Inflation Expectations in a Highly Volatile Environment:

Evidence from a Firms' Survey

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Abstract

This study provides new evidence about inflation expectations formation in a highly volatile environment, in which inflation dropped dramatically from three-digits annual rate to less than 3%. Our findings, based on an Israeli survey of firms' expectations, support information rigidity theories, and at the same time point to the presence of asymmetric preference towards forecast errors. Most importantly, both inattentiveness and asymmetry depend on inflation, being more pronounced when inflation is sufficiently decreasing. This pattern applies both for high and low inflation regimes. Our evidence demonstrates the complexity of inflation expectations, having important implications for macroeconomic dynamics and policy issues.

Keywords: Inflation, Expectations, Information Rigidity, Rational Inattention.

JEL Codes: D84, E31, E37.

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1. Introduction

The Rational expectations hypothesis has dominated the macroeconomic literature for many years. However, in recent years, a growing body of research has proposed to modify this hypothesis by accounting for information rigidities (e.g. Mankiw and Reis, 2002, Woodford, 2003 and Sims, 2003). Thus, agents may still behave rationally but in a more realistic environment, in which they choose to be inattentive to relevant information due to the costs involved in acquiring and processing information. Moreover, extending New Keynesian macroeconomic analysis with inattentive expectations may provide a better explanation for macroeconomic dynamics that are hard to reconcile with rational expectations (see review by Coibion et al., 2017).

The aim of this study is to provide new evidence on expectations formation in a highly volatile economy, based on a unique firms' survey of inflation forecasts in Israel. While evidence of information rigidities has been accumulated in recent years (e.g. Mankiw et al., 2004, Coibion and Gorodnichenko, 2012, 2015, Andrade and Le Bihan, 2013, Dovern et al., 2015), it is mainly based on surveys of expectations from the U.S. and other developed countries, in which the economy in general and inflation in particular, are fairly stable. In contrast, the inflation process in Israel went through major transitions, from three-digit annual inflation rate at the beginning of the 1980s to less than 3% in the last decade of the survey. Hence, examining inflation forecasts in such economy provides a special opportunity to obtain better insights about expectations behavior and their responsiveness to information rigidities.

Since inattention is an outcome of some optimal choice taken by firms or consumers (e.g. Reis, 2006), it is important to better understand the determinants of such behavioral parameter. Exploiting the special inflation process in Israel, as a kind of a quasi-natural experiment design, we can better examine how inattention depends on the inflation environment.

Additional important advantage of the Israeli survey is that the forecasts are provided by firms. Most of the survey data incorporated by the literature relies on professional (e.g. Survey of Professional Forecasts) or consumers' forecasts (e.g. Michigan Survey). However, as firms are the price-setters, their expectations play a key-role in macroeconomic models, hence the great importance of studying firms' forecasts, as stressed in Coibion et al. (2016), who employ an extensive new survey of firms from New-Zealand (see also the discussion in Coibion et al., 2017, in the context of estimating the New Keynesian Philips Curve). Thus, to our knowledge, the Israeli survey is currently the only survey to provide firm-level inflation forecasts for an extensive period of almost 30 years (1980Q1:2009Q1)[1].

This study relies on various empirical approaches, involving the path of the average forecast across firms, as well as looking at the cross section of individual forecasts over the survey period. Several tests of expectations used in the literature are extended to enable us examining the possibility of state-dependency as well. A theoretical justification for such an extension is provided in an appendix.

The findings from the Israeli survey support leading theories of information rigidities (sticky information as in Mankiw and Reis, 2003, and noisy information as in Sims, 2003, and Woodford, 2003). At the same time, they also support an asymmetry towards the sign of forecast errors, which is another kind of behavioral deviation from rational expectations, proposed by some

[1] The last extensive use of the Israeli survey was made by Kandel and Zilberfarb (1999) who employed only the first years of the survey (until 1993), thus, considering just the time of high inflation. Referring to the literature on learning, they find evidence for heterogeneity in interpretation of information among firms.

other studies (e.g. Elliot et al., 2008 and Capistrán and Timmermann, 2009). Thus, our evidence suggest that expectations formation can be dominated simultaneously by *several* kinds of behavioral characterizations.

Most importantly, both inattentiveness and asymmetry are found to depend on the inflation environment. They are both more pronounced in a low inflation environment, while during high inflation times forecasts are closer to follow rational expectations. This dependent behavior is quite dynamic as the behavioral changes do not just correspond to the major regime shifts in the inflation process. Rather, within each regime, forecasters react to shocks that affect the inflation level considerably. For example, even when inflation levels began to fluctuate around a low rate similar to the U.S., since the late 1990s, a substantial decrease in inattentiveness and asymmetry is documented in response to a high enough increase in the inflation level. A difference which does appear between inattentiveness to asymmetry is related to their pattern across forecast horizons – while information rigidities are quite similar across horizons, asymmetries seem stronger at longer forecast horizons.

Our results concerning the state-dependence of information rigidities have important implications for macroeconomic dynamics and monetary policy. In particular, the close relationship we find between firms' inattention and inflation, may suggest an additional benefit from sustaining a low inflation environment, which provides a channel to a more effective monetary policy due to a higher rigidity in inflation expectations. More generally, our evidence is in line with the recent models of Gorodnichenko (2008), Branch et al. (2009), Woodford (2009), Maćkowiak and Wiederholt (2015) and Matějka (2015). In these models the degree of information rigidity is endogenous, and is related to the choice of how to allocate resources to face information constraints or to the exposure level to economic shocks.

Despite the growing theoretical interest, direct evidence about inattention patterns of change is quite rare. Few other studies which provide some empirical evidence for state dependence of information rigidity, based on expectations data, should be mentioned. Coibion and Gorodnichenko (2015) showed how information rigidity has changed after the great moderation and during the business cycle. Dovern (2013) and Loungani et al. (2013) found that forecasters updating behavior differs in recessions. The findings of these studies are based on pooling different variables or countries to produce general patterns of state dependency. Instead, the approach in this paper is to identify state-dependency of expectations while focusing on the process of a single variable (inflation) and exploiting the great variations in that process during the survey period. In addition, we do not split the sample in advance according to the business cycle (which might be unknown to forecasters in real time).

Two additional studies focus on inflation expectations made by households. Dräger and Lamla (2017) use the Michigan Survey of consumers in the U.S. and find that adjustment of expectations corresponds to inflation volatility and news. Cavallo et al. (2017) use survey experiments conducted in the U.S. and Argentine and find evidence for higher inattentiveness in a low inflation country (U.S.). While our evidence is overall in line with the above findings, we differ from them by exploiting for the first time a firm survey over a long period in a highly transitional economy. This allows us to characterize a close and dynamic relationship between inattention and inflation. Furthermore, we provide evidence not just for state dependent information rigidity, but also for state dependent asymmetry[2].

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[2] In a related paper, Mertens and Nason (2015) estimate a model of U.S. inflation, in which they incorporate survey forecasts governed by dynamic information stickiness. They show a co-

The next section describes in more detail the survey data and the inflation dynamics in Israel, during the sample period. Section 3 presents preliminary estimations of information rigidity. Section 4 examines the state-dependency of information rigidity and find some mixed results, which indicate the presence of forecast asymmetry as well. Section 5 clarifies the above results by providing a more direct kind of evidence for the variation of both information rigidity and forecast asymmetry in response to inflation and across forecast horizons. Summary and concluding remarks are provided in Section 6.

2. Data

The data set is based on a survey conducted quarterly since 1980q1 until 2009q1 among economists and business executives from industrial, commercial and financial Israeli firms[3]. Overall, 11 sectors of the Israeli economy are covered, including all major firms in each sector. At the beginning of each quarter, participants were asked to forecast CPI inflation rates for the next one, two, three and four quarters. Thus, we can also calculate the *quarterly* inflation rate forecasts for

movement between inflation persistence and information stickiness. However, they do not model the stickiness parameter as state-dependent, but rather as an exogenous random walk.

[3] The survey was arranged by Ungar and Zilberfarb from Bar-Ilan university. Part of the data (corresponding to the high inflation period) was utilized in few former studies like Ungar and Zilberfarb (1993) and Kandel and Zilberfarb (1999), which didn't address the issue of the present study. More recent evidence, provided by Goldstein and Zilberfarb (2017), will be discussed later.

each of the next 4 quarters[4], thereby forming 4 fixed-event forecasts. Hence, a quarterly forecast was updated 3 times until the actual quarterly inflation figure was realized. These updates are crucial for detecting information rigidities, as will be demonstrated later.

Questionnaires were mailed at the 15th of the first month of the quarter, after the inflation rate for the previous month was published[5]. The sample includes all forecasts that were mailed back until the 15th of the following month (before the next publication of monthly inflation). Along with the questionnaire, participants were also informed about the survey average results in the previous quarter.

New participants were added if they took over a position of a former participant, or when the survey was expanded to other firms. A participant that left his job continued to be on the mailing list if he could be traced. Participants that didn't respond for several consecutive quarters were dropped from the list and not approached again. On average, there are about 85 quarterly forecasters[6].

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[4] For example, in the first quarter of year 2000, the survey provided forecasts for the inflation during the 2 and 3 first quarters of 2000, denoted as $f_{2000:1,2000:1-2000:2}$ and $f_{2000:1,2000:1-2000:3}$, respectively. The implied forecast for the inflation in the third quarter of the year, $F_{2000:1,2000:3}$, is therefore calculated as $F_{2000:1,2000:3} = \frac{f_{2000:1,2000:1-2000:3}+1}{f_{2000:1,2000:1-2000:2}+1} - 1$.

[5] The Israeli Central Bureau of Statistics publishes the CPI index for the month t on the 15th of month $t + 1$.

[6] The number of participants is relatively large comparing to most popular surveys, like the SPF, Livingston survey or the Economic Consensus.

The Israeli economy had witnessed dramatic changes in the inflation process over the survey period. A closer look at the data presented in figure 1 reveals three distinct sub-periods[7]. The first, 1980-1985, was a high inflation sub-period, with inflation rates averaging 30% per quarter, and reaching almost 60% at the peak. A successful stabilization program was implemented in July 1985[8]. The program included freezing of prices, exchange rate and wages, as well as cutting the budget deficit dramatically from roughly 15% of GDP to 1.3% surplus at the end of 1985. The anti-inflation program was extremely successful, bringing quarterly inflation rate down to 6.5% in 1985q4, and a further gradual decline in the second sub-period of 1986-1996. The average inflation rate per quarter during that period was 3.5%. Since 1997, the Bank of Israel adopted an inflation target regime, putting the fight against inflation as its only target. As a result, inflation has declined towards the rates characterizing developed countries. The quarterly average inflation rate since 1997 until 2009 was about 0.65%.

The three distinct sub-periods would be referred to as the high (1980Q1-1985Q4), moderate (1986Q1-1996Q4) and low (1997Q1-2009Q1) inflation sub-periods. In the next section we address the question whether these three sub-periods also differ in their associated degree of information rigidity.

[7] The upper panel of the graph describes the whole survey period, while the bottom panel starts from the second sub-period to provide a better resolution.

[8] For more on this program see Bruno (1993).

3. Information rigidity: preliminary results

The two leading models of information rigidities are the sticky information model of Mankiw and Reis (2002) and the noisy information model due to Woodford (2003) and Sims (2003). According to the first model, agents are not fully informed at each date. Specifically, at any particular date there is a constant probability λ to remain uninformed. In the noisy information framework, in contrast, agents are always updated, but the new information includes noise due to information rigidities. Coibion and Gorodnichenko (2015) have proposed a simple test for information rigidity, which suits both models, based on the following regression:

$$A_{t+h} - F_{t,t+h} = \alpha + \beta\left(F_{t,t+h} - F_{t-1,t+h}\right) + v_{t,t+h} \qquad (1)$$

where A_{t+h} is the actual value at time $t+h$, $F_{t,t+h}$ and $F_{t-1,t+h}$ are the average forecasts for this time, made at times t and $t-1$, respectively. The error term, $v_{t,t+h}$, should be the standard rational expectations error (that is, $A_{t+h} - E_t A_{t+h}$). Thus, it is a simple regression of forecast errors on forecast revisions. The degree of information rigidity is represented by the parameter β. As Coibion and Gorodnichenko (2015) derived, this parameter should equal $\frac{\lambda}{1-\lambda}$ under the sticky information model, or $\frac{1-G}{G}$ under the noisy information model, where G is the relative weight placed on the current noisy signal in the optimal forecast, and $1-G$ is the weight placed on old information (the previous forecast)[9]. Under the standard rational expectations hypothesis with full information $\lambda = 0$ (agents are always updated) or $G = 1$ (the forecast is solely based on the new

[9] Such a weighted forecast is the optimal forecast produced by a Kalman filter in this model. See Coibion and Gorodnichenko (2015) for further details.

signal, which does not contain noise). In each case, β should equal zero, so that we can test for the presence of information rigidities by testing for the significance of β.

The results of applying this regression to the inflation forecasts of the Israeli survey are presented in table 1. Since there are 4 forecast horizons in the survey, we have 3 forecast revisions, thus, $h = 0,1,2$. We ran the regression for each forecast horizon separately, and a fourth regression, which pools the horizons together.

Considering the large differences in inflation levels between the three sub-periods of the sample, as described in the previous section, we might expect β to change as well. In the model of Branch et al. (2009) the degree of inattention from the sticky information model is a decision variable, depending on the amount of resources invested in updating. According to this framework, in times of high inflation the losses from prediction errors are higher. Forecasters are expected to invest more in updating their information. This will result in a reduced degree of information rigidity relative to low inflation times. The choice to acquire more information in a high inflation environment can be beneficial in the noisy information setup as well, if it can improve the precision of signals, like in Maćkowiak and Wiederholt (2009, 2012). In addition, inflation shocks are more remarkable during high inflation times, making the forecasters more exposed to the new information, which may also reduce the information rigidity degree, as in the state-dependent models of Gorodnichenko (2008) and Woodford (2009). Hence, we expect an increase in β between the first sub-period of high inflation (1980-1985) and the second sub-period of moderate inflation (1986-1996), and a further increase in the third sub-period of low inflation (1997-2009).

Before discussing the results in table 1, as well as the results in the following section, a reconsideration of regression equation (1) is warranted. In Coibion and Gorodnichneko (2015), this specification is derived under the assumption of constant degree of information rigidity.

Namely, the parameters λ and G, described above, are fixed. Allowing them to change, could potentially alter the whole structure of equation (1). Nevertheless, as shown in Appendix A, for both sticky and noisy information models, the same relationship between forecast error and forecast revision can still be derived when letting λ and G to change in the most general form, albeit the coefficient β is also time or state-dependent, which is exactly the issue examined here and in what follows.

The results in table 1 are quite confusing. There is no evidence for information rigidity, when estimating the regression for the whole sample period. However, this may reflect the dominant effect of the first sub-period of very high inflation (notice the high standard errors). Indeed, in all estimations for the 1980-1985 sub-period β is not significant. Therefore, we focus on the narrower sample of 1986-2009 (which follows the stabilization program). Here there are differences between the forecasting horizons. For $h = 0$ and $h = 1$, as well as for the estimation pooled across the three horizons, β is still insignificant, supporting the standard rational expectations hypothesis. But for $h = 2$ $\hat{\beta}$ =0.656 and is significant. The period 1986-2009 contains two distinct sub-periods of moderate inflation (1986-1996) and low inflation (1997-2009), but the results for these sub-periods reveals more inconsistency. For $h = 0$, though, there is now evidence of a significant rigidity during the low inflation period, which is in line with the above hypothesis. However, for $h = 1$ the estimated β is insignificant in both sub-periods. More surprisingly, for $h = 2$, there is a significant β, but actually in the moderate inflation sub-period. Thus, information rigidity is unexpectedly present only under higher inflation rates and not under lower rates, which is at odds with the above hypothesis. In the pooled estimation, β is insignificant for the both sub-periods, which does not help in reconciling the findings.

In sum, there is no clear evidence of whether and in which case information rigidity is present in the forecasts of the Israeli survey. Consequently, in the next section we suggest a more sophisticated strategy of splitting the sample.

4. State dependent information rigidity

A closer look into the Israeli inflation data, presented in figure 1, reveals a potential limitation in dividing the sample, following the stabilization program, to the moderate and low inflation sub-periods. Although these sub-periods may be distinguished by their inflation regime and the average inflation level, there are few irregularities in each of the sub-samples, produced by the dynamic process of inflation. In the low inflation sub-period, there are few episodes of much higher inflation rate and the moderate inflation sub-period also contains few observations with much lower inflation. If information rigidity is indeed state-dependent, in the spirit of the models mentioned above, expectations might respond sharply to such shocks to the inflation process, affecting the sub-periods' rigidity estimates reported above.

In order to address this limitation, we propose to split the sample according to the inflation level, while letting the particular splitting be determined in the estimation process itself, using the threshold regression methodology of Hansen (1996, 2000). Specifically, we consider the following regression model:

$$A_{t+h} - F_{t,t+h} = \alpha + \beta^{i}\left(F_{t,t+h} - F_{t-1,t+h}\right) + v_{t,t+h} \tag{2}$$

where i is a subscript specified as follows:

$$i = \begin{cases} 1, & T_t \leq \theta \\ 2, & T_t > \theta \end{cases}.$$

In this specification, the information rigidity coefficient β^{i} may change depending on whether the threshold variable T_t is above or below the value of the threshold parameter θ. The threshold variable T_t is specified to represent the inflation level in the economy, which is known to the forecaster while providing his forecast at quarter t. Two specifications for T_t will be considered: (a) $T_t = 0.25 \times \sum_{k=1}^{4} A_{t-k}$ – the average actual quarterly inflation over the last four quarters; (b) $T_t = 0.25 \times \sum_{h=0}^{3} F_{t,t+h}$ - the average predicted quarterly inflation over the four next quarters. Thus, the threshold parameter θ would distinguish between quarters with relatively low and high inflation level (actual or predicted).

If θ is known, we could estimate this regression equation by OLS using dummy variables. Suppose the least sum of squares will be $S(\theta) = \hat{v}_{t,t+h}(\theta)'\hat{v}_{t,t+h}(\theta)$. The estimation technique suggested by Hansen (1996) is to search for the threshold level θ in the range of the sample data T_t (truncated by some portion, say 30%, consisting the extreme values) and estimate it as $\hat{\theta} =$ arg $minS(\theta)$.

A test for the significance of the estimated threshold $\hat{\theta}$ is also available. The null hypothesis is that β is constant (it should further equal the specific value of zero, according to the rational expectations hypothesis with full information). Since under the null θ is not defined (a nuisance parameter), standard tests cannot be employed. Following Hansen (1996, 2000), we apply an LM-based test, using a bootstrap technique (see there for details). Finally, if θ is found to be significant we can use standard testing for the coefficients β^i, as is also shown there. In the present case, if information rigidity is state-dependent as previously described, we would expect $\beta^1 > \beta^2$, that is, the degree of information rigidity should be higher during times of lower inflation rates.

The estimation of regression equation (2) was applied to the sample period of 1986-2009[10], that follows the stabilization program, to avoid the dominant effect of the very high inflation rates, during the first sub-period, on the results[11]. As in the previous section, we ran the regression for each of the three forecasting horizons separately. Table 2 provides the estimation results in two panels for each specification of the threshold variable T_t.

Starting with the first column, which refers to current quarter forecasts, the state dependence of information rigidity is now supported by the threshold results. The estimated threshold in terms of actual inflation is 3.8% (panel A), which is very similar to the estimated threshold of 3.7% in terms of perceived inflation (panel B). These estimates are also highly significant. Moreover, depending on these thresholds, the pattern of information rigidity degree is $\hat{\beta}^1 > \hat{\beta}^2$. In particular, a significant degree of information rigidity is now present under low

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[10] Due to the four quarters lag in the first threshold variable used for estimation, t actually starts from 1987Q1, so that the year of the stabilization program is not included in the lag either.

[11] It should be noted that even when excluding those very special six years, the uniqueness of the Israeli inflation data still holds. As mentioned in the previous section, the average rate of quarterly inflation during the moderate inflation sub-period of 1986-1996 was 3.5%, while in the low inflation sub-period of 1997-2009, it came down to 0.65%. As a point of reference, the figures of the US inflation for the same sub-periods were 0.85% and 0.6%, respectively. Even before the Great Moderation, between 1973 and 1985, when US inflation level was at its peak, the average quarterly rate was only 1.84%. Thus, the changes in inflation levels were much more pronounced in Israel. Lastly, there is no evidence for information rigidity in the first su-period as reported in table 1, which is in line with the state-dependent hypothesis.

inflation rates (below the threshold) in both panels, but this rigidity fades away under higher levels of inflation ($\hat{\beta}^2$ is not positive).

Relating to the results of the previous section, when splitting the sample to distinct sub-periods in a pre-determined manner, it is now evident that in the low inflation sub-period of 1997-2009, as a whole, information rigidities have dominated to some extent. However, two remarkably positive inflation shocks in 1998Q4 and 2002Q2 (see figure 1), caused a sudden information updating by the forecasters. Likewise, the moderate inflation sub-period of 1986-1996 includes several quarters of relatively low levels of inflation, which were followed by an increasing inattention. Thus, the threshold estimation technique has improved the “unclean” sample splitting of the previous section, demonstrating the more tight nexus between the degree of information rigidity and the inflation level.

Notice, though, that for the high inflation regime a negative significant coefficient is estimated (in both panels). A negative correlation between forecast errors and forecast revisions also represents a deviation from the rational expectation hypothesis. However, it is not consistent with the two theories of information rigidity that are considered here (recall the construction of β, as described in the previous section). As shown in Coibion and Gorodnichenko (2015), a negative β is in line with an alternative recent theory of expectations, which suggests an asymmetric loss function over forecast errors (Elliot et al. 2008, Capistrán and Timmermann, 2009). Accordingly, forecasters may prefer to overshoot or undershoot inflation systematically, reflected in a negative correlation between forecast errors and forecast revisions[12]. Thus, it is possible that both

[12] Quite similar asymmetric pattern is also suggested by the model of "Diagnostic Expectations" (Bordalo et al. 2017a, 2017b), in which forecasters overreact to news, being too optimistic or

information rigidity and forecast asymmetry dominate the behavior of firms' expectations in our survey.

In fact, this possibility is highly supported by the results of the longer forecast horizons (the columns $h = 1$ and $h = 2$ in the table). Strikingly, the results for these horizons are very different from the results for the current quarter forecasts. In panel A of the table (actual past inflation as the threshold variable), inflation threshold estimates are 1.203% for $h = 1$ and 1.356% for $h = 2$ but they are not significant at the 10% level. Still, there is a considerable difference between $\hat{\beta}^1$ and $\hat{\beta}^2$, but not in the same manner as for the current quarter forecast. For both more distant horizons $\hat{\beta}^2$ is not significant, in accordance with rational expectations when inflation level is high, but $\hat{\beta}^1$ is strongly negative and also significant, which suits forecast asymmetry instead of information rigidity. Moreover, while for the current quarter forecasts asymmetry is indicated for high inflation ($\hat{\beta}^2 < 0$), here it is obtained for low inflation ($\hat{\beta}^1 < 0$).

Turning to panel B of the table the results for the longest horizon ($h = 2$) are quite similar to panel A, except that the estimated threshold is significant. Again $\hat{\beta}^1$ (low inflation) is strongly negative and highly significant, while $\hat{\beta}^2$ is not significant. In contrast, for $h = 1$, $\hat{\beta}^2$ is significantly negative and not $\hat{\beta}^1$ (threshold is not significant).

What are the reasons for the great differences between the forecast horizons as reflected by the results in table 2, especially the difference between current quarter forecasts and the longer horizons? Can the explanation be in line with the above theories of information rigidities or forecast asymmetry? In the next section we attempt to facilitate such explanation based on further

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pessimistic. Thus, in the same way, ex-post forecast errors will be negatively correlated with forecast revisions (representing news).

evidence, which will be provided. Before that we would like to concentrate again on the current quarter forecasts, for which the results do demonstrate dependency of information rigidity on the inflation level and examine the robustness of this finding.

Alternative threshold variables. So far, our threshold estimations based on equation (2) have used two alternatives for the threshold variable T_t - the average quarterly inflation over the last four quarters (actual) or over the next four quarters (predicted). As a first robustness check, five additional alternatives for T_t were considered, including inflation rates over shorter or longer periods as well as the *change* in inflation. Specific details and results for current quarter forecasts are provided in Appendix B. the findings are similar to those reported in table 2. In particular, a significant threshold effect is obtained in each case, with an evidence for information rigidity only at the low side of T_t (below threshold).

At this stage, an interpretation is warranted regarding the amount of information rigidity prevailing under the low inflation levels, that is, the size of $\hat{\beta}^1$. As discussed in the previous section, the coefficient on forecast revision can be directly converted into the underlying parameters in the sticky and noisy information models. The estimates in tables 2 and the table in appendix B (current quarter forecasts) range from 0.410 to 0.778. In terms of the sticky information model, the corresponding probability to remain not updated during a quarter, λ, ranges from 29% to 44%, meaning that the time between updates is approximately around 5 months. In terms of the noisy information model, the Israeli business executives update their forecasts, while putting a weight between 29% to 44% on their previous forecasts (which is $1 - G$, as demonstrated in the previous section). Hence, by interpreting the $\hat{\beta}^1$s in terms of the rigidity behavior implied by the models, the range of estimates in all specifications is quite narrow.

Previous empirical studies, which have used surveys from other countries, reached different estimates of information rigidities. Studies like Mankiw et al. (2004), Kahn and Zou (2006) and Döpke et al. (2008), which estimated information rigidity in a non-direct approach usually found higher degrees of rigidity, while other studies like Coibion and Gorodnichenko (2015), Andrade and Le Bihan (2013) and Dovern et al. (2015), which apply direct approaches to estimate information rigidity as in the current study, derived estimates of rigidity degree quite close to our estimates. Recall though, that our estimates refer only to a part of the sample, in which inflation levels were relatively low, while under high inflation, above the threshold, there is no evidence for information rigidity[13]. At the same time, the possibility of forecast asymmetry as discussed above, could bias $\hat{\beta}^1$ measure of rigidity downward (this point will be explored further in the next section).

Seasonal bias. In a recent work, Goldstein and Zilberfarb (2017) found a seasonal bias in the forecasts of the Israeli survey[14]. Specifically, they ran regressions of the forecast errors on dummy variables for the calendar quarter of the year, and find significant and different coefficients for these dummies, implying some form of a bias related to the seasonal component in the inflation process.

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[13] However, it should be noticed that the inflation data used by the aforementioned studies, from the US and other developed countries, mainly correspond to the low inflation range determined by our threshold estimations for the Israeli data.

[14] This examination exploits the fact that unlike other surveys employed in the literature the forecasts in the Israeli survey refer to the quarterly inflation which is not adjusted to seasonality.

Consequently, we should examine if the current results based on a regression of forecast errors on forecast revisions are robust to the inclusion of quarterly dummies as additional regressors. Hence, equation (2) will be estimated again while defining α as follows:

$$\alpha = \alpha_1 \times Q1 + \alpha_2 \times Q2 + \alpha_3 \times Q3 + \alpha_4 \times Q4$$

where $Q1, \ldots, Q4$ are dummy variables for the calendar quarter of the year at time $t + h$ (e.g. $Q1$ equals 1 if $F_{t,t+h}$ forecasts the inflation rate that will be realized at the first quarter of the year and so on).

The results of the augmented threshold regressions are reported in table 3 for several threshold variables. The first two columns of results refer to the threshold specifications as in table 2 based on inflation level (corresponds to the first column in both panels) and the third column refers to the change in inflation (corresponds to specification (f) in Appendix B and the fourth column of results in the table therein). Evidently, the estimates of the thresholds as well as the coefficients of forecast revision for the two inflation regimes are very similar to the estimates in the previous table, and demonstrate again the state dependence of information rigidity. At the same time, in each specification significant coefficients of the quarter-of-the-year dummies were obtained, specifically, α_1 and α_4, which is in line with the evidence provided in Goldstein and Zilberfarb (2017). Thus, our findings suggest that biases in the survey forecasts are originated in information rigidities prevailing in the low inflation environment, as well as some additional form of bias related to the seasonal component of inflation.

Smooth information rigidity parameter. The threshold estimation method revealed a significant relationship between inflation and the degree of information rigidity for the current quarter forecasts. It is possible that the path of information rigidity takes a more smooth and continuous form, which corresponds to the inflation process. However, our sample is limited in that respect, since it does not contain a cross-section of several countries or variables, so as to provide estimates of information rigidity degree at each quarter (as was done, for example, by Coibion and Gorodnichenko, 2015). To overcome this problem, we modify the framework of regression equation (1), and estimate information rigidity in the following way[15]:

$$A_{t+h} - F_{t,t+h} = \alpha + \beta\left(F_{t,t+h} - F_{t-1,t+h}\right) + v_{t,t+h} \tag{3}$$

where

$$\beta = f(T_t)$$

Thus, the coefficient β which represents the degree of information rigidity, according to both sticky and noisy information models, is a function of the inflation environment of time t, represented by the same threshold variable used in the threshold equation (2). However, instead of allowing just two regimes, the more general function $f(T_t)$ could be continuous in T_t. Specifically, three simple smooth functions were considered - linear, exponential and quadratic:

$$f(T_t) = \beta_1 + \beta_2 T_t \tag{3a}$$

$$f(T_t) = \beta_1 + \beta_2 e^{\beta_3 T_t} \tag{3b}$$

$$f(T_t) = \beta_1 + \beta_2 T_t + +\beta_3 {T_t}^2 \tag{3c}$$

Accordingly, the regression is estimated using Non-linear Least Squares methods. The parameter α is also augmented to include the effect of quarterly dummies as observed before.

Apparently, the most significant results were obtained with the simplest linear function for β specified in (3a). These results are presented in table 4 for three alternative specifications of the

[15] In the next section, alternative and more direct approaches to estimate the degree of information rigidity and forecast asymmetry at each quarter will be introduced, based on the cross-section of individual forecasts.

variable T_t, as in the previous table. In all the three estimations, both $\hat{\beta}_1$ and $\hat{\beta}_2$ are highly significant, which rejects the rational expectations hypothesis ($\beta_1 = \beta_2 = 0$) in favor of information rigidity. Moreover, the significance of $\hat{\beta}_2$ implies that the degree of information rigidity is related to inflation. In particular, the signs of the coefficients demonstrate an inverse relationship, so that β rises as inflation falls, in line with the state-dependency models.

Figure 2 illustrates graphically this relationship, by depicting the estimated β functions from table 4. The solid, dashed and dotted lines in the graph corresponds to the left, middle and right columns of results in table 4, respectively. The solid and dashed lines, display quite similarly the relationship between information rigidity and the inflation level (actual or predicted). When inflation levels fall near zero, β climbs to about 1, which implies about two quarters between information updates on average, in terms of the sticky information model, for example. As inflation increases, rigidity decreases, until around 3%-3.5% β is roughly zero, reflecting an absence of information rigidity. When inflation rates are higher (until roughly 6% which represents the highest inflation rate during the sample period of 1986-2009), β becomes negative, in accordance with forecast asymmetry, which was also observed in the threshold estimation for the high inflation region.

As for the dotted line which draws information rigidity against *change* in inflation, β reaches its highest level, which again is close to 1, when inflation is not expected to change. As the predicted change is growing information rigidity falls, and becomes zero when the (absolute) change in inflation is predicted to be about 0.8% (quarterly). For large changes there is again evidence for forecast asymmetry.

Recalling the previous threshold estimation results, it can be verified that inflation thresholds received in those estimations are close to the points in the graph where the lines cross the zero level of β. For low inflation (below threshold) β was estimated around 0.6, while under high inflation levels (above threshold) β was negative (see table 2). Thus, expectations behavior illustrated in figure 2 resembles quite well our previous results. Although the current approach of choosing continuous β functions is quite ad hoc, it demonstrates that introducing a more dynamic characterization of information rigidity, should also be considered as a more realistic possibility, in spite of the empirical limitations.

In sum, for the current quarter forecasts there is a robust evidence for the presence of information rigidity related to inflation. Significant rigidity is observed for a low (or steady) inflation environment, which vanishes for high (or volatile) inflation. Still, there is a need to better explain the forecast asymmetry indicated for high inflation and especially the very different results for longer forecast horizons, which seem to indicate only forecast asymmetry and for low rather than high inflation. The next section attempts to shed light on these patterns.

5. Information rigidity and forecast asymmetry: Direct evidence

The methodology applied in sections 3 and 4, based on regressing forecast errors on forecast revisions, has the advantage of directly interpreting revision coefficients in terms of rigidity parameters from the sticky and noisy information models, as derived in Coibion and Gorodnichenko (2015). However, in light of the several negative coefficients obtained above, which are not in line with these theories (nor with the rational expectations hypothesis), we would like to apply additional methods to asses more directly the existence of information rigidities as well as forecast asymmetries, by utilizing the cross-section of individual forecasts.

The first approach evaluates information rigidity by measuring the rate of forecast revisions, as suggested by Andrade and Le Bihan (2013). The second approach measures forecast asymmetry in the sample, based on Capistrán and Timmermann (2009). This would also allow to explore the possibility that both information rigidities and asymmetries play a role in governing forecasters' behavior. Going beyond the basic approaches, we would examine the variations in those measures across time and forecast horizons, thereby providing a complete picture of the state dependency which characterizes the inflation forecasts of the Israeli firms.

5.1.Frequency of forecast revisions and the inflation level

Recently, Andrade and Le Bihan (2013) have proposed to use the portion of revised forecasts, as a measure for the degree of attention which forecasters pay to new information. This measure corresponds to the sticky information model, in which there is a probability λ to remain uninformed at each time t, so that only a proportion $(1-\lambda)$ of the forecasters should revise their forecasts. Denote $(1-\lambda)$ by the parameter ϕ. Letting ϕ be time specific, an estimate for ϕ_t can therefore be derived as follows:

$$\hat{\phi}_t(h) = \frac{1}{n_t}\sum_{i=0}^{n_t} I\left(F_{it,t+h} \neq F_{it-1,t+h}\right) \qquad (4)$$

where h is the forecast horizon as denoted above, n_t is the number of participating forecasters in the survey at quarter t, $F_{it,t+h}$ and $F_{it-1,t+h}$ are fixed-event forecasts of individual i for quarter $t+h$, provided at quarters t and $t-1$, respectively. If the forecast is revised between the two quarters, that is, if $F_{it,t+h} \neq F_{it-1,t+h}$, then $I\left(F_{it,t+h} \neq F_{it-1,t+h}\right)$, an indicator function, receives the value of 1 (and 0 otherwise).

In the Israeli survey, a forecaster reports four forecasts each quarter, thus updating three of his former forecasts (which were provided on each of the three previous quarters). As a consequence, $h = 0,1,2$ implying three time series of attention rate $\hat{\phi}_t(h)$ for each horizon. In addition, $\hat{\phi}_t$ will denote the degree of attention which averages $\hat{\phi}_t(h)$ across forecast horizons. The number of forecasters in a certain quarter n_t, which is taken into account, includes only those who reported both the forecast $F_{it,t+h}$ and $F_{it-1,t+h}$.

Several issues concerning the robustness of this attention measure are discussed in Andrade and Le Bihan (2013). Another important issue is specific to the design of the Israeli survey. Recall from section 2, that participants do not report explicitly the *quarterly* inflation rates for each of the next four quarters (besides the forecast for the current quarter inflation rate), but rather the cumulative rates between the present quarter and the future quarter. Revisions are relevant, however, only for the implied quarterly forecasts, which were denoted by $F_{it,t+h}$. But then, it might be that a forecaster who didn't wish to revise his quarterly forecasts will still make small changes, just because of a rounding effect (to avoid reporting accumulated rates with several decimal places). Indeed, simply calculating $\hat{\phi}_t$ produces estimates of virtually 100% of revising rates. We, therefore, take account of this bias issue by considering $F_{it,t+h} = F_{it-1,t+h}$ if rounding the implied quarterly forecasts to the first decimal place makes them equal[16].

The estimated degree of attention after this adjustment, for the 1986-2009 period, is presented in figure 3. The graph in the figure describes $\hat{\phi}_t$ which average across horizons, while

[16] As an alternative, we have also tried a percentage rule. Specifically, $F_{it,t+h}$ and $F_{it-1,t+h}$ are considered the same, if they do not differ by more than 2% (in relative terms). The results were similar.

separated estimates for the different horizons are provided below. The estimates displayed by the graph range from 75% to 100%. The average across the whole sample is 90%. This seems still too high rate of attention, especially compared to the previous regression based estimates. For example, according to the threshold regressions the minimum estimate for λ (probability of remaining not updated), during low inflation periods was about 29% (for current quarter forecasts), which corresponds to 71% average degree of attention. But such a rate is less than the lowest value of $\hat{\phi}_t$, as appeared in figure 3. Even though, the difficulty to evaluate the bias in $\hat{\phi}_t$ is of less concern, since our main interest at this point is not to evaluate the true rate of attention, but to examine the variations in $\hat{\phi}_t$, searching for possible state-dependency. Indeed, another look at figure 3, which also depicts a graph of the inflation rate, reveals an interesting co-movement of the two series, $\hat{\phi}_t$ and inflation, during the period of 1986-2009. The general decreasing trend of $\hat{\phi}_t$, also matches very well the high and low stages of the inflation process during this period.

More formal evidence is provided by running regressions of the attention rate on the inflation rate. Table 5 reports the results of three such regressions (in the three panels), one includes inflation of time t (A_t), a second one includes lagged inflation (A_{t-1}), and the third one includes lagged quarterly inflation averaged over the last four quarters ($0.25 \times \sum_{k=1}^{4} A_{t-k}$). In addition, results are reported for $\hat{\phi}_t$ as well as for each forecast horizon separately, by regressing $\hat{\phi}_t(h)$ for each h on inflation. Interestingly, the results of all regressions are very similar and demonstrate highly significant positive coefficients, as indicated in the graph. The revision rate for a zero inflation rate, as represented by the regression constant is estimated between 82%-90% and it grows by 1.4%-3.1%, for any additional 1% increase in the inflation rate. Thus, our attention rate estimates, despite their limitation, show a close reaction of information rigidity to the inflation level, which supports the state-dependent hypothesis (at least of the kind which is based on the sticky information model).

Even more importantly, there is not any notable difference in the attention rate pattern between forecast horizons. Thus, it suggests that the results of table 2 in the previous section, which showed evidence for state dependent information rigidity only for current quarter forecasts, are not because it is absent at longer horizons (attention rates are actually a little bit lower for longer horizons), but rather due to some other forecasting aspect which causes the apparent difference between horizons.

5.2.Forecast asymmetry and the inflation level

Elliot et al. (2005, 2008) and Capistrán and Timmerman (2009) proposed that forecast bias common in surveys is a result of loss aversion, by preferring forecast errors to be either positive or negative. Following Capistrán and Timmermann (2009) this asymmetry is modeled by a LINEX loss-function over forecast errors:

$$L\big(e_{it,t+h};\ \theta_i(h)\big) = \big[exp\big(\theta_i(h)e_{it,t+h}\big) - \theta_i(h)e_{it,t+h} - 1\big]/\theta_i(h)^2$$

where $e_{it,t+h} \equiv A_{t+h} - F_{it,t+h}$ is the forecast error of forecaster i and $\theta_i(h)$ is the asymmetry parameter which may depend on forecast horizon. Positive $\theta_i(h)$ implies loss-aversion towards positive errors, while negative $\theta_i(h)$ implies loss-aversion towards negative errors. As $\theta_i(h)$ goes to zero, the loss function converges to symmetry, corresponding to standard minimization of the mean squared error.

Assuming that the forecasted variable is normally distributed with conditional mean $\mu_{t+h|t}$, and variance $\sigma^2_{t+h|t}$, the optimal individual forecast should be

$$F_{it,t+h} = \mu_{t+h|t} + \frac{1}{2}\theta_i(h)\sigma^2_{t+h|t}$$

Thus, the term $\frac{1}{2}\theta_i(h)\sigma^2_{t+h|t}$ represents the forecast bias which is due to asymmetry. As in Capistrán and Timmerman (2009), this equation can be exploited to derive estimates for the asymmetry parameter $\theta_i(h)$. Again, instead of averaging across sample time, we would like to estimate asymmetry for each quarter, therefore averaging across (n_t) forecasters to obtain a cross-sectional based estimate for the asymmetry parameter at each quarter as follows:

$$\hat{\theta}_t(h) = \frac{2}{n_t}\sum_{i=0}^{n_t}\frac{e_{it,t+h}}{\hat{\sigma}^2_{t+h|t}} \tag{5}$$

The conditional variance of inflation is estimated by fitting an AR(4) model for the inflation data with GARCH(1,1) for the conditional variance[17]. $\hat{\theta}_t$ will denote the estimated asymmetry when further averaging across forecast horizons.

In order to examine the state dependency of forecast asymmetry, we exploit the series of $\hat{\theta}_t(h)$ in a similar way applied to the attention rate series above, by running regressions of forecast asymmetry on inflation level measures. The absolute value of asymmetry parameter, $|\hat{\theta}_t(h)|$, is used as the dependent variable in the regressions, since both positive and negative values with the same magnitude may represent the same strength of asymmetry (deviation from the zero level corresponding to symmetry).

[17] The model was estimated for the post high inflation period, 1987-2009 (starting a year after due to the lags). Similar to Capistrán and Timmermann (2009), this model fits the Israeli inflation well, considering other alternatives for the number of lags and including MA components. The third lag of inflation is not included in the AR(4) specifications for significance reasons.

The results, reported in table 6, demonstrate a clear difference from the attention results in table 5. There is now a notable distinction between horizons. In all regressions the estimated coefficient is negative, implying a decrease in asymmetry as inflation rises. However, only for the longest horizon ($h = 2$) coefficients are consistently significant. The estimated regression constants for $h = 0$ (around 2) are considerably lower relative to the longer horizons (around 3), reflecting less asymmetry bias for the current quarter forecasts.

In light of these interesting findings, the puzzling results obtained in the previous section (table 2) can now be addressed. In the last section we used the approach of Coibion and Gorodnichenko (2015) to detect information rigidity in the Israeli survey and applied the threshold methodology to demonstrate its dependency on the inflation level. Apparently, the fact that this result was valid and robust only for current quarter forecasts, is due to the profound effect of an additional feature dominating forecasters' behavior, namely, asymmetric loss-aversion. As discussed above, the presence of forecast asymmetry, biases the coefficient on forecast revisions downward to be negative. Since asymmetry is founded to be moderate for current quarter forecast, we still got a positive coefficient for low inflation levels (below threshold). Only for high inflation where information rigidities are weaker the coefficient was driven to be negative by asymmetry. In contrast, for the longer horizons, which are much more affected by asymmetry as demonstrated here, the coefficients on revisions were all biased toward negativity. In particular, for the longest horizon ($h = 2$), significant negative coefficients were obtained precisely for low inflation as asymmetry also seems to be negatively related to inflation, at least for this horizon. Finally, for the middle horizon, results are somewhere in between.

The presence of both information rigidity and loss-aversion in the Israeli survey is also applicable to other forecast surveys used in the literature. For example, Coibion and

Gorodnichenko (2015) present solid evidence for information rigidities in several countries and for several macroeconomic variables, due to the positive correlation between forecast errors and forecast revisions. Our results suggest that the presence of loss-aversion may not be ruled out completely. It may just bias the correlation downwards, implying an under-estimation of the information rigidity parameters.

6. Conclusion

Recent studies have provided rich evidence on information rigidities, based on survey forecasts from fairly stable economies. The aim of this study is to show how information rigidities might take a very dynamic and state-dependent form, by utilizing a special data set of inflation forecasts of Israeli firms. The Israeli survey is unique in providing forecasts at the firm-level, which are rare in the literature. Furthermore, we exploit the peculiar inflation experience in Israel during the survey period, which covers great transitions in the inflation environment. Applying various empirical approaches, we find a close relationship between the degree of information rigidity and the inflation level. A significant degree of information rigidity is documented in times of relatively low inflation, while at times of high inflation firms' inattention vanishes. The changes in inattention are not just due to major shifts in the inflation regime between the distinct sub-periods of the Israeli sample, but rather depends on the inflation dynamics *within* each regime. This points out to a more dynamic characterization of firms' inattention.

In addition, asymmetric loss-aversion towards forecasts errors also dominates the firms forecasting behavior in the Israeli survey. This is especially evident at longer forecast horizon, where it is again stronger for low inflation levels.

Our findings have several implications for future research. First, further attempts to model information rigidity in an endogenous manner, like in the studies of Gorodnichenko (2008), Branch et al. (2009), Woodford (2009), Maćkowiak and Wiederholt (2015) and Matějka (2015)., might be fruitful for understanding price-setting, macroeconomic dynamics and policy issues. More specifically, the close correspondence of inattention to inflation, as demonstrated by the Israeli firms' expectations, may suggest an additional beneficial channel from a low inflation environment, in which monetary policy can be more effective due to a higher rigidity in inflation expectations.

Second, our evidence highlights the possibility that information rigidity does not depend solely on the general conditions of the economy, but rather is variable-dependent, related to the process of the specific forecasted variable. Future research may investigate this possibility in more depth. Third, former empirical studies have examined which alternative theory of expectations behavior is best supported by data. Our results suggest that an approach which allows co-existence of several types of behavior simultaneously is worth considering. Empirical research would then try to differentiate and evaluate the effect of each behavior separately.

References

Andrade, Philippe and Herve LeBihan (2013). “Inattentive Professional Forecasters.” *Journal of Monetary Economics*, 60 (8), 967-982.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2017a). "Diagnostic Expectations and Credit Cycles." *Journal of Finance*, forthcoming.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta and Andrei Shleifer (2017b). "Diagnostic Expectations and Stock Returns." NBER working paper 23863.

Branch, William A., John Carlson, George Evans and Bruce McGough (2009). “Monetary Policy, Endogenous Inattention, and the Volatility Trade-Off.” *Economic Journal*, 119 (534), 123-157.

Bruno, Michael (1993). *Crisis, Stabilization and Economic Reform: Therapy by Consensus*. Clarendon press, Oxford.

Capistrán, Carlos and Allan Timmermann (2009). "Disagreement and Biases in Inflation Expectations." *Journal of Money, Credit and Banking*, 41 (2-3), 365-396.

Cavallo, Alberto, Guilermo Cruces and Ricardo Perez-Truglia (2017). "Inflation Expectations, Learning and Supermarket Prices: Evidence from Field Experiments." *American Economic Journal: Macroeconomics*, 9 (3), 1–35.

Coibion, Olivier and Yuriy Gorodnichenko (2012). “What Can Survey Forecasts Tell Us About Informational Rigidities?” *Journal of Political Economy*, 120 (1), 116-159.

Coibion, Olivier and Yuriy Gorodnichenko (2015). “Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts.” *American Economic Review*, 105 (8), 2644-2678.

Coibion, Olivier, Yuriy Gorodnichenko and Rupal Kamdar (2017). " The Formation of Expectations, Inflation and the Phillips Curve." *Journal of Economic Literature*, Forthcoming.

Coibion, Olivier, Yuriy Gorodnichenko and Saten Kumar (2015). "How Do Firms Form Their Expectations? New Survey Evidence." NBER Working Paper 21092.

Döpke, Jörg, Jonas Dovern, Ulrich Fritsche and Jirka Slacalek (2008). “Sticky Information Phillips Curves: European Evidence.” *Journal of Money, Credit, and Banking*, 40 (7), 1513-1520.

Dovern, Jonas (2013). ”When are GDP Forecasts Updated? Evidence from a Large International Panel.” *Economics Letters*, 120 (3), 521–523.

Dovern, Jonas, Ulrich Fritsche, Prakash Loungani and Natalia Tamirisa (2015). “Information Rigidities: Comparing Average and Individual Forecasts for a Large International Panel.” *International Journal of Forecasting*, 31 (1), 144-154.

Dräger, Lena and Michael J. Lamla (2017). "Imperfect Information and Consumer Inflation Expectations: Evidence from Microdata" *Oxford Bulletin of Economics and Statistics, doi*:10.1111/obes.12189.

Driscoll, John C., and Aart C. Kraay (1998). “Consistent Covariance Matrix Estimation with Spatially Dependent Panel Pata.” *Review of Economics and Statistics*, 80 (4), 549–560.

Elliott, Graham, Ivana Komunjer and Allan Timmermann (2005). “Estimation and Testing of Forecast Rationality under Flexible Loss,” *Review of Economic Studies*, 72 (4), 1107–1125.

Elliott, Graham, Ivana Komunjer and Allan Timmermann (2008). “Biases in Macroeconomic Forecasts: Irrationality or Asymmetric Loss?” *Journal of the European Economic Association* 6 (1), 122–157.

Goldstein, Nathan and Ben-Zion Zilberfarb (2017). “Rationality and seasonality: Evidence from inflation forecasts” *Economics Letters* 150 (2017), 86-90.

Gorodnichenko, Yuriy (2008). “Endogenous Information, Menu Costs and Inflation Persistence.” NBER Working Paper 14184.

Hansen, Bruce (1996). "Inference When a Nuisance Parameter Is Not Identified under the Null Hypothesis." *Econometrica*, 64 (2), 413-430.

Hansen, Bruce (2000). "Sample Splitting and Threshold Estimation," *Econometrica*, 68 (3), 575-603.

Kandel, Eugene and Ben-Zion Zilberfarb (1999). “Differential Interpretation of Information in Inflation Forecasts.” *Review of Economics and Statistics*, 81 (2), 217–226.

Khan, Hashmat and Zhenhua Zhu (2006). “Estimates of the Sticky-Information Phillips Curve for the United States.” *Journal of Money, Credit and Banking*, 38 (1), 195-207.

Loungani, Prakash, Stekler, Herman and Natalia Tamirisa (2013). " Information Rigidity in Growth Forecasts: Some Cross-Country Evidence" *International Journal of Forecasting*, 29 (4), 605-621.

Maćkowiak, Bartosz and Mirko Wiederholt (2009). “Optimal sticky prices under rational inattention." *American Economic Review*, 99 (3), 769–803.

Maćkowiak, Bartosz and Mirko Wiederholt (2012). “Information Processing and Limited Liability.” *American Economic Review*, 102 (3), 30-34.

Maćkowiak, Bartosz and Mirko Wiederholt (2015). “Business Cycle Dynamics under Rational Inattention." *Review of Economic Studies*, 82 (4), 1502-1532.

Mankiw, N. Gregory and Ricardo Reis (2002). “Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve.” *Quarterly Journal of Economics*, 117 (4), 1295-1328.

Mankiw, N. Gregory, Ricardo Reis and Justin Wolfers (2004). “Disagreement about Inflation Expectations.” *NBER Macroeconomics Annual*, 18, 209-248.

Matějka, Filip (2015). "Rationally Inattentive Seller: Sales and Discrete Pricing." *Review of Economic Studies*, 83 (3), 1156-1188.

Mertens, Elmar and James M. Nason (2015). "Inflation and Professional Forecast Dynamics: An Evaluation of Stickiness, Persistence, and Volatility." CAMA Working Papers 2015-06.

Reis, Ricardo (2006). “Inattentive Producers.” *Review of Economic Studies*, 73 (3), 793–821.

Sims, Christopher A. (2003). “Implications of Rational Inattention.” *Journal of Monetary Economics*, 50 (3), 665-690.

Ungar, Meyer and Ben-Zion Zilberfarb (1993). “Inflation and Its Unpredictability—Theory and Empirical Evidence.” *Journal of Money, Credit, and Banking*, 25 (4), 709–720.

Woodford, Michael (2003). “Imperfect Common Knowledge and the Effects of Monetary Policy.” In: *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, edited by Philippe Aghion, Romain Frydman, Joseph Stiglitz and Michael Woodford, Princeton University Press.

Woodford, Michael (2009). “Information-Constrained State-Dependent Pricing.” *Journal of Monetary Economics*, 56 (S), S100–S124.

TABLE 1
Estimation of Information Rigidity

Period	Forecast Horizon	α	β	R^2
1980Q1-2009Q1 (whole sample)	0	-0.183	0.171	0.060
		(0.234)	(0.192)	
	1	0.501	0.435	0.058
		(0.658)	(0.476)	
	2	0.653	0.820	0.112
		(0.766)	(0.579)	
	Pooling	0.306	0.384	0.058
		(0.509)	(0.327)	
1980Q1-1985Q4 (high inflation)	0	0.725	0.129	0.034
		(1.331)	(0.266)	
	1	3.788	0.302	0.030
		(3.076)	(0.582)	
	2	4.340	0.632	0.068
		(3.590)	(0.568)	
	Pooling	3.034	0.257	0.026
		(2.418)	(0.390)	
1986Q1-2009Q1 (after stabilization)	0	-0.370***	0.124	0.012
		(0.118)	(0.266)	
	1	-0.281**	0.208	0.012
		(0.138)	(0.241)	
	2	0.207	0.656***	0.118
		(0.155)	(0.189)	
	Pooling	-0.305	0.273	0.031
		(0.118)	(0.230)	
1986Q1-1996Q4 (moderate inflation)	0	0.398*	0.027	0.000
		(0.219)	(0.332)	
	1	-0.282	0.266	0.035
		(0.203)	(0.216)	
	2	-0.188	0.700***	0.217
		(0.233)	(0.191)	
	Pooling	-0.325	0.263	0.042
		(0.187)	(0.259)	
1997Q1-2009Q1 (low inflation)	0	0.389***	0.668***	0.190
		(0.107)	(0.187)	
	1	-0.276	-1.647	0.052
		(0.212)	(1.048)	
	2	-0.317	-1.340	0.025
		(0.206)	(1.045)	
	Pooling	-0.289	0.343	0.011
		(0.152)	(0.210)	

Notes: The table reports the coefficient estimates in Eqs. (1), where β represents information rigidity. Robust standard errors for the regressions' coefficients are in parentheses. For the horizon-specific estimates standard errors are Newey-West. For the pooling horizons estimates standard errors are of Driscoll and Kraay (1998). * , ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

TABLE 2
Threshold Estimation of Information Rigidity, 1987Q1-2009Q1

	$h = 0$	$h = 1$	$h = 2$
		Panel A: $T_t = 0.25 \times \sum_{k=1}^{4} A_{t-k}$	
θ	3.808***	1.203	1.356
α	-0.337***	-0.255	-0.293*
	(0.101)	(0.160)	(0.164)
Low Inflation:			
β^1	0.646***	-2.470**	-2.922**
	(0.168)	(0.965)	(0.236)
Obs.	68	35	38
High Inflation:			
β^2	-0.572**	-0.890	-0.308
	(0.227)	(0.746)	(0.393)
Obs.	21	54	51
R^2	0.190	0.081	0.049
		Panel B: $T_t = 0.25 \times \sum_{h=0}^{3} F_{t,t+h}$	
θ	3.724***	3.724	0.709**
α	-0.298***	-0.240	-0.298*
	(0.093)	(0.149)	(0.157)
Low Inflation:			
β^1	0.591***	-0.246	-4.406***
	(0.148)	(0.841)	(1.394)
Obs.	69	69	25
High Inflation:			
β^2	-0.650***	-2.238**	0.152
	(0.212)	(0.919)	(0.393)
Obs.	20	20	64
R^2	0.210	0.110	0.042

Notes: The table reports the threshold estimation results by Eqs. (2), for the period 1987Q1-2009Q1. Threshold regressions were estimated for each forecast horizon using two different threshold variables as specified in the two panels. Threshold significance is computed by a robust bootstrap method, following Hansen (1996, 2000). Newey-West standard errors for the regressions' coefficients are in parentheses. * , ** and *** denote significance at the 10%, 5% and 1%, respectively.

TABLE 3
Threshold Estimation of Information Rigidity with Seasonal Dummies, Current Quarter Forecasts, 1987Q1-2009Q1

	$\sum_{k=1}^{4}\frac{A_{t-k}}{4}$	$\sum_{h=0}^{3}\frac{F_{t,t+h}}{4}$	$\left\lvert\sum_{h=0}^{3}\frac{F_{t,t+h}}{4} - \sum_{k=1}^{4}\frac{A_{t-k}}{4}\right\rvert$
θ	3.729***	3.638***	0.699***
Seasonal Dummies:			
α_1	-0.692***	-0.682***	-0.619***
	(0.172)	(0.171)	(0.192)
α_2	0.169	0.198	0.231
	(0.229)	(0.213)	(0.251)
α_3	-0.100	-0.101	-0.010
	(0.242)	(0.243)	(0.205)
α_4	-0.706***	-0.708***	-0.579**
	(0.214)	(0.216)	(0.222)
Low Inflation:			
β^1	0.612***	0.657***	0.490***
	(0.136)	(0.145)	(0.154)
Obs.	67	68	75
High Inflation:			
β^2	-0.495**	-0.528**	-0.483*
	(0.225)	(0.212)	(0.277)
Obs.	22	21	14
R^2	0.293	0.316	0.265

Notes: The table reports the threshold estimation results by Eqs. (2) including seasonal dummies, for the period 1987Q1-2009Q1. Threshold regressions were estimated for current quarter forecasts ($h = 0$) using different threshold variables as specified in the header of each column. Threshold significance is computed by a robust bootstrap method, following Hansen (1996, 2000). Newey-West standard errors for the regressions' coefficients are in parentheses. * , ** and *** denote significance at the 10%, 5% and 1%, respectively.

TABLE 4
Estimation of Smooth Information Rigidity, Current Quarter Forecasts, 1987Q1-2009Q1

	$\sum_{k=1}^{4}\frac{A_{t-k}}{4}$	$\sum_{h=0}^{3}\frac{F_{t,t+h}}{4}$	$\left\lvert\sum_{h=0}^{3}\frac{F_{t,t+h}}{4}-\sum_{k=1}^{4}\frac{A_{t-k}}{4}\right\rvert$
Seasonal Dummies:			
α_1	-0.715***	-0.575***	-0.578***
	(0.186)	(0.172)	(0.191)
α_2	0.176	0.208	0.212
	(0.231)	(0.220)	(0.252)
α_3	-0.141	-0.114	-0.008
	(0.243)	(0.227)	(0.204)
α_4	-0.703***	-0.666***	-0.603***
	(0.216)	(0.215)	(0.218)
Non-linear rigidity:			
β_1	0.975***	1.215***	0.885***
	(0.200)	(0.187)	(0.223)
β_2	-0.338***	-0.335***	-1.111***
	(0.080)	(0.044)	(0.174)
R^2	0.290	0.349	0.306

Notes: The table reports the estimation results by Eqs. (3) and (3a), for the period 1987Q1-2009Q1. Regressions were estimated for current quarter forecasts ($h = 0$) using different variables for the non-linear specification as specified in the header of each column. Newey-West standard errors for the regressions' coefficients are in parentheses. * , ** and *** denote significance at the 10%, 5% and 1%, respectively.

TABLE 5
Regressions of the Forecast Revision Rates on Inflation,, 1986Q1-2009Q1

	$h = 0$	$h = 1$	$h = 2$	*Averaging horizons*
		Panel A: $\hat{\phi}_t = c + \gamma A_t + u_t$		
c	0.896***	0.861***	0.847***	0.868***
	(0.009)	(0.013)	(0.010)	(0.007)
γ	0.016***	0.019**	0.019***	0.018***
	(0.002)	(0.004)	(0.003)	(0.002)
R^2	0.277	0.256	0.272	0.381
		Panel B: $\hat{\phi}_t = c + \gamma A_{t-1} + u_t$		
c	0.898***	0.859***	0.841***	0.866***
	(0.009)	(0.014)	(0.009)	(0.008)
γ	0.014***	0.019***	0.021***	0.018***
	(0.002)	(0.004)	(0.003)	(0.002)
R^2	0.232	0.276	0.343	0.405
		Panel C: $\hat{\phi}_t = c + \gamma \times (0.25 \times \sum_{k=1}^{4} A_{t-k}) + u_t$		
c	0.883***	0.837***	0.818***	0.846***
	(0.009)	(0.014)	(0.007)	(0.007)
γ	0.021***	0.029***	0.031***	0.027***
	(0.003)	(0.004)	(0.002)	(0.002)
R^2	0.320	0.389	0.510	0.594

Notes: The table reports the estimation results of the specified equations at the top of each panel. $\hat{\phi}_t$ is the estimated degree of attention as explained in the text and A_t is the actual inflation rate. Newey-West standard errors are in parentheses. * , ** and *** denote significance at the 10%, 5% and 1%, respectively.

TABLE 6
Regressions of Forecasters' Asymmetry on Inflation, 1987Q1-2009Q1

	$h = 0$	$h = 1$	$h = 2$	*Averaging horizons*
	Panel A: $\left\|\hat{\theta}_t\right\| = c_2 + \gamma_2 A_t + u_t$			
c_2	2.154***	2.763***	2.892***	2.603***
	(0.552)	(0.912)	(0.634)	(0.681)
γ_2	-0.335*	-0.323	-0.394**	-0.351*
	(0.156)	(0.245)	(0.182)	(0.188)
R^2	0.074	0.023	0.075	0.056
	Panel B: $\left\|\hat{\theta}_t\right\| = c_2 + \gamma_2 A_{t-1} + u_t$			
c_2	1.956***	2.991***	2.874***	2.607***
	(0.620)	(0.973)	(0.661)	(0.728)
γ_2	-0.223	-0.433	-0.374*	-0.343*
	(0.184)	(0.276)	(0.192)	(0.208)
R^2	0.033	0.041	0.068	0.055
	Panel C: $\left\|\hat{\theta}_t\right\| = c_2 + \gamma_2 \times (0.25 \times \sum_{k=1}^{4} A_{t-k}) + u_t$			
c_2	2.174***	3.177***	3.114***	2.821***
	(0.696)	(1.085)	(0.748)	(0.817)
γ_2	-0.323	-0.508	-0.478**	-0.436*
	(0.224)	(0.329)	(0.232)	(0.252)
R^2	0.049	0.040	0.080	0.063

Notes: The table reports the estimation results of the specified equations at the top of each panel. $\hat{\theta}_t$ is the estimated degree of asymmetry as explained in the text and A_t is the actual inflation rate. Newey-West standard errors are in parentheses. * , ** and *** denote significance at the 10%, 5% and 1%, respectively.

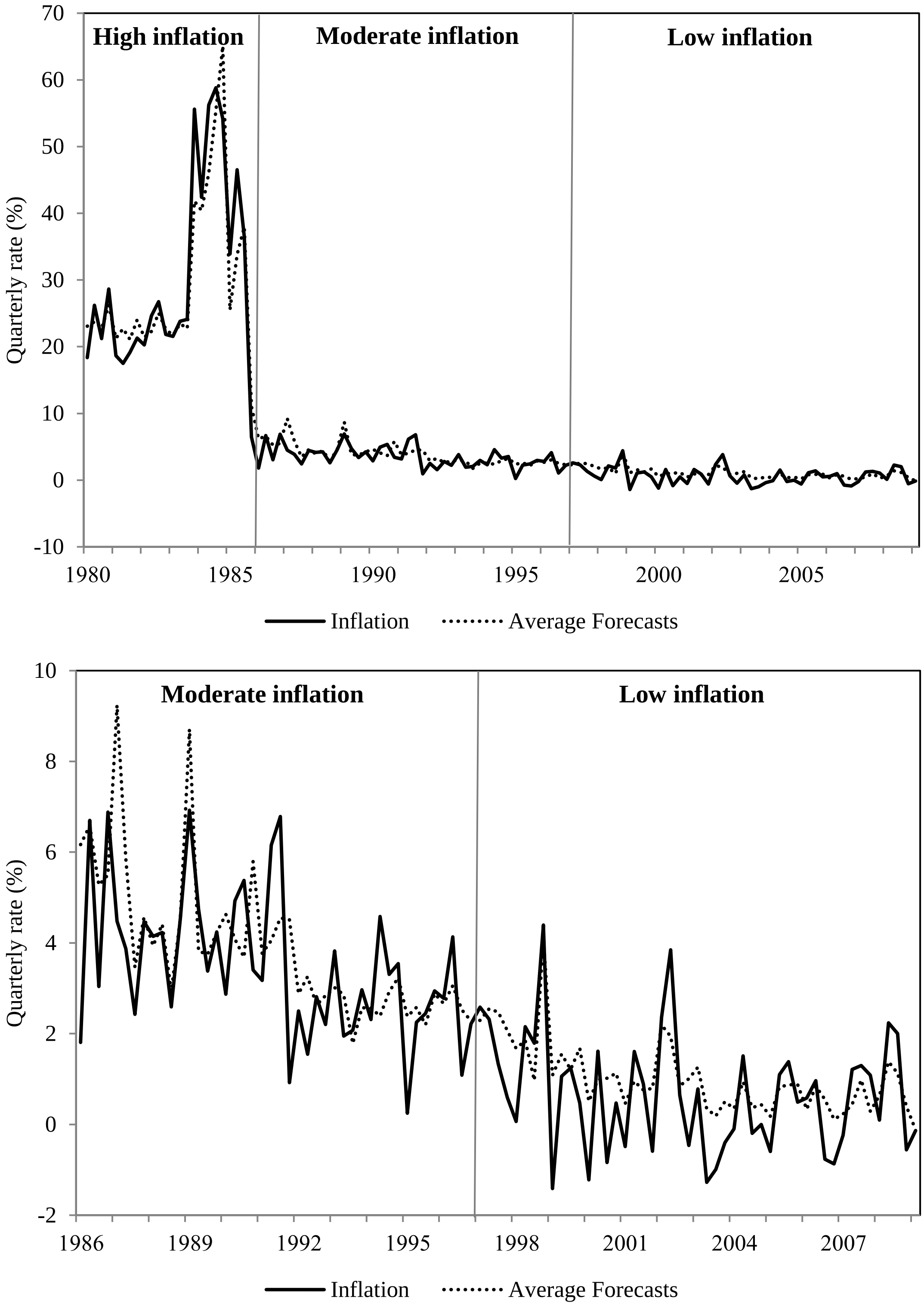

Fig. 1. Quarterly Inflation Rates and Current Quarter Forecasts

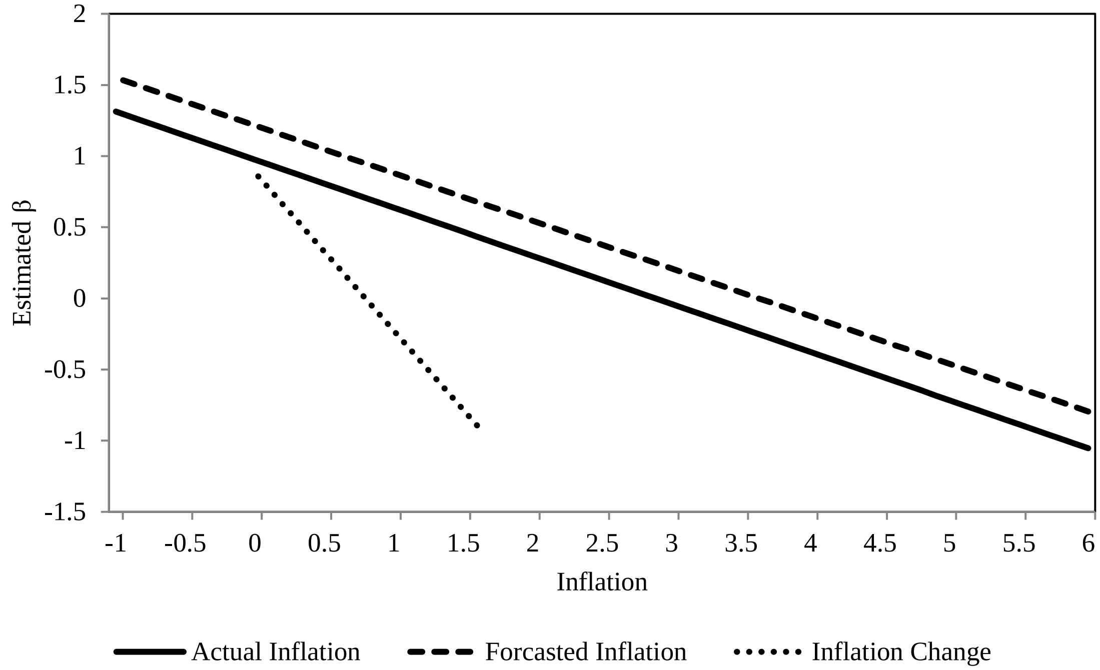

Fig. 2. Estimated Information Rigidity Function

Notes: The figure displays estimated βs by Eqs. (3) and (3a), as a function of the inflation variable (T_t). The three graphs correspond to the three columns of results reported in table 4, depending on the specification for T_t.

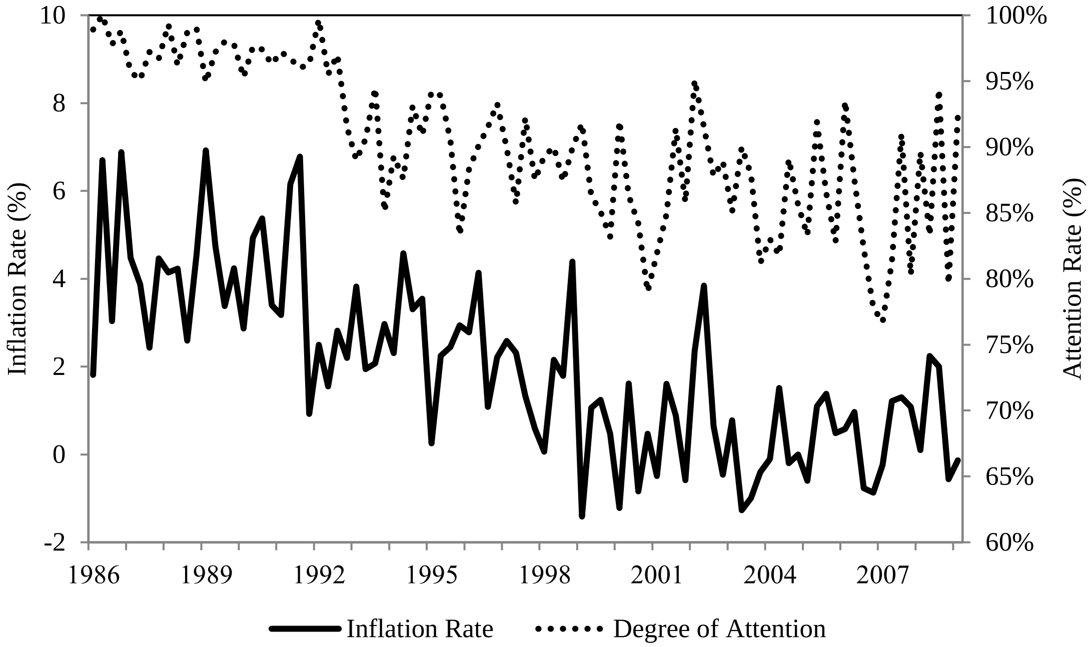

Fig. 3. Estimated Degree of Attention and the Inflation Rate

Notes: The figure displays estimated degree of attention, denoted by $\widehat{\emptyset}_t$ in the text, and the inflation rate. $\widehat{\emptyset}_t$ is calculated as the rate of revised forecasts at each quarter. Further computational details are detailed in the text.

Appendix A: The relationship between forecast errors and forecast revisions under non-constant information rigidity parameters

This appendix validates the relationship in regression equation (1) for both sticky and noisy information models, when it is not assumed that the rigidity parameter is constant overtime as in Coibion and Gorodnichenko (2015).

(a) Sticky information

As in the basic framework, there is a probability at each date to remain uninformed, but now we let this probability to change between periods. Without referring to the specific determinants, we just denote the probability by λ_t, thus, letting it to change between periods in the most general form. $E_{t-j}A_{t+h}$ is the rational forecast at time t for A_{t+h}, that is provided by agents that updated their information j periods ago. Accordingly, the frequency of forecasters at time t, which provide this forecast is $\left(1-\lambda_{t-j}\right)\prod_{k=1}^{j}\lambda_{t-(k-1)}$, except for the case of $j=0$ (most updated forecasters), where the frequency (of the most updated forecast among forecasters) is $(1-\lambda_t)$.

Taking the average forecast across agents we get

$$F_{t,t+h}=(1-\lambda_t)E_tA_{t+h}+\sum_{j=1}^{\infty}\left(1-\lambda_{t-j}\right)\left[\prod_{k=1}^{j}\lambda_{t-(k-1)}\right]E_{t-j}A_{t+h}$$

where it can easily be verified that the sum of the weights on expectations, $(1-\lambda_t)+\sum_{j=1}^{\infty}\left(1-\lambda_{t-j}\right)\left[\prod_{k=1}^{j}\lambda_{t-(k-1)}\right]$, converges to 1. Similarly, the previous average forecast for A_{t+h}, made at time $t-1$ is given by

$$F_{t-1,t+h} = (1-\lambda_{t-1})E_{t-1}A_{t+h} + \sum_{j=1}^{\infty}(1-\lambda_{t-1-j})\left[\prod_{k=1}^{j}\lambda_{t-k}\right]E_{t-1-j}A_{t+h}$$

Hence, it follows that

$$\begin{aligned}
&F_{t,t+h} - \lambda_t F_{t-1,t+h} \\
&= (1-\lambda_t)E_tA_{t+h} + \sum_{j=1}^{\infty}(1-\lambda_{t-j})\left[\prod_{k=1}^{j}\lambda_{t-(k-1)}\right]E_{t-j}A_{t+h} \\
&- \lambda_t\left((1-\lambda_{t-1})E_{t-1}A_{t+h} + \sum_{j=1}^{\infty}(1-\lambda_{t-1-j})\left[\prod_{k=1}^{j}\lambda_{t-k}\right]E_{t-1-j}A_{t+h}\right) \\
&= (1-\lambda_t)E_tA_{t+h} + \sum_{j=1}^{\infty}(1-\lambda_{t-j})\left[\prod_{k=1}^{j}\lambda_{t-(k-1)}\right]E_{t-j}A_{t+h} \\
&- \lambda_t(1-\lambda_{t-1})E_{t-1}A_{t+h} - \sum_{j=2}^{\infty}(1-\lambda_{t-j})\left[\prod_{k=1}^{j}\lambda_{t-(k-1)}\right]E_{t-j}A_{t+h} \\
&= (1-\lambda_t)E_tA_{t+h} + \sum_{j=1}^{\infty}(1-\lambda_{t-j})\left[\prod_{k=1}^{j}\lambda_{t-(k-1)}\right]E_{t-j}A_{t+h} \\
&- \sum_{j=1}^{\infty}(1-\lambda_{t-j})\left[\prod_{k=1}^{j}\lambda_{t-(k-1)}\right]E_{t-j}A_{t+h} = (1-\lambda_t)E_tA_{t+h}
\end{aligned}$$

Substituting $E_tA_{t+h} = A_{t+h} - \nu_{t,t+h}$, where $\nu_{t,t+h}$ denotes the rational expectations error between time t and $t+h$ (with full information), we finally have

$$F_{t,t+h} - \lambda_t F_{t-1,t+h} = (1-\lambda_t)\left(A_{t+h} - \nu_{t,t+h}\right)$$

$$A_{t+h} - F_{t,t+h} = \frac{\lambda_t}{1-\lambda_t}\left(F_{t,t+h} - F_{t-1,t+h}\right) + \nu_{t,t+h}$$

which corresponds to regression (1) in the text, of forecast errors on forecast revisions. Note that for clarification reasons, we do not use the subscript t for the coefficient on forecast revisions β, except for the specification in equation (3) of section 4, where the most dynamic case for the rigidity parameter is considered.

(b) Noisy information

In this framework, allowing changes in the degree of information rigidity is expressed by changes in the Kalman gain, that is denoted accordingly (with subscript t) by G_t. For the state variable A_t, we consider, as in Coibion and Goronichenko (2015), the simple AR(1) process:

$$A_t = \rho A_{t-1} + \nu_t$$

where $0 \leq \rho \leq 1$ and $\nu_t \sim iid\ N(0, \sigma_\nu^2)$ is a macroeconomic shock. The signal observed by individuals obeys:

$$a_{i:t} = A_t + \varepsilon_{i:t}$$

Where $\varepsilon_{i:t} \sim iid\ N(0, \sigma_\varepsilon^2)$ represents the noise. The individual's optimal forecast for A_t, derived by the Kalman filter, will then be

$$F_{i:t,t} = F_{i:t-1,t} + G_t\left(a_{i:t} - F_{i:t-1,t}\right)$$

where the gain of the Kalman filter G_t is determined by the constant parameters ρ, σ_ν^2 and σ_ε^2, as well as some set of macroeconomic variables. Since the h periods ahead forecast is given by $F_{i:t,t+h}$=$\rho^h F_{i:t,t}$, we get by substituting in the above equation that

$$F_{i:t,t+h} = F_{i:t-1,t+h} + G_t\left(\rho^h a_{i:t} - F_{i:t-1,t+h}\right)$$

Averaging across individuals drops the noise in $a_{i:t}$. As a result, the average forecast for A_{t+h} is

$$F_{t,t+h} = F_{t-1,t+h} + G_t\left(\rho^h A_t - F_{i:t-1,t+h}\right)$$

The first term in the parentheses, $\rho^h A_t$, is the rational expectation for A_{t+h}, at time t, with full information (no noise). Therefore, it can be substituted by $A_{t+h} - \nu_{t,t+h}$, and after rearranging it follows that

$$A_{t+h} - F_{t,t+h} = \frac{1 - G_t}{G_t}\left(F_{t,t+h} - F_{t-1,t+h}\right) + \nu_{t,t+h}$$

which, again, corresponds to the relationship in regression equation (1).

Appendix B: Further threshold estimation results of information rigidity

In section 4 of the study we estimate information rigidity by equation (2), using the threshold methodology of Hansen (1996,2000). Two alternatives for the threshold variable T_t were considered:

(a) $T_t = 0.25 \times \sum_{k=1}^{4} A_{t-k}$ – the average actual quarterly inflation over the last four quarters.

(b) $T_t = 0.25 \times \sum_{h=0}^{3} F_{t,t+h}$ - the average predicted quarterly inflation over the next four quarters.

This appendix provides evidence for five additional alternatives for T_t, specified as follows:

(c) $T_t = A_{t-1}$ – the actual inflation rate during the last quarter.

(d) $T_t = \sum_{k=1}^{8} \frac{A_{t-k}}{8}$ – the average quarterly inflation over the last eight quarters.

(e) $T_t = F_{t,t}$ - the inflation rate predicted for the current quarter (for which the ex-post forecast error is the dependent variable in the regression).

(f) $T_t = \left|\sum_{h=0}^{3} \frac{F_{t,t+h}}{4} - \sum_{k=1}^{4} \frac{A_{t-k}}{4}\right|$ – the absolute predicted *change* in the inflation level between next year and last year (in average quarterly terms).

(g) $T_t = \left|\sum_{h=0}^{3} \frac{F_{t,t+h}}{4} - F_{t,t}\right|$ - the absolute predicted *change* in inflation level between next year (in average quarterly terms) and the current quarter.

The appendix table 1 provides estimation results for current quarter forecasts ($h = 0$), where columns refer to each of (c)-(g) specifications of T_t.

APPENDIX TABLE 1
Threshold Estimation of Information Rigidity for Several Threshold Variables, Current quarter forecasts, 1987Q1-2009Q1

	A_{t-1}	$\sum_{k=1}^{8} \frac{A_{t-k}}{8}$	$F_{t,t}$	$\left\lvert \sum_{h=0}^{3} \frac{F_{t,t+h}}{4} - \sum_{k=1}^{4} \frac{A_{t-k}}{4} \right\rvert$	$\left\lvert \sum_{h=0}^{3} \frac{F_{t,t+h}}{4} - F_{t,t} \right\rvert$
θ	4.242**	3.343***	3.819***	0.672***	0.538**
α	-0.229**	-0.282***	-0.207**	-0.235**	-0.255***
	(0.103)	(0.092)	(0.090)	(0.096)	(0.091)
Low Inflation:					
β^1	0.410***	0.687***	0.664***	0.552***	0.778**
	(0.137)	(0.181)	(0.132)	(0.155)	(0.297)
Obs.	76	64	73	74	75
High Inflation:					
β^2	-0.692**	-0.310*	-0.644**	-0.579**	-0.376
	(0.263)	(0.178)	(0.266)	(0.261)	(0.247)
Obs.	13	21	16	15	14
R^2	0.172	0.122	0.214	0.167	0.111

Notes: The table reports the threshold estimation results by Eqs. (2), for the period 1987Q1-2009Q1. Threshold regressions were estimated for current quarter forecasts ($h = 0$) using different threshold variables as specified in the header of each column. For the second column the estimation period starts in 1988Q1. Threshold significance is computed by a robust bootstrap method, following Hansen (1996, 2000). Newey-West standard errors for the regressions' coefficients are in parentheses. * , ** and *** denote significance at the 10%, 5% and 1%, respectively.

According to the reported results, threshold estimates are highly significant for each specification. For specifications (c) to (e) the threshold estimates, which refer to the inflation level, are quite in the range of the thresholds estimates in table 2 (for current quarter forecasts). The other two specifications (f) and (g), which refer to change in inflation also produce threshold estimates quite similar to each other. The estimated threshold of (f), for example, implies a split of the sample depending on whether the predicted (absolute) change in inflation is over or below 0.673% (in quarterly terms). In addition, thresholds (f) and (g) split the sample with similar proportions like the previous specifications.

Finally, coefficients estimates, $\hat{\beta}^1$ and $\hat{\beta}^2$, are also fairly similar across specifications and show the same pattern as in table (2), for which $\hat{\beta}^1$ is positive representing information rigidities for low inflation and $\hat{\beta}^2$ is negative, implying an absence of rigidities and the presence of forecast asymmetry (for specification (e), the negative coefficient is not significant).