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(Ragadós áras infláció: Alternatív maginflációs mutató)

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Abstract

We show that in both time-dependent and state-dependent sticky price models, prices of sticky price products (i.e. whose price changes rarely) contain more information about medium term inflation developments than those of flexible price products (i.e. whose price changes frequently). We do this by establishing a novel measure for the extent of forward-lookingness of newly set prices, and showing that it is at least 60% when the monthly price change frequency is less than 15%. This result is robust across various sticky price models. On the empirical front, we show that the Hungarian sticky price inflation index indeed has a forward-looking component, as it has favorable inflation forecasting properties on the policy horizon of 1-2 years to alternative inflation indicators (including core inflation). Both theoretical and empirical results suggest that the sticky price inflation index is a useful indicator for inflation targeting central banks.

JEL: E31, E37, E58.

Keywords: sticky prices, core inflation, inflation measurement.

Összefoglalás

Megmutatjuk, hogy mind az időfüggő, mind az állapotfüggő ragadós áras modellekben a ragadós áras termékek (azaz amelyek ára ritkán változik) több információt nyújthatnak a középtávú inflációs folyamatok alakulásáról, mint a rugalmas áras termékek inflációja (azaz amelyek ára gyakran változik). Létrehozunk egy új mutatót, mely az előretekintés mértékét fejezi ki az újonnan megállapított árakra vonatkozóan. Ezen indikátor alapján megmutatjuk, hogy amennyiben a havi árváltoztatási gyakoriság kisebb, mint 15%, az előretekintés mértéke legalább 60%. Az eredmény robusztusnak tekinthető több ragadós áras modellben is. Empirikusan is megmutatjuk, hogy a magyar ragadós áras infláció előretekintő és 1-2 éves policy horizonton kedvező előrejelző tulajdonságokkal rendelkezik az alternatív trendmutatókhoz képest (beleértve a maginflációt is). Az elméleti és empirikus eredmények alapján elmondható, hogy a ragadós áras inflációs index hasznos mutató az inflációs célkövető rendszerben működő jegybankok számára.

1 Introduction

The main goal of inflation targeting central banks is to bring medium term inflation rate to a pre-announced level.[1] This medium term objective implies that central bank decision makers should not respond to short term shocks to inflation which die out in the medium term. However, these temporary cost shocks – like rising food and oil prices or changing tax rates -, are abundant in the last decade. It is therefore very important for central banks to separate temporary shocks and high frequency movements in the inflation processes from the more fundamental (or ”underlying”) developments. The resulting underlying inflation indicators should capture medium and long term movements that are not affected by transitory shocks and are also informative about expected inflation in the relevant policy horizon.

This raises the empirical question of how to define the underlying inflation measure which will guide central bank decision makers in their attempts to meet the medium term inflation target. The traditional underlying indicator is core inflation, which excludes the relatively volatile unprocessed food and raw energy prices from the consumer basket, along with regulated prices that are not informative about the underlying inflation developments for obvious reasons. But core inflation measures still contain elements that change with a relatively high frequency (e.g. processed food prices, which might strongly co-move with the very volatile unprocessed food prices). As an alternative, some central banks use pure statistical indicators as underlying inflation measures, which try to identify the low frequency elements of the inflation process by appropriate statistical methods; examples are the (across items) median or trimmed inflation rates or the volatility-weighted Edgeworth-index of inflation. But there is no consensus in the literature on which particular inflation measure is the best underlying indicator. For example, Rich and Steindel (2005) do not find a single underlying inflation measure that performs better relative to other indicators from all points of view.[2] Similarly for Hungary, Bauer (2011) finds that although some statistical inflation measures outperform the traditional core inflation indicator, none of them is equally good from all aspects (smoothness, forecasting ability and small revision).

The goal of this paper is to build a theory-based (i.e. not purely statistical) underlying inflation indicator for Hungary that outperforms the core inflation measure and is at least as good as the best statistical indicators. The point of departure is the Atlanta Fed's sticky price inflation index for the US by Bryan and Meyer (2010), who argue that prices that change less frequently are more forward-looking and hence better describe medium term developments in the inflation series; a recent application of the same idea is for the UK (Millard and O'Grady 2012). The intuition is the following: as gasoline prices change every week, they are unlikely to contain information about future inflation expectations, as price setters will be able to account for future changes in the inflation in any week's price revision. In contrast, restaurant prices typically change about once a year, say in each January. Therefore when deciding about the price of meals, restaurant managers know that those newly set prices are likely to stay effective for the entire year. But they also know that they will have to buy materials at spot prices throughout the year, so if they expect large food inflation for the coming year, they will set higher meal prices for the whole year.

Following this idea, we prepare a sticky price inflation index for Hungary and study its properties in terms of forecasting the inflation in the relevant policy horizon of 6-8 quarters. Our main contribution is on the theoretical side: we use prominent sticky price models to justify the intuitive argument of Bryan and Meyer (2010) that less frequently changing prices have more information content about the longer run inflation developments. In doing so, we first construct a theory-based measure that describes the extent of forward-lookingness of newly set prices; and then we show that less frequently changing prices are indeed more forward-looking, and hence contain more information about future developments of inflation. We

[1] The reason behind targeting the medium term inflation rate is the time lag with which the economy responds to monetary policy decisions.

[2] They took into account the following performance criteria: construction of indicators should be transparent and straightforward, the indicators should have a similar mean to the target inflation, it should track the underlying inflation, and should have reasonable forecast ability.

also show that this result is robust across model variants (i.e. state-dependent vs time-dependent sticky price models) and across model parameterizations.

The intuition of our extent of forward-lookingness measure is that in sticky price models, firms setting a new price try to make a compromise between two objectives: while they would like to set a price that maximizes current profits (the "static optimum"), they also would like their newly set price to maximize their expected profits until the next price change (the "forward-looking optimum"). The fully optimal price (or the "dynamic optimum") will be a compromise between these two objectives: it will always be a weighted average of the static and the forward-looking optima. Our extent of forward-lookingness indicator then shows how close the fully optimal dynamic price is to the purely forward-looking optimum: it gives the weight of the purely forward-looking optimum price in the dynamic optimum.[3]

For the construction of the sticky price inflation index, we use the results of Gábriel and Reiff (2010), who report product-level price change frequencies for the Hungarian retail sector. Based on store-level individual price data, they find that the average frequency of price change is 21.5 percent in Hungary, but behind this average figure there is substantial product-level heterogeneity. For example, the frequency of price change in the unprocessed food category is 50.4 percent, while the same figure for services is 7.4 percent. In general, services' and traded products' prices seem to be much stickier than food and energy prices, which is not surprising given the large international price shocks in the latter two categories. We use this product-level heterogeneity in price change frequencies to develop our sticky price inflation index indicator: products whose price changes less frequently than a certain threshold will qualify to the sticky inflation basket of consumer goods.

We find that the extent of forward-lookingness of newly set prices decreases in the steady-state frequency of price changes. Quantitatively, the extent of forward-lookingness is at least 60 percent for price change frequencies below 15 percent per month. This is because less frequently changing prices are expected to stay effective for a longer time period, so firms must give a higher weight for future expected profits when deciding about the dynamically optimal price. We show that this result remains true also in the state-dependent sticky price models, when the timing of the price change is endogenous.

With respect to the empirical forecasting ability of the sticky price inflation measure, we find that it outperforms the traditional core inflation measure both in terms of medium term forecasting ability (in forecast RMSE) and predicting the direction of future changes in headline inflation. We also find that the sticky price inflation index is less volatile and more persistent than the traditional underlying inflation indicators, while flexible price inflation mainly responds to current shocks to inflation.

As discussed, our paper is most closely related to the empirical literature on sticky price measures of inflation in the US and UK (Bryan and Meyer 2010, Millard and O'Grady 2012). These papers find that sticky prices contain more information about future inflation and inflation expectations, while flexible prices are noisy as they mostly respond quickly to changing macroeconomic conditions. These papers, however, do not provide a formal argument for their intuition of why exactly sticky prices are more forward-looking. Millard and O'Grady (2012) show that these results are in compliance with a simple DSGE model using a particular parameterization of a time-dependent Taylor pricing rule; in contrast, we do this for both time-dependent and state-dependent pricing rules and a lot of alternative parameterizations. Macallan et al. (2011) also note that sticky prices are important for underlying inflation: if their inflation remains low, that indicates that firms do not expect accelerating inflation in the future. Aoki (2001) also highlights the importance of "core measures" modeled in dynamic general equilibrium framework with nominal price stickiness, and shows that inflation in the sticky sector is a persistent part of inflation. His conclusion is that sticky inflation is useful for forecasting and an optimal monetary policy should target sticky price inflation. Finally, Eusepi et al. (2011) show that welfare-maximizing central banks should target an inflation index in which stickier products get disproportionally larger weights; thus the sticky price inflation index studied here is close to what welfare-maximizing central banks would want to look at.

The paper is organized as follows. In section 2, we present the theoretical background of sticky prices. Section 3 presents the empirical investigation: properties of sticky prices, their forecast performance compared to other underlying inflation measures and robustness checks. Section 4 concludes.

[3] Therefore the extent of forward-lookingness indicator has a percentage interpretation.

2 Extent of forward-lookingness: theoretical background

This section provides theoretical arguments for the claim that sticky prices contain information about inflation expectations of price setters, and therefore about medium term inflation developments as well. First, we introduce a measure to express the forward-looking content of prices, and then we show evidence that stickier prices are more forward-looking.

2.1 MEASUREMENT

As a starting point, we describe a general sticky price framework in which one can measure the extent of forward-lookingness. In the baseline sticky price model we have in mind, there is a representative consumer with a CES consumption aggregator over a continuum of imperfectly substitutable individual consumption goods, and a continuum of firms, all producing one of the consumption goods with single-input, constant returns to scale technology. Firms are heterogeneous with respect to their marginal costs, and they also face some form of price stickiness, but we do not specify the exact form of this. The sticky price economy of Calvo (1983) and the menu cost economy of Golosov and Lucas (2007) are nested in this general specification; details can be found in Karádi and Reiff (2012).

The *representative consumer's* CES-aggregator over the different consumption goods (indexed by i) leads to the familiar constant elasticity of substitution demand curve: $C_i = C\left(\frac{P_i}{P}\right)^{-\theta}$, where C_i is the representative consumer's demand for product i (produced by firm i), C is the consumer's CES consumption aggregate, P_i is the nominal price charged by firm i, P is the aggregate price level (consistent with the consumption aggregator), and $\theta > 1$ is the elasticity of substitution parameter.

The form of the *firms'* single input linear technology is $Y_i = A_i L_i$, where Y_i is the output of firm i, A_i is the exogenous productivity of firm i, and L_i is its labor input, available at perfectly elastic supply at an exogenously given wage rate w. Because of the linear technology, the constant marginal cost of firm i is $\frac{w}{A_i}$, so shocks to productivity can also be interpreted as inverse marginal cost shocks for firm i. We assume that log productivity follows an exogenous mean-zero AR(1) process with persistence $0 \leq \rho_A < 1$ and (conditional) standard deviation σ_A. Each firm's objective is to maximize the expected discounted sum of all future profits, where the per-period profit is given by $\Pi(P_i, A_i) = \left(P_i - \frac{w}{A_i}\right) Y_i(P_i)$, and the firms' output are given by the representative consumer's demand defined above.

We close the model with a simple constant nominal growth assumption: the *monetary authority* keeps increasing the money supply – which is equal to nominal output – at a constant rate. As real growth rate is assumed to be zero, and there is no other source for aggregate uncertainty, the constant nominal growth rate is equal to the inflation rate, π.[4]

In the absence of any form of price stickiness, firms would set their price in each period to maximize this per-period profit, leading to the familiar constant mark-up over marginal cost result: $P_i^* = \frac{\theta}{\theta-1}\frac{w}{A_i}$. With price stickiness, however, the firms' pricing decision becomes dynamic, and whenever they set a new price, they have to maximize the sum of their current-period profits and future firm values:

$$V^C(a) = max_{p^*}\left[\Pi(p^*, a) + \beta E_{a'|a} V(p^*, a')\right] \tag{1}$$

[4] Under these assumptions, the aggregate wage rate w is also constant. For the Calvo-economy, with a linear approximation it can be expressed analytically, while in the menu cost economy it can be calculated numerically.

where function V^C stands for firm value whenever it changes price, V is the firms' value[5], and we have written the firms' problem in the logs of their relative price (p) and productivity (a).[6]

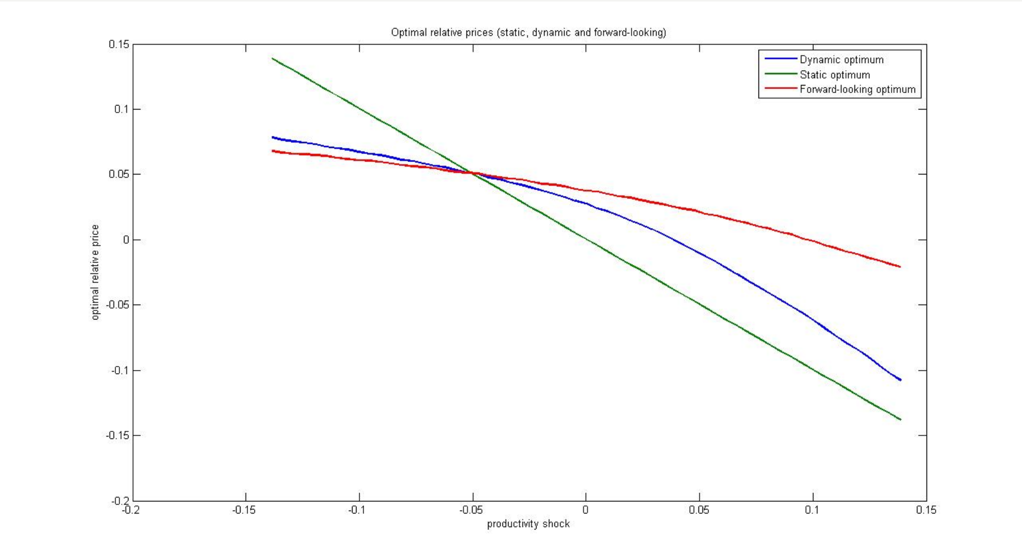
Equation (1) is the basis of our "extent of forward-lookingness"-measure. Its solution $p^*(a)$ is the policy function of the firm, which we call the *dynamically optimal price*. Notice that this dynamically optimal price is a compromise between the static optimum, i.e. the price that maximizes the current-period profit (the first term in the maximand), and the *forward-looking optimum*, i.e. the price that maximizes the future firm value (the second term in the maximand).

Formally, the static optimum is defined as $p^{*s}(a) = argmax_p \Pi(p,a) = \frac{\theta}{\theta-1}\frac{w}{A_i}$. It depends on the current productivity (or inverse marginal cost shock) of the firm, which summarizes all the relevant information for the firm today, but does not contain any expectation for the future. We call this term backward-looking, emphasizing the fact that this optimum is independent of what the firm expects of the future.

In turn, the forward-looking optimum is defined as $p^{*f}(a) = argmax_p \beta E_{a'|a} V(p,a')$. While this optimum formally only depends on the current productivity (or inverse marginal cost) shocks, through the expectation operator expected future productivity (or inverse marginal cost) shocks also influence it. This optimum is therefore inherently forward-looking.

Because of the monotonicity of the profit function around the static optimum, the dynamically optimal price $p^*(a)$ is always between the static optimum $p^{*s}(a)$ and the forward-looking optimum $p^{*f}(a)$. As an illustration, Figure 1 depicts these three types of optima (as a function of the log productivity shock) for a specific version of the menu cost model.[7]

Figure 1
Dynamic, static and forward-looking optimum in a menu cost model



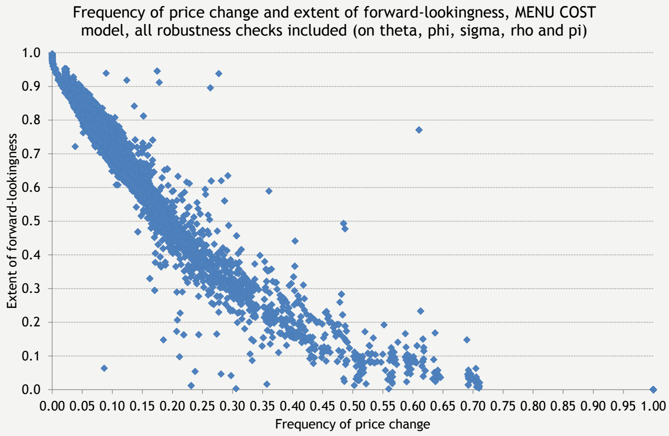
Notice that the dynamic optimum is indeed always between the static and the forward-looking optima, and hence when the two optima coincide for a log productivity shock of about -5 percent, then it is also equal to the dynamic optimum. Notice also that the slope of the static optimum is -1, meaning that any positive (negative) shock to the log productivity decreases (increases) the within-period log optimal price one-for-one, a direct consequence of the familiar constant mark-up over the marginal cost result.

[5] A similar expression defines the value of the firm whenever it does not change its price, V^{NC}. The firm value itself depends on these, but the equation that defines it depends on the exact form of price stickiness. In the Calvo-model with exogenously given price change probability λ, $V = \lambda V^C + (1-\lambda)V^{NC}$, while in a state-dependent model, where price changes are endogenous, $V = max_{(C,NC)}[V^C, V^{NC}]$.

[6] The formal derivation of equation (1) is in Karádi and Reiff (2012)

[7] Figure 1 is based on a numerical solution of a menu cost model under a particular parameterization. Changing the parameterization would not influence the qualitative results.

Figure 2
Frequency of price change and extent of forward-lookingness in the menu cost model



Now we can ask the question of how the extent of forward-lookingness could be measured. Intuitively, the closer the dynamic optimum is to the forward-looking optimum, the larger is the extent of forward-lookingness. If the dynamic optimum coincided with the forward-looking optimum, the extent of forward-lookingness would be 100 percent. On the other hand, if the dynamic optimum coincided with the static optimum (as in any flexible price model), the extent of forward-lookingness would be 0 percent.

Therefore, we define the formal measure of the extent of forward-lookingness as the average distance between the dynamic and static optima, relative to the distance between the forward-looking and static optima:

$$D = \Sigma_i \Pr(a_i) \frac{p^*(a_i) - p^{*s}(a_i)}{p^{*f}(a_i) - p^{*s}(a_i)} \tag{2}$$

As the dynamic optimum is always between the static and forward-looking optimum, the ratio in expression (2) is between 0 and 1 for all possible log productivity shocks a_i. Further, as Figure 1 makes it clear, there is no reason for this ratio to be independent from log productivity; therefore we take the weighted average of the ratio, with weights from the steady-state distribution of the firms above their log productivity levels (denoted by $Pr(a_i)$ in equation (2)).[8]

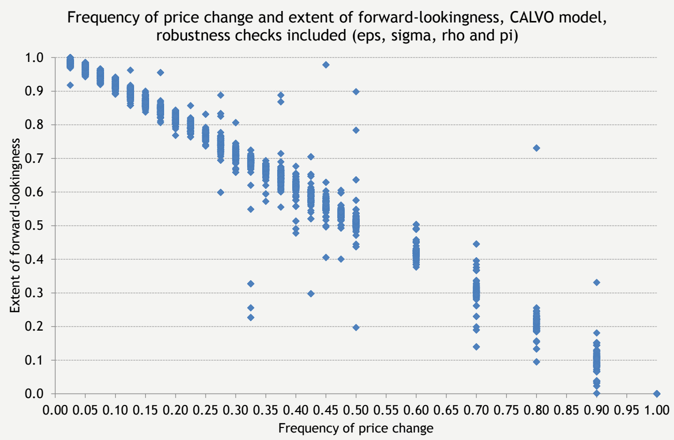
2.2 RESULTS

We computed the forward-lookingness measure defined in equation (2) for two different sticky price models (Calvo- and menu cost model) and for many possible parameterizations. Our main focus is on the relationship between the extent of forward-lookingness and the frequency of price changes.

Figure 2 shows the relationship between the frequency of price changes and the extent of forward-lookingness for a simple model in which the pricing friction is a small price adjustment cost (menu cost). We obtained this figure by solving the model for different elasticity of substitution parameters ($\theta = 3$ and 5), menu cost parameters ($\varphi = 0, 0.001, \ldots, 0.025$), shock standard deviation parameters ($\sigma_A = 0.03, 0.04$ and 0.05), shock persistence parameters ($\rho_A = 0, 0.5$ and 0.9) and

[8] We assume that log productivity a_i is exogenous, and follows an AR(1) process with persistence ρ_A and (conditional) standard deviation σ_A. This implies that a_i has a steady-state distribution, and $\Pr(a_i)$ refer to the probabilities of this steady-state distribution (on a certain grid of log productivity for which we solve the model).

Figure 3
Frequency of price change and extent of forward-lookingness in the Calvo-model



yearly inflation rates ($\pi = 0, 0.01, 0.02, \ldots, 0.12$), i.e. for 6,084 different model parameterizations altogether. Note that when the menu cost parameter was set to 0, that is, when there are no pricing frictions and the frequency of price change becomes 100 percent, then the extent of forward-lookingness is always 0 percent: in this case firms always change their price, so the dynamic optimum is always the same as the static optimum. On the other hand, when the menu cost is very large and thus the frequency of price change becomes very small, then the extent of forward-lookingness is almost 100 percent: firms know that their current price will prevail for a long period, and hence they set their price to maximize future profits instead of the current one. In the intermediate cases, i.e. when the frequency of price change is smaller than 100 percent but much larger than 1-2 percent, there is a negative relationship between the price change frequency and the extent of forward-lookingness.[9] In particular, when the frequency of price change is at most 15 percent (10 percent), the extent of forward-lookingness is always more than 60 percent (70 percent) (and sometimes more, depending on model parameters).[10]

Figure 3 depicts the same relationship between the frequency of price changes and the extent of forward-lookingness in the Calvo-model, where in each period a fixed proportion of firms is given the opportunity to set a new price. Again, we have solved the model for different price change frequency parameters ($\lambda = 0.025, 0.05, \ldots, 0.5, 0.6, \ldots, 1$), shock standard deviation parameters ($\sigma_A = 0.12$ and 0.15),[11] shock persistence parameters ($\rho_A = 0, 0.5$ and 0.9) and yearly inflation rates ($\pi = 0, 0.01, 0.02, \ldots, 0.12$), i.e. for 1,950 different parameterizations of the model. The same result emerges as for the menu cost model: there is a negative relationship between the price change frequency and the extent of forward-lookingness; the latter is even higher in this case than in the menu cost model for same price change frequencies. In the Calvo-model with 15 percent price change frequency, the extent of forward-lookingness is around 85 percent, while for a price change frequency of 10 percent, it mostly exceeds 90 percent.

[9] The reason of the outliers in the figure is numerical inaccuracy. In each of such cases, one grid of the log productivity shock is very close to the intersection of the different optima, and hence the difference between various optima is very small (smaller than the numerical accuracy of our solution method). Then there will be a term in equation (2) in which the numerator and denominator are both very close to zero, leading to relatively large numerical error.

[10] Figure 6 in the Appendix shows the same figure when only the menu cost and trend inflation parameters change (and the shock volatility and persistence parameters, the elasticity of substitution parameter are fixed). One can see that changing these two key parameters do not influence the stable negative relationship between the frequency of price change and the extent of forward-lookingness.

[11] We use different σ_A parameters for the Calvo-model (relative to the menu cost model) as that ensures that the average absolute size of price changes is roughly equal across the two models. In the Calvo-model, we need to have larger idiosyncratic shock innovations to generate the same average absolute size for price changes, as we will also have some very small price changes (which is not the case in the menu cost model).

3 Sticky inflation: empirical investigation

According to theory, sticky prices contain information about inflation expectations of price setters. In this section we study the empirical properties of the Hungarian sticky price inflation index. After defining the index, we investigate both its time-series properties and inflation forecast performance.

3.1 DEFINITION OF THE STICKY PRICES INDEX

Following the approach of sticky price index definitions in other countries,[12] we divide the product category-level consumer price indices into two subcategories: sticky and flexible prices. For this division, we use the Central Statistical Office's (CSO) store-level dataset about retail prices on all individual products in the consumption basket – the basis of the CSO's monthly inflation calculations. From this dataset, we calculate the frequency of price changes for about 160 product categories.[13] Price indices of categories with relatively small (large) frequencies belong to the sticky (flexible) CPI. For the construction of these two aggregate indices, we use the consumption expenditure weights of the CSO.

We make the following transformations of the data before actually weighting the category-level price indices. First, we get rid of product categories which contain regulated prices.[14] The reason is that these prices are not determined on the market and hence their information content about expected market developments is likely to be limited. Second, we correct the price index series with the effects of indirect tax changes (e.g. Value-Added Tax (VAT)). The VAT-changes in our sample were large (out of the six VAT-change episodes, three were as large as five percentage points), with large inflation effects in the monthly inflation series, so these episodes are huge outliers. Third, we seasonally adjusted the monthly inflation series. We do this adjustment at the sticky/flexible CPI level (i.e. on the weighted sum of indices), instead of doing it separately on each category-level price index, as this provides smoother seasonally adjusted series. Fourth, for the frequency calculations, we used posted prices as opposed to sales-filtered or regular prices. We did not filter out sales as they might be correlated with inflation developments.

Obviously, we need a threshold frequency value below which items belong to the sticky part of the CPI. The choice of this is arbitrary. Two natural candidates are the weighted median and the weighted mean frequencies. Based on the numerical results of Section 2, we consider a third threshold of 15 percent: for this – according to our measure –, the extent of forward-lookingness is always more than 60 percent. Table 1 shows the three threshold candidates. The weighted median is in fact close to our choice (17 percent vs 15 percent), hence the implied mean price duration is circa 6-7 month for both. For the weighted mean frequency, the implied mean duration between two price changes is somewhat shorter, less than 5 month.

For our baseline specification, we decided to use the threshold of 15 percent for two reasons. First, for this threshold about 40 percent of the consumption basket (excluding regulated prices) is in the sticky CPI index, so both the sticky and flexible CPIs are based on a relatively large number of product categories.[15] Second, the difference between this threshold and the weighted median threshold are product categories whose frequency is between 15 and 17 percent. These are

[12] See Bryan and Meyer (2010) for the US and Macallan et al. (2011) for the UK.

[13] In principle, we could use item-level frequencies as well, calculated for about 900 individual products. We do not do this as we only have official price indices for the 160 product categories. Most probably, this does not influence the results: products within the product categories are similar and in most cases their frequency of price change is similar. For example, in the "Pork" category the category-level frequency is 0.427, while the product-level frequencies are 0.420, 0.450, 0.454 and 0.413 (for short loin, pork ribs, pork leg and pork flitch, respectively).

[14] We exclude regulated prices from the whole investigation, including time series properties and forecast performance test, too.

[15] This implies that individual product categories cannot have a big impact on either of the sub-indices.

Table 1
The different threshold values

	Frequency (per cent)	Price change (month)	Weight of sticky prices
median	17	6.0	43.8
average	21	4.8	58.5
our choice	15	6.7	40.4

The last column shows the relative CPI weights of sticky prices, after excluding regulated prices.

mostly processed food items that are sensitive to the relatively volatile food price shocks; we preferred to allocate these items into the flexible CPI sub-index. Note that we performed robustness checks for the sensitivity of our results for the sticky-flexible threshold selection (see subsection 3.3), and found that this particular threshold value does not influence our results qualitatively.

Product categories that we include into the sticky price sub-index are listed in Table 6 in the Appendix. Most market services and industrial products belong to the sticky CPI sub-index. In turn, the flexible-price inflation index contains almost all food items, fuel, alcohol and tobacco, i.e. product categories that are subject to larger external shocks for obvious reasons. The total consumption weight (i.e. total CPI weight, including regulated prices) of the sticky CPI index is 32.6 percent, and almost all of this belongs to the core inflation.[16] Thus the sticky CPI index can be interpreted as a "super" core inflation measure, which contains the sticky components of the official core inflation measure.

We might be concerned about the stability of the basket of the relatively sticky products. As the Hungarian inflation rate was between 3.6 and 8 percent in our sample period, it might be possible that items that are relatively sticky in a low inflation environment are not that sticky when inflation rate is higher. Figure 7 in the Appendix shows product group-level yearly price change frequencies between 2002-2011.[17] It is apparent from the figure that price change frequencies are quite stable over time, which indicates that relative price stickiness is stable over inflation cycles.

3.2 TIME SERIES PROPERTIES OF STICKY PRICES

Figure 4 depicts the Hungarian sticky and flexible inflation series – as defined above – between January 2002 and 2011 December, together with the headline CPI series (excluding regulated prices and indirect tax changes). It is apparent from the figure that sticky-price inflation is much less volatile than flexible-price inflation. This observation is consistent with our theoretical argument that flexible prices tend to react to current shocks, while sticky prices reflect changes in expectations – which are much smoother – to a larger extent.[18]

In order to further investigate the empirical reasonability of this argument, we have also calculated the variance and the first-order autocorrelation (or persistence) of the different inflation series. We also capitalized on the large disinflation episode between 1998 and 2002, when headline annual inflation rates decreased from double-digit to 4-5 percent, by comparing volatility measures including and excluding this disinflation period. Table 2 contains the results.

In terms of volatility, there is indeed a reduction between 2002 and 2011 (relative to the 1998-2011 one). For the headline CPI, this reduction is about 35 percent (from 18.5 to 11.5).[19] Interestingly, this reduction seems to come almost entirely from the reduction in the volatility of sticky price inflation: there the reduction is from 10.2 to 3.2. In turn, the volatility of the flexible inflation series did not change significantly (43.7 vs 37.0). This is fully consistent with our view that flexible prices react to exogenous shocks (for which there is no reason to believe to have declined from 2002), while sticky prices contain more information about expectations, which might have been anchored once the headline inflation rate was moderated.

[16] Besides the headline CPI, the CSO also publishes a core inflation measure. 67% of the consumption basket belongs to the core inflation items. In essence, it excludes the unprocessed food, energy and regulated prices from CPI, so it is widely used as an underlying indicator to measure the inflation pressure.

[17] These figures are calculated from a balanced sub-sample of products so that composition effects do not affect the results.

[18] Of course, this is not the only possible explanation for the less volatile sticky inflation series.

[19] This reduction of volatility might be related to the introduction of inflation targeting in 2001, and setting targets which implied heavy disinflation.

Figure 4
Sticky versus flexible inflation

(Annualized monthly changes)

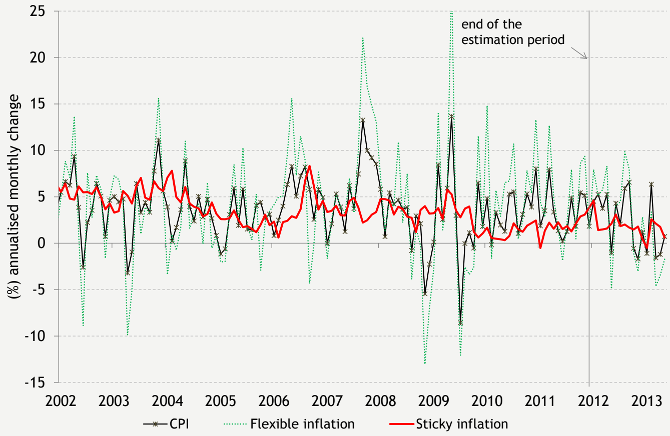


Table 2
Variance of sticky and flexible prices

(Variance is calculated from annualized monthly changes.)

	Sample	**Sticky CPI**	Flexible CPI	CPI
Variance	1998-2011	**11%**	44%	21%
	2002-2011	**4%**	37%	14%
AR-coefficient	1998-2011	**0.86**	0.43	0.55
	2002-2011	**0.67**	0.29	0.34

In terms of persistence, sticky inflation seems to be much more persistent than its flexible inflation counterpart. Given the absence of large shocks in the sticky inflation series, this is hardly surprising.

3.3 FORECASTING PERFORMANCE

In this sub-section we investigate whether the sticky inflation series contains more information about future headline inflation rates – which it should if it indeed contains an expectation component. We do this by studying the relative forecast performance of various inflation measures (including the sticky CPI), by comparing (1) their effect on the Root Mean Squared Errors (RMSEs) of out-of-sample forecasts and (2) their ability to predict future changes in headline inflation. First we describe the methodology in details, and then we turn to the results.

3.3.1 Forecasting performance: framework

We evaluate the forecasting performance of the sticky and flexible CPI indices in two ways. First, we study how the inclusion of various inflation measures changes the RMSE of out-of-sample forecasts of headline inflation, relative to a benchmark model. Second, we check whether the difference between the sticky and headline CPI is a significant predictor of future changes in the headline inflation rate.

More precisely, for the evaluation of the out-of-sample forecasting performance, we estimate the following regression[20]:

$$\sum_{i=1}^{h} \pi_{t+i} = \alpha + \beta(L)s_t + u_t \tag{3}$$

where π_t denotes the monthly change of headline CPI (excluding regulated prices), s_t is the monthly change of the explanatory variable (sticky or flexible CPI, core inflation, or other inflation measure, also excluding regulated prices), $B(L)$ is the lag operator, u_t is the error term, and h is the forecast horizon. We do the forecasting exercise for each explanatory variable separately, and in a recursive manner. First, we estimate equation (3) on data between 1998 and 2007. Based on the estimated parameters, we forecast the h-period ahead (cumulative) inflation rate, and compare it to its actual value. Then we add one observation and repeat the procedure: estimate model parameters, forecast the inflation rate, and compare with its actual value. Then we repeat this procedure until we forecast the cumulative inflation rate ending in December 2011. Finally, we calculate the RMSE from the forecast errors to have an RMSE figure for each candidate explanatory variable.

Our benchmark model is a simple autoregressive model (that is, when $s_t = \pi_t$). In the alternative models, we replace the CPI inflation variable with either the sticky or flexible CPI, or with one of the underlying inflation indicators of Bauer (2011): the Edgeworth-weighted inflation index or the demand-sensitive inflation measure.[21] The common underlying inflation measure is core inflation which excludes the volatile part of the price index. But the Hungarian core inflation measure still contains elements that change with a relatively high frequency (e.g. processed food prices, which might co-move with the very volatile unprocessed food prices). So an alternative measure can be constructed, which excludes processed food prices from core inflation. This measure contains prices that reflect the demand sensitive part of inflation instead of cost influenced volatile prices. This measure is called demand sensitive inflation.

Figure 5
Different underlying inflation indicators

(Yearly changes)

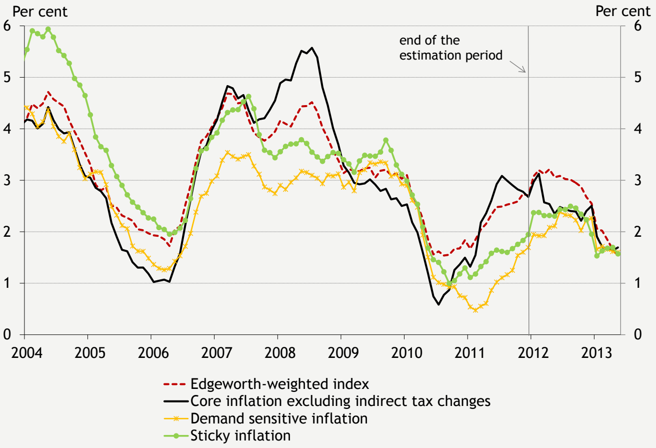


Figure 5 depicts these alternative inflation measures, while Table 3 provides their correlation matrix; both indicate strong co-movements. To evaluate their relative forecast performance, we always calculate relative RMSEs, which are relative to

[20] As discussed in Section 3.1, we eliminated the regulated prices and indirect taxes from the data, then we seasonally adjusted the time series

[21] Bauer (2011) concluded that among the several underlying inflation indicators he investigated, the Edgeworth-weighted index had the best properties in terms of smoothness, robustness to revisions and forecasting performance. This index is an inverse-volatility weighted index of category-level price indices.

Table 3
Correlation matrix of different underlying indicators

(Based on monthly changes.)

	Sticky	EW	Demand sensitive	Core
Sticky	1.000	0.911	0.899	0.876
EW	0.911	1.000	0.900	0.939
Demand sensitive	0.899	0.900	1.000	0.872
Core	0.876	0.939	0.872	1.000

the benchmark autoregressive model. A relative RMSE of less than 100 percent indicates better forecasting performance than that of the benchmark model.

We investigate the forecasting performance of the different inflation indicators on six different horizons: 1, 3, 6, 12, 18 and 24 months. If our theoretical argument about the expectation content of the sticky inflation measure is correct, then we should see a better forecasting performance of that indicator especially on the longer horizons.

For the recursive estimation, we always use real-time data, i.e. data that were available at the moment of forecasting. This means that we seasonally adjust the time series at each possible forecasting date, rather than simply using the seasonally adjusted series as of December 2011. This might be important because of uncertainty in the seasonal adjustment procedure or data revisions.[22]

Besides this RMSE-comparison, we also assess the forward-lookingness of the sticky price CPI in a more direct way. The idea is that if our theoretical argument about the expectation content of sticky prices is correct, then the actual gap between the sticky price index and the headline CPI can be informative about the future developments of the headline CPI. Following Cogley (2002), Amstad and Potter (2009) and Bauer (2011), we estimate the following equation:

$$\Pi_{t+h} - \Pi_t = \alpha + \beta(z_t - \Pi_t) + u_{t+h} \tag{4}$$

where Π_t and z_t are the yearly changes in the headline and the sticky CPI indices, respectively. The interpretation is quite straightforward. Parameter β tells us whether and how the evolution of the headline CPI (over a time horizon of h months) is connected to current differences between the sticky and headline CPI. If, for example, we find $\alpha = 0$ and $\beta = 1$, then the current deviation perfectly explains the future inflation developments. If β is less than unity, but significant then the deviation predicts the direction of the change in the headline CPI correctly, but understates its effect. If β is greater than unity, then the deviation overstates the effect. Equation (4) with core inflation as the explanatory variable serves as a benchmark model, and in this case we again do the estimation on real-time data.

3.3.2 Forecasting performance: results

The Table 4 reports the relative (to the simple AR model) RMSEs of the alternative inflation indicators estimating equation (3).[23] Overall, we find that the sticky-price-based inflation forecasts are more accurate relative to the benchmark autoregressive model. In short run (on 1-3 months horizons), the improvement is not significant and the core inflation-based model's forecast performance is close to the sticky price-based model. But the relative accuracy increases on longer forecast horizons. In 1 year horizon, sticky prices tend to be more accurate, in line with property that many sticky prices change only once in every 12 months. So because of this forward-lookingness, sticky price measures can serve as a proxy for inflation expectations. In contrast, flexible prices are noisy and do not improve the RMSE. As forecast horizons get longer,

[22] For the Edgeworth-weighted index, we do not have real-time data, so we do the calculations with the 2011 December version of the data. In the robustness section, however, we show that working with real time data – when available - actually does not change our qualitative results.

[23] The RMSE of the baseline autoregressive equation was 0.36%, 0.84%, 1.43%, 2.15%, 3.21% and 4.38% on the 1, 3, 6, 12, 18 and 24 month forecast horizon, respectively.

the accuracy of flexible prices is worsening, relative to the benchmark autoregressive model. The relative RMSEs of the demand sensitive inflation and Edgeworth-index(EW) show pretty good forecast performance compared to the benchmark autoregressive model.

Table 4
Relative performance of measures based on real time data

(EW based on last vintage sample.)

Horizon	**Sticky**	Flexible	Demand sensitive	EW	Core
1 month	**106%**	107%	103%	95%	104%
3 months	**96%**	108%	97%	90%	103%
6 months	**88%**	111%	89%	88%	98%
12 months	**85%**	122%	84%	87%	101%
18 months	**76%**	122%	77%	84%	98%
24 months	**66%**	119%	68%	79%	97%

Table 5 shows the estimated β parameters from equation (4). The estimated α parameters do not differ significantly from zero, so we do not report them. The results strengthen our claim about the forward-lookingness properties of sticky prices: the actual difference between the year-on-year sticky price index and headline inflation helps predicting the future headline inflation. In contrast, flexible prices are noisy and do not predict the direction of future changes in inflation. The estimated β parameters of flexible prices are zero even in the long run. So flexible prices are mainly determined by one-off shocks, and these shocks do not affect medium and long run inflation. As in the former empirical framework, the demand sensitive inflation and Edgeworth-index shows a similar result as the sticky-price inflation index. So these alternative indicators can also give indication about future inflation changes.

Table 5
Estimated parameter in forward-lookingness based on real time data

Horizon	**Sticky**	Flexible	Demand sensitive	EW	Core
1 month	0.03	0.02***	0.04**	0.09***	0.06***
3 months	0.18***	0.04**	0.14***	0.32***	0.14***
6 months	0.29***	0.03	0.21***	0.49***	0.17**
12 months	0.37***	0.00	0.32***	0.54***	0.05
18 months	0.42***	−0.03	0.38***	0.59***	0.05
24 months	0.59***	−0.05	0.56***	0.71***	0.13

*** Significant at the 5% level.*
**** Significant at the 1% level.*

3.3.3 Robustness checks

We performed several robustness checks for our results. First, we replaced real-time data with data as of December 2011 to evaluate the magnitude of the differences stemming from data and seasonal adjustment revisions. (This exercise is important for the evaluation of the previous results on the Edgeworth-weighted index, as we do not have real-time data for it.) Second, we changed the in-sample data period from 1998-2007 to 2002-2007, i.e. dropped the 1998-2001 period of heavy disinflation, which might have had a big impact on our results. Third, we estimated alternative specifications for equations (3) and (4). Finally, we changed the threshold value that we use to separate the consumer basket into sticky and flexible prices.

The main results are the following:

1. Tables 7 and 11 in the Appendix show that our results are quite similar when calculated on the last (December 2011) vintage of the data. The message is that revisions in the seasonally adjusted series are not significant. Comparing Tables 5 and 6 implies that under seasonal adjustment revisions, the sticky CPI gets slightly worse in terms of the relative RMSEs and slightly better in terms of forward-lookingness, but the changes are quantitatively small and our qualitative results are unchanged.

2. When we calculated on shorter sample, the results slightly changed for equation (3) (see Table 8 in the Appendix). The relative performance of sticky price index is quite similar to benchmark autoregressive model. But the sticky price index is still not worse than the other alternative underlying indices (demand-sensitive and Edgeworth-indices). The main reason of this change is that Hungary did not have a strong disinflation period after 2002, so the volatility of the explanatory variables is much smaller and hence the parameter estimates are less reliable. In contrast, Table 12 of Appendix shows that the estimated parameters were robust to alternative sample period in case of equation (4), so the sticky price index preserves its attractive predictive properties.

3. We estimated equation (3) in alternative specification as well: we included the lagged value of the headline CPI as an additional explanatory variable. As the headline CPI is a persistent process, the estimated parameters of this variable were highly significant. But despite the better fit of the forecast equation, the relative forecast errors did not improve notably (Table 9 in the Appendix). In case of equation (4), we also performed the estimation with annualized monthly changes of CPI (the baseline specification was on yearly inflation). The estimated β parameters improved significantly and do not differ from unity in long run (Table 13 in the Appendix).

4. In the baseline case, the threshold frequency is 15 percent. We repeated the estimations with two alternative threshold values: 10 and 20 percent. According to Tables 10 and 14 in the Appendix, the qualitative results did not change. It is apparent from Table 10 that the stricter is the sticky price threshold, the more forward-looking the sticky price index becomes, which is an intuitive result. According to Table 14, different threshold values do not change the results of estimating equation (4) significantly.

4 Conclusion

In this paper we construct a theory-based alternative underlying inflation measure, the sticky price inflation index. Intuitively, it can give indication about future price changes. We have shown in a general model of sticky prices why sticky prices are more forward-looking. To do so, first we have defined a formal measure of the extent of forward-lookingness, and then we have shown that in both time-dependent and state-dependent sticky price models, there is negative connection between the frequency of price change and extent of forward-lookingness, meaning that stickier prices are more forward-looking. Quantitatively, we found that when the monthly frequency of price changes is at most 15 percent, the extent of forward-lookingness is at least 60 percent.

Using a threshold value for the frequency of price change of 15 percent, we divided the consumer price index into sticky and flexible price indices. Our empirical investigation proved that sticky prices have smoother time series than flexible prices and their reaction to one-off price shock is limited. The empirical investigations underpinned their better forecast performance, so at longer horizon sticky prices tend to be more accurate than flexible prices. Also, sticky price measures can serve as a proxy for inflation expectations.

The comparison to alternative underlying inflation measures showed that the forecast performance of the sticky price index is similar to the best atheoretical underlying prices indices (Edgeworth-index and demand sensitive inflation). A clear advantage of the sticky price index is that it is more founded by theory. Another attractive feature is that the sticky price index is calculated from a fixed consumer basket, while the alternative statistical indices filter out the most volatile items from the whole CPI basket (e.g. trimmed mean) or change their weight system (e.g. Edgeworth-index) month by month, so their revision can be significant. In contrast, the only source of revision in the sticky price index is the one stemming from seasonal adjustment.

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5 Additional tables and figures

Table 6
List of products in the sticky price index

Description	Frequency	Description	Frequency
Theatres	0.024	Parts and accessories of "do it-yourself"	0.079
Health services without medical visit fee	0.031	Sport and camping articles, toys	0.080
Repairs of recreational goods	0.035	Educational services without tuition fee	0.081
Photographic services	0.035	Passenger cars, new	0.085
Cinemas	0.038	Passenger cars, second-hand	0.085
Repairs of major household appliances	0.039	Motorcycle	0.085
Taxi	0.041	Bicycle	0.085
Cup of coffee in catering	0.043	Computer, cameras, phone etc.	0.087
Transport of goods	0.044	Newspapers, periodicals	0.088
Repairs, maintenance of vehicles	0.046	Books	0.088
Non-local government rent	0.046	School and stationery supplies	0.090
Meals at restaurants not by subscription	0.049	Infant's clothing	0.091
Cleaning, washing	0.050	Household repairing and maintenance goods	0.092
Repairs and maintenance of dwellings	0.051	Recording media	0.094
Cost of owner occupied dwellings	0.051	Radio sets	0.100
Clothing materials	0.052	Pets foods	0.101
Personal care services	0.052	Confectionery and ice-cream	0.103
Repairs clothing and footwear etc.	0.053	Cooking utensils, cutlery	0.105
Services n.e.c. without burial and administration fee	0.053	Jewellery	0.106
Haberdashery	0.055	Heating and cooking appliances	0.112
Leather goods	0.055	Vacuum cleaners, air-conditioning	0.112
Tyres, parts and accessories for vehicles	0.064	Men's footwear	0.122
Maintenance cost at private houses	0.064	Recreation with prescription in the country	0.122
Cable television fee	0.064	Recreation abroad	0.122
Meals at canteens by subscription	0.065	Bijuo, gift	0.131
Men's underwear	0.067	Clothing accessories	0.131
Buffet products	0.069	Videos, tape recorders	0.135
Kitchen and other furniture	0.069	Beef	0.136
Furnishing fabrics, carpets, curtains	0.069	Other meat	0.136
Household paper and other products	0.072	Briquettes, coke	0.136
Membership fee, donation	0.074	Dried vegetables	0.139
Children's footwear	0.075	Firewood	0.140
Bed and table linen	0.075	Wine	0.142
Women's underwear	0.076	Edible offals	0.146
Living, dining- room furniture	0.078	Candies, honey	0.146

Table 7
Relative performance of measures on last vintage

Horizon	**Sticky**	Flexible	Demand sensitive	EW	Core
1 month	**100%**	107%	98%	95%	98%
3 months	**93%**	107%	94%	90%	97%
6 months	**87%**	110%	89%	88%	96%
12 months	**84%**	123%	84%	87%	98%
18 months	**77%**	121%	78%	84%	98%
24 months	**66%**	119%	68%	79%	95%

Table 8
Relative RMSE in different sample period

Horizon	**Sticky**	Flexible	Demand sensitive	EW	Core
1 month	**109%**	102%	105%	96%	103%
3 months	**105%**	102%	106%	96%	106%
6 months	**103%**	102%	103%	98%	103%
12 months	**100%**	100%	96%	92%	94%
18 months	**119%**	106%	108%	96%	94%
24 months	**134%**	93%	118%	96%	90%

Table 9
Relative RMSE in alternative specification

Horizon	**Sticky**	Flexible	Demand sensitive	EW	Core
1 month	**98%**	101%	97%	93%	99%
3 months	**92%**	101%	94%	90%	100%
6 months	**90%**	107%	90%	88%	98%
12 months	**84%**	114%	82%	86%	97%
18 months	**77%**	111%	76%	84%	95%
24 months	**65%**	104%	67%	79%	93%

Table 10
Relative RMSE at different threshold value

Horizon	Sticky10	**Sticky15**	Sticky20	Flex10	Flex15	Flex20
1 month	105%	**106%**	101%	106%	107%	111%
3 months	96%	**96%**	94%	107%	108%	114%
6 months	83%	**88%**	87%	110%	111%	118%
12 months	83%	**85%**	89%	119%	122%	133%
18 months	72%	**76%**	82%	119%	122%	130%
24 months	60%	**66%**	74%	117%	119%	125%

Table 11
Estimated parameter in forward-lookingness on last vintage

Horizon	**Sticky**	Flexible	Demand sensitive	EW	Core
1 month	0.04*	0.02***	0.05**	0.09***	0.08***
3 months	0.19***	0.03**	0.15***	0.32***	0.19***
6 months	0.33***	0.04**	0.26***	0.49***	0.26***
12 months	0.40***	0.03	0.39***	0.54***	0.12
18 months	0.44***	0.00	0.47***	0.59***	0.09
24 months	0.62***	−0.01	0.66***	0.71***	0.21

** Significant at the 10% level.*
*** Significant at the 5% level.*
**** Significant at the 1% level.*

Table 12
Estimated parameter in different sample period

Horizon	**Sticky**	Flexible	Demand sensitive	EW	Core
1 month	0.01	0.02***	0.03	0.06**	0.04*
3 months	0.10**	0.03*	0.07	0.26***	0.09*
6 months	0.19***	0.02	0.14*	0.38***	0.13*
12 months	0.22**	−0.02	0.22**	0.31***	−0.04
18 months	0.27**	−0.03	0.31***	0.39***	−0.01
24 months	0.38***	−0.03	0.42***	0.50***	−0.02

** Significant at the 10% level.*
*** Significant at the 5% level.*
**** Significant at the 1% level.*

Table 13
Estimated parameter in alternative specification

Horizon	**Sticky**	Flexible	Demand sensitive	EW	Core
1 month	0.49***	−0.26***	0.58***	0.62***	0.55***
3 months	0.75***	−0.45***	0.86***	0.92***	0.74***
6 months	0.98***	−0.60***	1.11***	1.23***	1.06***
12 months	0.85***	−0.64***	1.02***	1.02***	0.93***
18 months	0.73***	−0.72***	0.88***	0.92***	0.80***
24 months	0.89***	−0.86***	1.08***	1.06***	0.94***

**** Significant at the 1% level.*

Table 14
Estimated parameter at different threshold value

Horizon	Sticky10	**Sticky15**	Sticky20	Flex10	Flex15	Flex20
1 month	0.03	0.03	0.04*	0.03***	0.02***	0.01**
3 months	0.13***	0.18***	0.17***	0.04**	0.04**	0.02*
6 months	0.23***	0.29***	0.25***	0.04	0.03	0.01
12 months	0.25***	0.37***	0.31***	0.00	0.00	0.00
18 months	0.33***	0.42***	0.32**	−0.03	−0.03	−0.01
24 months	0.49***	0.59***	0.43***	−0.04	−0.05	−0.02

** Significant at the 10% level.*
*** Significant at the 5% level.*
**** Significant at the 1% level.*

Figure 6
Frequency of price change and extent of forward-lookingness in the menu cost model (only menu cost and inflation parameters change)

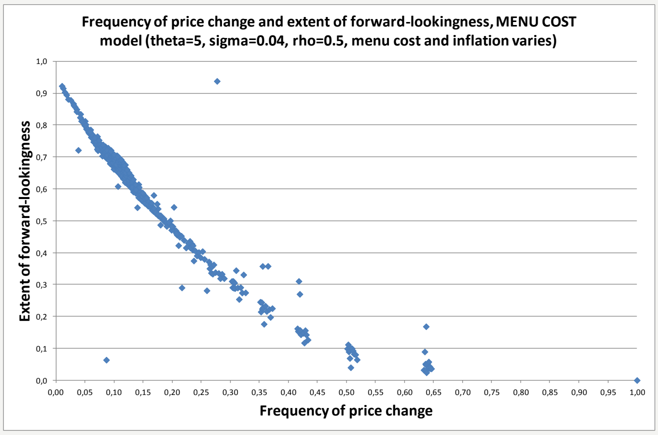
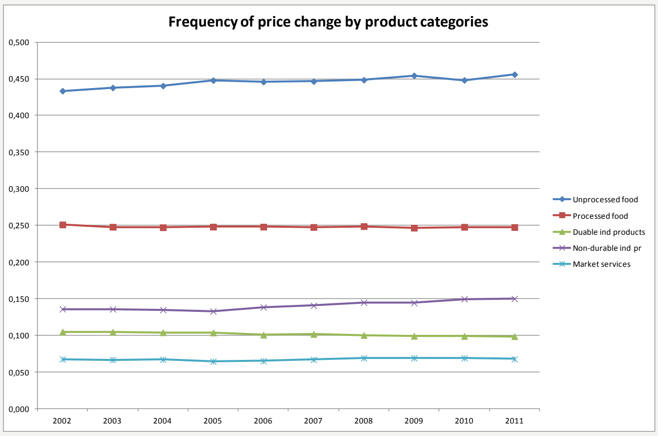


Figure 7
Category-level price change frequencies between 2002-2011



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