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Price Rigidity in Turkey: Evidence from Micro Data

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PRICE RIGIDITY IN TURKEY: EVIDENCE FROM MICRO DATA

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Abstract

In this study we investigate the duration of consumer price spells and the price change patterns for Turkey. The study employs the most comprehensive unofficial micro price data so far for Turkey covering around 6000 items over four years, which comprises a major part of the Consumer Price Index (CPI). In detail, we analyze how long a typical price spell lasts, the average size of price changes, the relationship between price change size and spell duration, distribution of price changes and synchronization of prices. Compared to advanced economies, we estimate a high frequency of consumer price changes in Turkey. Findings suggest substantial heterogeneity among sub-groups and underline the time-varying nature of frequency and synchronization indicators. The study confirms that the empirical regularity of mixed evidence of both state and time-dependent pricing generally cited for developed economies also holds for an emerging market economy, Turkey.

JEL Classification: *E31; C41; D40; E50*

Keywords: *consumer prices; price spell duration; price rigidity; distribution of price changes; state and time dependent pricing*

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1. Introduction

In this study we investigate the price change patterns and the duration of price spells for Turkey using micro level data. Assessment of a country's price stickiness is important for understanding the nature and the effects of monetary policy specific to that country. Since price stickiness introduces rigidity for monetary policy to have persistent effects at least in the short run, the degree of stickiness is a vital issue to investigate. Price rigidity is among the key concepts used in macroeconomic theory for monetary policy to have real effects in the short term (Taylor, 1999). If prices are sticky, i.e. they do not respond fully to nominal shocks, then monetary authority is able to influence the real quantities of goods and services produced while prices adjust partially in the short run. In other words, monetary policy can have real effects when prices are sticky as the aggregate price level is not flexible enough in responding to offset the real effects of the change in monetary policy. The frequency of the micro level price changes determines the level of aggregate price stickiness under the new Keynesian framework. In the class of such models frequency of micro level price changes has a direct relation with the degree of aggregate stickiness, implying that if the frequency of price changes is low then aggregate price level is highly sticky, and thus cannot adjust for the effects of monetary policy shocks.

Moreover, sectoral distribution of stickiness and characteristics of price changes contain information for a better understanding of the inflation dynamics. Recently, substantial interest in the analysis of price stickiness by employing micro data has built a strand of literature. One example for United States is Bils and Klenow (2004) and Dhyne et al. (2006) summarizes the vast researches on the subject for Euro Area[1]. Following this line of literature, this study is an attempt to describe the dynamics of consumer prices on a micro basis and to establish the grounds for further research, including the theoretical discussion of price rigidity and the determinants of the duration of prices[2]. The novelty of this study is that it studies the duration of consumer price spells in Turkey with such an extensive coverage of items, where we make use of a unique and comprehensive micro price data covering more than 6000 items over four

[1] Studies exist in the literature for many other countries. Examples include Eden (2001) for Israel, Creamer and Rankin (2008) for South Africa, Solange (2009) for Brasil, Hansen and Hansen (2006) for Denmark, Ikeda and Nishioka (2007) for Japan and Medina et al. (2007) for Chile.

[2] The scope of this working paper is similar to those of the Aucremanne and Dhyne (2004), Baudry et al. (2004), Baumgertner et al. (2005), Gouvea (2007) and more.

years, which matches a major part (around 75%) of the official Consumer Prices Index (CPI)[3].

In detail, we analyze how long a typical price spell lasts, how this differs across subgroups, how much the average size of the change is, in case a spell ends and the dynamic features of price changes such as time dependence of price spells and synchronization of price changes. Main findings are that the average duration of a price spell is about 7.4 weeks. The price changes are more frequent in food group while, the prices last longer for services. Overall, the price spells exhibit negative time dependence. In general price changes display a bi-modal distribution, where price cuts also occur frequently, along with increases. The median size of price change for the entire sample is 3.5 %. In addition, at a monthly frequency about 27% of the prices change, which shows that prices are less rigid compared to those reported in the studies relating to developed economies. Building on the existing literature, this study confirms that the empirical regularity of mixed evidence of both state and time dependent pricing generally cited for developed economies also holds for an emerging market economy, Turkey.

The results of study are mixed in the sense of fitting stylized facts regarding the pricing dynamics, summarized in Klenow and Malin (2010). Most striking finding is the high frequency of price changes estimated for Turkey, which implies shorter-lived price spells for Turkey than United States and Europe. On the other hand, observed relative flexibility of prices is similar to the ones estimated for developing countries. Second, although Turkey is among lower stickiness countries, price change synchronization in aggregate subgroups is substantially small compared with other high frequency countries. Third, bi-modality in the distribution of price changes supports the effectiveness of menu costs such that small price changes may be delayed by the firms to be accumulated. Last, our finding of non-increasing hazard function is in line with the stylized facts.

Depicting the pricing dynamics yield two major policy implications for Turkey. First one regards the heterogeneity of price spell durations, implying that consumer prices in Turkey have more rigid components on which effects of monetary policy can be more effective. This confirms the rationale for putting more weight on core inflation measures

[3] Among other studies, using consumer prices, for Turkey, Caglayan and Filiztekin (2008) uses data collected by the Istanbul Chamber of Commerce for the calculation of a cost of living index for wage earners in Istanbul. The data used, however, covers around 25% of the cost of living index. The authors show that average price duration depends on the market structure. Caglayan and Filiztekin (2006) show that nominal prices, covered in the sample, on average stay for 3 months, using data from Istanbul Chamber of Commerce.

by central banks on assessing the monetary policy relevant inflation developments. Under the presence of further heterogeneity within subgroups, in our context, results suggest that using exclusion based core inflation indicators may yield misleading interpretations of the course of inflation in Turkey (misinterpretation bias is also time-varying). Thus, monetary policy relevance, in terms of product groups, should be considered more carefully by the central bankers and should include dispersion, frequency and synchronization measures at micro level as well. Second, we show that even in more rigid pricing subgroups, prices are not as sticky as in developed countries. As a consequence, persistence of monetary policy in Turkey lasts less than the estimated durations for those countries when only micro rigidities considered.

The next section provides an overview of the theories explaining price rigidity and of the empirical framework of the current analysis. In Section 3, data, model and the empirical analysis are presented. Section 4 discusses the implications of the results for price rigidity and Section 5 concludes the paper.

2. An Overview of the Literature and Methodology

2.1. Overview of the Theories Explaining Price Rigidity

Literature branched for explaining price rigidity theoretically and finding empirical evidence to the size and the extent of stickiness in individual prices[4]. The former research effort also tries to find the best way to put price rigidity into the general equilibrium models instead of assuming exogenous stickiness like the time-dependent models of Calvo and Taylor. The most popular of these models are menu-cost models where price stickiness is a state-contingent phenomenon. The idea of costly price adjustment is modelled by Sheshinski and Weiss (1977), where firms set prices of a perishable good with an environment characterized by monopolistic firms and constant inflation. They show that optimal pricing policy for price setting firms is of the (s, S) type where the interval refers to a band of inaction. This standard model is extended by many papers in terms of its simplifying assumptions. For example, Sheshinski and Weiss (1983) allows for stochastic inflation while Danziger (1983) and (1984) studies the effects of stochastic inflation in certain forms, taking inflation as a Brownian and Poisson processes respectively. The perishable goods assumption is left in Bénabou (1989) where goods are considered to be storable[5].

[4] Dhyne et al. (2009) provides a comprehensive review of theories of sticky prices.
[5] There are generalizations in many other directions and extensions of menu-cost models such as introducing search models. Since focus of the paper is to empirically assess the price stickiness in Turkey

Recent literature stress the importance of information costs in addition to adjustment costs as a barrier to price flexibility. Mankiw and Reis (2002) proposes that updating information about the state of the economy is costly and only a fraction of firms are able to process the updated information set, whereas the others keep on charging prices based on older information.

Other theories focus on psychological aspects which prevent firms to keep their existing prices. A widely observed pattern especially in supermarkets is prices ending in nine. Kashyap (1995) is the first to propose that firms prefer to stay in some certain values (pricing points) when their optimal price change in small digits. Rationale behind attractive prices are discussed to be either due to information processing costs faced by customers or psychological reasons so that consumers do not care about the last digit or feel that the good is cheaper when the last digit is nine. Another example is proposed by Rotemberg (2005, 2011) who suggests a theory based on consumer anger. He supposes that consumers punish price setters who charge contrary to their beliefs regarding fair pricing. As a result, change in prices are highly in accordance with the perceptions of consumers which provides a source of rigidity deviating pricing dynamics from being purely dependent on changes in optimal price.

2.2. Overview of the Methodology

The empirical aim of the study is to understand how long the price spells last, i.e. for how long prices remain unchanged; how the spell durations differ for different groups of the CPI; and how the duration length depends on time. In this respect, survival analysis is the suitable approach to employ.

Survival analysis (or duration analysis) is an approach which specifically deals with modeling duration or time-to-event data[6]. That is, the time elapsed within a specific state, probability of exiting this state at any given time, changing of a price in our context, constitute the main purpose of survival analysis. Survival analysis is widely used in analyzing micro level price durations.

In our context of analyzing time-to-change of price data, survival analysis has sizable advantages compared to alternative methods. First of all, survival analysis deals with the interval censoring inherit in the non-continuous nature of price collection.

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and does not include testing any particular aspect of the mentioned models, we prefer to emphasize only the main reasons of price stickiness explored in the literature.

[6] Van den Berg (2001) presents a technical treatment of the duration analysis, while Kiefer (1998) provides a nice introduction of the use of duration models for economic analysis. In addition, Jenkins (2008) provides a rich and readable discussion of duration analysis along with a guide for empirical application.

Second, it provides the estimates of hazard rates –probability of a price being changed. Another advantage of survival analysis is that it takes into account the differences in time in which the duration variable is at risk, i.e. time dependence of the price spells. Finally, with survival analysis it is possible to use both parametric and non-parametric methods.

In survival analysis, continuous and discrete time models are used depending on the nature of the data. In our context, we observe prices at discrete time intervals of every two weeks. However, in a discrete interval prices may change at any time instance. Therefore, survival occurs in continuous time, even though the price spell lengths are observed in discrete intervals only. This type of setup is generally referred to as 'grouped data'. In this context of interval-censored discrete time survival data, we proceed with the complementary log-log model in the empirical part of the study.

3. Empirical Analysis

3.1. Data

The data used in this study covers item level prices of more than 6000 goods and services at a bi-weekly frequency for Turkey. This is a quite detailed micro level data set covering about ¾'s of the CPI basket. The time period considered in the study is from October 2006 to January 2011, therefore we have 106 bi-weekly observation periods.

3.2. Compilation methodology

Main approaches

In the micro level studies of price spells, generally three different types of data are used. Traditionally, item-level prices of the CPI compiled by the statistical agencies are used[7]. While this approach makes use of the official prices, those prices generally are only available once a month, rather infrequent for micro studies. Additionally, CPI type of data, by construction, deals with representative goods. For instance, not all the prices of entire brands of milk available in one store are collected. Instead, prices of representative brands of milk which can be found in most stores across the country are collected. Therefore trading off nation-wide availability for increased number of items considered might increase the efficiency of the analysis.

[7] Examples of studies using CPI data: Klenow and Kryvtsov (2008) for United States, Dhyne et al. (2006) for Euro Area, Saita et al. (2006) for Japan. Gagnon (2009) for Mexico and Medina et al. (2007) for Chile are examples form emerging market economies.

With this efficiency consideration in mind, scanner data are used as an alternative. This type of data is usually gathered from registry records (or scanner readings) of supermarkets or like, mostly on weekly basis, and includes quantity of sold information along with the purchasing price. Hawkes and Piotrowski (2003) report the benefits of scanner as more data and less variance, better data and less bias, and better methods. Indeed, with this approach it is possible to analyze all the information available, not only those regarding only the representative goods, providing an increased number of data points[8]. The simultaneous presence of matched price and quantity data enables researchers to make inference not only about the price durations, but also on the relative weights of the items or on the market shares of goods. Even though more frequently available than CPI data, the scanner data is usually limited to certain type of goods and services. Moreover, scanner type price information is generally only available in several developed countries and mostly provided by market research companies[9].

A third type of data recently available for the price spell duration studies is the so called scraped data. This type of data is collected from online supermarkets at a daily basis by searching the websites with for a unique product identification code and then by recording various product characteristics, including the price, electronically. Major advantage of the scraped data is that it is available in real time and it is possible to make cross country analysis with scraping. However, major drawback is that it covers a relatively low portion of the official CPI, as the data mainly contains food items and a portion of household goods[10].

Another type of data, which does not involve individual prices reported and is mostly qualitative in nature, is the surveys on firms about their pricing behavior. These surveys generally ask for how frequently prices are reviewed and how frequently they are changed. By construction, they mainly contain the decision of firms, which determines the producer prices, but not the consumer prices[11].

[8] Some statistical offices are already incorporating scanner data into the traditional CPI routine of reference goods and services. For example, Statistics Norway has replaced their food and non-alcoholic beverages subgroup comprised of 250 representative items with a scanner data based one with over 14000 items as reported by Rodriguez and Haraldsen (2006).

[9] For example, Nakamura (2008) and Campbell and Eden (2010) uses the database of AC Nielsen.

[10] Among the major studies using scraped data, Cavallo (2010) states that, for the sample in his study, scraped supermarket data covers about 40% of the CPI in Latin American countries. Lünnemann and Wintr (2006) also use scraped data.

[11] Blinder et al. (1998) is among the pioneers of such studies. An extensive survey on pricing behavior of producers in manufacturing industry is conducted by the Central Bank of Turkey and the main findings are reported by Karadaş et al. (2006). Using this survey, Şahinöz and Saraçoğlu (2008) find that the average duration of producer prices in manufacturing industry is 3 months.

Our approach

The data used in the study is collected within the CBRT as a part of a project regarding dynamics of consumer prices. Major part of the data is the scrapped data collected from several online resources. In addition to that, an experienced team of collectors visit several supermarkets and stores and collect the prices. They collect the price of same goods at a regular basis. If a product is not available, it is substituted with a close one and necessary adjustments are made[12]. The goods and services, whose prices are collected, are chosen in accordance with the practice and coverage of official CPI.

Our data collection methodology is a mixed approach combining CPI data with scraped data. First of all, even though we do not use the official disaggregated CPI data, we collect the prices of some items as they are done in the CPI, like for instance, publicly available prices of several communication services like phone cards or postal services. So, from this side, our methodology is close to studies using CPI data. Second, we use scrapped data from several online sources, but not only from supermarkets for food and household goods prices, but also from other sources for several other goods and services prices like airfares, white goods, automobiles, household appliances among others. Combining two methodologies, we collect price data twice a month. Third, we also collect prices of some items in person from the stores.

The advantage of our data is that, first it is more frequent than the official CPI, so we can observe price changes within a month. Second, the scraped portion of the data is not only limited to mainly food items. Third, sales prices are not collected and any forced change of a collected item is carefully dealt with by appropriate quality adjustment. Forth, our data covers around ¾'s of the official CPI, which is quite high for a study not using the official CPI data[13].

[12] When a good is not available at a particular time, for that period only, it is assumed that its price is unchanged. Meanwhile, price of a close substitute is being recorded simultaneously. If the item is not available for two consecutive periods, then, it is substituted with a new item whose price was already recorded in the previous period. Once a new item is adopted, its history of prices is adjusted using the history of the item for which the new is a substitute.

[13] The main drawback of the official CPI item prices is that the price of an item is not adjusted historically in case the reference item is changed with another one. For example, if the price of a computer configuration is not available in the market, it is changed with a new and possibly more expensive and better quality configuration. In this case, if the previous prices are not adjusted for this item change, an artificial price change will be recorded in the data. This disables us from using the official CPI prices. Moreover, the micro prices reported on TurkStat's website are at an aggregated level, but not at item level.

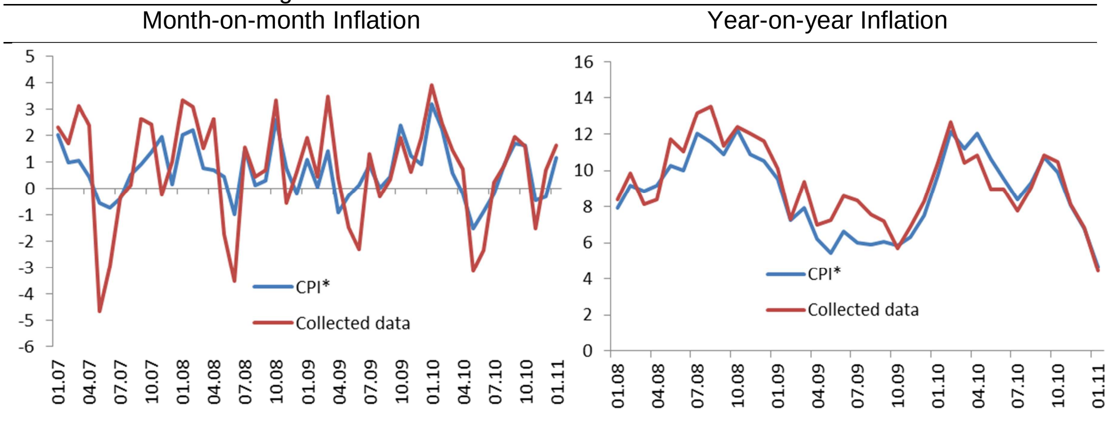
The major groups whose prices are not available in this study are clothing, rents and restaurant and hotel services. From the duration point of view, clothing prices change frequently with relatively short durations, yet with almost perfect seasonality. Moreover, it is hard to keep track of the price changes of clothing items as the items are replaced frequently and are subject to sales very often. On the other hand, rents may be considered as asset prices responding to macroeconomic fundamentals and not being subject to micro level pricing considerations. Finally, clothing, rents and restaurant prices are very heterogeneous across different regions and not very reliable data sources are available to track the effective prices correctly. Therefore, in terms of the purpose of the study, the non-availability of these prices is not crucial for the conclusions to be made on the micro level pricing behavior. A final remark for the representativeness of the services prices should be made. The majority of the services in our sample are transport and communication services, which are more competitive and whose prices are more flexible. Discarded services of mainly rents and restaurant and hotel services are likely to have more rigid prices, thus omitting them could only bring a downward bias on the durations observed[14].

Overall, the data used in this study covers item level prices of more than 6000 goods and services at a bi-weekly frequency for Turkey. The time period considered in the study is from October 2006 to January 2011. Our mixed approach enables us both to get closer to official CPI with a high level of coverage and to make better inference on duration with higher frequency of the data.

At this stage, it should be stated that even though the prices for the entire consumption basket are not available, our data does a good job mimicking the movements of the prices in the available consumption basket. In this respect, Figure 1 compares the monthly and yearly changes of index calculated by using our data, the official price indices corresponding to our coverage (around 75% of the CPI, denoted as CPI*). As our data successfully captures the dynamics of the CPI*, in the rest of the study our findings will be associated with the CPI*.

[14] The coverage of our basket is very high (around 75%), even in comparison with the studies using official CPI data. For instance, Aucremanne and Dhyne (2004), Baudry et al. (2004), Baumgertner et al. (2005), Gouvea (2007) use a dataset covering 68, 65 ,90, 85 % of the CPI respectively. Those studies using scrapped data cover a very low part of the official CPI basket, on the other hand. For instance, Cavallo (2010) uses a scrapped data set covering around 40 % of the basket for Argentina, Brazil and Colombia. Hence, our methodology gives us more frequent information without trading off the coverage.

Figure 1: Inflation Rates: CPI* versus Collected Data



Notes: CPI* refers to the official inflation which corresponds to the coverage in our data (which is around 75% of the official CPI). "Our data" refers to the price index calculated by the authors using the official weights of the CPI.

3.3. Calculating Price Spell Duration

In the literature, price spell durations are mainly calculated by two approaches. First one is the direct approach where each observed complete and censored spells are recorded as single durations for an item. Second one –frequency approach- is an indirect approach which takes into account the number of price changes observed for an item over a period and the number of possible time intervals in that period where the price of that item might have changed. These two approaches are intrinsically related in a way, that lower frequency of price changes refer to longer price spell durations, and thus more rigid prices.

3.3.1. Direct Approach

In the direct approach, using the prices of individual items in our sample, we calculate the duration of an individual price spell for all items by simply counting the number of periods in which a price remains unchanged[15]. Overall, we have 144,004 individual price spells, average duration of whom is 3.7 bi-weeks, i.e. 7.4 weeks (Table 1). The majority of the items in the data set belong to food group. Therefore, it is informative to see the descriptive statistics of the price spells with respect to different groups within data[16].

[15] When calculating spell durations, we employ a detailed strategy. First of all, as we have a large number of spells for individual items, we discard the censored spells at the end of the sample.
[16] Items collected for the study is determined according to the COICOP classification which is also taken as the basis of classification by TurkStat. The list of the items included in each subgroup is given in the Appendix 2.
The COICOP classification is available at: http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=5

Table 1: Price Spell Durations

Group	Obs	Mean	Std. Dev.	Min	Max
Consumer Prices	144004	3.69	5.61	1	95
Food	108757	3.16	4.80	1	87
Unprocessed Food	57626	2.03	2.82	1	62
Processed Food	51131	4.44	6.09	1	87
Services	2461	7.22	10.96	1	88
Energy	435	4.51	8.14	1	72
Goods exc. Food & Energy	32351	5.20	6.95	1	95

Notes: The values refer to bi-weekly periods.

An initial inspection of the descriptive statistics reveals that in fact the duration of price spells within consumer prices is not homogeneous. Food prices on average stay for shorter periods than the average of consumer prices, while services prices, on average, stay longer. As expected, unprocessed food prices have the lowest average duration of 4 weeks. When all the items considered, in fact, the weighted average duration (by sub groups) is 5.1 bi-weeks, i.e. 10.2 weeks.

Another important issue that stands out is that generally, prices change very often. For the entire sample of price spells, almost half of those last for only one period, i.e. two weeks. Overall, 90 percent of the spells are completed within 9 periods, i.e. in less than 5 months (Table 2).

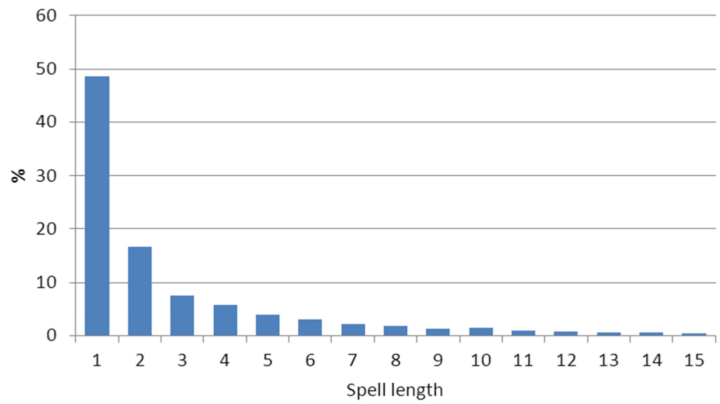
Table 2: Frequency of Price Spell Lengths

	Consumer Prices		Food		Non- Food	
Spell Duration	Frequency	Cumulative (%)	Frequency	Cumulative (%)	Frequency	Cumulative (%)
1	70,040	48.64	58,117	53.44	11,923	33.83
2	23,874	65.22	18,129	70.11	5,745	50.13
3	10,847	72.75	7,896	77.37	2,951	58.5
4	8,386	78.57	5,340	82.28	3,046	67.14
5	5,662	82.5	4,007	85.96	1,655	71.84
6	4,498	85.63	2,773	88.51	1,725	76.73
7	3,075	87.76	2,097	90.44	978	79.5
8	2,735	89.66	1,794	92.09	941	82.17
9	1,884	90.97	1,205	93.2	679	84.1
10	1,999	92.36	1,255	94.35	744	86.21
11	1,331	93.28	774	95.06	557	87.79
12	1,139	94.07	654	95.66	485	89.17
13	903	94.7	527	96.15	376	90.23
14	921	95.34	515	96.62	406	91.39
15	710	95.83	442	97.03	268	92.15

Notes: Frequency refers to the number of items whose prices change in a given spell duration. Shaded areas indicate the duration at which 90 percent of prices have changed cumulatively.

One general issue to observe is that studies using more frequently collected data find shorter durations. Our collection frequency of twice-a-month enables us to account for changes within the month, on one hand. On the other hand, the frequency of spell durations demonstrated in Figure 2 are very close to the ones reported by studies using even more frequent, daily, data. Moreover, the evolution of frequencies for the entire sample of price spells is quite similar to those witnessed for other emerging market economies[17].

Figure 2: Frequency of Price Spell Lengths (Whole Sample)



Notes: Unit spell length is bi-week.

3.3.2. Frequency Approach

Frequency approach directly computes frequency of price changes using the price data in hand, and then calculates the implied durations from these frequencies. Specifically, for each product category i, the frequency of price change, F_i, the ratio of number of price changes for that product to the total number of periods available, is computed. Therefore F_i gives the average frequency for all the items in i^{th} category over the entire sample. Considering the intrinsic discrete nature of observed data (twice a month), allowing for continuous time intervals for price changes between two collection dates, and assuming exponential distribution for the spell durations, we may compute the average implied durations as $T_i = (-1) / ln(1-F_i)$.

In sum, direct approach uses the actual spell durations whereas, frequency approach gives an implied measure of duration. In general, the duration coming from two approaches may differ significantly. In our context, however, average durations for sub groups from both methods do not differ much; direct approach being downward biased by just one week (Table 3). This one week difference is robust for all sub groups. Therefore, in the upcoming survival analysis of price spells we will use the actual durations from direct approach; while frequency approach will be used for analyzing the time varying nature of price spell durations.

17 See Cavallo (2010).

Table 3: Mean Durations from Direct and Indirect Approaches

	Actual Mean Duration (Direct)	Implied Mean Duration (Indirect)
Consumer Prices	7.4	6.3
Food	6.3	5.3
Energy	9.0	8.0
Goods exc. F & E	10.4	9.4
Services	14.4	13.4

Notes: Durations are reported in weeks.

3.4. Analysis of Duration of Price Spells

As discussed in Section 2, the data in the study is grouped data, as survival occurs in continuous time, even though the price spell lengths are observed in discrete intervals only. Therefore, in the context of interval-censored discrete time survival data, we proceed with the complementary log-log model. Basic concepts of the discrete time survival time analysis and of the complementary log-log model is explained in Appendix 1.

3.4.1 Estimates

In order to estimate a discrete time duration model, functional forms of the hazard rate and the duration dependence must be specified. As introduced above, we use the clog-log specification for the functional form of the hazard rate. For the specification of duration dependence, we employ one non-parametric and two parametric methods. The non-parametric method introduces period dummies individually in order to capture what the hazard rate is at every period. Parametric methods, on the other hand assume an explicit functional form of duration dependence in duration time. In the parametric analysis, duration dependence is a function of either log time or of time squared, which are the most common specifications in the literature. In order to estimate the clog-log model, the first thing to do is to expand the duration data into item-period format and, thus, to transform it to a binary duration variable.

We present the results of the discrete time clog-log survival regressions in Table 4. The first thing to notice is that we find negative duration dependence, as the coefficients in Spec (1) and Spec (4) are less than 1. The negative duration dependence refers to the fact that the hazard rate is decreasing in duration time. In other words, the probability that a price spell ends (the price is changed) decreases as time passes. This finding is not surprising when we consider the frequency of price spells previously discussed. Almost half of the durations in the sample last for only one period. Indeed, the probability of a price changing after staying for one period is quite high, and thus, the probability of a change in subsequent periods is relatively less than that.

Table 4: Discrete Time Survival (Clog-log) Regressions

Dependent var.:	Binary Spell Duration						
Time assumption:	Logarithmic time			Squared time			Non-parametric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
time dependence	0.5181***	0.5325***	0.5702***				
	(0.0016)	*(0.0016)*	*(0.0018)*				
time dependence				0.9976***	0.9978***	0.9983***	
				(0.0000)	*(0. 0000)*	*(0. 0000)*	
Food		1.7269***			2.0424***		
		(0.0354)			*(0.0418)*		
Unprocessed Food			2.6412***			3.5496***	2.6939***
			(0.0550)			*(0.0736)*	*(0.0562)*
Processed Food			1.3187***			1.4376***	1.3565***
			(0.0273)			*(0.0298)*	*(0.0282)*
Energy		1.4316***	1.4552***		1.5590***	1.5738***	1.4673***
		(0.0751)	*(0.0762)*		*(0.0814)*	*(0.0821)*	*(0.0769)*
Goods excl. Food & Energy		1.1399***	1.1615***		1.2083***	1.2294***	1.1931***
		(0.0239)	*(0.0244)*		*(0.0253)*	*(0.0258)*	*(0.0251)*
Services		base	base		base	base	base
# of obs.	531612	531612	531612	531612	531612	531612	531335
log-likelihood	-282492	-279995	-273972	-302513	-298355	-287835	-273147

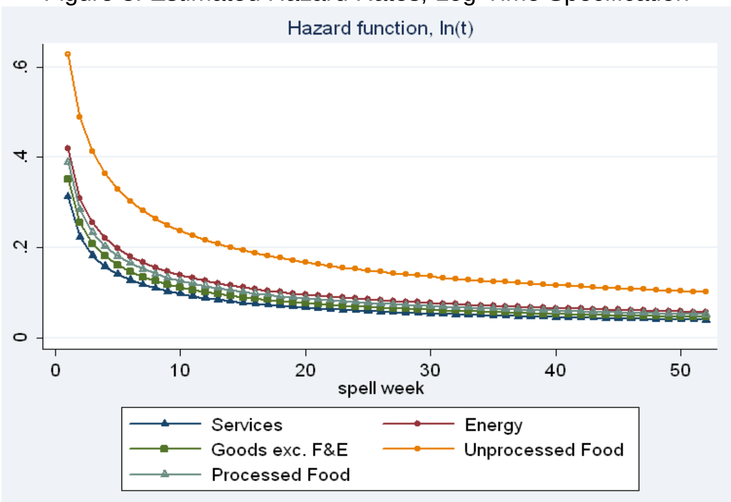
Notes: Standard errors in parenthesis. Exponentiated coefficients are reported. Time dependence refers to the coefficient of the parametric time expression. In Specifications 2, 3, 5 and 6, the base category is the “services” category. Specification 7 is the non-parametric specification where period dummies for each possible duration length is included in the regression. *** Significant at 1 % level.

Descriptive analysis has already showed that the duration of price spells is not homogeneous across sub groups of consumer prices. In order to statistically test this heterogeneity, in Specs 2 and 5, we introduce group dummies to the survival regression. The clog-log is inherently a proportional hazard specification. Therefore, keeping one of the categories as the base category, the coefficients of the remaining categories are readily interpretable hazard rates relative to that of the base category. In Spec 2 and 5, we see that food, energy and goods excluding food and energy categories are significantly more likely to experience failure than services category. In other words, their durations are more likely to end at any given period, and so they have shorter durations compared to services. One may interpret the coefficients of the clog-log model in a such way that, for instance, in Spec 2, -log time specification-food price spells on average are 76% more likely to end than price spells in services category in any period.

For the next specification we split the food category into two and analyze how durations differ for processed and unprocessed foods. As expected, unprocessed food prices have the highest probability of prices changing in a period. In Spec 3, we see that processed food prices 164% more likely to change compared to services, while processed food prices are only 32% more likely to change than services.

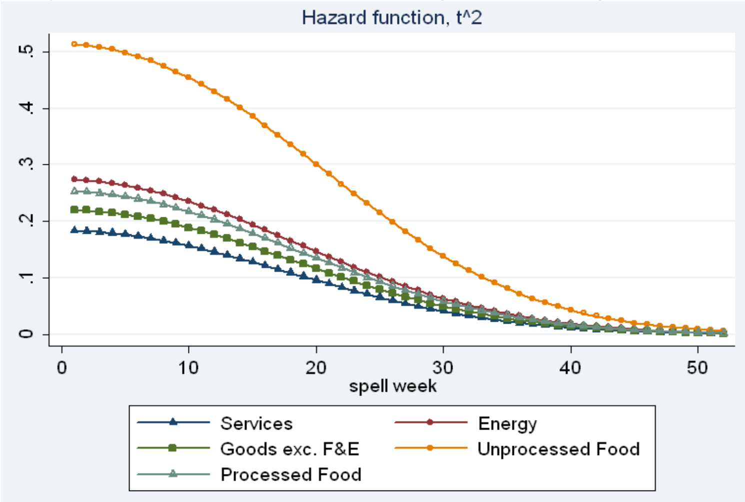
Overall, results of both parametric time assumptions point to the same direction, although the coefficients of squared time model are slightly higher. The negative duration dependence of hazard rates is also visible in Figure 3.

Figure 3: Estimated Hazard Rates, Log-Time Specification



Notes: First 52 periods (2 years) are plotted.

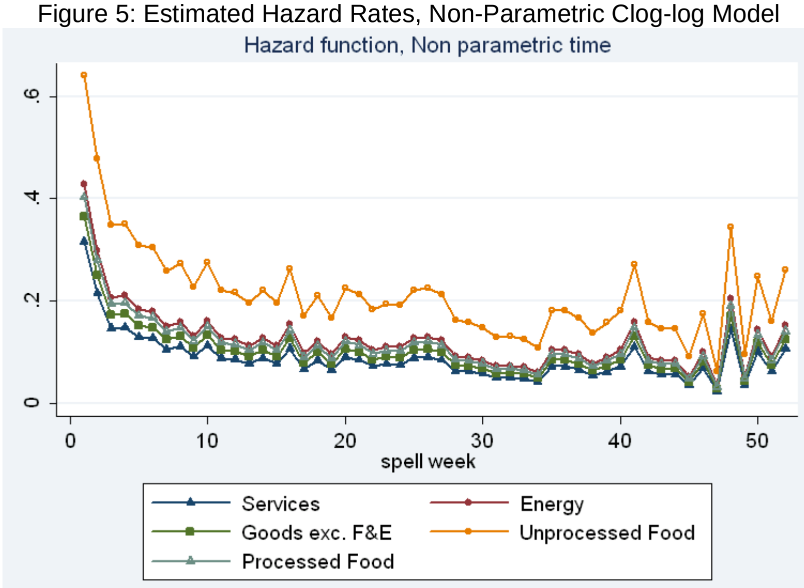
Figure 4: Estimated Hazard Rates, Squared-Time Specification



Notes: First 52 periods (2 years) are plotted.

Finally, Spec 7 reports the results from the clog-log model with no parametric time specification. Here, period dummies for each possible spell length are introduced into the model, yet they are omitted from the output but plotted below (there are 95 dummy variables). Although most of these period dummies are insignificant, what matters here is how the coefficients change as duration length increases. Overall, we see the negative duration dependence also with the estimated hazard rates from non-parametric specification (Figure 5).

Figure 5: Estimated Hazard Rates, Non-Parametric Clog-log Model



Notes: First 52 periods (2 years) are plotted.

What differs in parametric and non-parametric hazard rates is that, by assumption, parametric specifications give monotonic time dependence. In our case, the hazard rates are monotonically decreasing with duration length. However, the non-parametric hazard rates show that in fact the time dependence is not monotonic. Although downward sloping generally, hazard rates make a jump at around period 26, which is at around a year. Considering this non-monotonicity, we recalculate the duration dependence parameter for different moving samples in duration length. For instance, we first exclude spells that stayed one period from the sample; then we exclude spells that stayed one or two periods; and so forth. Then, each duration dependence parameter is plotted for two parametric time assumptions in Figure 6, 7. What we see is that after around 26^{th} period, the parameter turns larger than 1, which states that the duration dependence turns to positive in parametric specifications. As we have bi-weekly observations, 26 periods refer to a year. Then, this finding says that if a price stays unchanged for a year, then, the probability that it will change increases in duration length afterwards. Combining this with previous findings, we may say that majority of the prices change very quickly, within few periods. After that, the probability of a price changing decreases with duration. However, for those prices which survived for a year, the probability of change increases with duration length.

Figure 6: Level of time dependence in moving-window parametric clog-log models(*log**arithmic** time*)

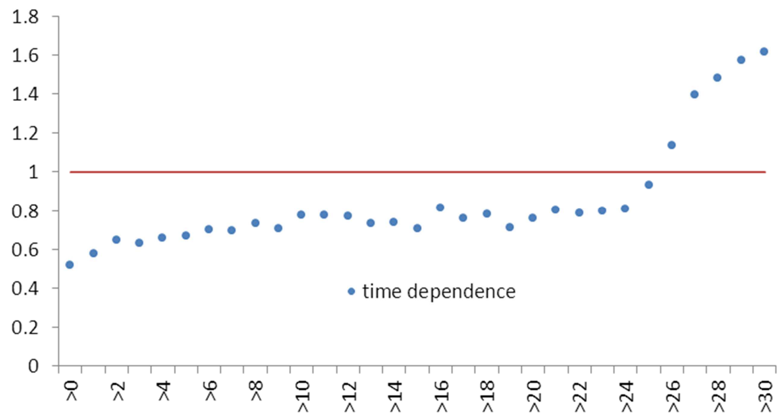
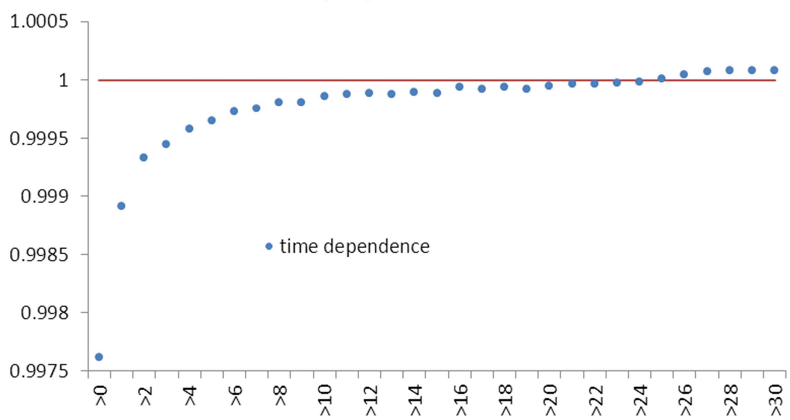


Figure 7: Level of time dependence in moving-window parametric clog-log models (*squared time*)

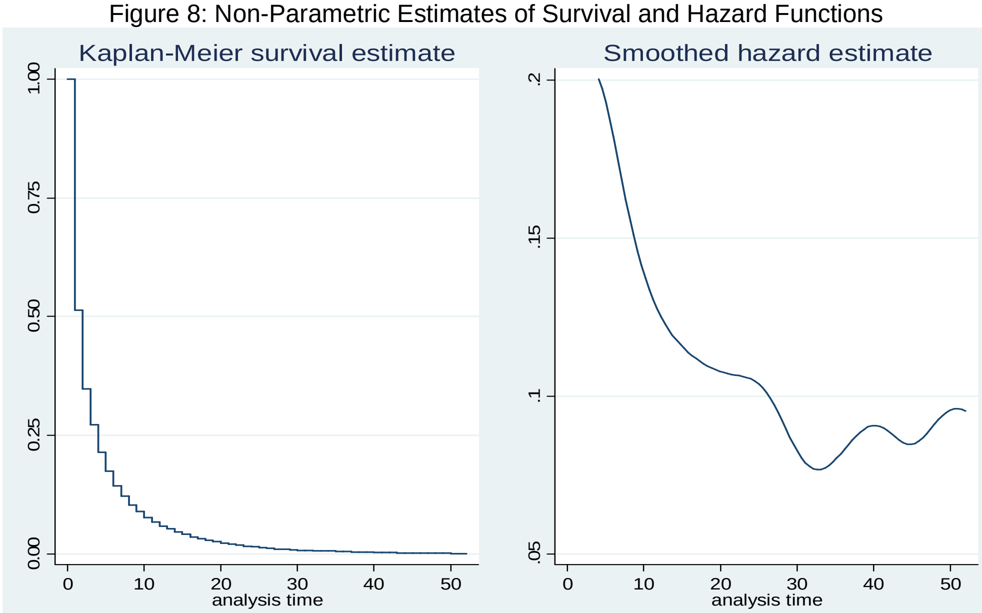


Notes: In Figures 6 and 7, each data point shows the time dependence parameter estimated for the sample of durations which survived at least for that period of time. For instance, the point ">2" refers to the coefficient estimated from the sample of all durations that lasted at least for 2 periods.

At this stage we employ some robustness checks on our analysis. Initial set of checks relates to the discrete time estimations. First of all, the first spell duration for each item in our sample is left censored. Yet, the portion of these durations is quite small overall. We have more than 144,000 duration observations and about 8000 of them are left censored. For robustness, we rerun our survival regressions by discarding these observations. However, the results do not change and therefore, we prefer to keep those observations in the sample for the analysis. We consider only the completed spells, so we ignored the right censored spells at the end of the sample. As a second check, we include the right censored spells and rerun the survival regressions controlling for censoring, yet the results are also robust to that. Third, we checked whether heterogeneity in terms of duration between all sub-groups is robust to base category selection. By changing the base category, we repeated the analysis and found that durations are heterogeneous between all sub-groups.

Further set of robustness checks relates to alternative forms of survival time modeling. For this, we assume that the survival times can be modeled in continuous time. First we look at the non-parametric survival and hazard estimates (Figure 8). Survival estimates show that survival probability monotonically decreases with duration length. Non parametric hazard estimates, on the other hand, are non-monotonic. The hazard rate mostly declines with duration time, i.e. negative duration dependence. Towards the end of the sample, hazard rate increases slightly with duration. In sum, non-parametric hazard rate estimates being downward sloping is in-line with the findings of the discrete time analysis.

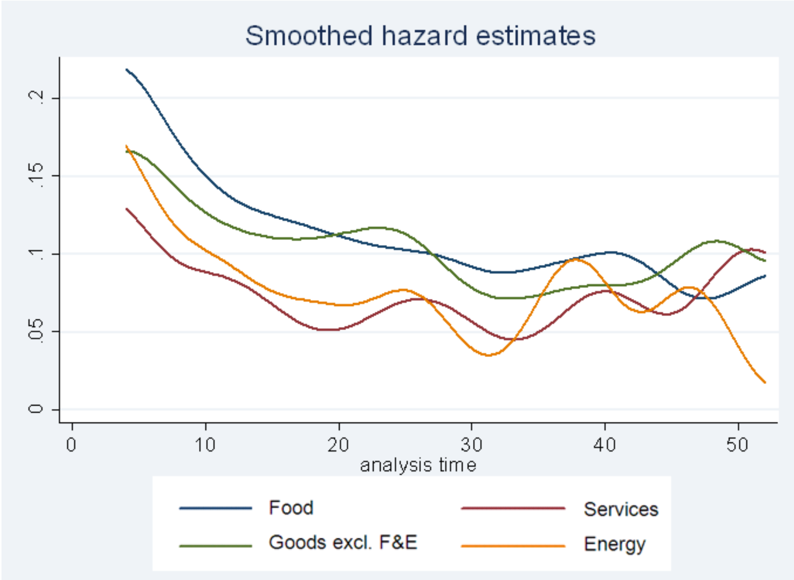
Figure 8: Non-Parametric Estimates of Survival and Hazard Functions



Notes: First 52 periods (two years) are reported. Hazard estimate is kernel smoothed with bandwidth size equal to 3.

The shape of the smoothed hazard estimates do differ, however, for sub-groups as presented in Figure 9. What we see is that for food items, the hazards rates are decreasing in duration. On the other hand, for other subgroups, hazard rates first decline with duration, while the hazard rates increase after around one year of duration.

Figure 9: Non-Parametric Estimates of Hazard Functions



Notes: First 52 periods (two year) are reported. Hazard estimate is kernel smoothed with bandwidth size equal to 3.

Second, we turn to parametric continuous time survival models. We estimate the model with two different distributional assumptions for the baseline hazard rate, Weibull and exponential[18]. The results of these estimations are reported in Table 5.

Table 5: Continuous Time Parametric Survival Regressions

Dependent variable:	Price Spell Duration			
Distribution assumption:	Weibull		Exponential	
	(1)	(2)	(3)	(4)
Food	2.1738***		2.2851***	
	(0.0640)		*(0. 0707)*	
Unprocessed Food		3.6017***		3.5618***
		(0. 1153)		*(0.0111)*
Processed Food		1.6352***		1.6276***
		(0.0515)		*(0.0507)*
Energy	1.5690***	1.6062***	1.6018***	1.6018***
	(0.1341)	*(0.1488)*	*(0.1469)*	*(0.1469)*
Goods	1.3535***	1.3939***	1.3889***	1.3889***
	(0. 0403)	*(0. 0443)*	*(0. 0437)*	*(0. 0437)*
Services	base category	base category	base category	base category
# of obs.	144004	144004	144004	144004
P	0.9491	1.0070	---	---
Pseudo log-likelihood	-218317	-210516	-218752	-210523

Notes: Standard errors in parenthesis. Exponentiated coefficients are reported. Base category is the “services” category. *** Significant at 1 % level.

[18] The clog-log model is in fact the discrete time version of continuous time Weibull model.

In the continuous time models, the duration can directly be modeled without making the item-period transformation. The estimated coefficients of the continuous time models are also very similar to those of discrete time models. Still, services prices are least likely to change, in other words, they have longer price spells compared to other sub groups.

Overall, we conclude that our findings for the discrete time clog-log model are robust to survival time choice and censoring.

3.5. Analysis of Distribution of Price Changes

A natural extension of the price spell duration analysis is the inspection of distribution of individual price changes. This type of analysis is useful in terms of determining whether prices are flexible also downwards; what the average size of price changes is, both for positive and negative changes; and whether the size of the change and the length of the duration are related.

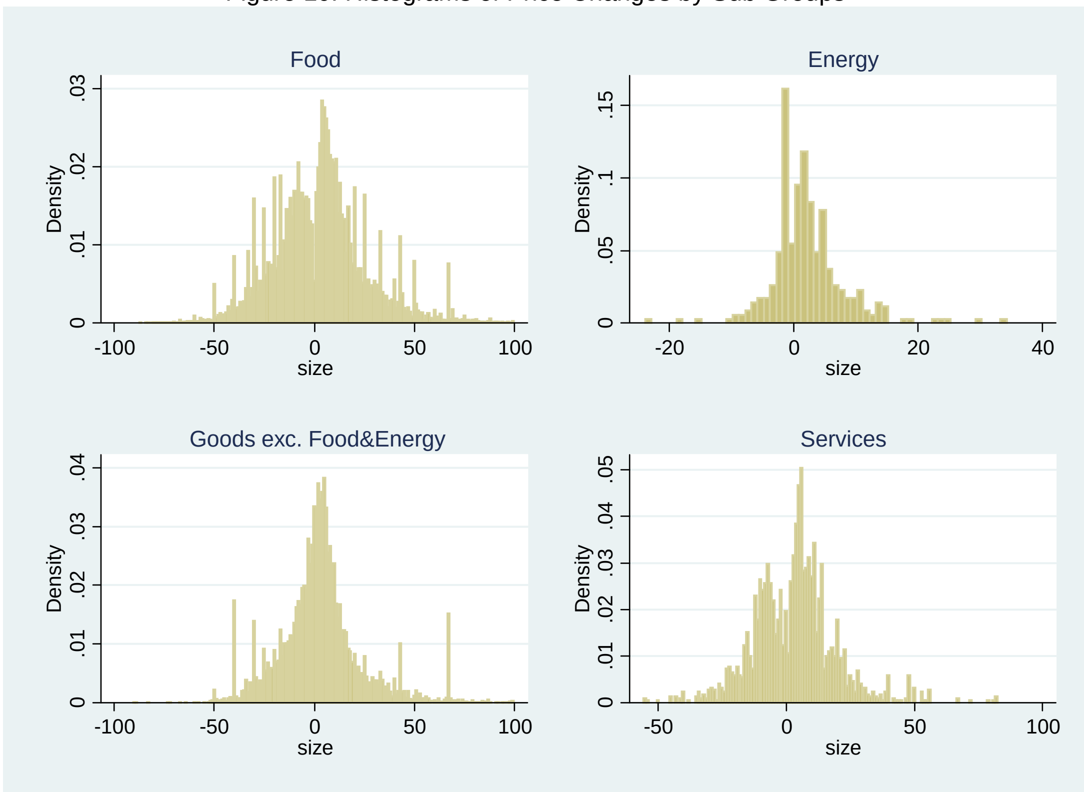
3.5.1. Histograms by category

We first start with the distribution of price changes by categories. When we consider the histograms by categories, what is striking is that price reductions are also common as well as price increases for all categories (Figure 10). It is generally argued that, for instance, services prices display downward rigidity, however, for those services in our study there is no evidence of that. Price changes in food and services categories display a bi-modal distribution, while those of goods excluding food and energy display a more symmetric distribution. Also, the distributions of price changes for different categories are slightly right-skewed, as previously documented for the price changes in Turkey[19].

One interesting point to note is that the histogram of price changes for the food items (Panel A) shows spikes at various different rates. The magnitudes of price changes at which spikes are observed point to the following rates of: -60%, -50%, -40%, -33%, -30%, - 25%, -20%,…, 20%, 25%, 30%, 33%, 40%, 50% and like. These spikes turn out to be informative as they suggest that when the food prices are changed, major portion of them are changed at non-odd ratios.

[19] As reported in Atuk and Özmen (2009).

Figure 10: Histograms of Price Changes by Sub Groups



3.5.2. Size and sign of price changes

The evidence from the item-level data in hand is that for all the categories, price decreases and price increases occur almost equally likely. For the consumer prices in general, 56% of the changes are in the direction of increase. The highest proportion of increases is for energy category with 63%. The average size of change in absolute terms is slightly higher for price increases than price decreases (Table 6). The magnitude of the changes seem to be high, however, when considered together with the average frequency of change and average duration information by categories they turn out to be plausible.

Table 6: Average Size of Price Changes

	Increase		Decrease	
	Obs	Mean	Obs	Mean
Consumer Prices	68180	18.06	52887	-16.78
Food	50959	19.20	40514	-17.75
Unprocessed Food	23699	23.12	21200	-20.98
Processed Food	27260	15.79	19314	-14.19
Services	1292	12.80	888	-11.32
Energy	218	5.09	129	-2.80
Goods exc. Food & Energy	15711	14.98	11356	-13.90

An additional finding relates to a level effect, where we observe that the rate of change of a price also differs with the level of the price itself. In other words, cheaper goods and services are subject to a higher percentage change. In our sample when we consider the price increases, for instance, goods which are cheaper than 10 TL are subject to increase of 21.2 percent on average; while prices higher than 100 TL increase by about 8 percent on average in the sample period (Table 7)[20].

Table 7: Average Rate of Change vs. Price Level

Price Level Range	Average Rate of Increase
< 10 TL	21.17
10 - 20 TL	16.18
20 - 50 TL	16.22
50 - 100 TL	11.64
100 - 1000 TL	8.09
> 1000 TL	8.3

3.5.3. Duration of price spell vs. the size of change

In this section we investigate whether duration of a price spell and the size of the price change terminating this duration is related. Given that some prices are adjusted infrequently, ex-ante, we expect the absolute change in long lasting prices to be higher than short lasting prices. However, the data reveals that the correlation between duration length and size of change is negative for consumer prices. Yet, on the ground of sub groups, this relation is negative only for food prices and for goods excluding food and energy group. On the other hand, the direction of the relation is as expected for services and energy groups, which reveals that prices with longer durations are adjusted with a higher magnitude (Table 8).

Table 8: OLS Regression of Size on Spell Duration by Groups

	Dependent Variable: Size of price increases				
	Consumer Prices	Food	Goods excl. Food & Energy	Energy	Services
Spell Duration	-0.57***	-0.67***	-0.47***	0.21***	0.22***
	(0.02)	*(0.02)*	*(0.03)*	*(0.03)*	*(0.03)*
Constant	22.09***	23.63***	18.17***	3.85***	11.32***
	(0.12)	*(0.15)*	*(0.24)*	*(0.37)*	*(0.44)*
# of obs.	69214	51871	15828	218	1297
R^2	0.01	0.01	0.01	0.16	0.04

Issues like menu costs or seasonal pricing behaviors might be the driver in services prices. Alternatively, in the energy group, administered prices of electricity and natural gas -which are kept constant for a while and then jump- is the main driver of the result.

[20] At the time of writing, 10 TL was equivalent to about 6 USD.

3.6. Dynamic Issues

3.6.1. Frequency of price changes by time

Frequency of price changes in a period refers to the share of goods and services whose prices changed in that period. For the micro prices in hand, we show that the average frequency of the price changes per period for the entire sample is 22%. As it is documented, food prices change more frequently than the rest. Each period on average 27% of the food prices change. On the other hand, on average, only 16% of the non-food item prices change in one period.

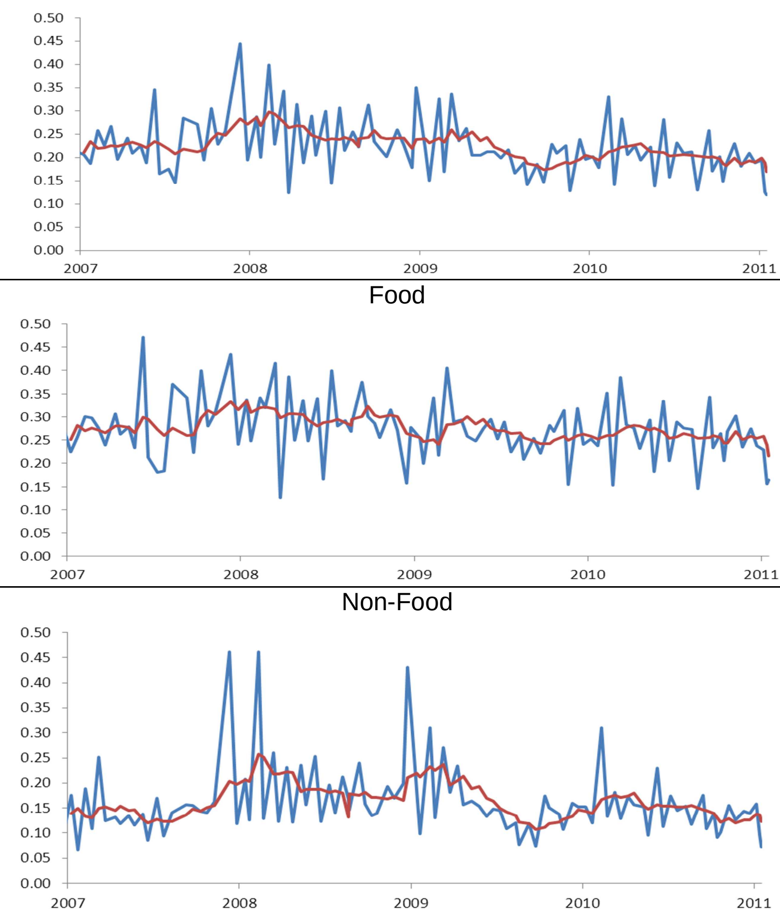
The evolution of this frequency in time is an indication of how spell durations evolved and whether pricing behavior change in time. The figures show that the frequency increases initially and then comes back to lower levels. Another interesting finding the frequency analysis reveals is that there is a pattern of sharp increase in the frequency at year-ends (Figure 11).

Figure 11: Frequency of Price Changes in Time

Consumer Prices

Food

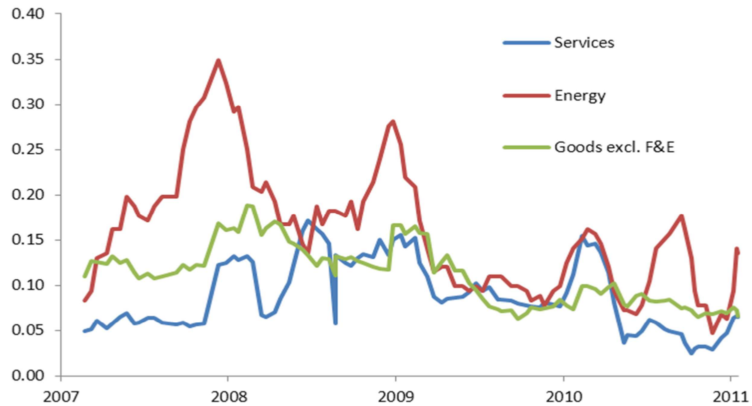
Non-Food



Notes: The red line refers to 3-month moving averages.

A detailed look at the non-food group shows that the frequencies have come down in energy and goods excluding food and energy groups, implying that the underlying spell durations are getting longer (Figure.12). On the other hand, for the services group, such a pattern is not observed. Main groups excluding food are substantially correlated.

Figure 12: Frequency of Price Changes in Time for Non-Food Items



Notes: Figures are 3-month moving averages of period wise frequencies.

3.6.2. Synchronization of price changes

An important dynamic implication of price changes is the degree to which those changes are synchronized. In a staggered price model theoretically no synchronization of prices is expected. Based on this point, distance from no synchronization can tell about the effectiveness of state-dependent pricing in consumer prices. We employ the measure introduced by Fisher and Konieczny (2000) which calculates the synchronization ratio (SR) by proportionally comparing time variation of frequencies. When there is no synchronization, i.e. the pricing is perfectly staggered, every period in time the frequency of prices changed is the mean frequency. Perfect staggering models expect that frequencies do not deviate from its mean. On the other hand, in perfect synchronization prices (for a given period) change (do not change) altogether with the probability being equal to mean frequency (one minus mean frequency). This allows calculating a theoretical standard deviation for perfect synchronization case[21].

[21] Suppose the average frequency is F_j under perfect synchronization. Then F_j of the time the frequency is 1 (all prices change) and 1- F_j of the time it is 0 (none of prices change). Hence the standard deviation under perfect synchronization is calculated as

$$SDps = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(F_{j,t} - F_j)^2} = \sqrt{(1 - F_j)\,(F_j)}$$

Theoretical standard deviation is the upper bound given the average frequency.

Thus, the ratio of observed standard deviation of frequencies to the theoretical standard deviation is 0 under perfect staggering and 1 under perfect synchronization.

SR for whole sample and main groups of the sample period is given in Table 9. It is possible to tabulate the corresponding SR for sub categories and even close product groups. Rather, here we focused on synchronization on a greater scale. It should be noted that heterogeneity of synchronization exists in the subcategories. SR is found to be low both for consumer prices and for all the sub groups. Energy and services groups have a higher degree of synchronization, but it is still below 30%. This suggests that in aggregate terms and at bi-weekly frequency, synchronization is weak for majority of the items of consumer prices. For the entire period, the picture exhibits a pattern more towards staggered prices. The results imply that even at bi-weekly frequency, potential synchronization of close products at higher frequencies do not resemble the same pattern for aggregate consumer product groups. Though requiring further investigation, synchronization is found not to be a global property for consumer prices.

Table 9: Synchronization Ratios for Consumer Prices and Sub-groups

	Consumer Prices	Food	Energy	Goods exc. F&E	Services
SR	0.14	0.13	0.29	0.20	0.25

Notes: Synchronization ratios are calculated following Fisher-Konieczny (2000).

SR can be used to assess the variability of synchronization itself when taken as a time series. By forming rolling windows of 12 months, SR for whole sample and sub groups is depicted in Figure 13, 14. It suggests that during the sample period, in bi-weekly terms, synchronization of consumer prices in general declined. Also for all groups except services and energy, a declining trend in SR is observed. One possible explanation is that synchronization of consumer items in general may be oppressed after the global crisis. Also this may be the reflection of high synchronization when import price pass through is high and import prices accelerate, i.e. when global inflation is effectively imported.

Figure 13: Evolution of Synchronization Ratio for Consumer Prices

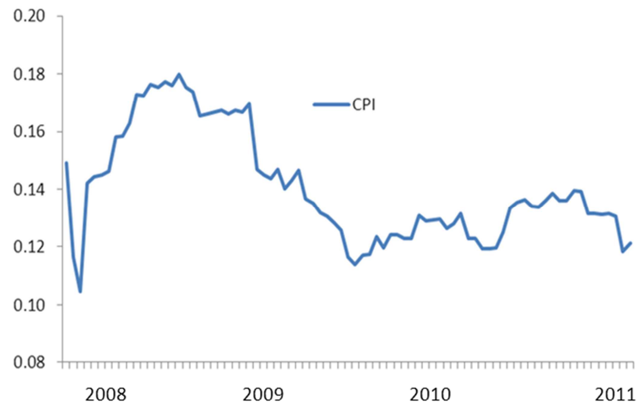
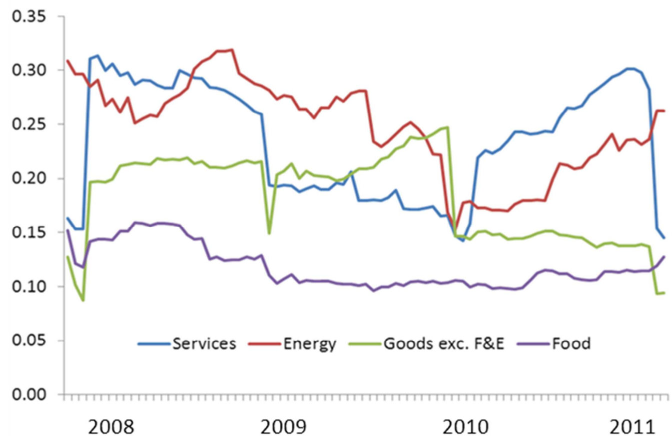


Figure 14: Evolution of Synchronization Ratio for Sub-groups



Correlation of inflation and synchronization ratios of groups is given in Table 10. In general, synchronization of prices seems not to be related with the overall inflation. A high correlation of Goods exc. F&E SR with the overall consumer prices inflation and a negatively high correlation of services SR with its own inflation are noteworthy.

Table 10: Correlation of Synchronization Ratios and Inflation

	Consumer Prices	Food	Energy	Goods exc. F&E	Services
Correlation with headline inflation	0.08	-0.12	-0.37	0.57	-0.36
Correlation with own inflation	0.08	0.29	-0.51	0.49	-0.63

With regards to the time series behavior of the frequency of price changes and synchronization ratios, a final remark concerning seasonality remains to be made. It is reasonable to argue that frequency and synchronization might be subject to seasonality; however, using standard seasonal adjustment packages, no detectable seasonality is recorded in these time series.

4. Implications for Price Rigidity

4.1. Theoretical Implications: Time-Dependence versus State-Dependence

In this section, results of the study are reviewed in terms of their alignment with the existing theoretical models explaining price rigidity. Before attaching the findings of price dynamics for Turkey to the expectations of theories, a brief introduction to models of price stickiness is presented below.

In the literature models proposed in order to explain the stickiness of prices are usually classified in two families. These two families are named after their main motivation regarding the cause of price changes: time-dependent or state-dependent.

Time-dependent pricing (TDP) models assume that price changes are basically determined by duration since the previous changes. In TDP models prices change either in every time period randomly with a given probability or only at given time periods with a fraction of firms updating their prices. Timing can be exogenously given or endogenous; however the main driver of price changes is the time dependence of price reviews, basically on the basis of costs of monitoring price reviews continuously.

State-dependent pricing (SDP) models, on the other hand, emphasize the importance of opportunity cost associated with updating current prices. Firms often do not operate at the optimal prices simply because they cannot adjust to marginal cost shocks immediately. The source of rigidity is the existence of so called menu costs. In order for a firm to change an ongoing price, gains from updating a price should be sufficiently large enough to meet the adjustment costs[22].

There are also models which employ the essentials of both families of pricing models. These models combine the information cost of time-dependence and the adjustment cost of state-dependence ways of characterizing pricing dynamics. Simply, in these models state dependence may be in charge if information cost of reviewing a price is not high enough to prevent the consideration of changing the price which implies a regime switching behavior in pricing decisions.

Results of our investigation are mixed in terms of what is to be expected from the models outlined above. However, this is not surprising as emphasized by many other studies attempting to link micro price facts to the theory. Some results are supported by at least one family of the models whereas some are supported by none. We discuss three dynamic features for which theoretical models have a typical prediction. These

[22] Examples are Taylor (1980) and Calvo (1983) for TDP, Caplin and Spulber (1987) and Dotsey et al. (1999) for SDP and Woodford (1999) for mixed models.

are distribution of size of price changes, shape of hazard function and synchronization of price changes.

TDP models specifically do not suggest a distribution of size of price changes. However, if cost shocks are independent and randomly distributed, it is natural to expect a uni-modal distribution of price changes. On the other hand, SDP models imply that small price changes are ignored in the very short term once faced. According to SDP setup, little changes in optimal price are postponed until adjustment costs are met. Thus, accumulation of shocks on prices is not expected to lead to a uni-modal size distribution. Small price changes occur only for products whose menu costs are substantially low. In this respect, the bimodal distributions found for the majority of prices (for consumer prices, food and services groups) support SDP model (Figure 10). Energy and goods excluding food and energy prices on the other hand, display distributions that are in line with the expectation of TDP models in terms of size distribution. Lower degrees of physical adjustment cost in the latter mentioned groups - which can even be ignored for some firms operating in energy and services sector- is likely to explain the difference.

Hazard functions of price durations as implications of theoretical models differ in their shapes. TDP models predict two kinds of hazards. Calvo (1983) assumes a constant hazard rate for all periods. This is because the probability of a price change is constant in every period. Also, some models predict hazards which present price changes as spikes at given moments. This reflects an economy where firms update their prices in exogenously determined periods of time. Whereas, SDP models assume upward sloping hazard functions. Since firms face a problem of charging optimal price subject to adjustment costs, incentive for changing a price increase with time as marginal cost shocks accumulate. Our results do not reflect any of these predictions at first glance (Figures 3, 4 and 5). We found a downward sloping hazard for whole sample such that the slope gets smaller for longer durations. This finding supports the stylized facts in the literature. Moreover, heterogeneity in the individual hazard rates may impose a survivor bias yielding the observed decreasing hazard function. In order to have an idea about this effect, Figure 9 shows hazard rates for main groups. Downward slope is common across groups though relatively straight shape is apparent in all groups with services being the flattest.[23] Also, no evidence is found towards

[23] We checked the individual prices as well, however decreasing hazard rates appears to be a common characteristic of individual spells most pronounced in food prices.

upward sloping hazard rates as SDP models suggest.[24] In addition to being decreasingly downward sloping, hazard rates also show a pattern of rise around one year period (Figures 6 and 7). This suggests a clustering of sticky price firms that update their prices once a year, which can be interpreted in TDP context.

Another issue about which models differ in interpretation is price change synchronization. If timing of price changes often coincides, TDP models argue that this reflects the weakness of staggering in the economy. Hence, low degree of synchronization increases the price rigidity in terms of the persistence of monetary policy effects. For SDP models, synchronization does not directly affect price rigidity. Rather, it is a reflection of firms producing close substitutes. In this context, if marginal cost shocks are postponed due to adjustment costs, existence of synchronization in this narrow term may imply a form of rigidity. In this paper, our focus aims to measure synchronization in a more aggregate manner, since it is rather complicated to assess the effect of microscopic synchronization on price rigidity. As shown in Table 9, synchronization level is found quite low in general. Most synchronized are the energy and services prices whose measured level of synchronization confirms the generality of the result among sub groups. This finding emphasizes the staggered nature of pricing in the economy. Although price changes happen frequently, low synchronization imposes considerable rigidity on prices.

4.2. Heterogeneity

One important finding from the frequency of price changes is the heterogeneity between and within groups. This makes it difficult to conclude whether prices are sticky in general. Hence, assessing price rigidity appears to be a highly individual concept for groups and products. On the other hand, the implications of heterogeneity on aggregate rigidity can be substantial. Carvalho (2006) shows that heterogeneity increases the macro rigidity implied by micro frequency of price changes three times more than an economy characterized by identical firms for calibrating the U.S. data by Bils and Klenow (2004). He defines two mechanisms to explain the effects of heterogeneity. The frequency composition effect is given by the dominance of slow adjusting firms over time after the economy hit by a shock. This effect causes the adjustment process slows down over time in the presence of relatively stickier pricing

[24] Indeed it is possible to find upward sloping hazard rates by some kernel and bandwidth parameters. Hence upward sloping hazard rate is not a robust finding. Moreover, the introduced method of recursively estimation of time dependence parameters which are shown in figures 6 and 7 proposes no positive hazard rate before one year.

firms. The second effect is strategic interaction effect which is effective when there are strategic complementarities in the economy. Slow adjusting firms disproportionately effects the pricing decisions of firms which change prices relative more frequently. As a result, a high degree of heterogeneity observed for Turkey may imply a longer period for aggregate adjustment process than what is suggested by high levels of average individual frequency estimates.

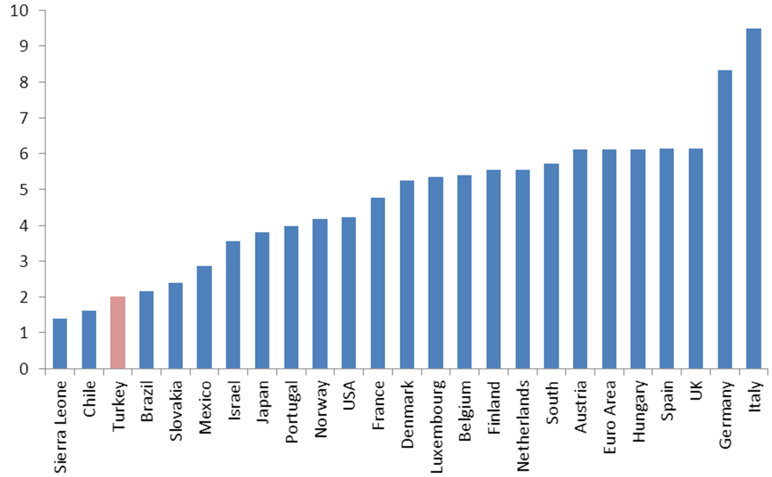
Results also suggest that frequency of price changes varies substantially with time. Hence, even if relatively stickier sectors are known, it is misleading to impose the same level of stickiness to the whole group or for a long period of time. As a result, in assessing the monetary policy relevant inflation we argue that permanent exclusion based core inflation measures may be far from presenting a robust measure. Relative stickiness across groups may change due to individual product level pricing behaviour in time and a given measure does not imply the same main trend of inflation for two distinct time periods. In this regard, monitoring price rigidity measures indicating frequency and synchronization of price changes could potentially provide a guide for understanding the underlying inflation at a particular time period. This more flexible version of main inflation trend concept based on changes in the rigidity of products is also of useful guidance for a better reasoning in the communication of monetary policy actions.

4.3. Implications for Emerging Markets

One important pattern of price change dynamics across countries is the higher frequency documented in emerging markets. According to studies, European countries are found to exhibit the greatest rigidity of prices with implied durations around 4 to 10 months.[25] In United States prices are relatively flexible compared with Europe with implied durations ranging approximately from 3 to 5 months. The majority of emerging markets (for which micro prices are analyzed in this manner) exhibit the most flexible price structure while the average duration is below United States (Figure 15).

[25] The estimated durations are based on the frequencies documented in Klenow and Malin (2010), assuming a constant interval hazard rate.

Figure 15: Average Price Spell Duration (Months)



Notes: Data for Turkey is from authors' calculations. The data for other countries is calculated using the figures from Table 1 of Klenow and Malin (2010), at page 236.

Although causes of the relative flexibility in emerging countries are not extensively discussed in the literature, high-inflation experience of these countries stands out as the most popular explanation. The argument is quite reasonable since pricing habit is very likely to possess its own rigidity. This could also be the case for Turkey. On the other hand, the main reasons could include more structural issues like industrial organization patterns in the emerging markets.[26] Investigation of potential sources of low price rigidity in Turkey is an important task in assessing price stickiness in Turkey and beyond the scope of this study. Nevertheless, implications of flexibility could be discussed given the existing theoretical framework if degree of stickiness is clearly determined. However, some points should be clarified to determine the degree of stickiness in emerging markets.

First, observed micro flexibility does not necessarily imply flexibility in the macro level. In this regard, low level of price synchronization may reflect the existence of less pronounced common factors as well as more important firm-specific shocks. Moreover, rigidity in spread of information of common shocks may strengthen the firm-specific content of pricing. This effect is also made possible by heterogeneity in organizational structure of firms and by the type of sectoral linkages. More staggered type of price setting probably induces a spillover of shocks in time for the whole economy which does not allow to conclude that evidence of micro flexibility in emerging economies for characterizing the rigidity as a whole in terms of monetary policy relevance.

[26] As an example, Matsuoka (2011) finds that higher concentration ratios significantly increase the price rigidity of a sector.

5. Concluding Remarks

In this study we explored the evidence of price rigidity in Turkey by making use of an extensive micro level price data. Our findings, first, point to a great degree of heterogeneity between subgroups of the headline inflation in terms of average price duration; frequency and synchronization of price changes; shapes of hazard functions; as well as distribution, size and sign of price changes. Second, these results suggest that there exists a mixed pricing strategy which is a combination of time and state dependent pricing. Such evidence is generally reported for developed economies, but we show that this empirical regularity holds also for a developing economy. Although the prices in Turkey are very flexible, as is the case for developing economies, the level of synchronization is rather low, which separates Turkey from its high-frequency peer countries. Third, the inherent heterogeneity of prices at subgroup level is also time varying, whose implication is that using permanent exclusion based underlying inflation measures may not be robust always, and thus measures taking frequency and synchronization of price changes into account should be considered as well in assessing inflation dynamics.

Analysis of pricing behavior using micro level has important implications for determining the level of price stickiness in a country, which is crucial in formulating monetary policy. In terms of price stickiness, our findings reveal that it is low in Turkey. The main aim of this study is to document the micro level stylized facts of consumer prices in Turkey in relation to price stickiness and from the perspective of short term inflation analysis. However, several issues demand further attention and exploration and provide us an extensive research agenda. Specifically, linking micro flexibility to macro rigidity is one needs further exploration. In addition, the reasons for low price rigidity, sources of heterogeneity and causes of high flexibility, for developing countries in general, should be analyzed.

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Appendix 1

The discrete time proportional hazard survival model

Basic Concepts

We first introduce basic concepts of the discrete time survival models. For T being a random variable denoting the duration spell, the probability that exit occurs (i.e. price changes) in the j^{th} time interval, $(a_{j-1}, a_j]$ is given by:

$$\Pr(a_{j-1} < T \leq a_j) = F(a_j) - F(a_{j-1}) = S(a_{j-1}) - S(a_j)$$

where $F(t)$ is the cumulative distribution function of T and $a_1\ to\ a_k$ are the interval boundaries. The discrete time hazard rate (interval hazard rate) is the probability of exiting at the j^{th} interval is:

$$\mathrm{h}\big(a_j\big) = \Pr\big(a_{j-1} < T \leq a \big| T > a_{j-1}\big) = 1 - \frac{S(a_j)}{S(a_{j-1})}$$

The discrete time survivor function is defined as the probability of surviving until the end of interval j. It is the product of the probabilities of not exiting the duration in each of the intervals up to and including the current interval:

$$S(j) \equiv S_j = \prod_{k=1}^{j}(1 - h_k)$$

The discrete time density function for the interval-censored case is the probability of exit within the j^{th} interval:

$$f(j) = \Pr(a_{j-1} < T \leq a_j) = S(j-1) - S(j) = \frac{S(j)}{1 - \big(h_j\big)} - S(j) = \frac{h_j}{1 - h_j}\prod_{k=1}^{j}(1 - h_k)$$

The discrete density is thus the probability of surviving up to the end of interval $j - 1$, times the probability of exiting in the j^{th} interval.

Clog-log model

Suppose that the survivor function at time a_j, the end of interval $(a_{j-1}, a_j]$, is given by

$$S(a_j, X) = exp\left[-\int_0^{a_j} \lambda(u, X)du\right]$$

where $\lambda(t, X)$ is the hazard rate. Suppose that the hazard rate satisfies proportional hazard assumption, so that $\lambda(t, X) = \lambda_0(t)exp(x'\beta) = \lambda_0(t)\phi$. Then, the survivor function can be written as: $S(a_j, X) = \exp[-\Lambda_j \phi]$, where $\Lambda_j \equiv \int_0^{a_j} \lambda_0(u, X)du$, cumulative hazard.

So the discrete time hazard function is:

$$h_j(X) = \frac{S(a_{j-1}, X) - S(a_j, X)}{S(a_{j-1}, X)} = 1 - \frac{S(a_j, X)}{S(a_{j-1}, X)} = 1 - exp[\phi(\Lambda_{j-1} - \Lambda_j)]$$

$$log(-log[1 - h_j(X)] = x'\beta + log[(\Lambda_j - \Lambda_{j-1})]$$

Similarly, the discrete time baseline hazard for interval $(a_{j-1}, a_j]$ is:

$1 - h_{0j} = exp(\Lambda_{j-1} - \Lambda_j)$, and hence

$$log(-log[1 - h_{0j}]) = log(\Lambda_j - \Lambda_{j-1}) = log\left[\int_{a_{j-1}}^{a_j} \lambda_0(u)du\right] = \kappa_j, let's\ call\ it\ so.$$

$$log(-log[1 - h_j(X)]) = x'\beta + \kappa_j$$

So, finally, the interval hazard rate is given by:

$$h(a_{j,}X) = 1 - exp[-exp(x'\beta + \kappa_j)]$$

This double log transformation is known as the complementary log-log transformation. Therefore the discrete time proportional hazard model is also called the clog-log model. In order to estimate the model, the generic likelihood function with right censoring is:

$$L = \prod_{i=1}^{n} [\Pr(T_i = j)]^{d_i} [\Pr(T_i > j)]^{(1-d_i)} = \prod_{i=1}^{n} [f_i(j)]^{d_i} [S_i(j)]^{(1-d_i)}$$

where $\mathrm{d}_i = 1$ if the i^{th} spell is uncensored, $\mathrm{d}_i = 0$ if right censored, for spells $i = 1\ to\ n$. As we drop the right censored observations from our sample, ignoring right censoring, the likelihood function becomes: $L = \prod_{i=1}^{n}\left[\frac{h_j}{1-h_j}\prod_{k=1}^{j}(1-h_{ik})\right]$.

The corresponding log likelihood function, where the coefficients of the covariates and the baseline hazard parameters are estimated, by substituting the clog-log hazard function and specifying the functional form of the duration dependence is as follows:

$$l = \sum_{i=1}^{n} ln\left(\frac{h_j}{1-h_j}\right) + \sum_{i=1}^{n}\sum_{k=1}^{j} ln\,(1-h_{ik})$$

Appendix 2

List of items included in the study:[27]

Unprocessed Food	
Rice	Dried apricot
Veal	Okra
Mutton	Green peas
Poultry	Sweet green pepper
Milk	Stuff pepper
Egg	Green pepper
Orange	Tomato
Grape	Green beans
Pear	Carrot
Quince	Spinach
Strawberry	Squash
Apple	Cauliflower
Plum	Onion
Grapefruit	Cabbage
Water melon	Red cabbage
Melon	Mushroom
Apricot	Lettuce
Cherry	Parsley
Lemon	Eggplant
Tangerine	Leek
Banana	Cucumber
Peach	Garlic
Walnut (Without shells)	Purslane
Hazelnut (Without shells)	Radish
Pistachio	Green onions
Peanut	Potatoes
Roasted chick-pea	Dry beans
Sun flower seed	Chickpeas
Pumpkin seed	Lentils
Raisins	Other pulse

[27] Items used in the study are grouped in the tables according to TurkStat 7-Digit classification list. Item-level data includes specific brand and place of collection information.

Processed Food	
Wheat Flour	Chips and appetizers
Rice flour	Powdered sugar
Baby food	Lump sugar
Boiled and pounded wheat	Jam
White bread	Honey
Biscuits	Grape molasses
Cracker	Halvah
Wafers	Chocolate
Patisserie	Chocolate bar
Cake	Chocolate cream
Desserts	Turkish delight
Thin dough	Chewing gum
Macaroni	Confectionery
Vermicelli	Ice-cream
Wheat starch	Condiment-spices
Cereals	Salt
Offal	Baking powder
Garlic-flavored sausage	Vinegar
Sausage	Ketchup
Salami	Mayonnaise
Yoghurt	Packaged soup
White cheese	Instant cake mix
Kosher cheese	Coffee
Cheese encased in a skin	Ready-made coffee
Cream cheese	Tea
Butter	Instant tea bag
Butter (for cooking)	Cocoa
Margarine	Cocoa beverages
Olive oil	Water
Sun-flower oil	Mineral water
Corn oil	Fruity beverages
Canned vegetables	Coke
Tomato sauce	Fruit Juices
Olive	

Services	
Refuse collection	Fee for cellular phone calls
Rent car fee	Subscription costs of telephone
Tolls	Internet
Bridge fare	Fee for phone calls (fixed rate)
Train fare (inter-urban)	Cable TV service fee
Underground	Cinema
Train fare (intra-urban)	Theater
City bus fare(inter-urban)	Horse racing
Mini bus fare	Lottery (Number 10)
Taxi fare	National lottery
Bus fare (intra-urban)	Lotto
Airplane fare	Lotto (sports)
Boat fare	Lottery
Cargo	Package holiday - weekend
Payment for delivery of letters	Package holiday - one week and more
Payment for delivery of parcels	Package holidays (abroad)
Fee for phone calls(inter-urban)	Health insurance
Telephone cards	Banking services

Energy	
Water fee	Coal
Electricity	Fuel
Natural gas	Liquid petroleum gas (LPG)
Tube gas	Diesel oil

Goods excluding Food and Energy		
Rakı	Bath stove	CD player
Whisky	Flash heaters	Photo camera
Wine	Space heaters	Camera
Beer	Aspirator	PC
Painter's fee	Vacuum cleaner	Printer
Expenditure on floor covering	Kitchen robot	Fax modem
Plumbing items	Toaster	PC equipment
Single table	Water heaters	Cassettes for tape recorder
Single chair	Iron	CD and VCD
Bed-room furniture	Other small electrical appliances	Unrecorded cassette and CD
Single-bed	Glass household utensils	Camera films
Double-bed	Steel kitchen utensils	Children's toys
Bed base	Other steel kitchen utensils	Newspaper
Bed-room furniture (junior)	Teflon household utensils	Magazines
Living room furniture	Plastic household utensils	Notebook
Dining-room furniture	Other non-electrical appliances	Pencil
Sofa	Battery	Box of colored pencils for painting
Tripod set	Electric bulb	Stationery papers
Carpet	Garden tools	Other stationery
Tulle	Door fittings	Electric razors
Bed covering	Detergents (for laundry)	Hair care appliances
Sleeping sets	Dishwasher detergents	Shaving articles
Quilt double	Disinfectants and insecticides	Articles for dental hygiene
Blanket	Articles for cleaning	Toilet soap
Furnishing fabrics-upholstery, etc.	Sponge for dish washing	Bath soap
Pillow	Aluminum and stretch foil	Perfumes
Towel	Kitchen paper and napkins	Deodorant for women
Refrigerator	Medicine	Cologne
Refrigerator No-Frost	First-aid tools	Body cream and lotion
Washing machine	Automobile (diesel)	Make-up products
Dish washing machine	Automobile	Hair care products
Oven	Spare parts and accessories	Toilet paper
Furnace with gas	Telephone machine	Paper tissue
Furnace with oven	Television	Cotton wool
Air conditioner	DVD player	Baby napkin
Radiator	Dish antenna and satellite receiver	Hygiene pad for women
Stove	Music set	Jewelry

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