DISAGREEMENT IN CONSUMER INFLATION EXPECTATIONS*

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Abstract

By carefully matching the datasets from the Michigan Survey of Consumers with the

Survey of Professional Forecasters, we show that there exists substantial heterogeneity

in the propensity of U.S. households to learn from experts in forming inflation expec-

tations. Additional results for a group of European economies broadly confirm this

observation. We advance an extended version of the sticky-information model in or-

der to analyse disagreement in consumer inflation expectations. Besides differences in

consumers' propensities to learn, disagreement in our model arises from heterogeneity

in consumers' fundamental inflation and past expectations and experts' different views

about future inflation.

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1 Introduction

Disagreement about expectations of the public matters. Recent advances in macroeconomics have emphasized the role of disagreement in signaling upcoming structural changes in the economy (Mankiw, et al., 2004), and as a proxy for uncertainty in driving business cycle fluctuations (Bloom, 2009). Yet, why ordinary people disagree in their expectations, and how best to model this heterogeneity, remains an open question. We answer this question by matching household and expert inflation expectations and by building a theory of consumer expectation updating.

Our theory has three key elements. First, consumers hold different beliefs about price changes, gained from personal experiences on shopping and the previous inflation rates experienced in their lifetime. Second, consumers obtain from experts public information about the trends in future inflation via newspapers and social media. Consumers are not constrained to rely on consensus expert forecasts, but are allowed to learn from different individual expert forecasts instead. Third, households can have different propensities to learn from experts. Consumers then combine public and private information in forming their inflation expectations.

The ingredients of our theory are motivated by the empirical findings. Our primary database of household forecasts comes from the Michigan Survey of Consumers that contains both quantitative and qualitative inflation expectations. We use both forms of expectations to estimate the central tendency and dispersion among consumers and in particular, quantify the qualitative responses following the probability method. By carefully matching the database of consumer expectations with that of experts from the U.S. Survey of Professional Forecasters, we find that inflation expectations between laymen and experts differ persistently from each other. It is consistent with the results reported in the literature that households – in contrast to experts – pay close attention to salient price changes, such as

oil and food prices; see, e.g. Coibion and Gorodnichenko (2015b), Berge (2018) and Binder (2018). By contrast, experts respond more to monetary policy and macro indicators. We also observe substantially higher levels of disagreement among the public than disagreement among professional forecasters that is reflected in the opinions voiced in media outlets.

Our model is closely related to the theoretical literature on expectations formation with information frictions. For instance, Mankiw and Reis (2002) propose the sticky-information model that explains agents' rational inattention in terms of limited resources and the cost of updating information sets. Carroll (2003) develops an epidemiological model of expectations formation that can be viewed as providing microfoundations for the Mankiw-Reis model. Our model differs from the sticky-information model in an important aspect. Disagreement in Carroll (2003)'s model, or in sticky-information model in general, arises only from different generations of consumers using different information vintages and there is no disagreement within a generation. In contrast, our model generates disagreement within a generation due to consumers' exposure to different expert views about inflation even under full information updating. Sims (2003), Woodford (2003) and Mackowiak and Wiederholt (2009) advocate the noisy information model that emphasizes the limited ability of economic agents to process new information from noisy signals. In contrast to the noisy-information model where agents always solve a signal extraction problem, households in our model observe different views of experts and use these views as direct inputs in forming their expectations. Importantly, households are allowed to differ from each other in terms of their propensities to learn from experts.

Our paper builds on the burgeoning literature exploring cross-sectional distribution of forecasts. One strand of the literature examines the disagreement among professional forecasters; see, e.g. Lahiri and Sheng (2008), Capistran and Timmermann (2009), Patton and

¹It should be noted that in another version of his study, Carroll (2006) mentions the possibility of heterogenous propensities to learn.

Timmermann (2010), Dovern, et al. (2012), Andrade and Le Bihan (2013), Dovern (2015) and Andrade, et al. (2016).² In contrast to these studies, our paper focuses on the disagreement among household expectations and is more closely related to a second strand of literature relying on consumer and business surveys to explore heterogeneity in expectations. For example, household inflation expectations from the Michigan Survey of Consumers are found to vary by gender, education levels, or age cohorts; see, e.g. Souleles (2004), Bruine de Bruin, et al. (2010), and Malmendier and Nagel (2016). Branch (2004) estimates a model in which consumers rationally choose from a set of predictors by evaluating costs and benefits of each predictor and shows that such a model is consistent with the response behavior of consumers. Drager and Lamla (2017a) explore disagreement among the general pubic in a multivariate context and find that disagreement on the interest rate is mainly driven by disagreement on inflation.

The basic structure of our model is similar to Lahiri and Sheng (2008) and Lamla and Maag (2012), but differs in two important aspects. First, consumers in our model observe and directly use experts' views about inflation in forming their expectations, rather than proactively estimate the rational forecast of inflation from noisy signals reported in the media. This assumption is supported by the evidence collected from dozens of surveys from the 1950s to 2014 in Binder (2017) that documents a lack of public awareness of the Federal Reserve and its objectives, and reasons for consumers' inattention to monetary policy. Second, besides estimating various model implications, we perform a battery of tests – both in sample and out of sample – that allow us to gauge the importance of each channel in

²Using expert forecasts from Consensus Economics, Lahiri and Sheng (2008) find that differential interpretation of public information explains most of forecast disagreement as forecast horizon gets shorter; Patton and Timmermann (2010) emphasize the role of heterogeneity in priors in explaining disagreement; and Dovern, et al. (2012) investigate determinants of disagreement about six key economic indicators in G7 countries. Using inflation forecasts from U.S. Survey of Professional Forecasters (SPF), Capistran and Timmermann (2009) offer a simple explanation of disagreement based on asymmetries in the forecasters' costs of over- and under-predicting inflation. Using the ECB SPF forecasts at the micro level, Andrade and Le Bihan (2013) find that forecasters fail to systematically update their forecasts and disagree even when updating. Dovern (2015) and Andrade, et al. (2016) analyze forecast disagreement in a multivariate context.

explaining household disagreement in their inflation expectations.

The main contribution of our study is the finding that there exists large cross-sectional heterogeneity in the propensity of households to follow expert forecasts. Our findings suggest that about 55-70% of US households adjust their expectations towards expert forecasts and the rest of households adjust their views in the direction opposite to experts. Regarding the average propensity of households to learn from experts, our empirical estimates show that before the global financial crisis this propensity was approximately 0.15-0.20, implying economically significant degrees of information rigidity among the public. This magnitude is broadly similar to those reported in the literature; see, e.g. Mankiw and Reis (2002), Carroll (2003), Coibion and Gorodnichenko (2012), and Hur and Kim (2017). Interestingly, taking into account changes in the formation of household expectations over time we show that since 2007 the propensity to learn has become statistically insignificant. It does not necessarily mean that households have stopped paying attention to expert forecasts, but rather it can suggest that the fraction of households whose expectations go in the same direction of expert forecasts have become very similar to the fraction of households revising their expectations in the opposite direction to experts. Regarding another source of household forecast disagreement – heterogeneity of expert forecasts, however, we do not find robust supporting evidence. Thus, it remains an open question about whether households update their expectations based on the consensus forecasts or divergent forecasts of experts.

The above findings are mostly confirmed in our additional analysis conducted with the use of data from selected European economies, including Germany, Spain, France, Italy, Netherlands and UK. The propensities of European and US consumers to learn from experts are on average similar to each other, and estimates of this learning parameter for individual European economies are broadly consistent with those reported in the literature (Döpke et al., 2008). Interestingly, since the global financial crisis European consumers have intensified their learning from experts, which contradicts the US evidence. Heterogeneity of the

propensity to learn across European consumers is smaller but displays more variations over time than in the US case.

The rest of the paper is organized as follows. Section 2 discusses the dataset from U.S. Survey of Professional Forecasters and Michigan Survey of Consumers and presents the stylized facts about consumer inflation expectations. Section 3 proposes a model of consumer expectation updating. Section 4 provides empirical estimation of the model and section 5 concludes. The details on quantifying qualitative inflation expectations are relegated to the online appendix.

2 Stylized Facts

In our study we analyze short-term inflation expectations of consumers and professional forecasters in the United States, formed in a one-year horizon. As far as professional forecasters are concerned, we use their inflation forecasts reported in the Survey of Professional Forecasters (SPF), conducted by the Federal Reserve Bank of Philadelphia. As the measure of central tendency we use medians of individual forecasts, while cross-sectional variance is the measure of disagreement among experts.³

In the case of consumers, we make use of two sets of measures of their inflation expectations based on Michigan Survey of Consumers (MSC) data. The first set relies on quantitative assessment of consumers concerning expected price developments. Average expectations are proxied with the median of individual declarations, while the dispersion is represented by the cross-sectional variance of individual responses. The second set of measures is based on quantification of qualitative survey data.⁴ Details are discussed in Online Appendix A.

We establish three stylized facts regarding inflation expectations in the US. While the

³The mean and median forecasts are almost the same for professional forecasters. Our choice of using the median is driven by household' forecasts.

⁴Drawing on relevant studies from economics, statistics, sociology and psychology, Mokinski, et al. (2015) provide a detailed review of the literature on measuring disagreement in qualitative survey data.

first two are documented in the literature, we include both facts for completeness and for motivation of our theoretical model in the next section. The third fact, to our knowledge, is novel to the literature.

Fact 1: Consumers' inflation expectations differ persistently from those of experts.

Figure 1 plots the median consumer and expert inflation expectations. Expert expectations are weakly correlated with those of households, correlation of about 0.40 with quantitative expectation and of 0.20 with quantified measure.⁵ Over the whole sample period during 1990Q1 to 2016Q4, the spread between median consumer and expert inflation expectations is 0.47 percentage points. And, this spread displays a different pattern around 1996Q1 – household inflation expectations are 0.32 percentage points lower than those of experts before 1996, but are 0.69 percentage points higher and more volatile afterwards. One possible explanation is that households pay close attention to salient price changes, such as oil and food prices; see, e.g. Coibion and Gorodnichenko (2015b), Berge (2018) and Binder (2018). By contrast, experts respond more to monetary policy and macro indicators, especially interest rates.⁶

Fact 2: Disagreement among the general public is substantially higher than professional forecasters.

Figure 2 plots the disagreement among consumers and experts, measured as the cross-sectional variance in MSC quantified expectations and in SPF inflation expectations, respectively. There are much larger degrees of disagreement among consumers than exists among experts.⁷ The contemporaneous correlation between the two series is about 0.30, implying d-

⁵The two series of consumer inflation expectations, i.e. quantitative and quantified, tend to move together, with a correlation of 0.76.

⁶We run regressions of household and expert expectations on a set of variables, including employment, Federal Funds rate, 10-Year Treasury yield, Consumer Price Index (CPI), CPI food price away from home (or CPI food at home) and west Texas intermediate spot crude oil price. We find that consumers' inflation expectations co-move with food and energy prices, while experts respond more to employment and 10-year Treasury yield. These results are very similar to those in Berge (2018) and thus omitted here.

⁷Note that, due to many extreme responses in the MSC dataset, the cross-sectional variance of quantitative expectations is much larger than that of quantified expectations with the probability method.

ifferent drivers for consumer and professional disagreement. Indeed, Lamla and Maag (2012) find that disagreement among consumers, but not professionals, is governed by the amount, the heterogeneity, and the tone of media reports about consumer price inflation. Ehrmann, et al. (2012) and Binder (2017) find evidence for a significant and sizeable effect of central bank transparency on forecast disagreement among professionals, but not on disagreement among the general public. Furthermore, disagreement among professional forecasters moves in advance of that among consumers. If we lag expert disagreement by one period, the correlation between the two series increases to 0.41, raising the possibility that heterogeneity in professional forecasters might later be transmitted to heterogeneity in households.

Fact 3: Disagreement among experts is reflected in the opinions voiced in media outlets.

We construct the series of US experts' inflation forecast disagreement reported in media relying on the complete set of articles published by Wall Street Journal (WSJ) from August 24, 1990 to November 8, 2016.⁸ To this end, we first get quarterly counts of articles that contain at least one term in each of four term sets: Country, Expert, Inflation and Forecast. Table 1 reports the terms in each set. We use judgment and informal auditing to select the terms in these sets based on human readings of 1,105 randomly sampled articles. To reduce the false positive rate, we further remove the articles that begin with a foreign country or city name, leaving us 22,711 articles during our sample period.

With inflation-related news articles at hand, we apply spaCy, a free open-source library for natural language processing in Python, to infer whether an article contains expert disagreement in inflation expectations. This process involves several steps, including sentence segmentation, word lemmatization and timing match. Figure 3 shows the number of articles mentioning expert inflation expectations and their disagreement in WSJ, and not surprisingly, these two series tend to move together. The disagreement series has experienced three

⁸We choose this starting date to match the timing in the SPF survey. The 1990Q2 survey was not taken in real time, because the Philadelphia Fed had not yet taken over the survey.

⁹See Honnibal (2015) for the introduction of spaCy.

big spikes. The spikes during 1994Q2-Q4 occurred at the beginning of a new round of rate hikes after years of relatively low rates. The spikes observed during 2006Q3-2007Q1 are mainly a reflection of "the inflation scare of 2006" and the fear of stagflation. The spike in 2008Q3 is largely caused by the collapse of the Lehman Brothers and concerns on the Fed's considerable rate cuts since January 2008.

3 A Model of Consumer Inflation Expectations

Imagine that a consumer forms his expectations about inflation in the future. He has access to two sources of information: private sources of information gained from personal experiences on shopping and pumping at gas stations and public information gathered from countless advertisements, news media report and expectations of experts.¹⁰ He then combines these two types of information to form his inflation expectations. To fix ideas, let c_{it} be consumer i's inflation expectations based on the information available at time t and p_{it} be the publicly available inflation forecast by the specific expert, whose opinions the individual i is following. We propose that consumer i's inflation expectation at time t evolves according to the following equation:

$$c_{it} = \mu_i + \lambda_i p_{it} + \beta_i c_{i,t-1} + e_{it}. \tag{1}$$

 μ_i is individual-specific intercept and captures consumer i's time invariant belief on the longrun level of inflation; see, e.g. Carvalho, et al. (2019). λ_i is consumer i's propensity to learn from experts, β_i is the weight on his own past forecast, and e_{it} is the random shock.

For convenience, we denote \bar{x}_t as the cross-sectional average of x_{it} , i.e. $\bar{x}_t = E_i(x_{it})$, and σ_{xt}^2 as the cross-sectional variance of x_{it} , i.e. $\sigma_{xt}^2 = Var_i(x_{it})$. Then the dynamics of mean

¹⁰This is consistent with Larsen, et al. (2021)'s assumption that households do not follow inflation as measured by the statistical agency per se, but get information about future prices primarily through the media.

inflation expectation, \bar{c}_t , can be derived as:

$$\bar{c}_t = \bar{\mu} + \bar{\lambda}\bar{p}_t + \bar{\beta}\bar{c}_{t-1} + \bar{e}_t. \tag{2}$$

The model for the level of inflation expectations – either at individual levels (equation (1)) or on aggregate (equation (2)) – has a nice economic interpretation inspired by the literature on hybrid models of expectations, e.g. Roberts (1997), Clarida, et al. (1999) or Łyziak and Paloviita (2018). The expected inflation results from consumers' past predictions, expert forecasts reported in media and a constant term, reflecting the fundamental (long-run) rate of inflation. The importance of the former two can be easily identified – their weights are given by $\bar{\beta}$ and $\bar{\lambda}$, respectively. Assuming that the above models fully describe consumers' way of setting expectations, the weight on constant expectations is by definition given by $1-\bar{\lambda}-\bar{\beta}$. On aggregate, these weights can be interpreted as the shares of consumers following different models of inflation expectations, i.e. their past opinions ("inertial consumers"), expert forecasts ("informed consumers") or the fundamental rate of inflation ("consumers with constant expectations").

The unknown fundamental rate of inflation, $\bar{\pi}^*$, averaged across consumers having constant expectations, can be introduced to equation (2):

$$\bar{c}_t = (1 - \bar{\lambda} - \bar{\beta})\bar{\pi}^* + \bar{\lambda}\bar{p}_t + \bar{\beta}\bar{c}_{t-1} + \bar{e}_t.$$
 (3)

Comparing equation (2) to (3) gives the fundamental rate of inflation, $\bar{\pi}^* = \bar{\mu}/(1 - \bar{\lambda} - \bar{\beta})$, to which consumers with constant expectations anchor their predictions.

Our model also governs the dynamics of consumers' disagreement in opinions on future inflation. Based on equation (1) and under the assumptions that $c_{i,t-1}$, λ_i , β_i and p_{it} are orthogonal to each other¹¹ and that each consumer randomly picks up a preferred professional

¹¹This assumption seems plausible and is not very restrictive given that λ_i and β_i are constant over

forecaster, we obtain consumer forecast disagreement as follows:

$$\sigma_{ct}^2 = \sigma_{\mu}^2 + (\sigma_{\beta}^2 + \bar{\beta}^2)\sigma_{c,t-1}^2 + (\sigma_{\lambda}^2 + \bar{\lambda}^2)\sigma_{pt}^2 + \sigma_{\lambda}^2 \bar{p}_t^2 + \sigma_{\beta}^2 \bar{c}_{t-1}^2 + \sigma_{et}^2. \tag{4}$$

Equation (4) posits that disagreement among consumer inflation expectations comes from six sources:

- (i) heterogeneity in fundamental inflation, σ_{μ}^2 ,
- (ii) consumers' divergent past expectations, $\sigma_{c,t-1}^2$,
- (iii) experts' different views about future inflation, σ_{pt}^2 ,
- (iv) differences in the weights placed on consumers' own past forecasts, σ_{β}^2 ,
- (v) differences in consumers' propensities to learn from experts, σ_{λ}^2 , and
- (vi) heterogeneity due to random shocks, σ_{et}^2 .

Our model specification is very general, and nests some interesting cases. We consider three simplified versions of the model.

The first version corresponds to the conventional sticky-information model. We assume that all consumers learn the same news from experts, mimicking the "common source" story in epidemiology where people get sick because of their common exposure to the polluted air in Washington, DC. In addition, consumers have the same propensity to learn from experts and place the same weight on their own past forecasts. In this case, consumer i's inflation

time – hence they are independent of $c_{i,t-1}$ and p_{it} , while p_{it} and $c_{i,t-1}$ are independent due to the fact that consumers are assumed to learn from experts, but not vice versa. The latter assumption is justified empirically in various studies showing that consumer inflation expectations do not Granger cause expert inflation forecasts (Carroll, 2003; Döpke et al., 2008). Furthermore, recent studies (Cavallo, et al., 2017; Meyer, et al., 2020) point out cognitive limitations of households (e.g. households still place a significant weight on inaccurate sources of information such as their memories of the price changes of the supermarket products) and households' misunderstanding of the concept of "inflation" (e.g. households respond to salient relative price changes instead of aggregate inflation). Given these findings, it is less likely that professionals learn from households' (past) inflation expectations, even if the underlying data generating process is an AR(1).

expectation can be written as:

$$c_{it} = \mu_i + \bar{\lambda}\bar{p}_t + \bar{\beta}c_{i,t-1} + e_{it}. \tag{5}$$

Consumers' forecast disagreement in this case is given by:

$$\sigma_{ct}^2 = \sigma_{\mu}^2 + \bar{\beta}^2 \sigma_{c,t-1}^2 + \sigma_{et}^2. \tag{6}$$

The second version of the model assumes that all consumers learn the same news from experts, but propensities to learn differ across consumers and this heterogeneity might reflect democratic characteristics, such as gender, education levels and age cohorts. Furthermore, consumers attach different weights to their own past forecasts, thus allowing for heterogeneity in the persistence of inflation expectations. In this case, consumer i's inflation expectation is given by:

$$c_{it} = \mu_i + \lambda_i \bar{p}_t + \beta_i c_{i,t-1} + e_{it}, \tag{7}$$

and disagreement across their forecasts is obtained as:

$$\sigma_{ct}^2 = \sigma_u^2 + (\sigma_\beta^2 + \bar{\beta}^2)\sigma_{c,t-1}^2 + \sigma_\lambda^2 \bar{p}_t^2 + \sigma_\beta^2 \bar{c}_{t-1}^2 + \sigma_{et}^2.$$
 (8)

In the third version we allow for the possibility that consumers learn different views about inflation from different newspapers and social media. As shown in Figure 3, even the same newspaper contains divergent views about future inflation. In line with Carroll (2003), we assume that consumers have the same propensity to learn from experts and that consumers place the same weight on their own past forecasts. In this case, consumer i's

inflation expectation can be described as follows:

$$c_{it} = \mu_i + \bar{\lambda} p_{it} + \bar{\beta} c_{i,t-1} + e_{it}. \tag{9}$$

Equation (9) allows for a simple variance decomposition where the covariance term between p_{it} and $c_{i,t-1}$ is zero:

$$\sigma_{ct}^2 = \sigma_{\mu}^2 + \bar{\beta}^2 \sigma_{c,t-1}^2 + \bar{\lambda}^2 \sigma_{pt}^2 + \sigma_{et}^2.$$
 (10)

We need to point out the key differences between our model and Carroll (2003)'s model. Carroll (2003) assumes that each consumer faces a constant probability λ of encountering and absorbing the contents of an article on inflation and that consumers who do not encounter an article simply continue to believe the last forecast they read about. As such, disagreement in his model arises only from different generations of consumers using different information vintages and there is no disagreement within a generation. In contrast, our model generates disagreement within a generation due to consumers' exposure to different expert views about inflation and/or differences in their propensities to learn from experts even under full information updating.

4 Empirical Estimation

4.1 Methods

We attempt to match theoretical models derived above with empirical data, in order to identify the best model specification, according to which consumers form their inflation expectations. We are interested in explaining both observed central tendency and disagreement in consumer inflation expectations.¹² In this respect we use two alternative approaches.

¹²The data in the Michigan survey are repeated cross sections, not panel data. That is why we estimate the model parameters using time series regressions based on the median and variance. If survey data were

4.1.1 Unconstrained estimation

Within the first approach we estimate the most general specification of the model, in which the median and variance of consumer inflation expectations are jointly estimated using the seemingly unrelated regression equations (SURE):

$$\bar{c}_t = \bar{\mu} + \bar{\lambda}\bar{p}_t + \bar{\beta}\bar{c}_{t-1} + \epsilon_t, \tag{11}$$

$$\sigma_{ct}^2 = \gamma_0 + \gamma_1 \sigma_{c,t-1}^2 + \gamma_2 \sigma_{pt}^2 + \gamma_3 \bar{p}_t^2 + \gamma_4 \bar{c}_{t-1}^2 + u_t.$$
 (12)

The above unconstrained model allows for testing different hypotheses concerning the formation of consumer inflation expectations. In particular, if $\bar{\lambda}$ is significantly positive, implying that the mean of consumer inflation expectations adjusts towards experts' forecasts, four versions of the model described in the previous section can be tested.

The first version assumes that propensities to learn from experts are the same among consumers and consumers consider the same consensus forecast of experts. Based on theoretical considerations presented above, this model requires the following conditions: $\gamma_1 = \bar{\beta}^2$, $\gamma_2 = 0$, $\gamma_3 = 0$ and $\gamma_4 = 0$. To facilitate further reading, this version of the model is labelled as " $P_{hom}E_{hom}$ " (homogenous propensities, homogenous experts).

The second version (" $P_{het}E_{hom}$ " – heterogeneous propensities, homogeneous experts) relaxes the assumption that propensities to learn are the same across consumers, but consumers are still assumed to read the same consensus forecast by experts, implying the following restrictions: $\gamma_1 = \gamma_4 + \bar{\beta}^2$, $\gamma_2 = 0$, $\gamma_3 > 0$ and $\gamma_4 > 0$.

The third version (" $P_{hom}E_{het}$ " – homogeneous propensities, heterogeneous experts) assumes that consumers do not differ from each other in terms of their propensities to learn from informed agents, but can follow different forecasts declared by professionals. This model is consistent with the data if $\gamma_1 = \bar{\beta}^2$, $\gamma_2 = \bar{\lambda}^2$, $\gamma_3 = 0$ and $\gamma_4 = 0$.

a proper panel, the model could be more directly tested.

Finally, in the fourth version of the model (" $P_{het}E_{het}$ " – heterogeneous propensities, heterogeneous experts), heterogeneity in the formation of consumer inflation expectations refers to both propensities to learn from experts and different expert forecasts considered by lay people, that is, $\gamma_1 = \gamma_4 + \bar{\beta}^2$, $\gamma_2 = \gamma_3 + \bar{\lambda}^2$, $\gamma_3 > 0$ and $\gamma_4 > 0$.

To discriminate among various versions of the model, we test the above hypotheses sequentially. We first check whether the propensity to learn is on average positive $(\bar{\lambda} > 0)$. If $\bar{\lambda} > 0$, we continue to test whether this learning parameter is the same across consumers $(\gamma_3 = 0)$. If this hypothesis is rejected and $\gamma_3 > 0$, we focus on the second and fourth versions of the model. On the other hand, if we do not reject the hypothesis that consumers have the same propensity to learn, we test the remaining conditions of the first and third versions of the model.

4.1.2 Constrained estimation

In the second analytical approach, instead of assuming a general model for consumer inflation expectations and testing theoretical conditions related to disagreement, we estimate four versions of the model with theoretical conditions already imposed. Equation (11) specifies the level of consumer inflation expectations and turns out to be the same for all versions of the model under consideration. The equations for forecast disagreement differ across the models. As described in the previous section, the disagreement in the models $P_{hom}E_{hom}$, $P_{hom}E_{het}$ and $P_{het}E_{het}$ is given by the equations (6), (8), (10) and (4), respectively.

4.1.3 Analytical set-up

In our estimations we use two sample periods. Both of them start in 1990Q1.¹³ The whole sample period ends in 2016Q4, while the shorter sample ends in 2007Q4.

¹³In this way we ignore the period of higher inflation in early 80's and have the sample period analogous to European economies considered in our study.

Estimation results based on the whole sample are used to test the unconstrained version of the model as well as to assess the empirical fit of different versions of the model estimated with imposed relationship among respective parameters. In addition, we estimate all versions of the model using the shorter sample and evaluate their out-of-sample forecasting accuracy. We perform this assessment based on a counterfactual exercise, in which we predict the level and dispersion of consumer inflation expectations in 2008-2016 using the model estimated till 2007. We use the test suggested by Romer and Romer (2000) to verify if the differences between squared forecast errors of various models are on average statistically different from zero. More specifically, we compare three versions of the model allowing for heterogeneity in propensities to learn and in expert forecasts being used by consumers to the canonical version of the sticky-information model, in which such heterogeneities are not considered.

In our benchmark specification we assume that the estimated parameters do not change over time. However, we also estimate models allowing for time-varying parameters, in particular for time-varying propensity of consumers to learn from experts.¹⁴ In this respect we apply the rolling-window estimation. The size of the rolling window is 72 quarters for US and 120 months for European economies.¹⁵

4.2 Results for the US economy

Implementing both empirical approaches characterized in the previous section, we rely either on US households' inflation expectations based on MSC quantitative survey question or on the mean and variance of the distribution of expected inflation quantified with probability method on the basis of qualitative survey data. The main results, based on unconstrained and constrained models, are shown in Tables 2, 3 and 4, while Figure 4 presents the results

¹⁴Lamla and Sarferaz (2012) show that the propensity to update inflation expectations by European households changes substantially over time and is related to the quantity and quality of news.

¹⁵The results remain robust if we apply 92 quarters for US and 156 months for European countries instead of 72 quarters and 120 months, respectively.

based on models estimated in the rolling regression manner.

4.2.1 Which model of expectations seems the most adequate?

The results based on the unconstrained model (Table 2) suggest that the propensity of households to learn from experts is not homogenous across households. The results of the Wald test, aimed at selecting the most adequate model of expectation levels and disagreement, differ slightly depending on the measure of consumer inflation expectations used. In the case of quantitative expectations both versions of the model with cross-sectional heterogeneity of the propensity to learn find support, i.e. $P_{het}E_{hom}$ model, in which consumers learn from the same expert forecast (consensus) and $P_{het}E_{het}$ model, in which consumers learn from forecasts of individual experts. In the case of the qualitative expectations restrictions behind these two models are rejected in spite of the fact that the propensity to learn remains heterogenous.

As far as the constrained models are concerned (Tables 3 and 4), the same two versions, as indicated with the unconstrained model, are the most adequate given their statistical fit in both sample periods. The results of Romer and Romer (2000) test on forecasting accuracy reveal that in terms of statistical significance there exist no differences among the analysed models. Yet, as the analysis based on rolling-regression estimates shows (Figure 4), in the majority of estimation windows, independently of the measure of household inflation expectations used, the best-performing models are the ones with cross-sectional heterogeneity in the propensity to learn from experts, i.e. $P_{het}E_{hom}$ model and $P_{het}E_{het}$ model. In the case of quantitative expectations $P_{het}E_{hom}$ model clearly outperforms the remaining ones, including $P_{het}E_{het}$ model. In the case of qualitative expectations the assessment is more nuanced. While $P_{het}E_{hom}$ model outruns the other ones in terms of statistical fit of the equation for the level of inflation expectations, there are various models with the best fit of the equation for forecast disagreement. In particular, since the beginning of the global financial crisis the

evolution of forecast disagreement seems consistent mainly with the $P_{hom}E_{het}$ model.

To conclude, we find strong evidence in support of heterogeneities in the propensity to learn from experts. At the same time most of the results suggest that households follow the same consensus forecasts rather than the forecasts of individual experts. This finding probably reflects the fact that disagreement in expert forecasts is very low, both in absolute and relative terms.

4.2.2 Propensity to learn from experts

The unconstrained estimation shows that, depending on the measure of inflation expectations, approximately 54-61% of households follow their previous forecasts, 27-31% have constant expectations, equal to the fundamental rate of inflation, while 12-15% of households adjust to expert forecasts (Table 2). The fundamental rate of inflation stays between 3.2% and 3.4%. The results based on the preferred versions of the model estimated with restrictions, which assume cross-sectional heterogeneity of propensity to learn from experts, give a broadly similar picture (Tables 3 and 4).

A comparison of the results based on the whole sample (1990-2016) and the shorter sample (1990-2007) reveals some changes in the formation of inflation expectations by households. Regardless of the measure of household inflation expectations, the propensity to learn is somewhat higher in the short sample than the whole sample period. This observation is consistent with the results based on rolling-window estimation (Figure 4) that since 2007 the propensity to learn has become statistically insignificant. Thus, households have modified their formation of inflation expectations since the global financial crisis. It does not necessarily mean that all households stopped paying attention to expert forecasts, but rather that the fraction of households with expectations going in the same direction as expert forecasts have probably become very similar to the fraction of households adjusting their views in the

 $^{^{16}\}mathrm{At}$ the end of the sample period the propensity to learn seems again statistically significant.

direction opposite to experts, after controlling for magnitudes of expectations in both groups of households.

Considering the shorter sample period, the average propensity to learn is approximately 0.14-0.19. This estimate corresponds broadly to the structural parameter of "the degree of attention" in the sticky-information model and implies economically significant degrees of information rigidity among the public. This magnitude is broadly consistent with estimates reported in the literature. For example, the average estimate of information rigidity in our dataset, 0.81-0.86, is close to the 0.75 value assumed by Mankiw and Reis (2002), which delivers very persistent effects of monetary policy shocks arising only from sticky information in price setting; to the 0.75 value calibrated by Hur and Kim (2017) that fits a dynamic stochastic general equilibrium model featuring agents' infrequent information updating and nominal rigidities to U.S. data; to the 0.73 value estimated by Carroll (2003) in which households' views about inflation derive from news reports of the views of professional forecasters; and to the 0.82 value estimated by Coibion and Gorodnichenko (2012) by studying the conditional responses of forecast errors and disagreement to shocks.

Importantly, propensities to learn from experts are quite heterogenous across households, independently of the measure of households' inflation expectations used. Standard deviations of the propensity to learn in the unconstrained models are very high, equal to 1.02 in the case of quantitative expectations and 0.30 in the case of qualitative expectations.¹⁷ In the constrained models the respective figures are 0.98 and 0.19. These estimates imply that U.S. consumers have very different propensities to learn. The unconstrained model with quantitative expectations predicts that about 45% of households have negative propensity to learn and 55% of households adjust their expectations towards expert forecasts.¹⁸ In the

¹⁷Note that the estimated parameter $\hat{\gamma}_3$ in Table 2 gives the variance.

¹⁸The above shares are calculated under the assumption of the normal distribution of the estimated propensity to learn. More specifically, the share of consumers with negative propensity to learn is given by the value of the cumulative normal distribution at zero, i.e. $F(0, \bar{\lambda}, \sigma_{\lambda}^2)$.

unconstrained model with qualitative expectations the respective shares are 31% and 69%. Our findings that about half of households revise their forecasts in the direction opposite to those of professional forecasters, together with the similar results in Pfajfar and Santoro (2013) based on micro-level data, might explain why the propensity to learn in the US, averaged across all households, has become statistically insignificant since 2007. On the top of that, some consumers overshoot expert forecasts, since their propensity to learn is larger than one. In the unconstrained version of the model with quantitative expectations this fraction equals 20%, while in the case of quantitative expectations it is negligible (0.3%).

4.3 European evidence

We extend our analysis using survey data for selected large European economies. This group includes Germany, Spain, France, Italy, Netherlands and UK with monthly surveys available since 1990.¹⁹

For professional forecasters, we use one-year-ahead inflation forecasts based on Consensus Economics survey (median and variance). In the case of consumers, we use median and variance of the distribution of expected inflation, quantified on the basis of qualitative survey data from the European Commission Consumer Survey.²⁰ Details of the measurement of consumer inflation expectations in European economies are discussed in Łyziak and Mackiewicz-Łyziak (2014) and Łyziak and Paloviita (2017); see Online Appendix B. Figures C1-C6 in Online Appendix C present consumer inflation expectations and those of experts for these countries.

Quantification of consumer inflation expectations based on qualitative survey data can be

¹⁹We also explore European countries with shorter samples of observations, including Czech Republic (sample starts in 1995), Sweden (sample starts in 1996), euro area as a whole (sample starts in 2004), Poland (sample starts in 2004) and Slovakia (sample starts in 2007). The results for these countries and the euro area are similar to those included in the paper.

²⁰Quantitative data on consumer inflation expectations in European economies are collected in this survey too. However, they are not available in the form of time series for single economies.

perceived as the way of transforming subjective qualitative opinions into numbers consistent with official measures of inflation. It implies that the bias of consumer inflation perception and expectations quantified in this way is substantially smaller than in the case of quantitative expectations declared by consumers. However, using averages of quantitative inflation perceptions and expectations in analysed European economies, presented in Arioli, et al. (2017), we observe that the bias of consumer inflation expectations is large, but expectations are lower than inflation perceptions.²¹ In the case of qualitative data it is reflected in the fact that consumer inflation expectations quantified with the probability method in respective economies stay on average below the current HICP inflation.

The results based on the unconstrained model are shown in Table 5, while the results based on constrained models for each country are presented in Tables C1-C6 in Online Appendix C. Figure 5 summarizes the results based on rolling-window estimation.

4.3.1 Which model of expectations seems the most adequate?

Looking through the lenses of unconstrained models, it turns out that in all European economies under consideration consumers differ from each other in terms of the propensity to
learn from experts (Table 5). However, restrictions identifying both $P_{het}E_{hom}$ and $P_{het}E_{het}$ models are rejected, implying that it is not evident whether European consumers learn from
the consensus expert forecast or from the forecasts of individual experts. The results based
on constrained models of expectations (Tables C1-C6) suggest that both models with heterogenous propensity to learn outperform the remaining ones in terms of the statistical fit.
Analysis of forecasting accuracy confirms this result for Spain, France, the Netherlands and
UK, while is not fully conclusive in the case of Italy and Germany.

 $^{^{21}}$ Average estimates of inflation perceptions and expectations during January 2004 – July 2015 are: Germany: 6.6%, 4.9% vs. 1.6% HICP inflation; Spain: 14.2%, 8.6% vs. 2.2% HICP inflation; France: 6.9%, 3.7% vs. 1.6% HICP inflation; Italy: 14.1%, 5.0% vs. 1.9% HICP inflation; Netherlands: 6.7%, 4.1% vs. 1.7% HICP inflation; UK: 9.6%, 7.6% vs. 2.5% HICP inflation. See Arioli, et al. (2017), p. 24.

Selection of the most adequate model in the rolling-window estimation (Figure 5) is in line with the results summarized above, suggesting that propensity to learn from experts is heterogenous among consumers not only across European economies, but also over time. The above results largely confirm the findings based on US data. However, expectation formation in the European economies displays more time variation than in the US, as shown by a larger volatility of the propensity of consumers to learn from experts.

4.3.2 Propensity to learn from experts

The degree of learning in European economies, estimated on the basis of unconstrained models, is on average similar to that in the US. It seems relatively low in the Netherlands (0.06) and France (0.09), moderate in Spain (0.14) and Germany (0.16) and high in the UK (0.24) and Italy (0.31). The estimates based on constrained models are lower for all the European countries under consideration, but the ranking of the economies remains largely the same as resulting from unconstrained estimation. The estimates of this parameter for individual European economies are broadly consistent with those reported in the literature (Döpke et al., 2008). Heterogeneity of propensities to learn across consumers looks smaller than in the US. A majority of European consumers adjust their expectations towards expert forecasts.

Finally, rolling-regression results indicate that since the beginning of the global financial crisis, European consumers have significantly changed the way in which they form inflation expectations. In particular, in all the economies, the propensity to learn from experts has substantially increased (Figure 5). This result goes in line with Łyziak and Mackiewicz-

 $^{^{22}}$ The only difference concerns Italy, for which the constrained model delivers much lower propensity to learn (0.06) than the unconstrained one.

²³Our results based on the unconstrained models vs. the range of Döpke et al. (2008) estimates are the following: 0.16 vs. 0.18-0.29 for Germany, 0.09 vs. 0.18-0.33 for France, 0.31 vs. 0.11-0.25 for Italy and 0.24 vs. 0.23-0.53 for UK. The difference in the French case becomes lower if we consider a similar sample period (1990-2004) as in Döpke et al. (2008). In this case the estimate of the propensity of French consumers to learn from experts is 0.14, while for the remaining countries it is close to the above figures.

Łyziak (2014) who found an increase of forward-lookingness of European consumers after the beginning of the financial crisis. It is however different from the findings based on US data. Even if there is a slightly upward trend of the propensity to learn in the US since 2007, as also pointed out by Drager and Lamla (2017b), the wide confidence intervals make this trend statistically insignificant.

5 Conclusions

We build a theory of consumer expectation updating to analyse disagreement in their inflation expectations. Our theory has three key elements. First, consumers hold different beliefs about price levels, gained from personal experiences. Second, consumers obtain public information from experts via newspapers and social media about the trends in future inflation. Third, households are allowed to have different propensities to learn from experts. Disagreement among consumers in our model arises from six sources: (i) heterogeneity in individual fundamental inflation, (ii) consumers' divergent past expectations, (iii) experts' different views about future inflation, (iv) differences in the weights placed on consumers' own past forecast, (v) differences in consumers' propensities to learn from experts, and (vi) heterogeneity due to random shocks.

The extended sticky-information model that allows for heterogeneous propensities of US consumers to learn from experts finds a very strong empirical support. According to our results, there exists a sizeable heterogeneity – about 55-70% of US households adjust their expectations towards expert forecasts and the rest of households revise in the opposite direction of experts. This heterogeneity has a direct impact on the disagreement in households' inflation expectations. In contrast, the relevance of heterogeneity of expert forecasts for consumers becomes less clear. These findings are largely confirmed in our additional analysis from selected European economies, including Germany, Spain, France, Italy, Netherlands

and UK. The propensity of European consumers to learn from experts is on average similar to US experiences, implying significant degrees of information rigidities in the economies under consideration. Compared to US consumers, European consumers since the global financial crisis have intensified learning from experts relative to the pre-crisis period, while heterogeneity of the propensity to learn across European consumers is smaller but displays more variations over time.

As aptly pointed out by Esady (2019), causes of the variation in disagreement have different effects on how price-setters respond to monetary shocks. The main result in her paper highlights a role for improved central bank communications that reduce disagreement among economic agents, which lessens output falls when implementing disinflationary monetary policies. We find that household forecast disagreement is a decreasing function of the weight on new information. Central bank communication should pierce the veil of inattention of the general public to reduce their disagreement. Furthermore, central bank communication should affect in the first place professional analysts and reduce their disagreement. If this disagreement affects opinions of ordinary people, central bank communication has an indirect channel for affecting household expectations.

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Figure 1: Inflation expectations of US consumers and experts

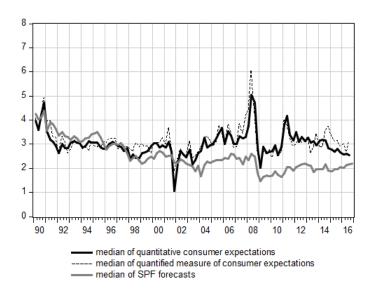


Figure 2: Disagreement among US consumers and experts

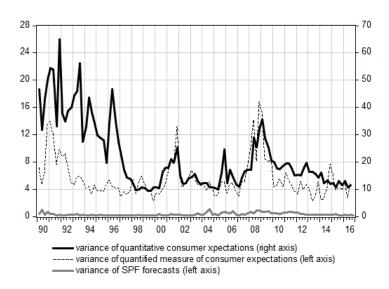
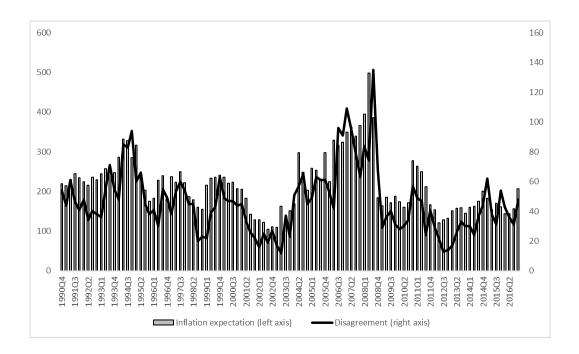


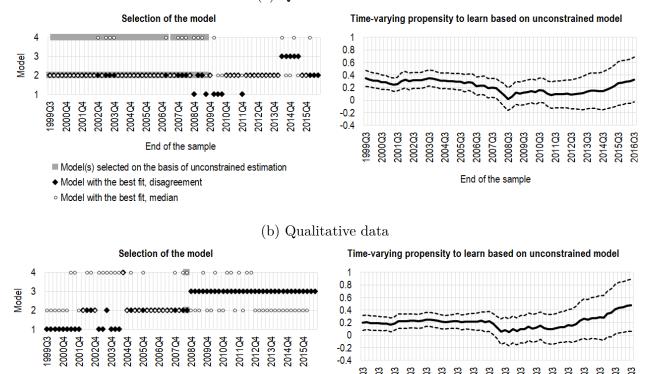
Figure 3: Articles mentioning expert inflation expectation and disagreement in Wall Street Journal



Notes: With inflation-related news articles from Wall Street Journal, we apply spaCy to infer whether an article contains expert disagreement in inflation expectations. This process involves seven steps: 1. Sentence segmentation: We divide each article into meaningful sentences and store the sentences that include "inflation". 2. Non-US-inflation sentence removal: We remove the sentences that talk about inflation in other countries. 3. Adjusted-for-inflation sentence removal: We remove the sentences that contain "inflation-adjusted", "adjusted-for-inflation" and "inflation into account". 4. Word lemmatization: We convert words in a sentence to their base form with no inflectional suffixes such as "-s", "-ed" and "-ing". This step is useful in constructing the dictionary of inflation-direction words. 5. Dictionary of directions: We use judgment and informal auditing to select the terms in the direction sets; see Table 1. 6. Disagreement within the same article: If an article contains at least two directions about future inflation, it is marked as having disagreement in inflation expectations. We extract 4,861 articles that contain expert disagreement. 7. Timing match: We count the number of disagreement-related articles for each quarter by matching the timing with the true deadline date for the SPF. For example, in 1990Q4, WSJ disagreement is calculated for the sample period during August 24, 1990 to November 22, 1990.

Figure 4: Results of rolling-regression analysis for US

(a) Quantitative data



■ Model(s) selected on the basis of unconstrained estimation

End of the sample

- ◆ Model with the best fit, disagreement
- Model with the best fit, median

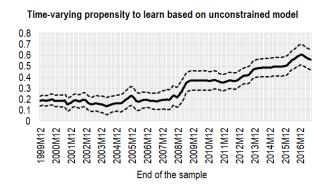
Notes: Model 1 is the " $P_{hom}E_{hom}$ " model (homogenous propensities, homogenous experts). Model 2 is the " $P_{het}E_{hom}$ " model (heterogeneous propensities, homogeneous experts). Model 3 is the " $P_{hom}E_{het}$ " model (homogeneous propensities, heterogeneous experts). Model 4 is the " $P_{het}E_{het}$ " model (heterogeneous propensities, heterogeneous experts).

End of the sample

Figure 5: Results of rolling-regression analysis for European economies

(a) Germany

- Model(s) selected on the basis of unconstrained estimation
- · Model with the best fit, disagreement
- o Model with the best fit, median

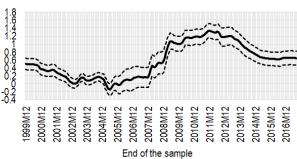


(b) Spain

Selection of the model 3 2 2002M01 2013M01 2001M01 2004M01 2005M01 2009M01 2010M01 2011M01 2012M01 2014M01 2015M01 2016M01 2017M01 2003M01 2006M01 2007M01 2008M01 End of the sample

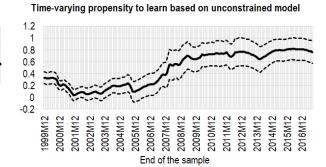
- Model(s) selected on the basis of unconstrained estimation
- Model with the best fit, disagreement
- o Model with the best fit, median

Time-varying propensity to learn based on unconstrained model

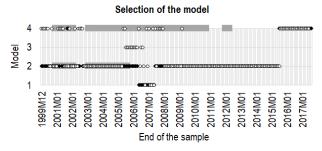


(c) France

- Model(s) selected on the basis of unconstrained estimation
- Model with the best fit, disagreement
- o Model with the best fit, median



(d) Italy



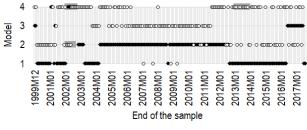
- Model(s) selected on the basis of unconstrained estimation
- · Model with the best fit, disagreement
- o Model with the best fit, median

2000M12 2010M12 2011M12 201

Time-varying propensity to learn based on unconstrained model

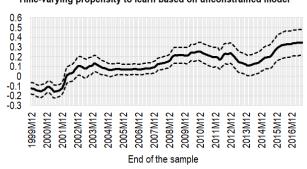
(e) Netherlands

Selection of the model



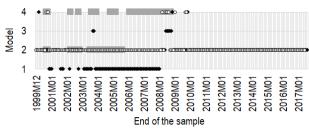
- Model(s) selected on the basis of unconstrained estimation
- · Model with the best fit, disagreement
- o Model with the best fit, median

Time-varying propensity to learn based on unconstrained model



(f) UK

Selection of the model



- Model(s) selected on the basis of unconstrained estimation
- Model with the best fit, disagreement
- o Model with the best fit, median

Time-varying propensity to learn based on unconstrained model 1.2 0.8 0.6 0.4 0.2 0 -0.2 2012M12 2000M12 2001M12 2003M12 2004M12 2005M12 2010M12 2013M12 2002M12 2011M12 End of the sample

Notes: Model 1 is the " $P_{hom}E_{hom}$ " model (homogenous propensities, homogenous experts). Model 2 is the " $P_{het}E_{hom}$ " model (heterogeneous propensities, homogeneous experts). Model 3 is the " $P_{hom}E_{het}$ " model (homogeneous propensities, heterogeneous experts). Model 4 is the " $P_{het}E_{het}$ " model (heterogeneous propensities, heterogeneous experts).

Table 1: Term Sets for experts' inflation forecast disagreement in the United States

Category	Terms
Country	U.S.; United States; Fed; Federal Reserve
Expert	analyst; economist; expert; forecaster; chair(wo)man; advisor;
Expert	director; president; investor; official; manager; professor
Inflation	inflation
Forecast	expect; predict; forecast; anticipate; outlook; inflation will; inflation is going to
Direction	Terms
Rise	rise; surge; up; increase; higher; raise; elevate; soar; grow;
Tuse	upward; uptick; boost; upswing; climb; upturn; add to; lift
Fall	dip; dwindle; decrease; fall; down; downward; decline; collapse;
ran	waning; slipped; drop; recede; diminish; decelerate; low
Unchanged	unchanged; stable; steady

Notes: We use judgment and informal auditing to select the terms in these sets based on human readings of 1,105 randomly sampled articles in Wall Street Journal from August 24, 1990 to November 8, 2016. We do not include "US" in Country term set, since it is rarely used in the printed edition of WSJ journal. Only "inflation" is included, because all other inflation-related terms (e.g. price index, consumer prices, producer prices, food and energy prices) have "inflation" in the same article.

Table 2: Unconstrained model, US

	Quantitative	Qualitative
	data	data
$\overline{\lambda}$	0.123**	0.148**
$rac{\lambda}{ar{eta}}$	0.612***	0.537***
$ar{\mu}$	0.852***	1.072***
$ \gamma_0$	0.222	0.842
γ_1	0.605***	0.674***
γ_2	0.642	0.373
γ_3	1.041***	0.093*
γ_4	0.192	0.035
fundamental inflation	3.212	3.412
% of agents with constant exp.	0.265	0.314
$adj.R^2 - \text{exp.level}$	0.443	0.377
$adj.R^2$ – disagreement	0.734	0.583
$\chi^2 - H_0: \ \sigma_{\lambda}^2 = 0$	14.833***	3.308*
$\chi^2 - H_0: \ \sigma_{\beta}^2 = 0$	0.601	0.507
$\chi^2 - H_0: \sigma_u^2 = 0$	0.012	2.498
$\chi^2 - H_0$: $P_{het}E_{het}$ model is correct	0.383	7.255**
$\chi^2 - H_0$: $P_{hom}E_{het}$ model is correct	_	_
$\chi^2 - H_0$: $P_{het}E_{hom}$ model is correct	0.092	7.137**
$\chi^2 - H_0$: $P_{hom}E_{hom}$ model is correct	_	_

Notes: *, ** and *** represent statistical significance at the 10%, 5% and 1% levels, respectively. Sample: 1990Q1-2016Q4 (quarterly data). Versions of the model differ from each other in terms of the assumptions concerning propensities to learn across consumers (P_{hom} – no differences among consumers in this respect; P_{het} – propensities to learn differ among consumers) and the expert forecasts used by consumers (E_{hom} – the median expert forecast followed by all consumers; E_{het} – consumers pay attention to forecasts by different experts).

Table 3: Constrained models, US, quantitative data

		*		
	$P_{hom}E_{hom}$	$P_{het}E_{hom}$	$P_{hom}E_{het}$	$P_{het}E_{het}$
	model	model	model	model
Sample: 1990Q1-2016Q4				
$ \bar{\lambda}$	0.053	0.122**	0.063	0.122*
$ar{eta}$	0.875***	0.611***	0.836***	0.613***
$ar{\mu}$	0.235	0.857*	0.328*	0.852***
σ_{λ}	_	0.983***	_	0.999
σ_{eta}	_	0.496***	_	0.485
σ_{μ}	2.064***	0.096	2.377***	0.071
fundamental inflation	_	3.210	3.233	3.210
% of agents with constant exp.	_	0.267	0.101	0.265
$adj.R^2 - exp.level$	0.379	0.443	0.396	0.443
$adj.R^2 - disagreement$	0.684	0.731	0.667	0.726
Sample: 1990Q1-2007Q4		1	l	
$\bar{\lambda}$	0.036	0.191**	0.046	0.183
$ar{eta}$	0.866***	0.546***	0.853***	0.561***
$ar{ar{\mu}}$	0.293	0.811***	0.306	0.786***
σ_{λ}	_	1.298***	_	1.271***
σ_{eta}	_	0.407**	_	0.403*
σ_{μ}^{-}	2.282***	0.114	2.492***	0.028
fundamental inflation	_	3.079	_	3.077
% of agents with constant exp.	_	0.263	_	0.255
$adj.R^2 - exp.level$	0.417	0.493	0.423	0.492
$adj.R^2 - disagreement$	0.663	0.702	0.653	0.688
Forecasting accuracy		1	I	I
RMSE – exp.level	0.492	0.498	0.490	0.495
RMSE-disagreement	3.592	4.411	3.940	4.031
SE vs. $P_{hom}E_{hom}$ model - exp.level	_	0.017	-0.001	0.015
SE vs. $P_{hom}E_{hom}$ model - disagreement	_	0.176	0.519***	0.043
$\overline{\text{SE vs.}P_{het}E_{hom} \text{ model - exp.level}}$	-0.017	_	-0.018	-0.002
SE vs. $P_{het}E_{hom}$ model - disagreement	-0.176	_	0.343	-0.133
SE vs. $P_{hom}E_{het}$ model - exp.level	-0.001	0.018	_	0.015
SE vs. $P_{hom}E_{het}$ model - disagreement	-0.519***	-0.343	_	-0.476
SE vs. $P_{het}E_{het}$ model - exp.level	-0.015	0.002	-0.015	_
SE vs. $P_{het}E_{het}$ model - disagreement	-0.043	0.133	0.476	_
	l .	l.	l .	<u> </u>

Table 4: Constrained models, US, qualitative data

	T =	<u> </u>		
	$P_{hom}E_{hom}$	$P_{het}E_{hom}$	$P_{hom}E_{het}$	$P_{het}E_{het}$
	model	model	model	model
Sample: 1990Q1-2016Q4				
$\bar{\lambda}$	0.056	0.115*	0.054	0.117*
$ar{eta}$	0.781***	0.659***	0.758***	0.659***
$ar{\mu}$	0.540*	0.773***	0.616***	0.768***
σ_{λ}	_	0.192	_	0.201
σ_{eta}	_	0.392***	_	0.390***
σ_{μ}	1.258***	0.487	1.085***	0.473
fundamental inflation	3.310	3.428	3.282	3.435
% of agents with constant exp.	0.163	0.225	0.188	0.224
$adj.R^2 - exp.level$	0.328	0.367	0.337	0.367
$adj.R^2 - disagreement$	0.471	0.490	0.484	0.486
Sample: 1990Q1-2007Q4				
$\overline{\lambda}$	0.026	0.139*	0.029	0.136*
$ar{eta}$	0.793***	0.612***	0.793***	0.614***
$ar{ar{\mu}}$	0.574**	0.821***	0.564**	0.825***
σ_{λ}	_	0.222	_	0.215
σ_{eta}	_	0.448***	_	0.447***
σ_{μ}	1.262***	0.148	1.160***	0.141
fundamental inflation	3.175	3.302	3.182	3.297
% of agents with constant exp.	0.181	0.249	0.177	0.250
$adj.R^2 - exp.level$	0.325	0.382	0.326	0.382
$adj.R^2 - disagreement$	0.480	0.525	0.483	0.518
Forecasting accuracy		1	I	
m RMSE-exp.level	0.576	0.558	0.576	0.558
${ m RMSE-disagreement}$	2.535	2.616	2.483	2.613
SE vs. $P_{hom}E_{hom}$ model - exp.level	_	-0.027	0.000	-0.027
SE vs. $P_{hom}E_{hom}$ model - disagreement	_	0.134	0.007	0.134
SE vs. $P_{het}E_{hom}$ model - exp.level	0.027	_	0.027	0.000
SE vs. $P_{het}E_{hom}$ model - disagreement	-0.134	_	-0.127	0.000
SE vs. $P_{hom}E_{het}$ model - exp.level	0.000	-0.027	_	-0.027
SE vs. $P_{hom}E_{het}$ model - disagreement	-0.007	0.127	_	0.127
SE vs. $P_{het}E_{het}$ model - exp.level	0.027	0.000	0.027	_
SE vs. $P_{het}E_{het}$ model - disagreement	-0.134	0.000	-0.127	_
	l .	I .	I	<u> </u>

Notes: See Table 3. *, ** and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5: Unconstrained model, European countries

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	Germany	Spain	France	Italy	Netherlands	UK
1	0.158***	0.142**	0.093**	0.310***	0.058***	0.236***
\mathcal{B}	0.782***	0.787***	0.778***	0.745***	0.855***	0.710***
$ar{\mu}$	-0.012	0.141**	0.146***	-0.065	0.079**	-0.124***
0,6	0.115***	0.208***	0.167***	0.100***	0.049*	0.261***
71	0.762***	0.837***	0.808***	0.924***	0.905***	0.737***
7.2	0.106	0.145	0.290**	0.097	0.054	0.083**
7/3	0.004**	0.007*	0.012***	0.008*	0.011***	0.007***
7.4	0.026***	0.003	0.000	0.001	0.005	0.013***
fundamental inflation	1	1.975	1.135	1	0.916	1
% of agents with constant exp.	1	0.071	0.129	1	0.086	1
$adj.R^2 - \exp.$ level	0.914	0.872	0.748	0.952	0.834	0.917
$adj.R^2$ – disagreement	0.906	0.820	0.797	0.917	0.911	0.917
$\chi^2 - H_0 \colon \sigma_\lambda^2 = 0$	4.563**	3.029*	23.312***	5.363**	14.804***	10.243***
$\chi^2-H_0\colon \sigma_{eta}^2{=}0$	15.625***	0.685	0.006	0.460	0.610	8.809
$\chi^2-H_0\colon \sigma_\mu^2{=}0$	48.819***	18.550***	45.167***	4.832**	3.736*	50.548***
$\chi^2 - H_0$: $P_{het}E_{het}$ model is correct	6.874**	12.91	18.061***	50.322***	8.565**	23.196***
$\chi^2 - H_0$: $P_{hom} E_{het}$ model is correct	l	l	l	I	l	I
$\chi^2 - H_0$: $P_{het}E_{hom}$ model is correct	6.519**	12.883***	17.730***	49.988***	8.513**	20.746***
$\chi^2 - H_0$: $P_{hom}E_{hom}$ model is correct	ı	ı	ı	I	I	ı

Notes: *, ** and *** represent statistical significance at the 10%, 5% and 1% levels, respectively. Sample: 1990M01-2017M09 (monthly data expressed as 3-month moving averages). Versions of the model differ from each other in terms of the assumptions concerning propensities to learn across consumers $(P_{hom}$ – no differences among consumers in this respect; P_{het} – propensities to learn differ among consumers) and the expert forecasts used by consumers $(E_{hom}$ – the median expert forecast followed by all consumers; E_{het} – consumers pay attention to forecasts by different experts).

Online Appendix

"Disagreement in Consumer Inflation Expectations" by Łyziak and Sheng

Appendix A: Quantification of consumer inflation expectations, US

Given the percentage of consumers declaring expected increase of prices (a_t^e) , stabilization (b_t^e) and reduction (c_t^e) , we use the Carlson-Parkin (1975) probability method in order to convert qualitative responses into quantitative inflation expectations. We assume that the expected inflation is normally distributed in the population, with unknown mean $\bar{\pi}_t^e$ and standard deviation σ_t^e . In addition, we assume that expectations of the respondent stating that prices will not change are located around zero, in the sensitivity interval (-l, l). Consequently, we can express the observed fractions of respondents a_t^e , b_t^e and c_t^e as the functions of cumulative standard normal distribution $\Phi(\cdot)$, the limit of the sensitivity interval l and the mean $(\bar{\pi}_t^e)$ and standard deviation (σ_t^e) of the distribution of expected inflation rate:

$$a_t^e = 1 - \Phi\left(\frac{-l - \bar{\pi}_t^e}{\sigma_t^e}\right) \tag{1}$$

$$c_t^e = \Phi\left(\frac{l - \bar{\pi}_t^e}{\sigma_t^e}\right) \tag{2}$$

The above equations can be solved simultaneously, yielding the following formulas for the parameters of the distribution of expected inflation:

$$\bar{\pi}_t^e = l \frac{\Phi^{-1}(c_t^e) + \Phi^{-1}(1 - a_t^e)}{\Phi^{-1}(c_t^e) - \Phi^{-1}(1 - a_t^e)}$$
(3)

$$\sigma_t^e = -l \frac{2}{\Phi^{-1}(c_t^e) - \Phi^{-1}(1 - a_t^e)}$$
(4)

Both parameters depend on the size of the sensitivity interval surrounding zero. To estimate the parameter l, we make an additional assumption. Instead of assuming unbiasedness of inflation expectations, as Carlson and Parkin (1975) did, we follow Mankiw, et al. (2004). More specifically, we make use of quantitative measures of consumer inflation expectations assuming that, on average, the quantified mean of expected inflation should equal the quantitative declarations, μ_t^e :

$$\sum_{t=1}^{T} \bar{\pi}_t^e = \sum_{t=1}^{T} \mu_t^e \tag{5}$$

The above condition implies that:

$$l = \frac{\sum_{t=1}^{T} \mu_t^e}{\sum_{t=1}^{T} \frac{\Phi^{-1}(c_t^e) + \Phi^{-1}(1 - a_t^e)}{\Phi^{-1}(c_t^e) - \Phi^{-1}(1 - a_t^e)}}$$
(6)

The sensitivity interval calculated in this way using the sample 1995-2016 gives an estimate of l = 1.0%. It suggests that, on average, the quantitative expectations of respondents declaring no change in prices are located in the interval (-1.0%, 1.0%).

The assumption that the sensitivity interval is constant over time leads to some unpleasant features of the quantification method. Changes in the distribution of survey responses may have disproportional or even counterintuitive impact on the estimate of the perceived rate of inflation. To illustrate this point, let us analyze the following numerical example based on two consecutive rounds of the Michigan Survey of Consumers, conducted in July and August 2015. Between these two rounds the fraction of respondents expecting prices to increase declined, the fraction of respondents expecting price stabilisation stayed the same, while the share of consumers expecting price reduction increased (Table A1). In such circumstances it is intuitive to believe that the expected inflation went down. However, quantification method implies that both the mean and the standard deviation of the distribution of expected inflation increased significantly.

Analyzing changes in the whole distribution of expected inflation, it becomes clear why its mean and standard deviation had to go up (Figure A1). Given that the sensitivity interval was constant, in order to fit the adjusted distribution of survey responses there must occur a substantial flattening of the distribution of expected inflation and an increase of its mean value.

To avoid outliers of this kind, we introduce a slight modification to the quantification method described above. We relax the assumption that the sensitivity interval is constant over time, making it (denoted as l_t now) react to changes in the disagreement among consumers. This modification absorbs some of the effects of specific changes in the distribution of survey responses, preventing from disproportional flattening of the distribution of expected inflation. More specifically, we model the sensitivity interval as a function of a constant term and the Index of Qualitative Variation (IQV) – one of the measures showing disagreement of qualitative survey data (Mokinski, et al., 2015), i.e.:

$$l_t = \delta_0 + \delta_1 I Q V_t \tag{7}$$

Given equation (7), the backward unbiasedness condition now becomes:

$$\delta_0 \sum_{t=1}^{T} \frac{\Phi^{-1}(c_t^e) + \Phi^{-1}(1 - a_t^e)}{\Phi^{-1}(c_t^e) - \Phi^{-1}(1 - a_t^e)} + \delta_1 \sum_{t=1}^{T} IQV_t \frac{\Phi^{-1}(c_t^e) + \Phi^{-1}(1 - a_t^e)}{\Phi^{-1}(c_t^e) - \Phi^{-1}(1 - a_t^e)} = \sum_{t=1}^{T} \mu_t^e$$
 (8)

We estimate equation (8) to obtain $\hat{\delta_0}$ and $\hat{\delta_1}$ and a time-varying sensitivity interval.

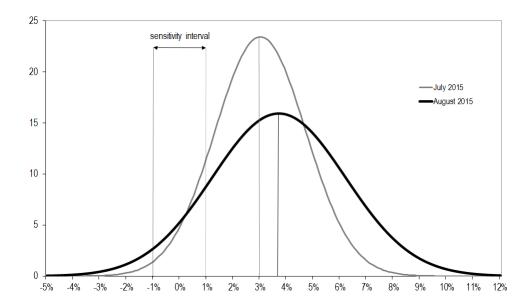


Figure A1: Changes in the distribution of expected inflation

Table A1: Problems with original Carlson-Parkin (1975) probability method

	July 2015 survey	August 2015 survey
response: "prices have risen"	0.88	0.85
response: "prices have stayed about the same"	0.11	0.11
response: "prices have fallen"	0.01	0.03
Quantified expected inflation	3.0%	3.7%
Quantified standard deviation	1.7 pp	2.5 pp
Sensitivity interval	(-1.0% ; 1.0%)	(-1.0% ; 1.0%)

The fraction of households who are not able to assess the direction of price chenges is not shown in the table.

Appendix B: Quantification of consumer inflation expectations, European economies

In the case of European economies we use survey data on expected price changes from the European Commission Consumer Survey, carried out every month in EU economies; see EC (2006) and EC (2007) for a detailed description. The qualitative question included in this survey has the following form:

"By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will... (1) increase more rapidly, (2) increase at the same rate, (3) increase at a slower rate, (4) stay about the same, (5) fall, (6) don't know".

There is an additional qualitative question concerning the perception of current price movements, whose results can be useful in quantifying the expected rate of inflation:

"How do you think that consumer prices have developed over the last 12 months? They have... (1) risen a lot; (2) risen moderately; (3) risen slightly; (4) stayed about the same; (5) fallen; (6) don't know".

In quantifying consumer inflation expectations in European economies we apply the probability method, modified by Batchelor and Orr (1988) in order to use all information embodied in the survey data. We express the observed fractions of respondents a_{1t}^e , a_{2t}^e , a_{3t}^e , b_t^e and c_t^e as the functions of cumulative normal distribution, $F(\cdot)$, the limits of sensitivity intervals surrounding zero, l_t and perceived inflation rate s_t :

$$a_{1t}^e = 1 - F_t^e(\pi_t^p + s_t) \tag{9}$$

$$a_{2t}^e = F_t^e(\pi_t^p + s_t) - F_t^e(\pi_t^p - s_t)$$
(10)

$$a_{3t}^e = F_t^e(\pi_t^p - s_t) - F_t^e(l_t) \tag{11}$$

$$b_t^e = F_t^e(l_t) - F_t^e(-l_t) (12)$$

$$c_t^e = F_t^e(-l_t) \tag{13}$$

Using the formula of cumulative normal density standardisation:

$$F_t^e(k) = \Phi_t^e(\frac{k - \bar{\pi}_t^e}{\sigma_t^e}) \tag{14}$$

where the mean and standard deviation of the distribution of expected inflation are denoted as $\bar{\pi}_t^e$ and σ_t^e , respectively, we obtain the following solution:

$$\bar{\pi}_t^e = \pi_t^p \frac{g_t^e + h_t^e}{g_t^e + h_t^e - (e_t^e + f_t^e)} \tag{15}$$

$$\sigma_t^e = \pi_t^p \frac{-2}{q_t^e + h_t^e - (e_t^e + f_t^e)} \tag{16}$$

$$s_t = \pi_t^p \frac{f_t^e - e_t^e}{g_t^e + h_t^e - (e_t^e + f_t^e)}$$
(17)

$$l_t = \pi_t^p \frac{h_t^e - g_t^e}{g_t^e + h_t^e - (e_t^e + f_t^e)}$$
(18)

where $e_t^e = \Phi_t^{-1}(1-a_{1t}^e)$, $f_t^e = \Phi_t^{-1}(1-a_{1t}^e-a_{2t}^e)$, $g_t^e = \Phi_t^{-1}(1-a_{1t}^e-a_{2t}^e-a_{3t}^e)$ and $h_t^e = \Phi_t^{-1}(c_t^e)$. In line with the survey question, the quantified expected inflation depends on the measure of perceived inflation. To quantify the latter, we use survey responses to the question on perceived price changes and apply the probability method analogous to this presented above. We assume that while selecting the response to the survey question, individuals compare currently observed price developments with the so-called moderate rate of inflation or trend inflation; see, e.g. Batchelor and Orr (1988). Following Łyziak and Mackiewicz-Łyziak (2014) and Łyziak and Paloviita (2017), we select the moderate inflation from different

proxies – including moving averages of current price dynamics (lags of 2 to 120 months) and cumulative means of inflation – on the basis of their correlation with survey data. According to this method, European consumers have a long memory of inflation and their assessment of trend inflation is based either on long-run cumulative means of inflation, e.g. Spain, France, Italy and UK since 1985, or moving average (MA) of inflation, e.g. Germany – 109-month MA and Netherlands – 119-month MA.

Appendix C: Additional figures and tables for European economies

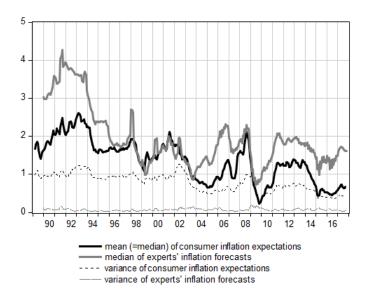


Figure C1: Inflation expectations and disagreement, Germany

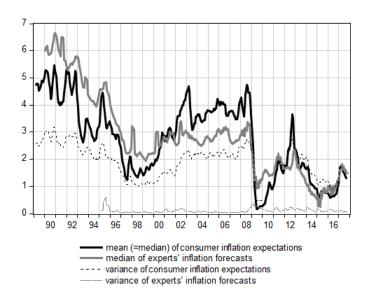


Figure C2: Inflation expectations and disagreement, Spain

Note: Individual forecasts and the corresponding disagreement are available since 1995 from Consensus Forecasts.

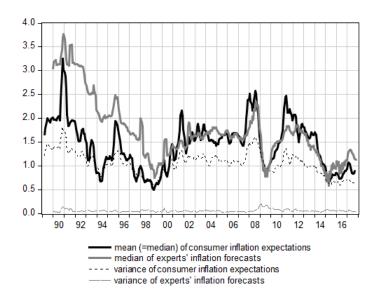


Figure C3: Inflation expectations and disagreement, France

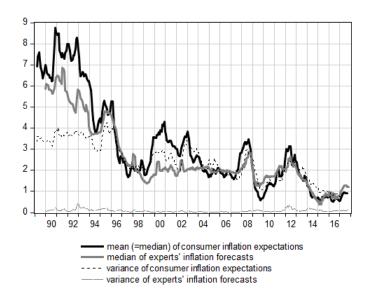


Figure C4: Inflation expectations and disagreement, Italy

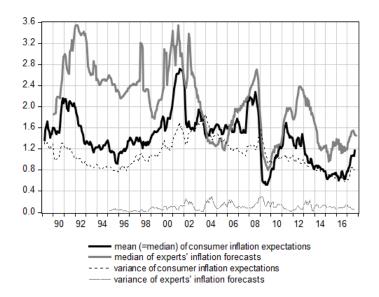


Figure C5: Inflation expectations and disagreement, Netherlands

Note: Individual forecasts and the corresponding disagreement are available since 1995 from Consensus Forecasts.

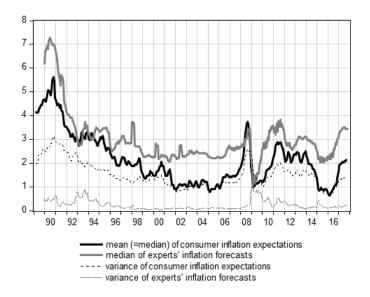


Figure C6: Inflation expectations and disagreement, UK

Table C1: Constrained models, Germany

Table C1. Consti	amed models	5, dermany		
	$P_{hom}E_{hom}$	$P_{het}E_{hom}$	$P_{hom}E_{het}$	$P_{het}E_{het}$
	model	model	model	model
Sample: 1990M01-2017M9				
$-\frac{1}{\lambda}$	0.026***	0.137***	0.049***	0.137***
$ar{eta}$	0.971***	0.814***	0.948***	0.813***
$ar{\mu}$	-0.020	-0.020	-0.032	-0.020
σ_{λ}	_	0.022	_	0.022
σ_{eta}	_	0.205***	_	0.205***
σ_{μ}	0.169***	0.338***	0.269***	0.337***
fundamental inflation	_	_	_	_
% of agents with constant exp.	_	_	_	_
$adj.R^2 - exp.level$	0.897	0.914	0.902	0.914
$adj.R^2 - disagreement$	0.895	0.903	0.888	0.903
Sample: 1990M01-2012M12				1
	0.034***	0.137***	0.059***	0.138***
$ar{eta}$	0.951***	0.792***	0.918***	0.791***
$ar{ar{\mu}}$	0.002	0.028	0.000	0.028
σ_{λ}	_	0.002	_	0.000
σ_{eta}	_	0.210***	_	0.210***
σ_{μ}	0.243***	0.377***	0.347***	0.376***
fundamental inflation	_	_	_	_
% of agents with constant exp.	_	_	_	_
$adj.R^2 - exp.level$	0.873	0.896	0.881	0.896
$adj.R^2 - disagreement$	0.859	0.872	0.847	0.871
Forecasting accuracy	,		,	
RMSE – exp.level	0.116	0.137	0.117	0.138
${ m RMSE-disagreement}$	0.059	0.057	0.087	0.057
SE vs. $P_{hom}E_{hom}$ model - exp.level	_	0.022***	0.000	0.022***
SE vs. $P_{hom}E_{hom}$ model - disagreement	_	-0.001	0.030***	-0.001
SE vs. $P_{het}E_{hom}$ model - exp.level	-0.022***	_	-0.022***	0.001***
SE vs. $P_{het}E_{hom}$ model - disagreement	0.001	_	0.031***	0.001***
SE vs. $P_{hom}E_{het}$ model - exp.level	0.000	0.022***	_	0.022***
SE vs. $P_{hom}E_{het}$ model - disagreement	-0.030***	-0.031***	_	-0.031***
SE vs. $P_{het}E_{het}$ model - exp.level	-0.022***	-0.001***	-0.022***	_
SE vs. $P_{het}E_{het}$ model - disagreement	0.001	-0.001***	0.031***	_
NI	1 1.	207 F07 1.11		. 1 37

Table C2: Constrained models, Spain

		,		
	$P_{hom}E_{hom}$	$P_{het}E_{hom}$	$P_{hom}E_{het}$	$P_{het}E_{het}$
	model	model	model	model
Sample: 1990M01-2017M9				
$-\frac{\bar{\lambda}}{\lambda}$	-0.015	0.064*	0.029	0.086***
$ar{eta}$	0.969***	0.905***	0.931***	0.867***
$ar{\mu}$	0.094*	0.046	0.073	0.081
σ_{λ}	_	0.025	_	0.038
σ_{eta}	_	0.112***	_	0.121***
σ_{μ}	0.059***	0.178***	0.217***	0.276***
fundamental inflation	2.074	_	_	_
% of agents with constant exp.	0.045	_	_	_
$adj.R^2 - exp.level$	0.859	0.867	0.864	0.870
$adj.R^2 - disagreement$	0.851	0.855	0.808	0.818
Sample: 1990M01-2012M12		1		1
$\overline{\lambda}$	-0.018	0.051**	0.009	0.076***
$ar{eta}$	0.969***	0.900***	0.944***	0.857***
$ar{\mu}$	0.131***	0.121	0.119	0.163**
σ_{λ}	_	0.016	_	0.046
σ_{eta}	_	0.114***	_	0.125***
σ_{μ}	0.051***	0.169***	0.169***	0.260**
fundamental inflation	2.670	_	_	2.447
% of agents with constant exp.	0.049	_	_	0.066
$adj.R^2 - exp.level$	0.817	0.827	0.822	0.830
$adj.R^2 - disagreement$	0.849	0.849	0.809	0.812
Forecasting accuracy				
RMSE – exp.level	0.344	0.311	0.330	0.304
${ m RMSE-disagreement}$	0.217	0.192	0.214	0.187
SE vs. $P_{hom}E_{hom}$ model - exp.level	_	-0.026***	-0.013***	-0.023***
SE vs. $P_{hom}E_{hom}$ model - disagreement	_	-0.029***	0.001	-0.035***
SE vs. $P_{het}E_{hom}$ model - exp.level	0.026***	_	0.013***	0.003
SE vs. $P_{het}E_{hom}$ model - disagreement	0.029***	_	0.030***	-0.006
SE vs. $P_{hom}E_{het}$ model - exp.level	0.013***	-0.013***	_	-0.010*
SE vs. $P_{hom}E_{het}$ model - disagreement	-0.001	-0.030***	_	-0.035***
SE vs. $P_{het}E_{het}$ model - exp.level	0.023***	-0.003	0.010*	_
SE vs. $P_{het}E_{het}$ model - disagreement	0.035***	0.006	0.035***	_
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Table C3: Constrained models, France

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	$P_{hom}E_{hom}$	$P_{het}E_{hom}$	$P_{hom}E_{het}$	$P_{het}E_{het}$
	model	model	model	model
Sample: 1990M01-2017M9				
$ar{\lambda}$	-0.029*	0.044*	-0.003	0.043**
$ar{eta}$	0.948***	0.868***	0.931***	0.868***
$ar{\mu}$	0.115***	0.102**	0.095**	0.104**
σ_{λ}	_	0.092***	_	0.091***
σ_{eta}	_	0.125***	_	0.125***
σ_{μ}	0.242***	0.345***	0.303***	0.345***
fundamental inflation	_	1.167	1.377	1.174
% of agents with constant exp.	_	0.088	0.069	0.089
$adj.R^2 - exp.level$	0.722	0.741	0.729	0.741
$adj.R^2 - disagreement$	0.783	0.794	0.780	0.793
Sample: 1990M01-2012M12		1		
$\bar{\lambda}$	-0.040**	0.053**	-0.010	0.052**
$ar{eta}$	0.924***	0.816***	0.901***	0.816***
$ar{ar{\mu}}$	0.188*	0.175***	0.164**	0.178***
σ_{λ}	_	0.095***	_	0.095***
σ_{eta}	_	0.134***	_	0.134***
$\sigma_{\mu}^{'}$	0.315***	0.438***	0.372***	0.438***
fundamental inflation	_	1.336	1.657	1.341
% of agents with constant exp.	_	0.131	0.099	0.133
$adj.R^2 - exp.level$	0.683	0.706	0.691	0.706
$adj.R^2 - disagreement$	0.702	0.725	0.701	0.724
Forecasting accuracy	l	ı	l	
m RMSE-exp.level	0.164	0.137	0.152	0.138
${ m RMSE-disagreement}$	0.082	0.089	0.094	0.090
SE vs. $P_{hom}E_{hom}$ model - exp.level	_	-0.019***	-0.009***	-0.018***
SE vs. $P_{hom}E_{hom}$ model - disagreement	_	-0.009***	0.013**	0.010***
SE vs. $P_{het}E_{hom}$ model - exp.level	0.019***	_	0.010***	0.001***
SE vs. $P_{het}E_{hom}$ model - disagreement	-0.009***	_	0.003***	0.001***
SE vs. $P_{hom}E_{het}$ model - exp.level	0.009***	-0.010***	_	-0.009***
SE vs. $P_{hom}E_{het}$ model - disagreement	-0.013**	-0.003***	_	-0.003***
SE vs. $P_{het}E_{het}$ model - exp.level	0.018***	-0.001***	0.009**	_
SE vs. $P_{het}E_{het}$ model - disagreement	-0.010***	-0.001***	0.003***	_
	_			<u> </u>

Table C4: Constrained models, Italy

		,		
	$P_{hom}E_{hom}$	$P_{het}E_{hom}$	$P_{hom}E_{het}$	$P_{het}E_{het}$
	model	model	model	model
Sample: 1990M01-2017M9				
$ \bar{\lambda}$	-0.017	0.062***	-0.010	0.062***
$ar{eta}$	0.981***	0.937***	0.978***	0.937***
$ar{\mu}$	0.051	-0.018	0.041	-0.018
σ_{λ}	_	0.021	_	0.021
σ_{eta}	_	0.073***	_	0.073***
σ_{μ}	0.024***	0.199***	0.002***	0.198***
fundamental inflation	_	_	_	_
% of agents with constant exp.	_	_	_	_
$adj.R^2 - exp.level$	0.945	0.948	0.945	0.948
$adj.R^2 - disagreement$	0.912	0.916	0.913	0.916
Sample: 1990M01-2012M12				
$\overline{\lambda}$	-0.006	0.102***	0.016	0.103***
$ar{eta}$	0.965***	0.904***	0.953***	0.903***
$ar{ar{\mu}}$	0.097	-0.002	0.072	-0.004
σ_{λ}	_	0.038	_	0.039
σ_{eta}	_	0.076***	_	0.075***
σ_{μ}	0.141***	0.331***	0.149***	0.332***
fundamental inflation	_	_	_	_
% of agents with constant exp.	_	_	_	_
$adj.R^2 - exp.level$	0.934	0.938	0.935	0.938
$adj.R^2 - disagreement$	0.871	0.880	0.875	0.880
Forecasting accuracy			·	
$ hootnote{RMSE - exp.level}$	0.248	0.216	0.240	0.216
${ m RMSE-disagreement}$	0.200	0.228	0.236	0.229
SE vs. $P_{hom}E_{hom}$ model - exp.level	_	-0.030***	-0.010***	-0.033***
SE vs. $P_{hom}E_{hom}$ model - disagreement	_	0.036***	0.031**	0.037***
SE vs. $P_{het}E_{hom}$ model - exp.level	0.033***	_	0.023***	0.000
SE vs. $P_{het}E_{hom}$ model - disagreement	-0.036***	_	-0.004	0.001***
SE vs. $P_{hom}E_{het}$ model - exp.level	0.010***	-0.023***	_	-0.024***
SE vs. $P_{hom}E_{het}$ model - disagreement	-0.031**	0.004	_	0.005
SE vs. $P_{het}E_{het}$ model - exp.level	0.033***	0.000	0.024***	_
SE vs. $P_{het}E_{het}$ model - disagreement	-0.037***	-0.001***	-0.005	_
		- 0404	0.4	

Table C5: Constrained models, Netherlands

	$P_{hom}E_{hom}$	$P_{het}E_{hom}$	$P_{hom}E_{het}$	$P_{het}E_{het}$
	model	model	model	model
Sample: 1990M01-2017M9				
$-\frac{\bar{\lambda}}{\lambda}$	-0.003	0.036**	-0.001	0.036**
$ar{eta}$	0.961***	0.907***	0.961***	0.909***
$ar{\mu}$	0.058*	0.053	0.053	0.050
σ_{λ}	_	0.030	_	0.090***
σ_{eta}	_	0.158***	_	0.147***
σ_{μ}	0.245***	0.284***	0.257***	0.258***
fundamental inflation	1.487	_	_	_
% of agents with constant exp.	0.039	_	_	_
$adj.R^2 - exp.level$	0.827	0.832	0.827	0.832
$adj.R^2 - disagreement$	0.880	0.886	0.890	0.904
Sample: 1990M01-2012M12				
$\overline{\lambda}$	0.004	0.031	0.009	0.031
$ar{eta}$	0.944***	0.896***	0.932***	0.900***
$ar{\mu}$	0.076*	0.089**	0.082*	0.084
σ_{λ}	_	0.004	_	0.084
σ_{eta}	_	0.160***	_	0.147***
σ_{μ}	0.309***	0.328***	0.346***	0.300***
fundamental inflation	1.357	1.219	1.206	_
% of agents with constant exp.	0.056	0.073	0.068	_
$adj.R^2 - exp.level$	0.757	0.764	0.759	0.763
$adj.R^2 - disagreement$	0.836	0.840	0.831	0.850
Forecasting accuracy				
m RMSE-exp.level	0.129	0.135	0.147	0.131
${ m RMSE-disagreement}$	0.072	0.058	0.748	0.059
SE vs. $P_{hom}E_{hom}$ model - exp.level	_	0.003**	0.001*	0.002
SE vs. $P_{hom}E_{hom}$ model - disagreement	_	-0.013***	0.016**	-0.017***
SE vs. $P_{het}E_{hom}$ model - exp.level	-0.003**	_	-0.002**	-0.001***
SE vs. $P_{het}E_{hom}$ model - disagreement	0.013***	_	0.029***	-0.003***
SE vs. $P_{hom}E_{het}$ model - exp.level	-0.001*	0.002**	_	0.001
SE vs. $P_{hom}E_{het}$ model - disagreement	-0.016***	-0.029***	_	-0.033***
SE vs. $P_{het}E_{het}$ model - exp.level	-0.002	0.001***	-0.001	_
SE vs. $P_{het}E_{het}$ model - disagreement	0.017***	0.003***	0.033***	_

Table C6: Constrained models, UK

	$P_{hom}E_{hom}$	$P_{het}E_{hom}$	$P_{hom}E_{het}$	$P_{het}E_{het}$
	model	model	model	model
Sample: 1990M01-2017M9				
$\bar{\lambda}$	-0.013	0.184***	-0.016	0.177***
$ar{eta}$	0.967***	0.773***	0.973***	0.775***
$ar{\mu}$	0.086*	-0.101**	0.081*	-0.082*
σ_{λ}	_	0.003	_	0.004
σ_{eta}	_	0.187***	_	0.184***
σ_{μ}	0.184***	0.521***	0.466***	0.517***
fundamental inflation	2.606	_	3.000	_
% of agents with constant exp.	0.033	_	0.027	_
$adj.R^2 - exp.level$	0.891	0.915	0.891	0.915
$adj.R^2 - disagreement$	0.904	0.910	0.903	0.910
Sample: 1990M01-2012M12			1	
$\bar{\lambda}$	-0.015	0.190***	-0.018	0.185***
$ar{eta}$	0.967***	0.760***	0.974***	0.760***
$ar{ar{\mu}}$	0.093*	-0.079	0.087*	-0.063
σ_{λ}	_	0.005	_	0.004
σ_{eta}	_	0.191***	_	0.188***
σ_{μ}	0.336***	0.536***	0.163***	0.534***
fundamental inflation	2.818	_	3.346	_
% of agents with constant exp.	0.033	_	0.026	_
$adj.R^2 - exp.level$	0.892	0.916	0.891	0.916
$adj.R^2 - disagreement$	0.908	0.913	0.906	0.913
Forecasting accuracy			ı	
$\overline{ m RMSE-exp.level}$	0.282	0.244	0.284	0.246
RMSE-disagreement	0.164	0.161	0.166	0.162
SE vs. $P_{hom}E_{hom}$ model - exp.level	_	-0.022	0.000	-0.021
SE vs. $P_{hom}E_{hom}$ model - disagreement	_	-0.004	0.001	0.004
SE vs. $P_{het}E_{hom}$ model - exp.level	0.022	_	0.023	0.002*
SE vs. $P_{het}E_{hom}$ model - disagreement	0.004	_	0.005	0.001
SE vs. $P_{hom}E_{het}$ model - exp.level	0.000	-0.023	_	-0.021
SE vs. $P_{hom}E_{het}$ model - disagreement	-0.001	-0.005	_	-0.004
SE vs. $P_{het}E_{het}$ model - exp.level	0.021	-0.002***	0.021	_
SE vs. $P_{het}E_{het}$ model - disagreement	0.004	-0.001	0.004	_
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