,0))/sum(if(log_pc is not null,1,0)) f
         from Sample
         group by sample, product, weight, region, store
      order by null ) as x
   group by x.sample, x.product
   order by null ) as y
group by y.sample with rollup
order by null;

# aggregate
select x.sample, sum(x.wf)/sum(x.weight) f
from (
         select sample, product, weight,
         weight*sum(if(log_pc!=0,1,0))/sum(if(log_pc is not null,1,0)) wf
         from Sample
         group by sample, product, weight
      order by null) as x
group by x.sample with rollup
order by null;
```

Sizes of price changes

```
#store level
select y.sample, sum(y.ws)/sum(y.weight) s
from (
   select x.sample, x.product, weight, weight*avg(s) ws
   from (
      select sample, product, weight, region, store,
      sum(if(log_pc<0 and sales!=1 and sales2!=1,log_pc,0))/...
```

```
        sum(if(log_pc<0 and sales!=1 and sales2!=1,1,0)) s
      from Sample
        group by sample, product, weight, region, store
      order by null) as x
    group by x.sample, x.product
    order by null) as y
group by y.sample
order by null;

# aggregate
select x.sample, sum(x.ws)/sum(x.weight) s
from (
    select sample, product, weight, weight*...
      sum(if(log_pc>0 ,log_pc,0))/sum(if(log_pc>0 ,1,0)) ws
      from Sample
      group by sample, product, weight
    order by null) as x
group by x.sample
order by null;
```

Synchronization Across Stores - weighted

```
#f_k
drop table f_k;
create temporary table f_k
select x.product, x.weight, avg(x.s)  as f_k_bar
from (
    select product, weight, year, month,
    sum(if(log_pc!=0 and sales!=1 and sales2!=1, 1,0))/...
     sum(if(log_pc is not null,1,0)) s
    from Sample
    where sample='A'
    group by product, weight, year, month
```

```
   having s is not null) as x
group by x.product, x.weight;

#formula for SI
select sum(y.w_sync)/sum(y.weight) as sync
from (
   select x.product, x.weight, x.f_k_bar,
     x.weight*sqrt(sum(x.sq)/(x.f_k_bar*(1-x.f_k_bar)*count(*))) w_sync
   from (
        select s.product, s.weight, f.f_k_bar f_k_bar, s.year, s.month,
          (sum(if(s.log_pc!=0 and s.sales!=1 and s.sales2!=1, 1,0))/...
      sum(if(s.log_pc is not null,1,0)) - f.f_k_bar)*^2 sq
      from Sample s
           join f_k f
           on f.product=s.product
           where s.sample='A'
      group by s.product, s.weight, f.f_k_bar, s.year, s.month
      having sq is not null) as x
group by x.product, x.weight, x.f_k_bar ) as y;
```

B.2 Chapter 2 Codes

B.2.1 Estimation exercise (STATA)

Unconditional Laplace specification

```
set more off
capture drop res
qui gen res=.
capture program drop my_lf
program define my_lf
  version 10.0
  args lnf mu s l xi
     tempvar temp p
```

```
     quietly gen double `p' = ...
       (`l')/(`l'+(1-`l')*(0.0320/abs($ML_y1))^`xi') if $ML_y1!=0
     quietly gen double `temp' = ...
       (`p')*exp(-abs($ML_y1-`mu')/`s')/(2*`s') if $ML_y1!=0
     quietly integ `temp' $ML_y1, replace
     quietly replace `lnf'=ln(cond($ML_y1!=0,`temp',1-r(integral)))
end
ml model lf my_lf (mu: log_pc = ) (s: log_pc = ) (l: log_pc  = )...
     (xi: log_pc = ), technique(bhhh dfp bfgs nr)
ml init /mu=0.05 /s=.1 /l=.2  /xi=0
ml maximize, difficult
set more on
```

Unconditional Normal specification

```
quietly gen double `temp' = ...
   (`p')*normalden($ML_y1,`mu',`s') if $ML_y1!=0
```

Euclidean distance

```
set more off
global  mu = [mu]_cons
global  s = [s]_cons
global  l = [l]_cons
global  xi = [xi]_cons
qui count if log_pc>-.5 & log_pc<.5&log_pc!=0
global  myN=r(N)
count if log_pc>-.5 & log_pc<.5
 local  fpc=$myN/r(N)
 local  fpc=1
 local  ED=0
 local  temp=0
 local  tempED=0
 local  area=0
```

```
 local  area2=0
 local  f1=0
 local  f2=0
forvalues i=-.5(0.04).5{
 local area2=`area'
 capture drop x
 qui range x -0.5 `i'
 capture drop f
 qui gen f = (`fpc')*($l)/($l+(1-$l)*(0.0320/abs(x))^...
     ($xi))* exp(-abs(x-$mu )/$s)/(2*$s)
 qui integ f x
 local  area=r(integral)
 di as text "area " as result `area'
 local  f2=`f1'
 count if log_pc <`i' & log_pc!=0 & log_pc>-.5
 local f1=r(N)
 di as text "freq at " as result %6.4f `i' as text " is " as ...
    result %6.5f (`f1' -`f2')/$myN as text " matching " as ...
    result %6.5f   `area' -`area2'
 local  temp = (`area' -`area2' - (`f1' -`f2')/$myN)
 local  ED = `ED' +  `temp'*`temp'
}
di sqrt($myLresult/25)
set more on
```

Autocorrelated errors

```
 gen dummy = .
sort product region store year month
 replace dummy=1 if product!=product[_n-1]
 replace dummy=1 if region!=region[_n-1]
 replace dummy=1 if store!=store[_n-1]
```

```
capture drop res
 qui gen res=.
set more off
capture program drop my_lf
program define my_lf
  version 10.0
  args lnf mu s l xi rho

tempvar temp p err y err_lag y_lag pom

 qui gen  double `err'=$ML_y1-`mu'
 qui gen  double `y'=$ML_y1
 qui gen  double `err_lag'=`err'[_n-1]
 qui gen  double `y_lag'=`y'[_n-1]

 qui gen  double `p' = (`l')/(`l'+(1-`l')*(0.0320/...
  abs(`y' - `rho'*`y_lag'))^`xi') if  $ML_y1!=0
 qui gen  double `temp' = (`p')*exp(-abs(`err' - `rho'*`err_lag')/`s')/...
  (2*`s') if  $ML_y1!=0
 qui gen  double `pom'=`err' - `rho'*`err_lag'
quietly integ `temp' `pom', replace
 quietly replace `lnf'= ln( cond($ML_y1!=0, `temp'  , 1-r(integral)  ) )
end
ml model lf my_lf (mu: log_pc= ) (s: log_pc= ) (l: log_pc= ) ...
(xi: log_pc= )  (rho: log_pc= ) if dummy!=1, technique(bhhh dfp bfgs nr)
ml init /mu=0.03 /s=.07 /l=.1  /xi=0.3 /rho=0.05
ml maximize, difficult
set more on
```


B.2.2 Dynamics exercise (MATLAB)

Laplace distribution definition

```
function cdf = Laplacecdf (x, m, sd)
```

```
      if(~ ((nargin == 1) || (nargin == 3)))
       error ('normcdf: you must give one or three arguments');
      end
     s=sd/sqrt(2);
      if (nargin == 1)
       m = 0;
       s = 1;
      end
      sz = size (x);
      cdf = zeros (sz);
   if (isscalar (m) && isscalar(s))
       if  (find (isinf (m) | isnan (m) | ~(s >= 0) | ~(s < Inf)))
         cdf = NaN * ones (sz);
        else
         cdf=0.5*(ones(sz)+sign((x-m)).*(ones(sz)-exp(-abs((x-m)./s))));
        end
    else
       k = find (isinf (m) | isnan (m) | ~(s >= 0) | ~(s < Inf));
       if (any (k))
         cdf(k) = NaN;
       end
       k = find (~isinf (m) & ~isnan (m) & (s >= 0) & (s < Inf));
       if  (any (k))
          cdf(k) = 0.5*(ones(sz)+sign(x(k)-m(k))...
                  .*(ones(sz)-exp(-abs((x(k)-m(k))./s(k)))));
        end
    end
    cdf((s == 0) & (x == m)) = 0.5;
end
```

B.3 Chapter 3 Codes

B.3.1 Calibration exercise (STATA)

```
set more off
set seed #
  /* DECLARE VARIABLES */
  drop _all
  clear
  set obs 20000000

  global gamma = 0.99
  global eps = 3
  global theta = .99 / (.99 + (1-.99)*$eps)

  global left_bound = -5.0
  global right_bound = 5.0
  global xi = 50
  global lambda = 0.2
  global sigma  =  0.047
  global alpha = 0.050

   global myN = _N

    /* generate desired price changes at time zero */
          qui gen dpc = $left_bound + ($right_bound - $left_bound)*runiform()
          qui gen fdpc = 0
          qui gen apc = 0
          qui gen apc_backup = .
          qui genn dpc_backup = .
          qui gen x = .
    /* define the hazard function */
          qui genn p = .
```

```
    /* convergence check variables */
          global binsize = .1
          global matsize = ($right_bound - $left_bound)/$binsize
          qui gen apc_rounded = .
          qui gen apc_backup_rounded =  .
          qui gen dist = .
          qui gen sum_dist = .
          global conv_old = 0
          global conv_new = $myN/1000 + 1
          global counter = 0
          global criter = 0.0001
 /* ITERATIONS */
while abs($conv_new - $conv_old) >  $criter{
   /* step a: add normal shock to last-period desired price changes */
     qui replace dpc=dpc+(-1)*$theta*$sigma*invnormal(runiform())/$gamma+$mu
   /* re-calculate the hazard function based on new desired price changes */
     qui replace p = $lambda/($lambda + (1-$lambda)*($alpha/abs(dpc))^$xi)
     qui replace p = 0 if p==.
   /* step b: apply hazard to get: */
         /* actual price changes from staggered desired price changes */
             qui replace apc_backup = apc
             qui replace apc = cond(p>runiform(), dpc, 0)
         /* new desired price changes */
             qui replace dpc_backup = dpc
             qui replace dpc = cond(p>runiform(), 0, dpc)
   /* evaluate convergence criteria */
  qui summarize apc if apc>0
    global conv_old = r(mean)
  qui summarize apc_backup if apc_backup>0
    global conv_new = r(mean)
    global counter  = $counter + 1
}
di as text "Number of iterations: " as result $counter
```

```
qui replace x = dpc_backup - apc
qui summarize x, detail
di as text "var x " as result r(Var)
di as text "Welfare losses: " as result ...
   round(-100*0.5*$eps*r(Var)/$theta,.000001)
qui summarize apc if apc!=0, detail
di as text "Frequency: " as result round(100*r(N)/_N,.000001) ...
   as text " matching 20 "
di as text "non-zero SD: " as result 100*round(r(sd),.000001) ...
   as text " matching 10.4 "
qui summarize apc, detail
di as text "overall SD: " as result 100*round(r(sd),.000001) ...
   as text " matching 4.6"
qui gen absapc=abs(apc)
qui summarize absapc if absapc!=0
di as text "Avg abs size: " as result 100*round(r(mean),.000001) ...
   as text " matching 7.7"
set more on
```