Asymmetries in Inflation Expectation Formation Across Demographic Groups*

Damjan Pfajfar†
University of Cambridge

Emiliano Santoro‡
University of Cambridge

April 7, 2008

Abstract. Relying on University of Michigan data on consumers' inflation expectations, we establish some stylized facts on the process of inflation expectation formation across different demographic groups. Percentile time series models are employed to test for rationality and to study learning dynamics across the whole cross-sectional spectrum of responses. These display a significant degree of heterogeneity and asymmetry. Income, education, and gender seem to be rather important characteristics when forecasting inflation. In particular, high income, highly educated, and male agents produce lower mean squared errors. Moreover, socioeconomically "disadvantaged" respondents assume as a reference point their specific consumption basket, while more advantaged respondents actually observe the general price level. A common observation applying to all socioeconomic groups is that agents positioned around the center of the distribution behave roughly in line with the rational expectations hypothesis. Agents on the left hand side of the median (LHS) of the distribution update information very infrequently. As to agents on the right hand side of the median (RHS), we can affirm that their expectations are consistent with adaptive learning and staggered information updating. However, the speed of learning can vary significantly across percentiles and different demographic groups.

JEL: E31, C53, D80, J10

Keywords: Heterogeneous Expectations, Adaptive Learning, Survey Expectations

---

*We would like to thank Sean Holly and Seppo Honkapohja for guidance and helpful discussions. We would also like to thank Leslie McGranahan and Anna Paulson for providing us with their dataset on inflation experience by demographic groups. We thank Chryssi Giannitsarou and other participants at the Catholic University in Milan, Cambridge University, IUE Conference 2007, and 2007 MMF Conference for their comments and suggestions. All remaining errors are ours.

†Faculty of Economics, Austin Robinson Building, Sidgwick Avenue, Cambridge CB3 9DD, UK. *E-mail*: dp316@cam.ac.uk. *Web*: http://www.econ.cam.ac.uk/phd/dp316/.

‡Faculty of Economics, Austin Robinson Building, Sidgwick Avenue, Cambridge CB3 9DD, UK. *E-mail*: es356@cam.ac.uk. *Web*: http://www.econ.cam.ac.uk/phd/es356/.

Introduction

Anchoring inflation expectations is of crucial importance for the conduct of monetary policy. Central banks have, as a primary task, the pursuit of price stability. The effectiveness of their action crucially depends on they way individuals perceive the course of monetary policy and future economic developments. Economists typically assume that agents possess perfect knowledge of the statistical properties of the variables they wish to forecast. Nevertheless, heterogeneity is pervasive in economic systems. Agents do not predict on the basis of the same information set, do not entail the same capacity to process information and do not employ the same model. As a matter of fact, when people rely on their beliefs, and engage in out-of-equilibrium learning or update their information sets asynchronously, heterogeneity and self-referentiality might determine a broad set of paths of the economy. Therefore, it is of utmost importance to observe and understand different sources of heterogeneity and asymmetry in the process of inflation expectation formation.

Relying on University of Michigan Survey data on households' inflation expectations, this paper assesses the influence of agents' socioeconomic background on their forecasts. We evaluate the significance of different theoretical models of expectation formation and explore asymmetries across demographic groups. Our analysis is centered around recent contributions advanced in the theoretical literature. Some of these models postulate the existence of informational frictions or conjecture that agents might act as econometricians when forecasting. The latter approach, widely known as adaptive learning, is thoroughly discussed in Evans and Honkapohja (2001), while the former is usually labelled as rational inattentiveness, according to Sims (2003, 2006).

Hicks (1939) has propounded expectations as one of the main drivers of economic dynamics. He can also be regarded as one of the first economists interested in the fundamental process of inflation expectations formation:

> 'It seems possible to classify three sorts of influences to which price-expectations may be subject. One sort is entirely non-economic: the weather, the political news, people's state of health their "psychology". Another is economic, but still not closely connected with actual price movements; it will include mere market superstitions, at the one extreme, and news bearing on future movements of demand or supply (e.g., crop reports), at the other. The third consists of actual experience of prices, experience in the past and experience in the present; it is this last about what we can find most to say.' (p. 204)

Throughout the history of economic thought expectations have been in the heart of the economic literature. Several theoretical contributions have been advanced to explain the fundamental process of expectation formation. Nevertheless, only few studies have focused on the empirical assessment of these frameworks. Despite the increasing availability of survey data, the empirical literature has generally disregarded the possibility to exploit the cross-sectional information available in these datasets and the opportunity to pursue a joint assessment of competing models of expectation formation.

As Hicks (1939) has pointed out, economists know very little about how agents form their expectations in the real world. Lately, a consensus has emerged on the view that agents form their expectations heterogeneously. The literature on heterogeneous expectations tends to classify three main sources of heterogeneity. Heterogeneous forecasts might be a consequence of: (i) employing different models;[1] (ii) different information sets; (iii) different capacities to process information. Contrary to previous contributions, this paper allows us to shed light also on the non-economic roots of heterogeneity advanced by Hicks (1939). Strictly speaking, socioeconomic characteristics are associated to the second and third source of heterogeneity. Agents with different socioeconomic backgrounds are likely to entail different degrees of access to the relevant information. Possibly, they also have different capacities to process information.

Moreover, socioeconomic indicators might constitute a reliable proxy to assess the importance of financial constraints. As gathering information is costly, some agents might be constrained to rely on less sophisticated methods of forecasting. The literature on rationally heterogeneous expectations explores this issue. The problem is treated from an utility maximization point of view, where agents choose between different competing models of expectation formation. Brock and Hommes (1997), Branch and McGough (2007) and Pfajfar (2007) analyze alternative switching mechanisms within a cobweb framework. In particular, Pfajfar (2007) stresses the importance of the capacity to process information. We argue that this factor can be importantly influenced by demographic characteristics.

As far as the empirical literature is concerned, the introduction of rationality tests and the empirical validation of models of adaptive expectations (see, e.g., Pesaran, 1985, 1987) have represented the only contributions in the last two decades. Only recently, the literature has been enriched by an empirical investigation of the degree of heterogeneity (Branch, 2004, 2007) and information stickiness (Mankiw, Reis and Wolfers, 2004 and Carroll, 2003a, 2003b). Furthermore, some empirical support has been provided for macroeconomic models implementing learning dynamics.[2]

Few studies have pointed out the significance of socioeconomic factors for the expectation formation process.[3] Jonung (1981) shows that female inflation forecasts are less accurate than those of their male counterparts (see also Bryan and Venkatu, 2001a, 2001b). As women are usually responsible for day-to-day food purchase, Jonung (1981) suggests that this bias is due to relatively larger rises in food prices compared to the general consumer price index (CPI). We further investigate on this argument in Section 4. To the best of our knowledge, only three other studies partly look at inflation expectations across different demographic groups. Maital and Maital (1981) implement some tests for rationality, both on individual and group-specific expectations about the average level of inflation.[4] They conclude that socioeconomic variables

[1] Namely, agents could have different underlying assumptions about the structure of the economy or different parameterisation (or priors) of the same model.

[2] See Milani (2007) and Orphanides and Williams (2003, 2005a, 2005b) who first advanced some empirical support for learning dynamics.

[3] Dominitz and Manski (2005) analyse heterogeneity of expectations about equity prices. They also present some evidence about heterogeneity across demographic groups. They find that young agents, males and more educated tend to be more optimistic compared to their counterparts.

[4] Expectations regarding different socioeconomic groups are obtained from the Current Survey of the Israel

such as age, trust and income exert a strong influence on the expectation formation process. Palmqvist and Strömberg (2004) show that inflation opinions in Sweden are lower among male, more-educated and high income respondents. Lindén (2004) reaches analogous conclusions when comparing perceived and expected inflation in the Euro area. Granato, Lo, and Wong (2004) detect a boomerang effect in the inflation diffusion process across different educational groups. They argue that, due to misinterpretation occurring in the phase of information acquisition, less informed agents' forecasts tend to confound those of more informed agents.

In this paper we rely on monthly micro data on inflation expectations provided by the University of Michigan Survey Research Center. As the pseudo panel employed is highly unbalanced, we compute percentiles of the empirical distribution in each period. Therefore, we obtain monthly time series for each percentile, which carry information on individuals comprised in different parts of the empirical density.

Compared to previous studies, where tests of rationality are only applied to measures of central tendency, this paper extends these testing procedures to the whole cross-sectional spectrum of responses. We find that the null hypothesis of rationality cannot be rejected just for few percentiles centered around or slightly above the median. We also estimate several additional time series models of expectation formation. These confirm a significant degree of asymmetry in the expectation formation process across demographic groups. Income, gender and education seem to be particularly important characteristics when forecasting inflation. In particular, high income, male, and highly educated agents produce lower mean squared errors.

These conclusions cannot abstract from considering that different demographic groups are likely to be exposed to different CPI inflations. As a matter of fact, the representative consumption basket can significantly differ across demographic groups. We assess the importance of this factor for the observed degree of heterogeneity, by employing the dataset of McGranahan and Paulson (2005) reporting CPIs for each demographic group. We also compare the forecasting performance of different groups with respect to the general and group-specific inflation, showing that the latter constitutes a reference point for the forecast process of socioeconomically less advantaged groups.

Overall, agents positioned around the center of the distribution roughly behave in line with the rational expectations (RE) hypothesis.[5] However, our results suggest that respondents on the left hand side of the median (LHS) generally display an autoregressive behavior. Furthermore, inflation expectations formed by these LHS agents display a consistent degree of digit preference. Often these respondents do not observe any of the relevant macroeconomic variables. Conversely, agents on the right hand side of the median (RHS) are generally proven to be too pessimistic and usually tend to overpredict actual inflation. Their inflation expectations are more consistent with adaptive behavior (learning), although their speed of learning can vary considerably. Furthermore, we argue that they exhibit some inherent features pointed out by recent advances in the macroeconomic and financial literature on rational inattentiveness and

Institute for Applied Social Research.

[5] For more detailed results, see Pfajfar and Santoro (2007).

rationally heterogeneous expectations models.[6] We must bear in mind that the cost of being inattentive increases as inflation increases.

The remainder of the paper reads as follows: Section 1 reports in more detail the dataset employed; Section 2 delivers some preliminary descriptive statistics; Section 3 discusses the relative importance of different perceived inflations for each demographic group; Section 4 focuses on the percentile time series analysis, with a special attention for learning dynamics and information stickiness; last section concludes and gives some suggestions for further research.

1. The Survey of Consumer Attitudes and Behavior

The Survey of Consumer Attitudes and Behavior, conducted by the Survey Research Center (SRC) at the University of Michigan, has been available on a monthly basis since January 1978. The survey comprises an average of 591 households, with a peak of 1479 in November 1978 and a minimum of 492 in November 1992. From January 1987 onward it reports an average of approximately 500 responses. Following a first interview, each respondent is reinterviewed after six months. The sampling method is designed in a way that, in any given month, approximately 45% of prior respondents is reinterviewed, while the remaining 55% are new households. There are two relevant questions about price level changes: (i) first, households are asked whether they expect prices to go up, down or to stay the same in the next 12 months; (ii) second, they are asked to provide a quantitative answer about the expected change.[7]

Rather than reporting the actual forecasts, available data are summarized in intervals (e.g. "go down", "stay the same or down", go up by 1-2%, 3-4%, 5%, 6-9%, 10-14%, 15+%). There might be some confusion about the category "stay the same or down". In the remainder of the paper we follow Curtin (1996) and treat this response as 0. A word of caution is in order for households that expect prices to go up, without providing any quantitative statement. In this case, we redistribute their response across the six ranges of price change, depending on their relative share. We exclude an extremely small proportion of "do not know" responses from our sample.

As agents report unbounded inflation forecasts, we need to determine points at both ends of the distribution beyond which observations should be excluded.[8] Curtin (1996) suggests two alternative truncations, namely at -10% and +50% and at -5% and +30%. Overall, there seems to be poor evidence supporting the choice of one truncation rule over the other. In the remainder of the paper we rely on the second truncation rule.

[6] Inattentiveness – agents who update their information sets only occasionally – has been advanced by Sims (2003, 2006) and first implemented in the macroeconomic model by Mankiw and Reis (2002). The theory of rationally heterogeneous expectations has been put forward by Brock and Hommes (1997). Their basic argument is that it might not always be optimal from a utility maximisation point of view to use a costly-sophisticated predictor that produces lower mean squared error. Thus, some agents might be better off with a slightly worse predictor, which is less costly to use.

[7] In case any respondent expects prices to stay the same, the interviewer must make sure that the respondent does not have in mind that prices will keep changing at the current rate of growth.

[8] It is important to recall that the exact specification of the truncation rule only influences the mean and the variance of the distribution, but has no effect on the median. It is also relevant to take into account that the upper tail of the distribution is not only long but also sparse, frequently with large gaps between observations. Technical considerations regarding the cut-off procedure are outlined in Curtin (1996).

As far as the socioeconomic groups under scrutiny are concerned, we focus on respondents classified depending on their gender, income level (low 33% [Y13], middle 33% [Y23] and top 33% [Y33]), educational level (high school or less [EHS], some college degree [ESC] and college degree [ECD]), age (between 18-34, 35-54, and 55+) and territorial location (east [E], south [S], north west [NW] and north center [NC]).

2. A Preliminary Look at the Data

This section is devoted to a preliminary inspection of the dynamic pattern of the empirical moments retrieved from the University of Michigan Survey Research Center (MSHE) distribution of inflation expectations. Table 1 reports the time average of the empirical moments of the MSHE distribution, together with the time average of actual inflation for the whole period and for different demographic groups.

Demographic Group	Mean	Median	Variance	Int. Range	Skew	Kurt	Inflation
Male	4.28	3.8	20.6	4.44	1.79	8.69	
Female	5.37	4.16	34.9	5.55	1.54	5.6	
18-34	5.14	4.16	29.5	4.93	1.64	6.52	
35-54	4.95	4.09	27.6	4.81	1.72	7.12	
55+	4.48	3.46	28.1	4.9	1.69	6.71	
West	4.91	4.09	27.1	4.89	1.61	6.69	
North/Centre	4.77	3.9	27.6	4.79	1.73	7.1	
North/East	4.82	3.92	28.9	5.09	1.61	6.54	
South	4.95	3.94	30.2	4.99	1.66	6.41	**4.19**
Bottom Income Level	5.28	3.95	36.7	5.83	1.44	5.08	
Middle Income Level	4.59	3.71	26.8	4.71	1.79	7.36	
Top Income Level	4.01	3.57	19.2	4.29	1.9	9.41	
HS or less	5.23	3.97	34.8	5.43	1.53	5.47	
Some college	4.78	3.96	26.4	4.77	1.66	6.97	
College degree	4.51	4.11	20	4.27	1.79	8.95	
Overall	**4.87**	**4.16**	**28.7**	**5.55**	**1.73**	**6.98**	

Table 1: Demographic groups and empirical moments (overall sample).

In accordance to the evidence provided by Palmqvist and Strömberg (2004) and Lindén (2004) for Sweden and Euro area respectively, the mean of male, top level income, highly educated and elderly individuals is smaller with respect to that of their counterparts within the same group. As to the median, lower values are associated with elderly and top income population, while higher values correspond to young and female respondents. Analysis of the empirical second moment points out that well educated and high income respondents provide less volatile predictions with respect to other groups. Our evidence confirms the conclusions advanced by Fishe and Idson (1990), as the degree of dispersion in inflation forecasts is smaller for agents with potentially greater demand for information. However, skewness and kurtosis seem to be higher for economically more advantaged groups. On average these produce lower inflation forecasts.

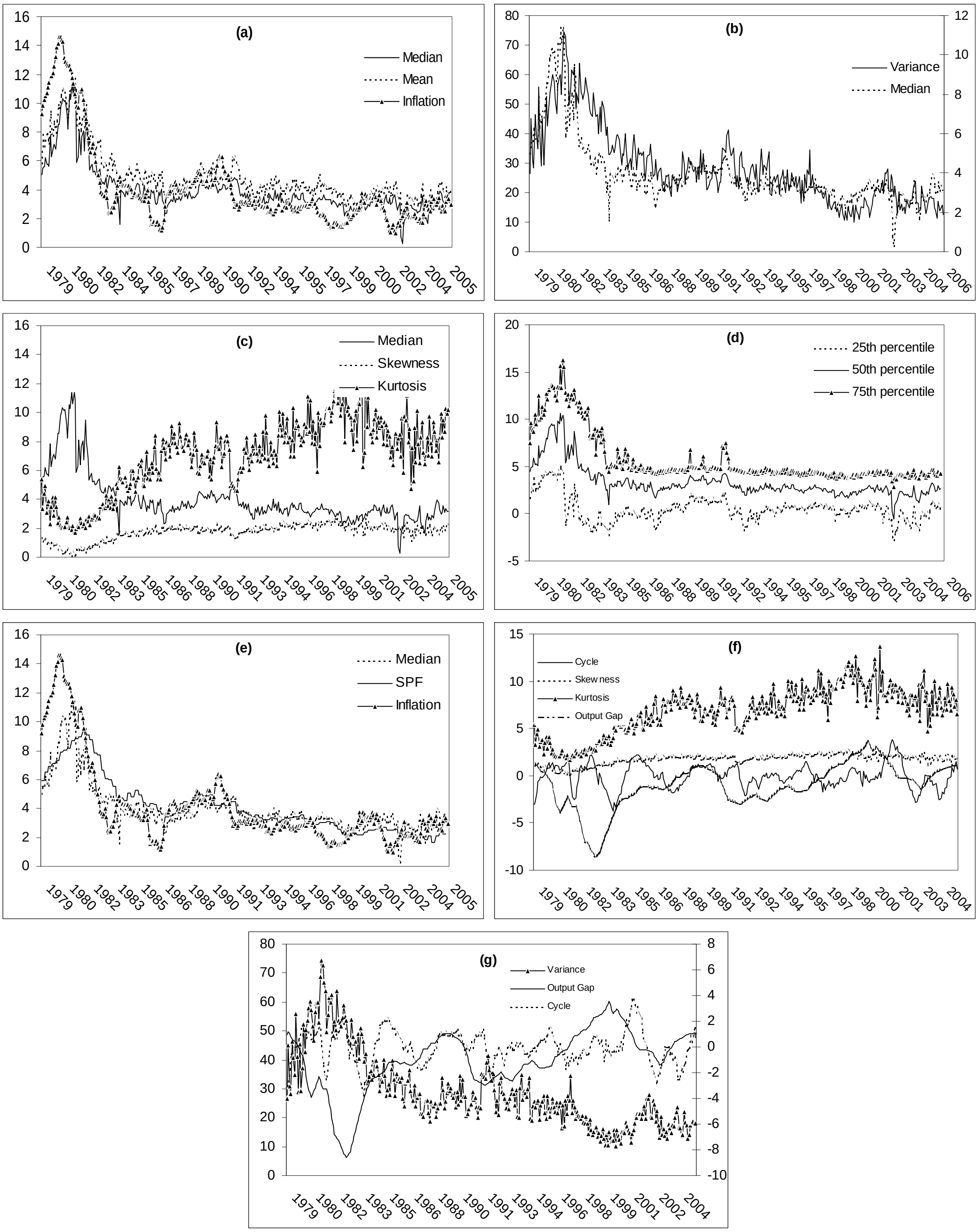
Table 2 focuses on the comparison between the mean and median in terms of prediction accuracy. We report the sum of squared errors (SSE) for each measure of central tendency. It is important to mention that the classification based on the income level has started in October 1979. To allow for comparability between groups, we adjust the index for an average error, in order to account for the time gap. We must bear in mind that, as inflation is higher in the first part of the overall sample, errors are on average higher. Therefore estimates for these groups are likely to be downward biased. Furthermore, we perform a robustness check by splitting the time window into two sub-periods, namely pre- and post-1988. This choice allows us to take into adequate account the highly inflationary period characterizing the first part of the sample and the subsequent disinflation, as it can be observed in Figure 1(a). Table 2 shows that, on average, the median matches actual inflation more closely than the mean. Nonetheless, the mean is a better predictor compared to the median during the high inflation period.

Demographic Group	**Mean**	**Mean SSE**	**Median**	**Median SSE**	**Inflation**
Male	4.28	741	3.8	849	
Female	5.37	1474	4.16	1089	
18-34	5.14	1143	4.16	900	
35-54	4.95	1035	4.09	810	
55+	4.48	1253	3.46	1560	
West	4.91	1021	4.09	834	
North/Centre	4.77	1021	3.9	1030	
North/East	4.82	1115	3.92	1106	
South	4.95	1174	3.94	1033	**4.19**
Bottom Income Level	5.28	1610	3.95	772	
Middle Income Level	4.59	834	3.71	507	
Top Income Level	4.01	431	3.57	392	
HS or less	5.23	1420	3.97	1183	
Some college	4.78	1012	3.96	980	
College degree	4.51	759	4.11	745	
Overall	**4.87**	**1015**	**4.16**	**1089**	

Table 2: Demographic groups, SSEs for mean and median.

The demographic analysis points out that respondents in the top income range are generally more efficient. Gender and education are also proven to be important determinants for the rise of heterogeneous forecasts.[9] Our data show that, for more biased groups, the mean is a better predictor compared to the median, and vice versa. This evidence clearly reflects in the dynamic pattern of the skewness. The forecasting performance of some demographic groups is explored further in the next section, where we consider group-specific inflation data.

[9] We do not deepen the analysis in the case of the regional partition. In this case it would be necessary to take into account the presence of asymmetric shocks within the US.



Figures 1(a)-(g): Empirical moments of the MSHE distribution (realized date).

In Appendix A, Tables A1 and A2 report the empirical moments of the MSHE distribution for the two sub-samples. The analysis shows a lower level of skewness and kurtosis in the first part of the sample, while opposite evidence holds for the variance. The characteristic differences detectable between and within demographic groups generally maintain the same features after the sample is split in pre- and post-1988.

Figure 1(a) plots mean and median against actual inflation.[10] It is evident how both measures of central tendency constantly underestimate the rise in inflation in the first part of the sample, although the forecasting performance improves remarkably during the subsequent disinflation. This improvement is probably due to the credibility that the Federal Reserve (FED) acquired in lowering inflationary pressures. In the post-1988 subsample, expectations appear to be quite stable, although they almost systematically fail to match periods of low inflation. We can also observe how expectations do not match the marked rise in price level during the first Gulf War, by reacting with a consistent delay. This over-reaction is also present after 9/11, but with the opposite sign.

Figures 1(b) and 1(c) plot the dynamics of higher empirical moments against cycle and actual inflation. The cross-sectional variance of inflation expectations exhibits a marked countercyclical behavior, i.e. it increases during recessions and decreases during booms. Opposite evidence holds in the case of skewness and kurtosis.[11] Moreover, these are fairly stable and low during the high inflation period, while they increase and become more volatile in the second part of the sample when inflation stabilizes (opposite evidence holds for the variance). Higher kurtosis and higher positive skewness suggest a higher number of outliers in the right tail of the overall distribution. At a first glance, a higher number of outliers is at odds with a situation of stable inflation. However, it is important to recall that the opportunity cost of being inattentive, or relying on a simple forecasting rule (characterized by a lower degree of accuracy), is higher when inflation is high and highly volatile, rather than in periods when inflation is kept under control. In addition, we argue that in periods of stable inflation there is less media coverage on these issues. This drives up the cost of updating information. We further explore this effect in the remainder as we have data on the share of agents hearing (favorable or unfavorable) news about prices.

Figure 1(e) plots the mean of the MSHE and the mean forecast of the Survey of Professional Forecasters (SPF) against actual inflation. It is striking how the latter, generally more accurate in the second part of the sample, is more biased than the household survey during the period of high inflation. The two predictions are remarkably similar from 1984 to 1990. From this point onward, the SPF seems to provide a more accurate prediction.

3. Group-Specific Inflation and Forecasting Performance

This section is designed to assess which measure of inflation agents consider when they articulate expectations in survey interviews. We evaluate the performance of different demographic groups in forecasting one-year ahead inflation by alternatively assuming group-specific inflation and overall CPI inflation as benchmarks. Bryan and Venkatu (2001a) argue that some agents might use group-specific inflation as a benchmark for their forecasts, and advance this as a possible explanation of the observed differences in inflation expectations across demographic groups. Data on group-specific inflation have only recently been collected for the US, allowing us to perform a comparative study. Our empirical approach allows us to understand whether

[10] All the series describing expectational variables are reported at the realised date.

[11] These results have been confirmed also by regression analysis. See Pfajfar and Santoro (2007).

individuals might be "fooled" by their own experience when forecasting general CPI inflation. The forecast accuracy of each group is evaluated with respect to the inflation rate computed from group-specific CPIs. Socioeconomic indicators affecting the composition of the consumption basket might play an important role in determining the inflation that different individuals perceive. As Valev and Carlson (2003) point out, there are two processes that positively affect the distance between agents' perceived inflation and the percentage change in the official CPI. Inflation increases by more as the composition of consumer-specific consumption basket diverges from the overall one, and as the degree of heterogeneity in individual price changes increases. Although the objective of the Michigan Survey is to collect participants' forecast about changes in the general price level, we believe that some groups produce responses based on their own experience. Agents in this groups do not necessarily consider the overall inflationary dynamics when forecasting. This element is especially relevant in periods of stable inflation, when agents do not update their information set or do not hear any news about inflation. In such circumstances, they necessarily have to rely on their own experience. In the remainder of this section we test our conjecture about the importance of group-specific inflation to explain differences in the sum of squared errors (SSE) across different groups.

Relying on the Consumer Expenditure Survey and on item-specific CPI data, McGranahan and Paulson (2005) calculate monthly chain-weighted inflation measures for thirteen different demographic groups and for the overall urban population from 1982 to 2005. They show that inflation experiences of different groups are highly correlated with (and similar in magnitude to) those of the overall urban population. Nevertheless, the inflation rate for the elderly population is generally higher than the one of the overall urban population. Furthermore, inflation volatility is higher for less advantaged (e.g. elderly, less educated, bottom income level) groups and lower for more advantaged groups. We argue that this effect might result from higher expenditure shares on necessities among less educated agents. In fact, prices of these goods are generally more volatile, especially in the case of food and energy.[12]

It is worth pointing out that it is not possible to employ the whole dataset provided by McGranahan and Paulson (2005) due to a different classification strategy. To make their data compatible with the classification adopted in the Michigan Survey, it is necessary to transform some of their series. McGranahan and Paulson (2005) only consider two categories regarding age, namely elderly and not elderly. In their taxonomy, the elderly population is regarded as 65+. To retrieve an indicator for 55+ CPI inflation, we construct a weighted average of the series for the group-specific inflation of elderly and not elderly agents. Weights are computed by considering the share of population falling in the interval [55, 64] and the overall share of 65+ population, respectively. Data on the demographic structure in the US are obtained from the US Census. We follow a similar approach to obtain price indices comparable to the inflation expectations of our three income classes. McGranahan and Paulson (2005) compute these series for each quartile in the per-capita income distribution. By relying on the evolution of the per-capita income over the period 1981-2004, and in particular on the contribution brought by each

[12] However, this difference in variability is fairly modest. It is found that inflation rate of the least educated is 3.0% more volatile than inflation for all urban households.

quartile in the income terzile, we are able to compute opportune weights for evaluating price indices for top, middle, and bottom income level individuals.

Table 3 shows that, even in the case of group-specific inflation, the median constitutes a better predictor with respect to the mean. In addition, the 50^{th} percentile always lies above the actual average inflation for every group but the elderly respondents. The median seems to be an accurate forecast measure for different groups, especially when agents are classified depending on their educational level. Table 3 reports the SSE for both predictors with respect to the general inflation (SSE_{mean}, SSE_{median}) and to the group-specific inflation measure (SSE^{*}_{mean}, SSE^{*}_{median}).

	Mean	SSE mean	SSE* mean	Median	SSE median	SSE* median	Infl
Age 55+	4.08	587	466	3.07	466	523	3.53
Bottom	5.11	1389	971	3.77	441	413	3.56
Middle	4.33	730	645	3.45	370	350	3.43
Top	3.7	363	445	3.26	295	408	3.4
EHS	4.79	1058	955	3.55	397	415	3.47
ESC	4.23	663	661	3.44	364	441	3.43
ECD	3.89	468	521	3.5	345	460	3.46
Overall							**3.23**

Table 3: Group-specific forecasts based on the mean and the median of the MSHE distribution.

As most of the times the median is found to be a better predictor than the mean, we focus on the description of its predictive power with respect to the general and group-specific inflation. For all the income groups, both SSE^{*}_{median} and SSE_{median} display a declining pattern as the level of economic advantage increases, i.e. an increasing income level is associated to better predictions. It is immediate to verify that SSE^{*}_{median} is lower than SSE_{median} for the bottom and middle income group, while for the top income level SSE_{median} is a better predictor. This signals that wealthy agents are likely to observe the general price level. As to the educational level, the results for the mean are similar to those observed for income classes. Conversely, in the case of the median the SSE^{*}_{median} is always greater than SSE_{median}. As the level of social advantage increases, the forecast accuracy changes in favor of the general index.

A separate digression is in order for the 55+ group. These agents' forecasts are more accurate if we assume that they observe the general inflation. However, this evidence is reversed when assessing the forecast accuracy for the mean. Overall, the mean produces the lowest $SSEs$ if we take into consideration the group-specific inflation. This is in line with the results obtained by McGranahan and Paulson (2005). They find that the eldest group is also the one with the largest deviation of group-specific inflation from overall inflation, as their cumulative inflation is 5% higher than the average inflation.

Generally speaking, our results point out that socioeconomically less advantaged individuals are likely to form inflation expectations assuming as a reference point their specific consumption basket. Conversely, more advantaged classes are less concerned with the inflation computed from their specific price index. They also seem to take into consideration overall inflation dynamics. Therefore, as respondents in the Michigan Survey are asked to forecast changes in the "general" price index, it appears that these agents fully address the question. Even though group-specific inflation cannot entirely explain the differences in the accuracy of predictions, it is proven to be quite important, especially for the bottom income group. Perceived inflation can vary markedly across socioeconomic groups.

In particular, some surveys ask the interviewees to state the actual inflation they perceive, along with inflation forecasts. If we assume that agents forecast based on their perceived inflation, we can compare our results, in terms of difference between group-specific and actual inflation, with the evidence retrievable in these surveys.[13] It turns out that, our results cannot account for the whole bias that is generally observed between perceived an actual inflation, albeit it is quite important for less socially advantaged groups. As to the remaining part of the bias, it is also important to recall that less advantaged groups are likely to be less exposed to news reports about inflation.

4. Asymmetries in the Expectation Formation Process

One of the main tasks of this work is to uncover the mechanism at the root of asymmetries in the expectation formation process. Previous research has advanced different explanations. Souleles (2004) suggests that a wedge between people's expectations may arise due to group-specific shocks. Another wide strand of the literature explores the role of information in consumers' behavior. In fact, individuals might gather their information from local or private sources.[14] Their information set can be affected by a selection bias if they tend to rely on information about the specific industry in which they are employed. These elements might give rise to structural differences in the expectation formation process of respondents located in different industrial districts.

McGranahan and Toussaint-Comeau (2006) also show that individuals form their expectations based on both individual experiences and exposure to news. One of the most important findings is that many agents in the sample report having heard no news. Therefore, they are considerably dependent on their idiosyncratic experiences and perceptions. In general, hearing no news and having a good past year render respondents more optimistic, while hearing no news and having a bad year render respondents more pessimistic.

In this section we implement a number of tests based on percentile time series. We aim at deepening our insight on the informational and operational content of the forecast produced by individuals with different socioeconomic background. Output gap, current inflation, short and long term interest rates carry relevant information for the process of inflation expectations formation. To assess the importance of any diffusion process, we also introduce in the set of regressors the mean forecast retrievable from the SPF.[15] Carroll (2003a, 2003b) designs an epidemiological framework to describe how respondents to the Michigan Survey form their expectations. For this purpose, he models the evolution of inflationary expectations based on

[13] For example, Lindén (2004) reports the statistics for perceived inflation and inflation forecasts in the Euro area.

[14] See, for instance, Dunn and Mirzaie (2006).

[15] This survey is currently conducted by the Federal Reserve Bank of Philadelphia. From 1968 to 1990 NBER and ASA were responsible for its conduction. Before 1981 data exist only for GDP deflator forecasts. We merge the two series in order to fill the gap in the first few years of our sample.

the assumption that households update their information set from news reports. These reports are likely to be influenced by the expectations of professional forecasters. Carroll (2003a, 2003b) finds that the mean of the MSHE distribution has, on average, a mean square error almost twice the one of the SPF. Moreover, SPF inflation expectations are found to Granger-cause household inflation expectations but household expectations do not seem to Granger-cause professional forecasts. However, the diffusion process is slow due to households' inattentiveness.[16] We argue that this process exerts an asymmetric effect on households with different socioeconomic backgrounds.

Time series of percentiles allows us to capture the degree of heterogeneity in different regions of the MSHE distribution. As a first step we need to derive a distribution of responses. Given the nature of the data at hand, interpolation is a convenient way to compute the empirical distribution of responses. As different interpolation techniques and non-parametric estimations deliver very similar results, we rely on an empirical density obtained via linear interpolation. Our methodology is designed to assess the relevance of different theoretical models proposed in the literature, but it is also driven by a practical consideration. The pseudo-panel retrievable from the MSHE is highly unbalanced, as households interviewed change over time. Computing percentiles for each year allows us to obtain a set of time series that carry information about the cross-sectional evolution over time. We regard the expected change in price level in the next 12 months as a random variable, denoted by $\pi_{t+12|t}$. This is assumed to be distributed according to some continuous distribution, $F(\cdot)$. The k^{th} quantile of the distribution, $\pi^k_{t+12|t}$, is the value below which $(100k)\%$ of the distribution lies. Therefore $F(\pi^k_{t+12|t}) = k$. Following this strategy, we can compute a set of ordered statistics for each month, obtaining $99(= k)$ time series of percentiles. Of course, the number of observations in the cross-section varies over time. Given our sample size, at each cut-off, we can be confident that empirical quantiles are good estimates of the population quantiles. For any two sample ordered statistics $\pi^k_{t+12|t}$ and $\pi^{k+h}_{t+12|t}$, the amount of probability in the population distribution contained in the interval $(\pi^k_{t+12|t}\ ,\ \pi^{k+h}_{t+12|t})$ is a random variable, which does not depend on $F(\cdot)$.

We are aware of the methodological limits implicit in our approach, as the survey is not conducted on the same agents for the whole time period. In fact, each household is interviewed only twice. Nevertheless, several empirical (Pfajfar and Santoro, 2007 and Curtin, 2005) and theoretical studies support the view that agents with similar characteristics tend to behave similarly. We find these considerations to be even more appropriate in our case, as we condition the distribution of responses to the socioeconomic background. As a matter of fact, inflation forecasting is common in every-day life and not just when households are asked to provide forecasts. Therefore, we can argue that when one respondent is replaced by another with analogous intrinsic characteristics, his information set is likely to be nested within that of the newcomer. This argument is in line with the structure of overlapping generation models. Strictly speaking, we consider a representative agent for each percentile. Therefore our approach does not allow individuals to switch across percentiles. Branch (2004, 2007) provides some support

[16] Also Pesaran and Weale (2006) point out that, even if the expectations of professional forecasters were rational, households' expectations would adapt slowly.

for time varying degrees of heterogeneity. Although we find traces of this switching in our data, it occurs only at a small scale. We acknowledge that these limitations are rather important. Nevertheless, we think that it is still possible to retrieve some valuable information about the inflation expectation process by exploiting the logitudinal dimension of the data at hand.

4.1. Tests for Rational Expectations. The rational expectations hypothesis (REH) can be interestingly tested with survey expectations data[17] to determine different degrees of forecast efficiency. To satisfy the REH, the forecasting procedure should not yield predictable errors. A test of bias can be applied by regressing the expectation error of each percentile on a constant.[18] This allows us to verify whether inflation expectations are centred around the right value:

$$\pi_t - \pi^k_{t|t-12} = \alpha + \varepsilon_t, \tag{1}$$

where π_t is inflation at time t and $\pi^k_{t|t-12}$ is the k^{th} percentile from the MSHE. The following regression represents a second test for rationality:

$$\pi_t = a + b\pi^k_{t|t-12} + \varepsilon_t, \tag{2}$$

where rationality implies that conditions $a = 0$ and $b = 1$ are jointly satisfied. Equation (2) can be simply augmented to test whether available information is fully exploited:

$$\pi_t - \pi^k_{t|t-12} = a + (b-1)\,\pi^k_{t|t-12} + \varepsilon_t. \tag{3}$$

Under the null of rationality, these regressions are meant to have no predictive power.[19]

4.2. Sticky Information.

Testing for Sticky Information. As explained before, the updating frequency can vary considerably across different socioeconomic groups. We estimate a simple regression introduced in Carroll (2003a), to investigate the relevance of a static sticky information model for the whole cross-sectional spectrum:

$$\pi^k_{t|t-12} = \lambda_1 \pi^s_{t|t-12} + (1-\lambda_1)\,\pi^k_{t-1|t-13} + \varepsilon_t. \tag{4}$$

As Carroll (2003a) points out, news about inflation spread slowly across agents, reaching only a fraction λ_1 of the population in each period. The model is estimated under the assumption that coefficients sum up to 1, although this restriction is not likely to be satisfied across all percentiles.[20]

[17] See Pesaran (1987); Mankiw, Reis, and Wolfers (2004); and Bakhshi and Yates (1998) for a review of these tests.

[18] See, for an application, Jonung and Laidler (1988) and Mankiw, Reis, and Wolfers (2004).

[19] An alternative test for rationality takes into account that inflation and inflation expectation data are I(1). The REH suggests that these series cointegrate, i.e. expectations errors are stationary. Moreover, the cointegrating vector has no constant terms and the coefficients on expected and actual inflation should be equal in absolute value (Bakhshi and Yates, 1998).

[20] It should be pointed out that this model is derived under the following assumptions: (i) inflation follows a

4.3. Estimating Simple Learning Rules. Our analysis then moves on to assess the importance of adaptive behavior. Different learning rules are considered in order to test whether agents' expectations converge toward rational expectations (perfect foresight). For a comprehensive discussion on different learning rules and convergence to rational expectations see Evans and Honkapohja (2001). The following regression model is equivalent to an adaptive expectations formula:

$$\pi^k_{t|t-12} = \pi^k_{t-13|t-25} + \vartheta \left(\pi_{t-13} - \pi^k_{t-13|t-25}\right) + \varepsilon_t, \tag{5}$$

where ϑ is the constant gain (CG) parameter. Under this learning rule, agents revise their expectations according to the error of the last realized forecast. As interviewees are asked to forecast inflation for the next year (hence they make their forecast at time $t-12$), the revision will be based on the previous period's forecast, which has been carried out at time $t-25$.

The following formula represents an adaptive mechanism featuring a decreasing gain (DG) parameter:

$$\pi^k_{t|t-12} = \pi^k_{t-13|t-25} + \frac{\iota}{t} \left(\pi_{t-13} - \pi^k_{t-13|t-25}\right) + \varepsilon_t. \tag{6}$$

The empirical approach consists of the estimation of ϑ and ι. If the estimated parameters turn out to be significantly different from 0, then we could conclude that agents actually update their forecasts with respect to past mistakes.

Recursive Representation of Simple Learning Rules. The above specifications are designed to test for the existence of adaptive behavior. In the adaptive learning literature, it is assumed that agents behave like econometricians using all the available information at the time of the forecast. We now specify a recursive model of adaptive learning. In this version, we test if agents update their coefficients with respect to the last observed error. We assume that agents have the following perceived law of motion (PLM):[21]

$$\pi^s_{t|t-12} = \phi_{0,t-1} + \phi_{1,t-1}\pi_{t-13} + \varepsilon_t. \tag{7}$$

When agents estimate their PLM, they exploit all the available information up to period $t-1$. As new data become available, they update their estimates according to a constant gain learning (CGL) rule or a decreasing gain learning (DGL) rule. First, we focus on stochastic gradient learning and then on least squares learning, both under CG or DG. Let X_t and $\widehat{\phi}_t$ be the following vectors: $X_t = \begin{pmatrix} 1 & \pi_t \end{pmatrix}$ and $\widehat{\phi}_t = \begin{pmatrix} \phi_{0,t} & \phi_{1,t} \end{pmatrix}'$. When agents rely on stochastic gradient learning, they update coefficients according to the following rule (see Evans, Honkapohja and Williams, 2005):

$$\widehat{\phi}_t = \widehat{\phi}_{t-1} + \vartheta X'_{t-25}\left(\pi_{t-12} - X_{t-25}\widehat{\phi}_{t-13}\right). \tag{8}$$

In the updating algorithm for DGL, we just replace ϑ with $\frac{\iota}{t}$.[22] Therefore we find ϑ and ι that

random walk process; (ii) $\pi^k_{t|t-13} \approx \pi^k_{t-1|t-13}$ (see Döpke et al., 2006a).

[21] In the remainder of the paper we analyse several different PLMs.

[22] This is always the case when applying DGL.

minimize the sum of squared errors (SSE), i.e. $\left(\pi^s_{t|t-12} - \pi^k_{t|t-12}\right)^2$.

The drawback implicit in this approach is that we have tu assume initial values of $\widehat{\phi}_t$ for 12 periods. When we recursively estimate learning, the main difficulty is how to set initial values. This is extensively discussed in Carceles-Poveda and Giannitsarou (2007). Strictly speaking, this problem should not occur in our case since we simply try to replicate our time series data as closely as possible. Thus, we design an exercise in order to search for the best combination of gain and initial values to match each percentile.[23] This strategy can also be regarded as a test for learning dynamics. If the gain is found to be positive under this method of initialization, then the series would exhibit learning for all other initialization methods with a higher (or equal) gain.

4.4. "General" Models of Expectation Formation. We also estimate some more general models of expectations formation to consider the macroeconomic factors likely to affect inflation forecast. The first model investigates which variables agents take into account when forecasting inflation. We also estimate some more general models of expectations formation. The first model investigates which variables agents take into account when forecasting inflation. We specify the following percentile regression:

$$\begin{aligned} \pi^k_{t|t-12} &= \alpha + \sum_i \gamma_i \pi_{t-i} + \sum_i \beta_i y_{t-i} + \mu i_{t-24} + \delta r_{t-24} + \zeta \pi^k_{t-1|t-13} + \eta \pi^F_{t|t-12} + \varepsilon_t, \\ k &= 1, ..., 99; \qquad i = 12, 14, 24, 30. \end{aligned} \tag{9}$$

We denote with $\pi^k_{t|t-12}$ the k^{th} percentile of the 12 months ahead expected change in prices, while $\pi^F_{t|t-12}$ denotes the mean of the 12 months ahead expected change in prices derived from the SPF. Furthermore, y_t denotes the cycle indicator (detrended industrial production index [IPI]), π_t is actual inflation, i_t is the real short term interest rate (3 months t-bill coupon rate), r_t is the long term interest rate (10 years t-bond yield).

In order to capture the determinants of monthly changes in inflation expectations, the following percentile time series regression is specified:

$$\begin{aligned} \pi^k_{t|t-12} - \pi^k_{t-13|t-25} &= \alpha + \sum_i \beta_i \left(\pi_{t-i} - \pi^k_{t-i|t-i-12}\right) \\ &\quad + \sum_j \psi_j \left(\pi^k_{t-j|t-j-12} - \pi^k_{t-j-12|t-j-24}\right) + \boldsymbol{\gamma}\boldsymbol{\Delta}\mathbf{X}_t + \varepsilon_t, \qquad (10) \\ k &= 1, ..., 99; \qquad i = 13, 14; \qquad j = 1, 2, \\ \mathbf{X}_t &= \begin{bmatrix} y_t & i_t & r_t & (i_{t-1} - r_{t-1}) & \pi^F_{t|t-12} \end{bmatrix}' \end{aligned}$$

where the operator Δ denotes the difference between the current value of the variable and its

[23] However, this approach has an obvious practical inconvenience, as running a grid search on several variables is computationally very intensive.

lagged (13 periods backwards) counterpart.

To further investigate the nature of the forecast error, we estimate model (11). Evidence of serial correlation in the forecast error process indicates that there is an inefficient exploitation of information from last year's forecast, thus violating the RE hypothesis. We also include the SPF forecast error in the set of regressors:

$$\begin{aligned} \pi_t - \pi^k_{t|t-12} &= \alpha + \beta\left(\pi_{t-13} - \pi^k_{t-13|t-25}\right) + \delta(\pi_t - \pi^F_{t|t-12}) + \boldsymbol{\gamma}\boldsymbol{\Delta}\mathbf{X}_t + \varepsilon_t, \\ k &= 1, ..., 99; \qquad \mathbf{X}_t = \begin{bmatrix} y_t & \pi_t & (i_t - r_t) \end{bmatrix}'. \end{aligned} \tag{11}$$

Model (11) is similar to the regression in Mankiw, Reis, and Wolfers (2004) and in Ball and Croushore (2003). In their regression, the forecast error is regressed on the levels of the variables we introduce in the set of regressors. However, our model features past errors and changes in the relevant regressors as determinants of the current forecast error.

4.5. Results. We first consider the results for the overall population of respondents. These constitute a useful benchmark to compare the results obtained for different demographic groups.

group	α=0 (1%)	α=0 (5%)	a=0,b=1	CGL*	CGL peak	mCGL coef.	DGL*	DGL peak	mDGL coef.
male	55-58	54-58	never	44-99	75 (37%)	62 (0.50)	42-94	76 (77%)	77 (37)
female	50-53	50-53	never	42-97	71 (34%)	58 (0.37)	43-87	68 (69%)	70 (30)
18-34	51-54	50-54	never	36-97	66 (39%)	55 (0.53)	36-87	68 (72%)	70 (32)
35-54	51-54	51-54	never	40-98	72 (38%)	57 (0.47)	40-92	70 (72%)	72 (33)
55-97	57-60	56-60	never	54-98	78 (27%)	78 (0.35)	52-94	76 (57%)	79 (36)
West	51-54	51-54	never	39-98	62 (39%)	55 (0.56)	39-92	70 (74%)	71 (35)
Nort-centr.	53-56	52-56	never	44-98	76 (30%)	61 (0.40)	44-90	72 (60%)	73 (34)
Northeast	53-56	52-56	never	42-98	64 (34%)	60 (0.50)	43-91	70 (59%)	75 (33)
South	53-55	52-56	never	42-98	73 (35%)	59 (0.40)	43-90	72 (65%)	73 (32)
Bottom	49-52	48-53	never	60-97	71 (26%)	72 (0.29)	17-31, 58-95	67 (50%)	64 (39)
Middle	52-55	51-55	never	48-98	75 (38%)	77 (0.33)	14-33, 57-97	71 (65%)	62 (47)
Top	54-57	53-58	never	50-99	81 (43%)	58 (0.51)	12-34, 54-98	76 (71%)	61 (51)
HS or less	52-55	51-55	never	48-96	73 (30%)	73 (0.31)	47-89	71 (66%)	72 (32)
Some coll.	53-55	52-56	never	40-98	72 (35%)	57 (0.53)	40-91	73 (67%)	74 (33)
Coll. degree	52-54	51-55	never	35-99	64 (43%)	56 (0.60)	35-94	73 (74%)	75 (36)
Overall sample	52-53	51-55	never	44-98	74 (35%)	59 (0.42)	42-90	72 (75%)	73 (33)

* R^2 above 5%

Table 4: Tests for rationality and learning.

It turns out that the most interesting insights arise when respondents are classified depending on their income level. Therefore, in the remainder we devote particular attention to the influence of individuals' wealth on their process of expectation formation. Table 4 presents the results from rationality and learning tests. In the first two columns we report the results of the test for bias (1), while in the third one we present the results for the second test for rationality, outlined in equation (3). The next three columns report the results of the test for adaptive behavior with CG, while the last three columns refer to the same test under DG. Table 4 also reports the range of percentiles for which the variance of the explanatory variable (past forecast error) explains more than 5% of the variance of the dependent variable. In the middle column we also report the highest R^2 and the percentile in correspondence of which this is achieved. The last column reports the percentile with the highest gain, both under CG and DG, and the corresponding gain.

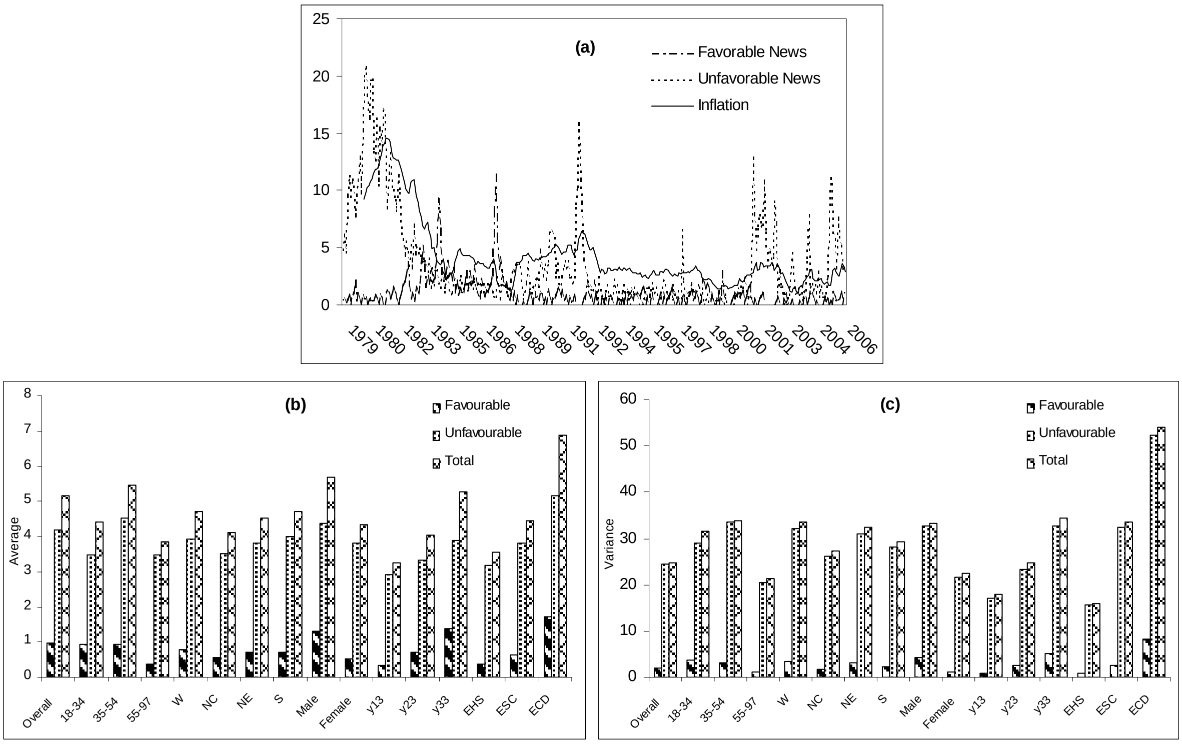
It is interesting to outline the results obtained from models (9)-(11).[24] These provide important information about the information structure underlying the process of expectation formation. We assess the relevance of each regressor depending on the value of the associated partial correlation coefficient. The general features outlined for the overall sample are generally preserved at a more disaggregated level. Nevertheless, some quantitative differences among groups can be detected. As mentioned, model (9) aims at explaining how one-year-ahead inflation expectations are made. The model reported in (10) is designed to explain the determinants of the change in forecasts, whereas model (11) provides a deeper understanding of the determinants of forecast errors. As to the latter, evidence of serial correlation in the forecast error process indicates an inefficient exploitation of information from last year's forecast. This violates the REH. Our results suggest that agents on the LHS are static or highly autoregressive. The middle range is characterized by nearly rational agents, while on the RHS of the distribution, agents behave in accordance with adaptive learning and sticky information. The latter generally react too pessimistically to changes in contemporaneous inflation.

Figures 4(a)-(o) report, for every percentile of each demographic group, the inverse of the estimated parameter λ_1 from model (4). This provides us with an estimate of the average updating period. Generally speaking, our estimates confirm the existence of static behavior in the information structure up to the 40^{th} percentile for all demographic groups. From this point up to the 91^{st} percentile, we can detect the presence of a U-shaped pattern of the average updating frequency, with a minimum occurring around the 50^{th} percentile. For agents in the middle part of the distribution the average updating period is around $6 - 12$ months. Figures 2(a)-(c) allow for a comparison, in terms of SSEs, between different demographic groups.

The interviewees of the Survey of Consumer Attitudes and Behavior are also asked whether they have heard of different favorable or unfavorable changes in business conditions in the past month. From these data we can also retrieve the percentage of agents that have heard any news about prices. Special attention has to be paid when interpreting the informational content of the data on news. In fact, the share of respondents hearing news about business conditions can be viewed as a proxy for the amount of business information released by the media. Moreover, it can also be interpreted as an indicator on how agents actually perceive the importance of these news. Figure 2(a) plots the dynamic path of the flow of favorable and unfavorable news about prices observed by respondents against actual inflation, while Figures 2(b) and 2(c) report the time average and the variance for each demographic subgroup, respectively. As to the overall share of agents hearing news about prices, we can observe sudden shifts in periods when inflation abruptly changes, especially to higher levels. On average, 5.2% of agents have heard news about prices in each month. Nonetheless, significant differences emerge among the demographic groups

[24] For the overall sample, these are reported in Appendix B. Results for demographic subgroups are available upon request from the authors.

considered in this study.



Figures 2(a)-(c): Favorable and unfavorable news about prices.

Another question is in order at this stage. Do agents have a different perception when hearing news? To address this question, it can be noticed that the level of favorable news is almost constantly below the level of unfavorable ones. The share of respondents hearing unfavorable news is far more volatile, displaying a number of peaks in correspondence to sudden rises in inflation. This evidence of asymmetry is in line with the prospect theory advanced by Kahneman and Tversky (1979).[25] Furthermore, as expected, the percentage of agents hearing favorable news is negatively (but weakly) correlated with positive changes in inflation while the evidence is reversed when considering the share of respondents hearing bad news. This evidence carries an important informational content, as it indicates how agents pay attention to news about inflation mostly during adverse periods, characterized by high and volatile inflation. Conversely, general or specialized media coverage is somewhat disregarded in times of stable and low inflation. Based on German data, Lamla and Rupprecht (2007) disentangle two possible channels of influence from media to households' expectations. They argue that volume of news improves the accuracy of forecasts. However, they acknowledge that reports can contain opinions that are likely to bias households' expectations.

Curtin (2005) suggests that less advantaged groups face higher costs of collecting and processing information. Thus, they less frequently update their information set and they exhibit greater heterogeneity in forecasts. To study the incentives to gather and process information,

[25] Curtin (2005) finds similar evidence when comparing the change in inflation forecasts between the first and second interview in episodes of rising and falling inflation.

the European Commission has designed a survey that collects information about households' future consumption plans (house, car) along with inflation expectations. Lindén (2004) shows that inflation expectations of agents that plan to buy a house or a car are lower. Therefore he argues that incentives to collect information matter when forming expectations.[26]

The results of the recursive estimation for adaptive learning for the overall sample are reported in Appendix B. These suggest that agents on the RHS of the distribution tend to behave in an adaptive manner, whereas agents on the LHS do not exhibit such behavior. In particular, agents between the 65^{th} and 98^{th} percentile behave in accordance with the CG version of gradient learning. The estimated gain, plotted in Figure B5, follows a hump-shaped pattern reaching a peak at 2.1×10^{-4}. This maximum is located between the 71^{st} and 73^{rd} percentile. The DG version of gradient learning exhibit similar characteristics to CG version. To compare both versions of gradient learning, we plot their SSEs in Figure B7. Our results suggest that the CG version of gradient learning generally provides a better description of agents' behavior, especially around the 70^{th} percentile.

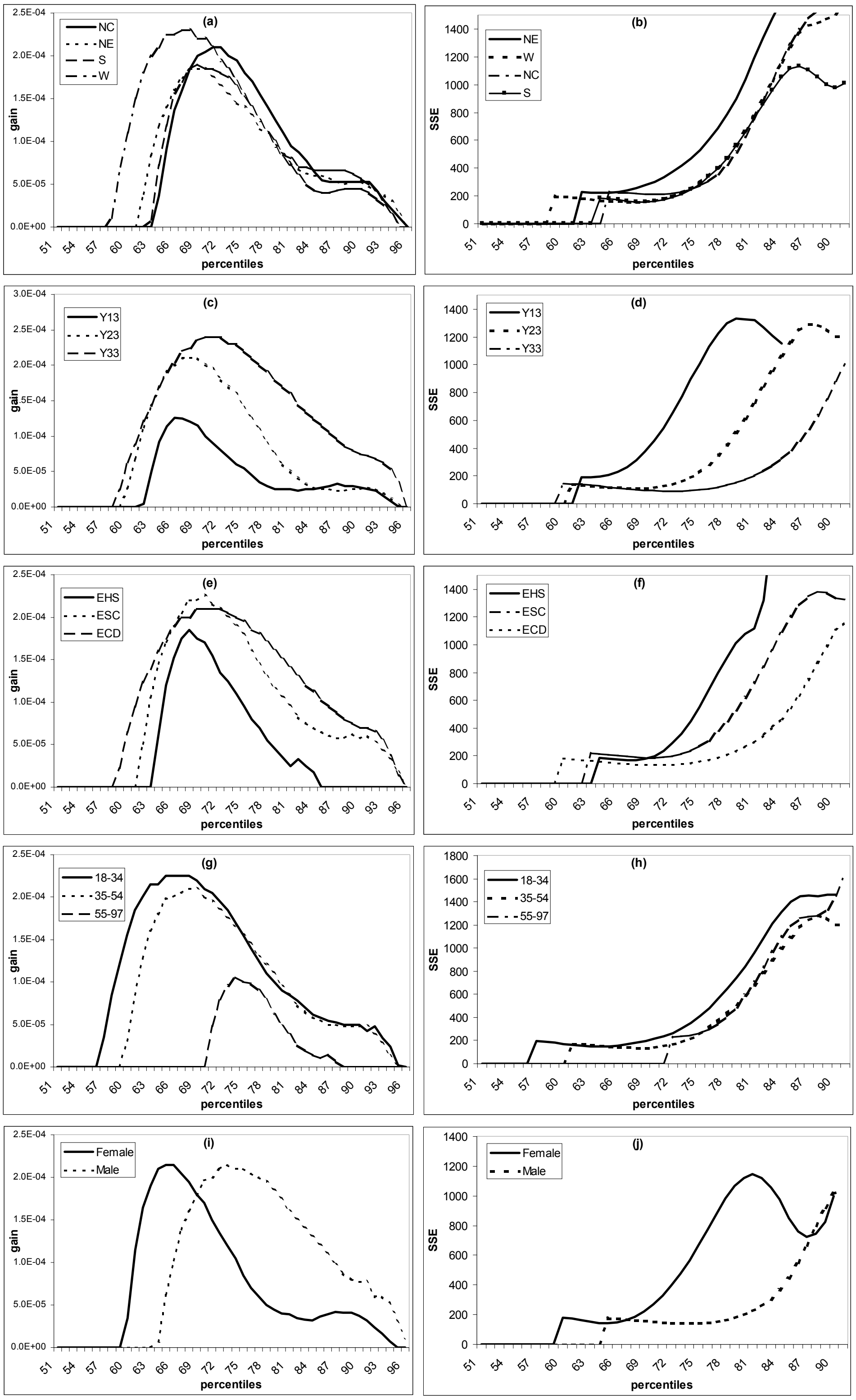
Orphanides and Williams (2005a) suggest a value of gain coefficient between 0.01 and 0.04, whereas Milani (2007) obtains an estimate of 0.0183. Relying on experimental data, Pfajfar and Žakelj (2007) find that most of the gains are in the range $0.01 - 0.07$. They estimate an average gain of 0.041 with standard deviation of 0.047. Our estimates are significantly smaller. A partial explanation we can point to is that previous estimates are obtained with quarterly data, while our data have a monthly frequency. An estimate of 0.02 with quarterly data suggests that agents rely on 12.5 years of data. At the same time, an estimate of 2.1×10^{-4} with monthly data implies that agents roughly use 400 years of data. However, we only regard these estimates as the lower bound of the gain coefficient.

Gender. The results obtained from the sticky information model suggest that, on average, women on the RHS update information more frequently than their male counterparts [see Figures 4(a) and 4(b)]. However, a closer look at the SSEs suggests that this model performs better for male respondents [see Figure 5(a)]. Figures 2(b) and 2(c) show that male respondents entail both higher average and variance in the perception of favorable and unfavorable news, compared to the female population. Agents on the RHS are also associated with adaptive behavior. On average, a higher proportion of female agents behave in this fashion. Nevertheless, the gain is usually higher for the male population. The adaptive process better reflects male respondents' forecasts, except for agents up to the 67^{th} percentile [see Figure 3(j)].

As suggested by model (9), current inflation accounts for most of the variability in the forecast of male respondents. The associated coefficient follows a monotonically increasing pattern up to the 95^{th} percentile. Furthermore, the autoregressive term exerts a greater impact for men, even at higher percentiles. As to women, actual inflation looses importance in favour of the SPF forecast around the 65^{th} percentile. This evidence signals that women in the upper end of the distribution may rely less on their own past forecasts. Model (11) shows that men's

[26] It is worth pointing out that it is more likely that highly educated and wealthy households are those who make these investments. Therefore, it is necessary to analyse these results within demographic groups.

forecast errors on the RHS are better described by changes in actual inflation. At the same time, SPF forecast errors acquire greater importance around the median of the distribution. The general fit of the model is better for men, especially in the RHS.



Figures 3(a)-(j): Constant Gain learning across demographic groups. Gain parameter (left panels) and SSE (right panels).

As there are considerable differences in the forecasting performance of men and women, it would be helpful to access data on inflation experienced by different genders. These would allow us to evaluate to what extent these differences can be ascribed to different inflation perceptions. Jonung (1981) puts forward an argument about differences in the accuracy of inflation forecasts between men and women. He points out that men and women have different expenditure habits and that women are usually responsible for day-to-day shopping. As the Food and Beverage component of the CPI has been rising faster than the overall CPI during the early 1980s, he argues that this phenomenon is at the root of the observed discrepancies. We assess the relevance of this explanation in our data. We find that SSE_{median} is lower when we take into account the Food and Beverage CPI, although this is also the case for men. Otherwise, SSE_{mean} is always higher if we take into account Food and Beverage CPI. Therefore, we cannot confirm the conjecture advanced by Jonung (1981). Bryan and Venkatu (2001b) report that there are differences in the perception of inflation between women and men, although these differences are not high enough to explain the large gap persistently observed in survey data.[27] We also examine other possible explanations. In particular, does the fact that women read newspapers less often help at describing the observed pattern?[28] Overall, this conjecture finds little support in our data, as women behave less in accordance with the sticky information model. Also Lamla and Rupprecht (2007) find that there is little evidence of asymmetries across gender regarding the impact of media on inflation expectations.

Age. The sticky information model suggests that older respondents (55+) update their information set more regularly than younger respondents (18-34) [see Figures 4(c)-(e)]. Nevertheless, the middle age group (35-54) displays the lowest SSE. Compared to the other subgroups, medium aged respondents are significantly more associated with this root of heterogeneity. Figures 2(b) and 2(c) show that medium aged respondents entail both higher average and variance in the perception of favorable and unfavorable news compared to younger and older agents. On the one hand, it is striking how the share of elderly respondents hearing news about prices is, on average, very low. On the other hand, the share of people within this subgroup hearing unfavorable news is similar to the one in the younger group. This evidence might signal a higher degree of pessimism among older respondents. Such an attitude actually shows up in the data at different stages of the analysis. A marked difference in the adaptive behavior is detectable in Figures 3(g) and 3(h), as only agents between the 69^{th} and 88^{th} percentile appear to learn in the group 55-97. Furthermore, their gains are notably different from those of the other two age subgroups. However, young agents learn between the 55^{th} and 99^{th} percentile. From the 65^{th} percentile onward this model performs worse for younger agents compared to other age subgroups [see Figure 3(h)].

As to the macroeconomic determinants of the process of expectation formation, model (9) points out a homogeneous impact of inflation for younger people in the middle range of responses.

[27] Bryan and Venkatu (2001b) find that disagreement in expectations might be due to both different shopping habits and to the fact that less women observe official statistics compared to men. However, none of these observations can explain large differences in survey data.

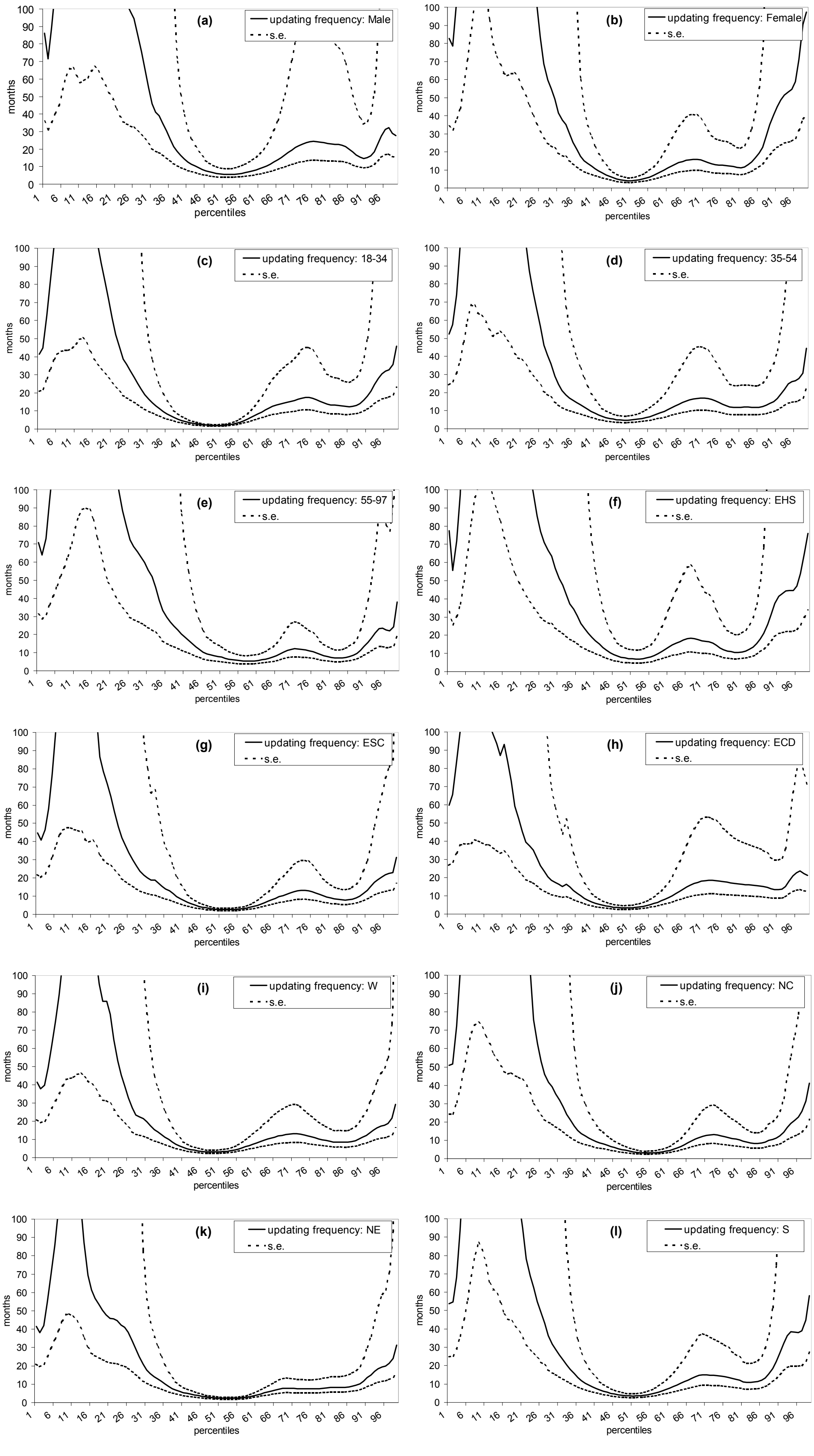
[28] This fact is generally observed in polls about the demographic structure of newspaper readers.

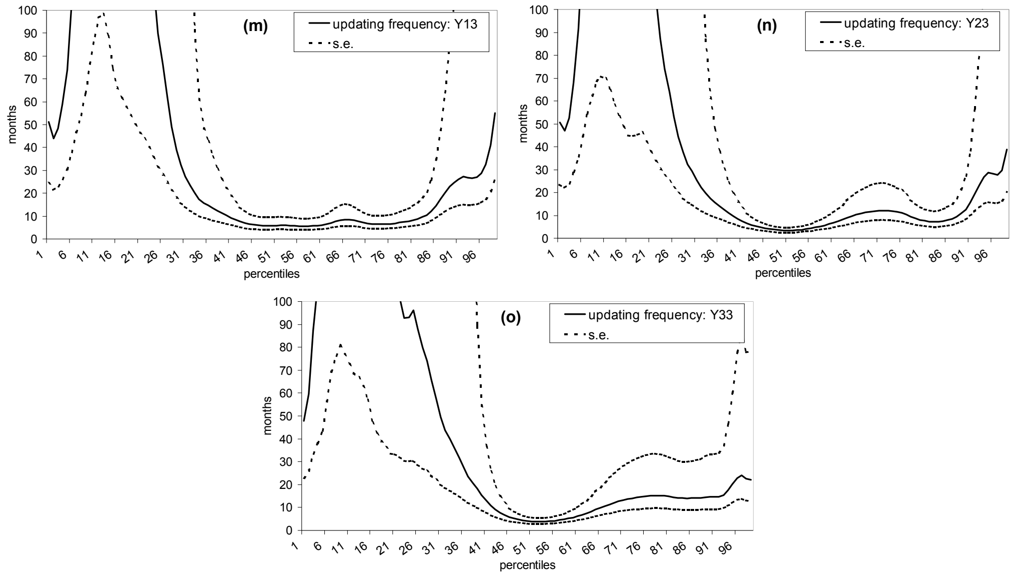
This regressor acquires more importance for elderly respondents at higher percentiles. Younger people also rely less on their autoregressive term and more on the SPF forecast. Overall, there are many similarities in the explanatory power of these regressors for the first two classes (18-34, 35-54). Elderly respondents's forecast errors seem to depend less on changes in actual inflation and to be more correlated with the contemporaneous SPF forecast error. This finding can be due to the fact that US pensions are indexed to inflation. Thus, elderly agents are more exposed to information about actual inflation. Here we also take into account that elderly respondents entail a different expenditure pattern compared to that of the younger population. As a matter of fact, they are likely to allocate a higher share of their expenditure on health care. Curtin (2005) suggests that both the oldest and the youngest subgroup display greater heterogeneity in forecasts than the middle age subgroup. However, Lamla and Rupprecht (2007) argues that older population is less exposed to media bias.

Location. Previous empirical studies on the determinants of inflation expectations have posed little or no attention on the role of agents' location for their forecasts. One of the possible objections to this view arises from the possibility that individuals place a consistent weight on their own experience. For example, Dunn and Mirzaie (2006) calculate manufacturing employment concentration as a proxy to measure agents' private information. They use this measure to explain regional variations in consumers' confidence. They base their analysis on the conjecture that information about a particular manufacturing sector may be better known to the local population. For example, layoffs in a particular industry may be more visible and have a bigger impact on agents who are closer to the industry itself. These households may perceive an earlier or even a different signal of change on which to base their assessments of future economic trends.

One interesting finding is that agents living in the NE of the US seem to update their information set more regularly, compared to agents in the rest of the country. This evidence might constitute a further confirmation of the thesis advanced by Dunn and Mirzaie (2006). In fact, people located in the manufacturing belt (NE of the US) might be more exposed to the flow of information about the manufacturing sector. Nevertheless, in this case the sticky information model does not account for the main features of the expectation formation process. At the same time, the adaptive learning model performs worse in the case of agents from the NE with respect to other regional subgroups. The gain in the adaptive learning rule seems to follow similar patterns for all agents on the RHS of their respective distributions [see Figures 3(a) and 3(b)]. Nevertheless, we find that agents living in the W of the US are more associated with adaptive learning compared to other subgroups. Within this subgroup, only agents between the 57^{th} and 99^{th} percentile learn.

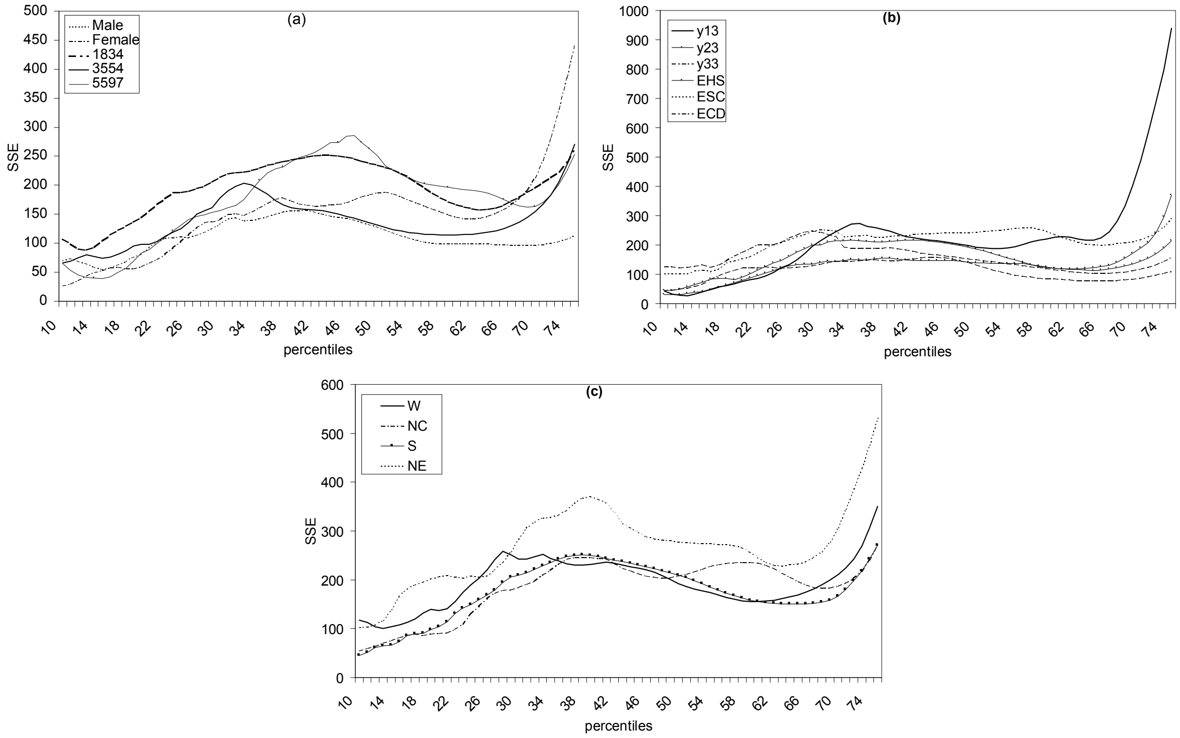
Models (9)-(11) do not point at any major difference across the US territory. Nevertheless, as in the test for sticky information, model (9) shows that forecasts produced by NE agents are more influenced by the SPF component. Moreover, model (11) shows that the forecast errors of W and S agents on the RHS are more associated with changes in actual inflation.


(a)
updating frequency: Male
s.e.
(b)
updating frequency: Female
s.e.
(c)
updating frequency: 18-34
s.e.
(d)
updating frequency: 35-54
s.e.
(e)
updating frequency: 55-97
s.e.
(f)
updating frequency: EHS
s.e.
(g)
updating frequency: ESC
s.e.
(h)
updating frequency: ECD
s.e.
(i)
updating frequency: W
s.e.
(j)
updating frequency: NC
s.e.
(k)
updating frequency: NE
s.e.
(l)
updating frequency: S
s.e.
months
percentiles



Figures 4(a)-(o): Sticky information model across demographic groups.

Income. We recall that responses coded depending on the income classification have been sampled from 1979 onwards. Therefore results about this group are not entirely comparable to the ones regarding other socioeconomic categories. Income classification probably represents the most important demographic characteristic when forecasting inflation. This is especially evident from the analysis of the adaptive learning. Figures 3(c) and 3(d) show that model (7) delivers a highly heterogeneous picture as we move across income groups. On the one hand, it appears that a consistent number of agents learn in the least advantaged group. Nonetheless, within this range the model produces higher SSEs. We argue that low income agents possibly have to fill a higher gap, in terms of predictive accuracy, before their expectations converge to unbiased inflation forecast. On the other hand, respondents in the highest income group achieve a higher gain compared to their less economically advantaged counterparts. Furthermore, adaptive behavior seems to provide a more reasonable explanation for the behavior of this class of agents. In fact, within this subgroup, model (7) produces lower SSEs for a wide range of the distribution on the RHS. Similar evidence arises from the implementation of the sticky information model (4) as, on average, low income agents update their information set more frequently than higher income agents. Nevertheless, they still have "a lot of work" to catch up with the performance of more advantaged groups [see Figure 3(d)]. Approximately 68% of high income agents report hearing news about business conditions, while only 44% of the poorer households report hearing any news about business conditions on average in each quarter. Figures 2(b) and 2(c) show the emergence of a clear pattern in the average and variance of the share of agents hearing news about prices. Both moments increase as the level of economic disadvantage decreases. It is natural to expect that, on average, a higher proportion of wealthy agents hear news about prices compared to more economically disadvantaged agents. It is interesting to notice that the volatility increases in the degree of economic advantage. This can confirm the presence of a rational inattention mechanism at work. In fact, albeit richer interviewees produce better forecasts, at the same time they tend to adapt quickly to the arrival of new information, especially when this signals negative projections about prices.



Figures 5(a)-(c): Sticky information model across demographic groups (SSE).

Percentile regressions reported in equations (9)-(11) deliver the most interesting results. In particular, model (11) shows that the top income group entails a considerable degree of rationality. Moreover, agents classified within this category are possibly even better forecasters than their professional counterparts in the SPF. In addition, the autoregressive component gradually loses importance as we move from the bottom income level to the top one. Model (11) also shows how top income agents' forecast errors are just described by changes in actual inflation after the 70^{th} percentile, while in the middle range these are mainly accounted for by SPF forecast errors. The area in this range of response follows a clear hump-shaped pattern. We have to point out that results from (11) for this subgroup are significantly different from those obtained for other groups. High income agents really stand out in their forecasting performance, and according to Curtin (2005) they exhibit less heterogeneity than other income groups. These results are probably driven by differences in expenditure patterns across different income subgroups. As a matter of fact, poorer households tend to spend a higher proportion of their income for food and housing. Indeed, in Section 3 we report that especially low income households might rely on their group-specific inflation when forecasting. Richest respondents also achieve the best fit for model (9), meaning that relevant macroeconomic determinants are exploited in order to produce forecasts.

Education. Results for income and educational groups are usually highly correlated in demographic studies. However, compared to the evidence reported in the previous section, conclusions from the analysis based on agents classified in educational subgroups are partly reversed. In terms of forecast accuracy, less educated respondents perform significantly worse than agents classified in more advantaged groups. Additionally, less educated agents also achieve lower gains under the adaptive learning scheme. Only agents above the 62^{nd} percentile bahave in line with adaptive learning [see Figures 3(a) and 3(f)]. Agents with some college education or with a college degree perform similarly, although more agents seem to learn in the latter class. On average, agents with some college education are the ones who most frequently update their information set. Nevertheless, they produce higher SSEs compared to other groups [see Figures 4(f)-4(h) and 5(a)-5(c)]. In addition, 72% of college graduates report hearing news about current business conditions while only 38% of agents with high school or less education hear this sort of news in every quarter. We then consider the share of agents hearing news on prices. As for the case of population grouped depending on the income level, also in this case we can detect effects correlated with the level of socioeconomic disadvantage.

There are no major differences between the two higher levels of education when analyzing the general models of expectation formation (9)-(11). As to individuals comprised in the category "High School or Less", we observe how the autoregressive component gains high importance at higher percentiles. Model (11) clearly shows that the forecast errors of more educated respondents are just described by changes in actual inflation after the 70^{th} percentile, while in the middle range these are mainly accounted for by SPF forecast errors. Generally, one could argue that agents with higher education might be more interested in inflation reports in the newspapers. Souleles (2004) suggests that less educated agents might be disproportionately adversely affected during contractionary episodes, while Curtin (2005) advances that the cost of collecting and processing information declines as education increases. Curtin (2005) also points out that the average change in inflation expectations in the lowest educational subgroup is almost three times larger than the average one when comparing inflation forecasts in the first and second interview. This element can be advanced as an explanation of the joint observation that the least educated agents update their information set quite frequently and that the sticky information model does not perform well in explaining their expectation formation process.

5. Concluding Remarks

This paper establishes new stylized facts about the process of inflation expectation formation across different socioeconomic subgroups. The interest in this fundamental process arises from the consideration that different demographic groups entail different degrees of access and different capacities to process the relevant information. Gathering information is generally considered a costly task, and some agents might be constrained to rely on simpler rules to form their own predictions about future inflation because of their socioeconomic background.

In line with Pfajfar and Santoro (2007), we confirm that, for every socioeconomic group, agents positioned around the center of the distribution behave in line with the REH and that agents on the LHS of the median are highly autoregressive. Furthermore, it can be argued that inflation expectations of these left-of-centre agents are stable around some focal points (digit preference) and that they simply do not observe movements in any of the relevant macroeconomic drivers. In contrast, on the RHS of the distribution, agents are generally too pessimistic and usually tend to overpredict actual inflation. As noted above, these RHS agents' inflation expectations are more consistent with adaptive behavior (learning), although their speed of learning can vary significantly. Furthermore, we argue that they exhibit some features pointed out by recent advances in the macroeconomic and financial literature on inattentiveness and rationally heterogeneous expectations models.

Our percentile time series models confirm a significant degree of asymmetry in the expectation formation process across demographic groups.[29] Income, gender and education seem to be particularly important characteristics when forecasting inflation. In particular, high income, male, and highly educated agents produce lower mean squared errors. Not surprisingly, agents classified in the less educated and in the bottom income subgroups attain the highest level of biasedness.

Expectations formed by least educated agents seem to be less compatible with adaptive learning, which could help them in the future to reduce their bias. Otherwise, the gain parameter in adaptive learning is found to be higher for the groups that generally produce higher forecast errors. Within these subgroups, people on the RHS of the distribution also update their information set at least as regularly as more advantaged groups. Nevertheless, the sticky information model might not explain their true underlying forecasting model to the same extent as for their more advantaged counterparts.

Overall, our evidence seems to point out that socioeconomically less advantaged individuals are likely to form inflation expectations assuming as a reference point their specific consumption basket, as they achieve a higher predictive accuracy with respect to their group-specific inflation. Conversely, more advantaged classes seem to observe overall inflation dynamics when forecasting inflation. This aspect has a clear implication for monetary policy making, especially for central banks pursuing inflation targeting. If this institutions want to maximize the effectiveness of their monetary policy, the general prescription is to allocate more time for the communication of the inflation target (forecasts). They especially have to make sure that less advantaged socioeconomic groups understand the qualitative (in terms of composition of the CPI) and the quantitative features of their objective.

[29] Similar results have been pointed out in analyses on consumer sentiment indices. McGranahan and Toussaint-Comeau (2006) highlight significant differences regarding educational attainment and gender and find that these differences are constant over time.

References

Bakhshi, H., and A. Yates (1998): "Are U.K. Inflation Expectations Rational?," Discussion Paper 81, Bank of England Working Paper.

Ball, L., and D. Croushore (2003): "Expectations and the Effects of Monetary Policy," *Journal of Money, Credit and Banking*, 35(4), 473–484.

Branch, W. A. (2004): "The Theory of Rationally Heterogeneous Expectations: Evidence from Survey Data on Inflation Expectations," *Economic Journal*, 114(497), 592–621.

——— (2007): "Sticky information and model uncertainty in survey data on inflation expectations," *Journal of Economic Dynamics and Control*, 31(1), 245–276.

Branch, W. A., and B. McGough (2007): "Replicator Dynamics in a Cobweb Model with Rationally Heterogeneous Expectations," *Journal of Economic Behavior and Organization*, forthcoming.

Brock, W. A., and C. H. Hommes (1997): "A Rational Route to Randomness," *Econometrica*, 65(5), 1059–1096.

Bryan, M. F., and G. Venkatu (2001a): "The demographics of inflation opinion surveys," *Economic Commentary*, (Oct 15).

——— (2001b): "The curiously different inflation perspectives of men and women," *Economic Commentary*, (Nov).

Carceles-Poveda, E., and C. Giannitsarou (2007): "Adaptive learning in practice," *Journal of Economic Dynamics and Control*, 31, in press.

Carroll, C. D. (2003a): "Macroeconomic Expectations Of Households and Professional Forecasters," *The Quarterly Journal of Economics*, 118(1), 269–298.

——— (2003b): "The Epidemiology of Macroeconomic Expectations," NBER Working Papers 8695, National Bureau of Economic Research, Inc.

Curtin, R. (1996): "Procedure to estimate price expectations," Mimeo, University of Michigan.

——— (2005): "Inflation Expectations: Theoretical Models and Empirical Tests," Mimeo, University of Michigan.

Dominitz, J., and C. F. Manski (2005): "Measuring and Interpreting Expectations of Equity Returns," NBER Working Papers 11313, National Bureau of Economic Research, Inc.

Dunn, L. F., and I. A. Mirzaie (2006): "Turns in Consumer Confidence: An Information Advantage Linked to Manufacturing," *Economic Inquiry*, 44(2), 343–351.

Döpke, J., J. Dovern, U. Fritsche, and J. Slacalek (2006a): "The Dynamics of European Inflation Expectations," Discussion Papers of DIW Berlin 571, DIW Berlin, German Institute for Economic Research.

Evans, G. W., and S. Honkapohja (2001): *Learning and Expectations in Macroeconomics.* Princeton University Press.

Evans, G. W., S. Honkapohja, and N. Williams (2005): "Generalized Stochastic Gradient Learning," NBER Technical Working Papers 0317, National Bureau of Economic Research.

Fishe, R. P. H., and T. L. Idson (1990): "Information-Induced Heteroscedasticity in Price Expectations Data," *The Review of Economics and Statistics*, 72(2), 304–12.

Granato, J., M. Lo, and M. C. S. Wong (2004): "The Diffusion of Inflation Expectations: Theory and Evidence," *SSRN eLibrary.*

Hicks, J. R. (1939): *Value and Capital.* Oxford University Press, New York.

Jonung, L. (1981): "Perceived and Expected Rates of Inflation in Sweden," *American Economic Review*, 71(5), 961–68.

Jonung, L., and D. Laidler (1988): "Are Perceptions of Inflation Rational? Some Evidence for Sweden," *American Economic Review*, 78(5), 1080–87.

Kahneman, D., and A. Tversky (1979): "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47(2), 263–91.

Lamla, M. J., and S. M. Rupprecht (2007): "The Role of Media for Consumers' Inflation Expectation Formation," Mimeo, KOF, ETH Zurich.

Lindén, S. (2004): "Quantified perceived and expected inflation in the Euro Area - How incentives improve consumers inflation forecasts," Mimeo, European Commision.

Maital, S., and S. Maital (1981): "Individual-rational and group-rational inflation expectations: Theory and cross-section evidence," *Journal of Economic Behavior and Organization*, 2(2), 179–186.

Mankiw, N. G., and R. Reis (2002): "Sticky Information Versus Sticky Prices: A Proposal To Replace The New Keynesian Phillips Curve," *The Quarterly Journal of Economics*, 117(4), 1295–1328.

Mankiw, N. G., R. Reis, and J. Wolfers (2004): "Disagreement about Inflation Expectations," *NBER Macroeconomics Annual 2003*, 18, 209–248.

McGranahan, L., and A. Paulson (2005): "The incidence of inflation: inflation experiences by demographic group: 1981-2004," Working Paper Series WP-05-20, Federal Reserve Bank of Chicago.

McGranahan, L., and M. Toussaint-Comeau (2006): "Variations in consumer sentiment across demographic groups," *Economic Perspectives*, (Q I), 19–38.

Milani, F. (2007): "Expectations, learning and macroeconomic persistence," *Journal of Monetary Economics*, 54(7), 2065–2082.

Orphanides, A., and J. C. Williams (2003): "Imperfect Knowledge, Inflation Expectations, and Monetary Policy," NBER Working Papers 9884, National Bureau of Economic Research, Inc.

——— (2005a): "The decline of activist stabilization policy: Natural rate misperceptions, learning, and expectations," *Journal of Economic Dynamics and Control*, 29(11), 1927–1950.

——— (2005b): "Inflation scares and forecast-based monetary policy," *Review of Economic Dynamics*, 8(2), 498–527.

Palmqvist, S., and L. Strömberg (2004): "HouseholdsŠ inflation opinions Ű a tale of two surveys," *Sveriges Riksbank Economic Review*, 4, 23–42.

Pesaran, M. H. (1985): "Formation of Inflation Expectations in British Manufacturing Industries," *Economic Journal*, 95(380), 948–75.

Pesaran, M. H. (1987): *The Limits to Rational Expectations*. Basil Blackwell, Oxford, reprinted with corrections 1989 edn.

Pesaran, M. H., and M. Weale (2006): "Survey Expectations," in *Handbook of Economic Forecasting*, ed. by G. Elliott, C. W. Granger, and A. Timmermann. North-Holland, Amsterdam.

Pfajfar, D. (2007): "Formation of Rationally Heterogeneous Expectations," Mimeo, University of Cambridge.

Pfajfar, D., and E. Santoro (2007): "Heterogeneity and Learning in Inflation Expectation Formation: An Empirical Assessment," Mimeo, University of Cambridge.

Pfajfar, D., and B. Žakelj (2007): "Experimental Evidence on Inflation Expectation Formation," Mimeo, University of Cambridge and Universitat Pompeu Fabra.

Sims, C. A. (2003): "Implications of rational inattention," *Journal of Monetary Economics*, 50(3), 665–690.

——— (2006): "Rational inattention: Research agenda," Mimeo, University of Princeton.

Souleles, N. S. (2004): "Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys," *Journal of Money, Credit and Banking*, 36(1), 39–72.

Valev, N. T., and J. A. Carlson (2003): "Sources of dispersion in consumer inflation forecasts," *Applied Economics Letters*, 10(2), 77–81, available at http://ideas.repec.org/a/taf/apeclt/v10y2003i2p77-81.html.

6. Tables and Figures

Table A1: Demographic groups and empirical moments (pre-1988).

Demographic Group	Mean	Median	Variance	Int. Range	Skew	Kurt	Inflation
Male	5.64	5.05	29.7	5.77	1.41	6.38	
Female	6.65	5.15	46.6	7.58	1.18	4.02	
18-34	6.78	5.56	40.5	6.48	1.25	4.57	
35-54	6.41	5.37	37.8	6.36	1.32	5.19	
55+	5.27	4	37.2	6.37	1.4	5.32	
West	6.33	5.4	37.2	6.43	1.26	5.15	
North/Centre	6	4.92	37.9	6.39	1.36	5.19	
North/East	6.27	5.13	40.3	6.75	1.27	4.69	
South	6.18	4.99	40.7	6.58	1.32	4.81	**6.2**
Bottom Income Level	6.12	4.46	48.6	7.8	1.22	4.02	
Middle Income Level	5.7	4.6	37.2	6.27	1.46	5.49	
Top Income Level	5.28	4.73	28.9	5.7	1.48	6.6	
HS or less	6.29	4.77	45.4	7.19	1.25	4.24	
Some college	6.08	5.11	35.7	6.18	1.34	5.34	
College degree	6.12	5.71	28.2	5.38	1.3	6.19	
Overall	**6.18**	**5.15**	**39.3**	**7.58**	**1.33**	**4.96**	

Table A2: Demographic groups and empirical moments (post-1988).

Demographic Group	Mean	Median	Variance	Int. Range	Skew	Kurt	Inflation
Male	3.36	2.94	14.5	3.54	2.05	10.26	
Female	4.5	3.49	27	4.17	1.78	6.68	
18-34	4.03	3.21	22	3.89	1.91	7.85	
35-54	3.95	3.22	20.7	3.76	1.99	8.42	
55+	3.94	3.09	22	3.9	1.88	7.65	
West	3.94	3.19	20.3	3.83	1.85	7.74	
North/Centre	3.93	3.21	20.6	3.7	1.98	8.39	
North/East	3.84	3.09	21.2	3.96	1.84	7.79	
South	4.11	3.22	23.1	3.91	1.89	7.5	**2.98**
Bottom Income Level	4.81	3.65	29.9	4.7	1.57	5.69	
Middle Income Level	3.95	3.2	20.8	3.82	1.98	8.43	
Top Income Level	3.27	2.9	13.6	3.48	2.13	11.02	
HS or less	4.51	3.42	27.6	4.24	1.72	6.31	
Some college	3.89	3.18	20.1	3.81	1.88	8.08	
College degree	3.42	3.03	14.5	3.51	2.12	10.82	
Overall	**3.98**	**3.49**	**21.6**	**4.17**	**2.01**	**8.35**	

7. Appendix B: General models of expectation formation

Table B1: Percentile Time Series Regression - Model 1.

Percentile	α	Inflation	Cycle	AR(1)	Tbond Rate	Adj R^2	DW	LM
5	-0.095	-0.011	0.105	0.661	-0.006	0.591	1.865	3.419
	-1.126	-0.446	3.864	14.812	-0.142			
	0.000	0.001	0.093	0.502	0.001			
20	0.127	0.008	0.039	0.825	-0.011	0.784	2.108	1.241
	1.954	0.382	2.238	25.629	-0.361			
	0.000	0.013	0.024	0.758	-0.008			
35	0.414	0.112	0.079	0.692	-0.055	0.811	2.086	10.782
	4.119	3.464	3.067	16.277	-1.224			
	0.000	0.208	0.030	0.631	-0.055			
50	0.644	0.142	0.053	0.642	0.029	0.884	2.090	1.600
	5.454	4.041	2.100	14.244	0.624			
	0.000	0.234	0.009	0.614	0.027			
65	0.597	0.141	0.014	0.767	-0.002	0.960	2.201	5.630
	5.679	4.617	0.725	20.205	-0.064			
	0.000	0.195	0.001	0.766	-0.002			
80	0.830	0.222	-0.018	0.575	0.267	0.926	2.170	20.817
	5.356	4.669	-0.495	12.411	3.711			
	0.000	0.213	-0.001	0.557	0.158			
95	4.923	0.310	-0.113	0.379	0.728	0.885	2.073	5.272
	10.517	4.296	-1.833	7.054	5.675			
	0.000	0.216	-0.002	0.352	0.321			

first row: coefficient value; second row: t-test; third row: parcial contributions to R^2

Table B2: Percentile Time Series Regression - Model 2.

Percentile	α	ΔInflation	AR(1)	AR(2)	ΔCycle	ΔSPF Forecast	Adj R^2	DW	LM
5	0.022	-0.006	0.025	0.050	0.818	-0.014	0.744	2.002	1.547
	0.371	-0.559	0.424	2.688	13.819	-0.336			
	0.000	0.000	0.018	0.055	0.679	-0.003			
20	0.080	-0.031	0.083	0.033	0.832	-0.031	0.857	1.959	5.297
	2.076	-3.377	1.419	2.818	14.711	-1.080			
	0.000	0.019	0.066	0.027	0.749	-0.002			
35	0.044	-0.030	0.176	0.039	0.721	0.075	0.787	1.988	0.298
	0.934	-1.791	2.973	2.302	12.517	1.529			
	0.000	-0.005	0.131	0.029	0.609	0.026			
50	-0.009	-0.016	0.210	0.032	0.733	0.073	0.819	2.037	5.649
	-0.258	-0.713	3.508	1.813	12.993	1.407			
	0.000	-0.008	0.160	0.016	0.633	0.021			
65	-0.033	-0.021	0.222	0.011	0.749	0.111	0.892	1.996	4.886
	-1.001	-0.930	3.676	0.849	13.373	2.326			
	0.000	-0.014	0.178	0.005	0.674	0.051			
80	0.435	0.181	0.211	0.029	0.553	0.088	0.794	1.906	9.318
	3.305	3.656	3.532	1.193	9.566	1.050			
	0.000	0.155	0.155	0.007	0.457	0.024			
95	2.593	0.247	0.204	0.015	0.435	0.206	0.729	2.019	3.854
	4.738	4.835	3.605	0.370	7.712	1.665			
	0.000	0.199	0.150	0.002	0.349	0.033			

first row: coefficient value; second row: t-test; third row: parcial contributions to R2

Table B3: Percentile Time Series Regression - Model 3.

Percentile	α	AR(1)	Hor. Spread	ΔCycle	SPF Forcast Err.	ΔInflation	Adj R^2	DW	LM
5	0.725	0.831	-0.212	-0.012	0.411	0.569	0.913	0.877	96.006
	5.767	31.100	-9.282	-0.350	7.493	9.843			
	0.000	0.739	0.001	0.001	0.161	0.012			
20	0.377	0.882	-0.110	0.039	0.292	0.545	0.878	0.484	177.147
	3.598	28.692	-5.047	1.232	6.058	10.199			
	0.000	0.749	-0.005	-0.004	0.131	0.008			
35	0.536	0.714	-0.130	0.055	0.235	0.530	0.737	0.662	141.077
	5.703	15.311	-4.847	1.431	3.631	7.897			
	0.000	0.484	-0.005	-0.007	0.148	0.121			
50	0.098	0.213	-0.034	0.060	0.493	0.174	0.620	0.526	168.881
	1.984	3.634	-1.333	1.652	6.884	2.503			
	0.000	0.099	-0.004	-0.014	0.449	0.097			
65	-0.888	0.219	-0.006	0.056	0.254	0.428	0.751	0.534	167.783
	-14.176	5.284	-0.327	2.103	5.494	10.620			
	0.000	0.070	-0.001	-0.019	0.268	0.437			
80	-1.958	0.236	0.000	0.011	0.057	0.815	0.703	0.884	100.847
	-16.617	6.523	-0.003	0.252	1.076	17.487			
	0.000	0.047	0.000	-0.003	0.033	0.630			
95	-7.060	0.326	0.047	0.108	-0.321	1.240	0.619	1.112	67.128
	-16.674	8.625	1.007	1.583	-3.972	17.933			
	0.000	0.115	0.005	-0.011	-0.087	0.603			

first row: coefficient value; second row: t-test; third row: parcial contributions to R2

Figure B1: Percentile Time Series Regression - Model 1 (Partial R^2).

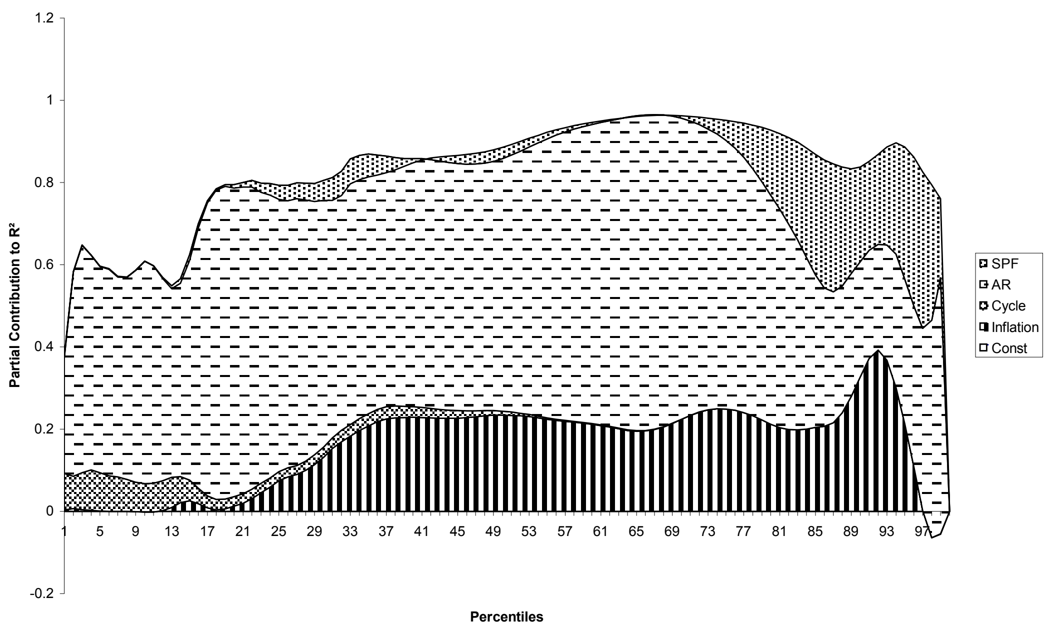


Figure B2: Percentiles Time Series Regression - Model 2 (Partial R^2).

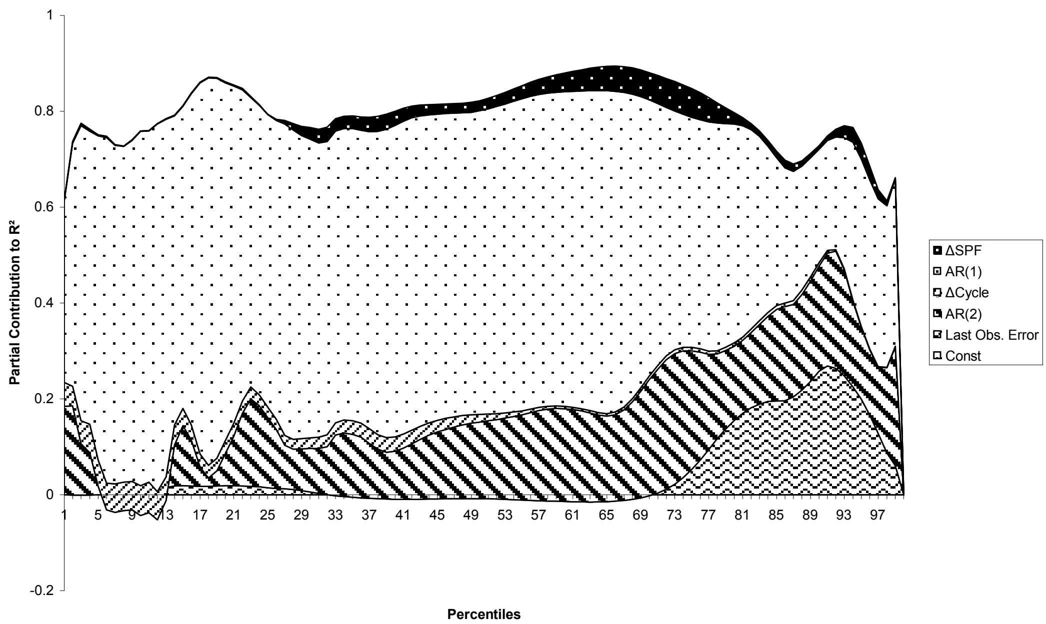


Figure B3: Percentiles Time Series Regression - Model 3 (Partial R^2).

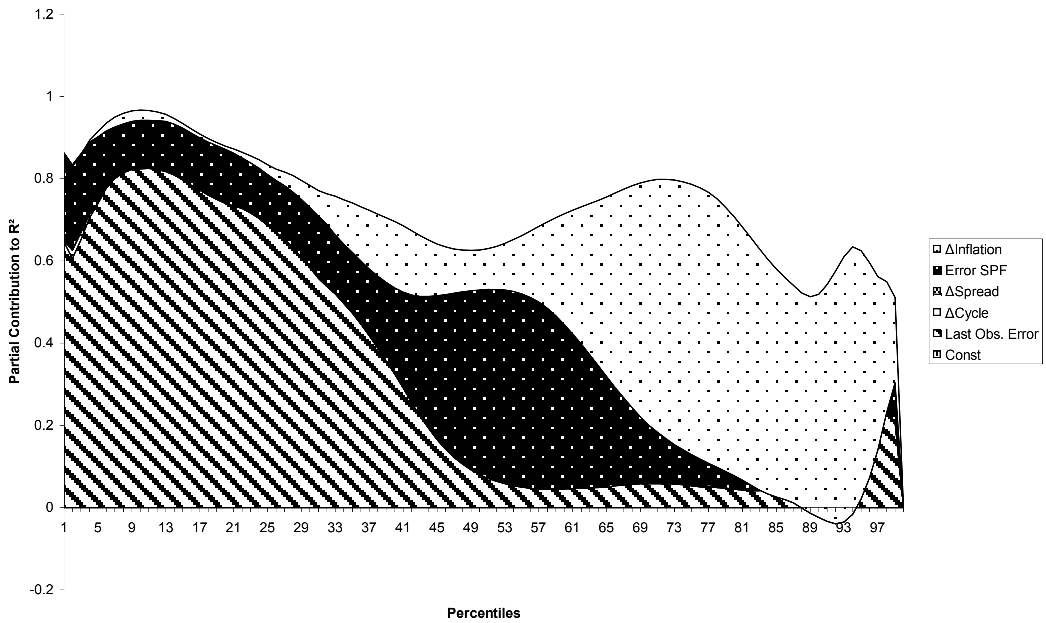
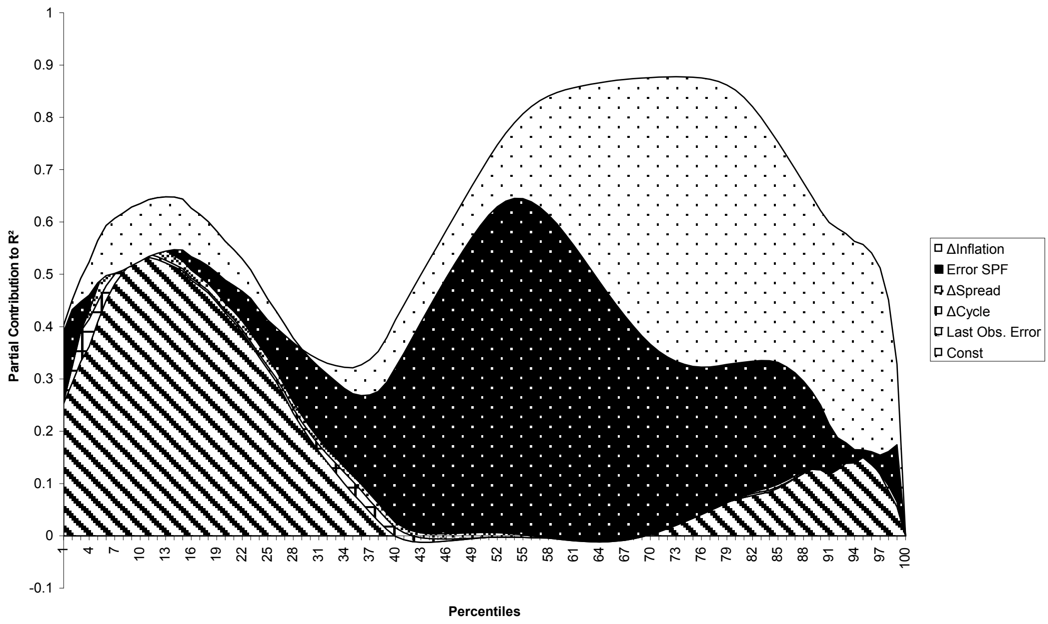
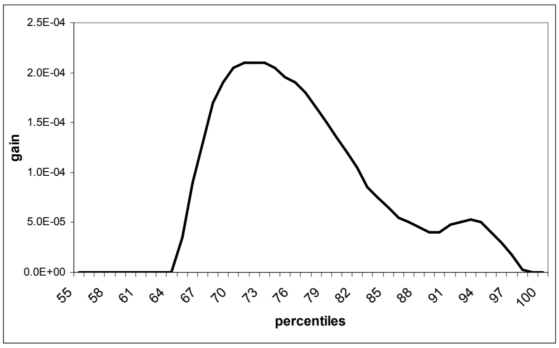


Figure B4: Percentiles Time Series Regression - Model 3: High Income subgroup (Partial R^2).



Figures B5 and B6: First model with recursive representation-CGL (left) and DGL (right) (PLM only considers current inflation).



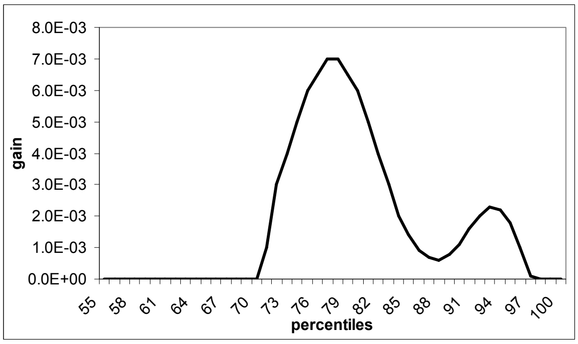


Figure B7: First model with recursive representation-comparison between CGL and DGL (PLM only considers current inflation).