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**Abstract**

We propose a simple model of expectation formation with three distinct deviations from fully rational expectations. In particular, forecasters' expectations are sticky, extrapolate the most recent news about the current period, and depend on the lagged consensus forecast about the period being forecast. We find that all three biases are present in the Survey of Professional Forecaster as well as in the Livingston Survey, and that their magnitudes depend on the forecasting horizon. Moreover, in an over-identified econometric specification, we find that the restriction on coefficients implied by our model is always close to being satisfied and in most cases not rejected. We also stress the point that using the past consensus forecast to form expectations is a rather smart thing to do *if* cognitive limitations and biases cause any attempt to build an own rational forecast to fail.

**Keywords:** expectation formation, sticky expectations, extrapolation, consensus forecasts, survey data

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# 1 Introduction

How are macroeconomic expectations formed? There is ample evidence that forecasters do not make fully efficient forecasts and have systematic biases.[1] That is, real-world expectations deviate (at least to some extent) from the fully rational, model consistent benchmark. The question of how exactly they deviate from full rationality is less easily answered. Answering this question is, however, crucial for judging the validity of macroeconomic models and their policy implications. First of all, because most macroeconomic models rely on the assumption that all agents form fully rational expectations, and secondly because empirical evidence for models that deviate from full-information rational expectations are often not fully convincing, especially when one considers expectations data of individual forecasters.

In this paper, we propose a simple model of expectation formation that allows for three distinct deviations from full rationality. We then confront this model with survey expectations to test whether our model is in line with the data, and to investigate to what extent the three proposed biases are present in survey data. We mainly focus on data from the survey of professional forecasters (SPF) which has become the benchmark data source to test models against expectations data.[2] However, we also consider extensions with the Livingston survey (Carlson, 1977).

The first two biases that we allow for are stickiness in expectations and the extrapolation of recent news about the current period. A combination of stickiness (under-reaction) and extrapolation (over-reaction) can explain why different studies have found conflicting evidence as to whether forecasters under-react or over-react to news. In particular, Coibion and Gorodnichenko (2015) find clear under-reaction at the aggregate level by showing that aggregate forecast errors are positively correlated with aggregate forecast revisions. Bordalo et al. (2018a), with a similar regression at the individual level, find negative relation between forecast errors and revisions, pointing toward over-reaction. Fuhrer (2018), on the other hand, finds evidence of expectations smoothing and stickiness also at the individual level. If individual forecasters have sticky expectations but also extrapolate recent news about the current period, then one can indeed find either under-reaction or over-reaction, depending on the methodology and the data used. In fact, whether forecasts over-react or under-react to a particular piece of news will then depend

[1] See e.g. Lovell (1986); Ehrbeck and Waldmann (1996); Loungani (2001); Fildes and Stekler (2002); Coibion and Gorodnichenko (2015).

[2] The advantages of using the SPF include the long time span of data availability at a quarterly frequency and the fact that one can observe forecasts made at different time points for different forecasting horizons for the same individual forecaster. The latter is necessary to calculate revisions and to investigate stickiness in expectations.

on which quarter is affected the most by the news. Due to extrapolation, forecasts about future periods will overreact to news that has a large impact on the current period. On the other hand, when the news has little effect on the current period and mainly concerns future periods, extrapolation will be weak. In this case, under-reaction to news due to stickiness in expectations will arise.

Furthermore, in a laboratory experiment where subjects form expectations about a simple AR(1) process, Landier et al. (2019) find that an expectations rule that combines stickiness and extrapolation fits well to their experimental data and outperforms other expectations rules. The estimated coefficients in this expectation rule are robust to the autocorrelation coefficient in the AR(1) process that is being forecast and to other parameters of the model, as well as to the framing of the experiment (e.g. as forecasts about a macroeconomic process).

An important difference between the experimental setup of Landier et al. (2019) and the real world is that, in the experiment, subjects have no information at all about what others in the economy have been forecasting. In the real world, there are many sources of information on what experts have recently been forecasting about future periods. For example, the consensus forecast of the survey of professional forecasters is published on the website of the Federal Reserve Bank of Philadelphia each quarter. Also, the SPF has a large audience: the Philadelphia's FED external webpages counted more than 45.000 unique hits because of the SPF in 2018 (Croushore et al., 2019). Further, numerous (economic) institutions frequently publish their forecasts which also find their way into newspapers and, therefore, to the large public. A lagged consensus forecast may, thus, be seen as a public signal that forecasters observe and could base their current expectations on. Fuhrer (2018) finds that there, indeed, is a strong dependence of current individual forecasts on the lagged consensus forecast, in the SPF and the Livingston survey as well as in the Michigan survey of consumer expectations.

For this reason, we allow for a further deviation of rational expectations. In addition to stickiness to past individual expectations and extrapolation of current news, expectations may further deviate from the fully rational benchmark by partly being based on the most recently observed consensus forecast about the period that is being forecast. Such a bias can be interpreted as meaning that individual forecasters do not have the skills or the time to efficiently use all available pieces of information to come up with a fully rational forecast all by themselves. Therefore, they instead only partly base their forecast on new information and form only part of the rational expectations solution. For the other part, they make use of the "wisdom of the crowd" and turn to an easy to use piece of information: the most recently observed consensus forecast.

When we fit our model, we find evidence that all three deviations from rationality are present in the survey data. Moreover, larger forecasting horizons turn out to imply more sticky expectations. All in all, we find (across different macroeconomic variables) estimates of stickiness in forecasts that lie between 0.24 and 0.58. Furthermore, for shorter forecasting horizons (one or two quarters) we find large estimates of the coefficient of extrapolation of current news between 0.85 and 0.98. For a forecasting horizon of three quarters, these estimates are somewhat lower, but still always larger than 0.3. Finally, expectations are for a significant part formed based on the most recent past consensus forecast about the period being forecast. In particular, forecasters are found to put weights between 0.62 and 0.89 on the most recently observed consensus forecast rather than on a rational expectations forecast that they would have to build by themselves. This indicates that individual forecasters have a hard time processing all available information and news and building a rational expectations forecast. This seems to be especially the case for shorter forecasting horizons.

Interestingly, we further show that 20-50% of the forecasters in the survey would have been better off in terms of forecasting performance if they would have abandoned all attempts to build their own forecast and instead blindly submitted the most recently observed consensus forecast in every period. Basing a forecast on the lagged consensus might, hence, be seen as a rational strategy for forecasters with large enough cognitive limitations. We further document that individual forecasts of the SPF can equivalently be modeled as depending on the lagged consensus forecast of the Livingston survey rather than the lagged consensus of their own survey. This supports the hypothesis that forecasters base their forecasts on a more general consensus forecast that can be obtained from different sources and that can reach a large audience.

Moreover, our results are not a specific artifact of the forecasting behavior of the SPF. We find qualitatively similar estimates when we perform our regression for the individual forecasts of the Livingston survey. These estimates are, however, somewhat different quantitatively which is due to the semi-annual structure of the Livingston survey compared to the quarterly structure of the SPF. For instance, a forecaster may regard her last individual forecast, which is half a year old, as less informative compared to an individual forecast that would have been only three months old. This then results in quantitatively different estimates of the stickiness bias.

In addition to fitting our model of expectation formation to survey data, we also *test* the validity of the model. This can be done because the theoretical formulation of our model implies that the sum of three of the coefficients should be equal to 1. We can, hence, estimate an over-identified specification of the model and see whether this restriction holds. We find for all our selected variables that the sum of the coefficients is always close to what the restriction implies. Moreover, for inflation and nominal GDP, the restriction on the coefficients cannot be rejected across all forecasting horizons and estimation techniques. For real GDP the restriction cannot be rejected at the five percent level for the two- and three-period ahead forecasts as well, but it can be rejected for the one-period-ahead forecasts. The only variable for which the restriction is statistically rejected in most cases is unemployment. However, given the size of the deviation from the restriction (estimates of the sum of coefficients lie between 1.01 and 1.02), these rejections are clearly only of statistical and not economic significance. We, therefore, conclude that our proposed model of expectation formation is not rejected by the data.

Many alternative models of expectations that deviate from full rationality have been proposed. A considerable body of literature assumes that expectations are formed in a backward-looking manner, either by all or by a fraction of agents in the economy. That is, (some) households and firms consider past realizations of macroeconomic variables and base their expectations about future variables solely on this. The most well-known example of such expectations is found in the *adaptive learning* literature (Evans and Honkapohja, 2012), where agents use statistical learning based on past realizations to learn the relations between economic variables. Further, in the *heterogeneous expectations* literature, backward-looking expectations take the form of a simple adaptive or extrapolative heuristic, where past realizations of a particular variable are used to predict future realizations of that variable (see e.g. Branch and McGough, 2010; De Grauwe, 2012; Hommes and Lustenhouwer, 2019).

A disadvantage of backward-looking expectations is that there can be little to no role for news and for announcements about the future. Backward-looking expectations can, hence, not meaningfully contribute to, e.g., the question of whether forecasts over-react or under-react to news. Moreover, the literature on empirical validation of backward-looking expectation formation is not large and not fully convincing. Backward-looking expectations generate persistence in expectations and in the macroeconomic model. This type of expectation is, hence, a potential explanation for the larger persistence that is found in survey data compared to rational expectations. This explains why expectation models that include backward-looking components improve the fit with the data (Branch, 2004; Milani, 2007; Slobodyan and Wouters, 2012; Cornea-

Madeira et al., 2019). However, there is no convincing evidence that backward-lookingness is the correct explanation for higher persistence in survey expectations and that expectations are actually formed by considering past observations.

In fact, when we add to our model a potential fourth bias, where forecasters partly use past observations to form expectations, the estimated magnitude of this backward-looking bias is very small and in most cases statistically insignificant. At the same time, the estimates of the other three biases are robust to adding the fourth bias. This is a clear indication that the persistence found in survey data is not caused by agents basing their expectations on past observations, but instead by other biases such as stickiness. Similar conclusions are drawn by Fuhrer (2018) from survey data and by Landier et al. (2019) in a laboratory experiment.

Other deviations from full-information rational expectations that have been proposed include models with sticky information or noisy information and rational inattention (Mankiw and Reis, 2002; Sims, 2003; Woodford, 2003; Mackowiak and Wiederholt, 2009). Moreover, Gabaix (2016) proposes a framework of sparsity to model deviations from fully rational expectations. These theoretical frameworks may offer partial explanations for e.g. why expectations are sticky. These explanations are, however, not fully in line with survey data of *individual* expectations (Bordalo et al., 2018a; Fuhrer, 2018).

In this paper, we do not focus on *why* forecasters have certain deviations from full rationality. Instead, we seek to converge on a model of expectation formation that combines different higher-level individual biases and that can explain actual expectations from survey data. Such a model of expectation formation can, in future research, be used as a building block to improve the realism of the assumptions made on expectations in macroeconomic modeling. In particular, our findings stress the importance of modeling the interaction between expectations of individual agents in the economy and of explicitly modeling (over-)reaction to news. We believe that deriving policy implications from models where expectation formation is more in line with individual expectation data can greatly help the field forward.

The rest of the paper is organized as follows. In Section 2, we outline our proposed model of expectations formation. In Section 3, we present two different specifications derived from this model that can be used to confront the model with survey data, and our main estimation results are presented in Section 4. Next, we discuss some extensions that contribute to the interpretation and robustness of results in Section 5. Section 6 presents a discussion on the role of the lagged consensus forecast and Section 7 concludes.

## 2 A behavioral model of expectation formation

We first discuss three behavioral deviations from fully rational expectations that have already found some empirical support. We then combine these three biases into a behavioral model of expectation formation. Subsequently, in Sections 4 and 5, we will confront this model with data from survey expectations to see whether the proposed biases are present in the data.

### 2.1 Stickiness

Fuhrer (2017) replaces, in a macroeconomic model, rational expectations with actual expectations from survey data. He shows that this makes usual modeling elements to generate macroeconomic persistence such as habit formation and price indexation obsolete. Also, Coibion and Gorodnichenko (2015) document that forecast errors of aggregate expectations in survey data are forecastable by aggregate revisions. This implies under-reaction to new information and considerable persistence in expectations.

There is also empirical evidence of sticky expectations at the *individual level* in the case of financial analysts (Bouchaud et al., 2019), firm managers (Ma et al., 2018) and participants in laboratory experiments (Landier et al., 2019). Furthermore, Fuhrer (2018) finds that individual forecasts are *intrinsically persistent*, supporting his early findings on the macroeconomic level.

Persistence, or stickiness, in individual expectations implies that expectations of individuals depend on their most recent own past forecast about the same period. From a rational perspective, there is no reason why this should be the case.[3] When an individual $i$ forms expectations with stickiness as the only deviation from rationality, then her expectations $h$ periods ahead can be written as

$$F^{st}_{i,t}x_{t+h} = \lambda F^{st}_{i,t-1}x_{t+h} + (1-\lambda)E_t x_{t+h}. \tag{1}$$

This is the first behavioral bias that we allow for and will let the data speak to.

[3] A psychological explanation for why forecasts may be formed in such a way could e.g. be a confirmation bias (Nickerson, 1998). See also the discussion at the end of Section 5.2. As mentioned in the introduction, our focus does, however, not lie on explaining *why* certain biases arise. Instead, we aim to come up with a higher-level model of expectation formation that is in line with individual survey data.

## 2.2 Forward-looking extrapolation

The second bias we consider is forward-looking extrapolation. This is a variation of diagnostic expectations (Bordalo et al., 2018b). In both cases, individual expectations contain a "kernel of truth" as they depend one-for-one on the associated rational expectations forecast. However, additionally, agents overreact to recent news. In the case of diagnostic expectations, this news is taken to be the most recent rational expectations revision about the period being forecast. Landier et al. (2019) find, however, that extrapolation of news about the *current* period better and more robustly fits their experimental data.

The motivation for such a behavioral bias is that people may be particularly affected by surprises and news that concern the *current* state of affairs. This explanation fits well with the notion of "representativeness" of Kahneman and Tversky (1973) where some new information that is regarded as representative is extrapolated when making a prediction. That is, news about today may be viewed as more "representative" about both current and future economic conditions than news that only concerns the future. Thus, if forecasters are surprised by a higher realization of a variable today than they were expecting before, they extrapolate this surprise also into the future. As a consequence, forecasters then adjust their expectations about the future upward, more than would be rational.

When extrapolation is the only behavioral bias, expectations are given by

$$F_{i,t}^{ext} x_{t+h} = E_t x_{t+h} + \gamma News_{t,t}, \tag{2}$$

where $News_{t,t}$ represents news arriving in period $t$ that concerns realizations in period $t$.

If the current period would be fully observed, as it is in the experiment of Landier et al. (2019), then this news term would take the form

$$News_{t,t} = x_t - E_{t-1} x_t. \tag{3}$$

In practice, however, current values are not fully observed at the time that forecasts are made. To be consistent with the empirical data, we, therefore, do not assume actual realizations in period $t$ to be observable in period $t$ in our model of expectations. Consequently, current news about the current period is equal to today's *rational nowcast* minus the previous rational forecast about today:

$$News_{t,t} = E_t x_t - E_{t-1} x_t. \tag{4}$$

Plugging this in into (2) gives

$$F_{i,t}^{ext} x_{t+h} = E_t x_{t+h} + \gamma (E_t x_t - E_{t-1} x_t). \tag{5}$$

### 2.3 Consensus forecast

The above two biases assume that forecasters, in principle, are able to build something like fully rational expectations, but that they systematically deviate from the rational forecast because of a behavioral bias.

Forming rational expectations, in a world were the true model and its parameterization are unknown and may vary over time is, however, not an easy task for an individual forecaster. In particular, it may be infeasible for an individual forecaster to try to combine all information on all relevant factors and variables in the economy in a rational way. Instead of trying to construct a fully rational expectations forecast all by herself, an individual forecaster may, therefore, also consider information on expectations of other forecasters when forming her own forecasts.

A consensus forecast of a large group of (professional) forecasters can be seen as a very valuable source of information for an individual forecaster. In particular, this is an example of the well known "wisdom of the crowd" (Surowiecki, 2004; Davis-Stober et al., 2014). As a consequence, we find that mean squared forecast errors of consensus forecasts are considerably lower than those of individual forecasters.

In real-time, a typical forecaster has only very little information available about what other forecasters are expecting and a general consensus forecast cannot be derived from this. However, with a time lag, there are plenty of direct and indirect sources of information that reflect a consensus forecast. For example, the consensus forecast of the survey of professional forecasters is published on the website of the Federal Reserve Bank of Philadelphia each quarter. Further, numerous institutions frequently publish their forecasts which also find their way into newspapers and blogs and, thus, to the larger public.

When forecasters partly base their forecasts on a lagged consensus forecast, they do not fully take into account all information that is available now but was not yet available in the previous period. We find, however, that even a *lagged* consensus forecast can still be seen as a useful piece of information for many forecasters. We will discuss this in detail in Section 2.3. Moreover, Fuhrer (2018) finds evidence that forecasters indeed base their forecasts significantly on a lagged consensus forecast. This holds for the survey of professional forecasters and the Livingston survey, as well as for the Michigan survey of consumer expectations.

When forecasters only partially are able to form rational expectations themselves, and for the other part base their expectations on a lagged consensus forecast, their expectations become

$$F^{co}_{i,t}x_{t+h} = (1-\delta)E_t x_{t+h} + \delta C_{t-1}x_{t+h}, \tag{6}$$

where $C_{t-1}x_{t+h}$ is a lagged consensus forecast (e.g. the median of the expectations of all expert forecasters).

## 2.4 Combining the three behavioral biases

Next, we will combine the three biases introduced above into a behavioral model of expectation formation. Suppose that when agents form expectations, they are only partially able to do this rationally by themselves. For the other part, they chose to base their expectations on a lagged consensus forecast, as in (6). Suppose further that they also have the stickiness bias of Section 2.1, so that they anchor their newly formed expectations to their previously formed own expectations. Expectations would then become

$$F^{st,co}_{i,t}x_{t+h} = \lambda F^{st,co}_{i,t-1}x_{t+h} + (1-\lambda)\left[(1-\delta)E_t x_{t+h} + \delta C_{t-1}x_{t+h}\right]. \tag{7}$$

Next, assume that forecasters also are subject to the forward-looking extrapolation bias of Section 2.2. That is, agents base their expectations on (7) and then deviate from this by extrapolating the most recent news. Replacing $E_t x_{t+h}$ with (7) in (5) gives our final model of behavioral expectations:

$$
\begin{aligned}
F_{i,t}x_{t+h} =& \lambda F_{i,t-1}x_{t+h} + (1-\lambda)\left[(1-\delta)E_t x_{t+h} + \delta C_{t-1}x_{t+h}\right] \\
&+ \gamma(E_t x_t - E_{t-1}x_t) + \mu_{i,t},
\end{aligned} \tag{8}
$$

where we have added an idiosyncratic white noise term, $\mu_{i,t}$, to allow for additional heterogeneity among forecasters.

Under this model of expectation formation, there can be both over-reaction and under-reaction to news. The deciding factor, here, is whether the piece of news only concerns the period that is being forecast $(t+h)$ or that the news also considerably impacts realizations in the current period $(t)$. If the news is only relevant for period $t+h$, then forecasters will under-react to it. This is because the news then only shows up in the term $E_t x_{t+h}$, to which forecasters respond in a dampened manner with coefficient $(1-\lambda)(1-\delta)$.

In general, however, one expects there to be a correlation between current news about $t+h$ $(news_{t,t+h})$ and current news about $t$ $(news_{t,t})$. In that case, there can also be over-reaction to news. This is because the news will now also affect $E_t x_t - E_{t-1}x_t (= news_{t,t})$. Forecasters will then, on the one hand, respond to the news in a dampened manner, but at the same time over-react to the news with coefficient $\gamma$. This can result in a net over-reaction to the news if $news_{t,t}$ is enough affected relative to $news_{t,t+h}$.

Note, further, that even though expectations are no longer one-for-one based on rational expectations, rational expectations still are a component of "base" expectations (7). Therefore, (although a smaller one) the behavioral expectations in (8) still contain a "kernel of truth". Moreover, since we will estimate the parameters of our model using survey data, we are not assuming that any of the above biases *must* be present. Instead, we will let the data decide which bias is present and with what magnitude. If it turns out that $\lambda = \gamma = \delta = 0$, then (in the absence of idiosyncratic noise) fully rational expectations are obtained in (8).

# 3 Empirical Model

Before we can confront the model of expectation formation derived in the previous section with survey data, we need to rewrite it somewhat. This is because rational expectations and the news term in Equation (8) are not directly observable.

As mentioned in Section 2.3, the consensus forecasts of the SPF are considerably better than the individual forecasts. This indicated that, for our purposes, it might be possible to approximate the news variable, $E_t x_t - E_{t-1} x_t$, with the revision in the consensus forecast about the current period:

$$News_{t,t} = E_t x_t - E_{t-1} x_t \approx C_t x_t - C_{t-1} x_t, \tag{9}$$

where $C_t x_t$ is the consensus nowcast and $C_{t-1} x_t$ the lagged consensus forecast about today.

Coibion and Gorodnichenko (2015) find, however, that for a longer forecasting horizon, there is a systematic bias in the consensus forecast that is reflected in a dependence of forecast errors on forecast revisions. We should, therefore, check whether this is also the case for consensus nowcasts and possibly control for this when approximating news.

In particular, modifying the steps of Coibion and Gorodnichenko (2015) to the case of nowcasts, we have the following: whereas nowcast errors under rational expectations are given by

$$x_t - E_t x_t = \varepsilon_{t,t}, \tag{10}$$

nowcast errors of the consensus might be given by

$$x_t - C_t x_t = \frac{\tilde{\lambda}}{1-\tilde{\lambda}}(C_t x_t - C_{t-1} x_t) + \varepsilon_{t,t}, \tag{11}$$

where $\varepsilon_{t,t}$ is the rational expectations nowcast error that reflects information about period $t$ that is not yet available when forecasts in period $t$ are made.

Combining (10) and (11), we can write

$$E_t x_t = C_t x_t + \frac{\tilde{\lambda}}{1-\tilde{\lambda}}(C_t x_t - C_{t-1} x_t). \tag{12}$$

Taking the lag of this equation and subtracting it gives, after rearranging,

$$E_t x_t - E_{t-1} x_t = \frac{1}{1-\tilde{\lambda}}(C_t x_t - C_{t-1} x_t) - \frac{\tilde{\lambda}}{1-\tilde{\lambda}}(C_{t-1} x_t - C_{t-2} x_t). \tag{13}$$

That is, we obtain an expression for news in terms of the observable consensus forecasts that is valid even when consensus revisions are inefficient.

In order to judge whether it is necessary to use (13), we estimate equation (11). Results are presented in Appendix B.1. It turns out that for two of the four variables that we consider, the resulting estimated value of $\frac{\tilde{\lambda}}{1-\tilde{\lambda}}$ is not statistically different from zero. Moreover, the estimated values of $\frac{\tilde{\lambda}}{1-\tilde{\lambda}}$ across all variables range from 0.06 and 0.23. This translates into values of $\tilde{\lambda}$ ranging from 0.06 to 0.19, which are considerably smaller than the values found for the case of $h = 3$ in Coibion and Gorodnichenko (2015).

This implies that the consensus revision is relatively close to being efficient when *nowcasts* are concerned. We, therefore, consider (9) to be a good enough approximation for current news and use this approximation for our estimations in the main body of the paper. However, in Appendix B.1 we show robustness to this approximation by also estimating our model using Equation (13) as the definition of $News_{t,t}$.

Next, we need to replace $E_t x_{t+h}$ in Equation (8) with an observable. Taking the consensus forecast about period $t + h$ would not be a good enough approximation here. However, similar to Coibion and Gorodnichenko (2015) and others, we can use the analog of (10) for h-period ahead rational expectations

$$x_{t+h} = E_t x_{t+h} + \varepsilon_{t,t+h} \tag{14}$$

where $\varepsilon_{t,t+h}$ is the current rational expectations error regarding period $t + h$. Again, this term reflects information about period $t + h$ that is not yet available when forecasts are made in period $t$. Moreover, to be as close as possible to the information set of forecasters, we use the first vintage realizations of the actuals in $t+h$. When considering actuals in this literature, using first vintages is a standard procedure (see Bordalo et al. (2018a) and Coibion and Gorodnichenko (2015)). We also provide a detailed description of our variables in Appendix A.

Using (14) and (9), we can write (8) as

$$\begin{aligned} F_{i,t}x_{t+h} =& \lambda F_{i,t-1}x_{t+h} + (1-\lambda)\left[(1-\delta)x_{t+h} + \delta C_{t-1}x_{t+h}\right] + \gamma(C_t x_t - C_{t-1}x_t) \\ & - (1-\lambda)(1-\delta)\varepsilon_{t,t+h} + \mu_{i,t}, \end{aligned} \tag{15}$$

which can be estimated with empirical data. Note that the rational expectations error term $\varepsilon_{t,t+h}$ is orthogonal to all information dated $t$ and earlier by definition. Therefore, this term can go into the error term of the regression without biasing the results. The same holds for the individual white noise term $\mu_{i,t}$.

Another specification of the model can be obtained by subtracting $F_{i,t-1}x_{t+h}$ from both sides of (15). We can then write

$$
\begin{aligned}
F_{i,t}x_{t+h} - F_{i,t-1}x_{t+h} =&(1-\lambda)\left[(1-\delta)(x_{t+h} - F_{i,t-1}x_{t+h}) + \delta(C_{t-1}x_{t+h} - F_{i,t-1}x_{t+h})\right] \\
&+ \gamma(C_t x_t - C_{t-1}x_t) - (1-\lambda)(1-\delta)\varepsilon_{t,t+h} + \mu_{i,t}. \qquad (16)
\end{aligned}
$$

Here, the revision in forecasters $i$ forecast about period $t+h$ depends on how the actual realization deviates from the individuals' lagged forecast. This term indicates how the forecast is revised (rationally) because of news about $t+h$ in period $t$, which was not yet available in period $t-1$ (when the previous forecasts were made). However, this rational updating to news is only partial, and for another part, the revision depends on how the most recently observed consensus forecast deviates from the forecaster's own previous forecast. Forecasters, hence, partly update their forecasts towards the consensus. Stickiness causes adjustments to be even more partial (i.e. smaller revisions), as can be seen from the scaling with $1-\lambda$. Finally, there still is the extrapolation term, just as in (15), that leads to larger forecast revisions when there is positive news about the current period.

## 4 Confronting the model with survey expectations

For our main results, we utilize expectations provided by the Survey of Professional Forecasters (SPF). The SPF is a quarterly survey published first in the fourth quarter of 1968 by the National Bureau of Economic Research and since 1990 published by the Federal Reserve Bank of Philadelphia. Around 40 participants provide forecasts about a variety of variables in the current and next four quarters. The survey is conducted at the end of the second month in each given quarter. Hence, forecasters know the realizations of quarterly data up to quarter $t-1$ and for unemployment up to the previous month. In our sample, forecasters stay in the survey for about 41 quarters on average.

As can be seen in Table 1, we calculate expectations about inflation, growth rates for nominal and real GDP, and the unemployment rate.[4] For actual realizations of variables, we use the Real-Time Data Set for Macroeconomists of the Philadelphia FED. A detailed description of our variable construction is given in Appendix A.

Using this data, we fit both forecast revisions based on Equation (16) (in Section 4.1) and

[4]We chose to calculate inflation expectations from expectations about the GDP price index as it covers the same time period as the rest of our variables. Expectations about the CPI inflation rate are available from 1981:Q3 only which we, therefore, do not consider.

**Table 1:** Expectation data based on SPF

| Variable | Period |
|---|---|
| Inflation | 1970:Q1 - 2019:Q3 |
| Nominal GDP Growth Rate | 1970:Q1 - 2019:Q3 |
| Real GDP Growth Rate | 1970:Q1 - 2019:Q3 |
| Unemployment Rate | 1970:Q1 - 2019:Q4 |

*Note*: The period covered for each variable may slightly vary with the forecasting horizon.

individual forecasts as in Equation (15) (in Section 4.2), using pooled OLS and fixed effects estimation. Note that the coefficients in equation (16) identify the underlying theoretical model parameters exactly. This is equivalent to imposing a restriction on the estimation of Equation (15) which we subsequently test.

Further, all test statistics are robust with respect to heteroscedasticity, autocorrelation, and general forms of spatial correlation due to Driscoll and Kraay (1998) standard errors. We take the results of our regressions with two-period-ahead forecasts ($h = 2$) as our baseline, but we also consider results with a forecasting horizon of $h = 1$ and $h = 3$ in Section 4.3. For a forecasting horizon of $h = 4$, no lagged individual forecasts about the same period are available, so we cannot perform our estimations for that case.

## 4.1 Fitting forecasting revisions

Based on (15) we first estimate a regression of the following form:

$$\begin{aligned} F_{i,t}x_{t+h} - F_{i,t-1}x_{t+h} =& a_1(x_{t+h} - F_{i,t-1}x_{t+h}) + a_2(C_{t-1}x_{t+h} - F_{i,t-1}x_{t+h}) \\ &+ a_3(C_t x_t - C_{t-1}x_t) + e_t. \end{aligned} \tag{17}$$

**Table 2:** Regression of Equation (17) with $h = 2$ based on SPF
Dependent Var.: $F_{i,t}x_{t+2} - F_{i,t-1}x_{t+2}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | -0.0002* | | -0.001*** | | -0.001*** | | 0.047*** | - |
| | (0.000) | | (0.000) | | (0.000) | | (0.009) | |
| $x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.116*** | 0.106*** | 0.159*** | 0.161*** | 0.138*** | 0.136*** | 0.110*** | 0.110*** |
| | (0.016) | (0.016) | (0.026) | (0.024) | (0.018) | (0.019) | (0.013) | (0.013) |
| $C_{t-1}x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.492*** | 0.593*** | 0.386*** | 0.464*** | 0.443*** | 0.551*** | 0.384*** | 0.448*** |
| | (0.042) | (0.044) | (0.032) | (0.031) | (0.033) | (0.040) | (0.022) | (0.023) |
| $C_t x_t - C_{t-1}x_t$ | 0.934*** | 0.929*** | 0.871*** | 0.870*** | 0.857*** | 0.850*** | 0.926*** | 0.925*** |
| | (0.049) | (0.049) | (0.043) | (0.042) | (0.066) | (0.062) | (0.036) | (0.036) |
| $R^2$ | 0.58 | 0.57 | 0.57 | 0.57 | 0.55 | 0.55 | 0.66 | 0.66 |
| $n$ | 5612 | 5612 | 5591 | 5591 | 5687 | 5687 | 5818 | 5818 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third digit after the comma (except for the point estimates of the intercept for inflation).

Table 2 presents the regression results for the SPF for the four different macroeconomic variables introduced above. In the table, we see that all included regressors significantly influence the individual forecasts. Not surprisingly and in line with earlier literature, this shows that the rational expectations hypothesis, i.e. in our case $\lambda = \gamma = \delta = 0$, is clearly rejected. Further, these results substantiate our proposed alternative: SPF forecasters indeed anchor their forecasts to their previous own forecast, extrapolate news about the current period into the future and make use of the lagged consensus forecast when forming their own expectations.

Moreover, when comparing the estimates across the five different variables, the estimated regression coefficients are relatively close to each other. This indicates, that the degree to which agents use the past consensus forecast and suffer from the stickiness and extrapolation biases is not very sensitive to the variable being forecast.

Next, we want to obtain estimates of $\lambda$, $\delta$ and $\gamma$. By comparing Equation (17) with (15) it follows that $\lambda = 1 - a_1 - a_2$, $\delta = \frac{a_2}{a_1+a_2}$ and $\gamma = a_3$. For each variable, and depending on whether OLS or fixed effect estimation is used, an estimate of $\lambda$, $\delta$ and $\gamma$ can so be obtained. The differences between these eight estimates of each model parameter are, however, not very large, and we are able to obtain a good indication in what range of values the parameters of the theoretical model may lie. In particular, we find estimates of $\lambda$ lying between 0.30 and 0.51, estimates of $\delta$ between 0.71 and 0.85 and estimates of $\gamma$ between 0.85 and 0.93. When we average the estimated model parameters across variables and estimation methods, we obtain that the average estimated stickiness is $\lambda = 0.40$. Moreover, the average estimated extent to which individuals are not able to form their own rational expectations but instead use the most recent consensus forecast is $\delta = 0.78$, and the average estimated extrapolation parameter is $\gamma = 0.90$. These results are also presented in Table 4, which will be discussed below.

Additionally, in Appendix B.2, we show that these results are hardly affected by limiting the sample to post-1984, i.e. where the Great Moderation started. Thus, forecasters do not seem to use a qualitatively different forecasting rule in a more stable economic environment. Also, in Appendix B.3, we discuss that our results, here and in the following sections, are robust with respect to excluding small samples which potentially cause biases under fixed effects (Nickell, 1981; Hjalmarsson, 2008).

### 4.2 Testing the model

Next, we run the following regression based on Equation (15):

$$F_{i,t}x_{t+h} = \beta_1 F_{i,t-1}x_{t+h} + \beta_2 x_{t+h} + \beta_3 C_{t-1}x_{t+h} + \beta_4(C_t x_t - C_{t-1}x_t) + e_t. \tag{18}$$

This specification is over-identified, as, according to our theoretical model, $\beta_1 + \beta_2 + \beta_3 = \lambda + (1-\lambda)\delta + (1-\lambda)(1-\delta) = 1$. Hence, this specification provides a good opportunity to test the validity of the restriction that our model of expectation formation implies. When the sum of these three coefficients in the above regression is close to 1, this indicates that expectation formation in the data is, at least to some extent, in line with our model.

**Table 3:** Regression of Equation X with $h = 2$ based on SPF
Dependent Var.: $F_{i,t}x_{t+2}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | -0.001* | | 0.000 | | -0.002* | | -0.037 | |
| | (0.000) | | (0.001) | | (0.001) | | (0.029) | |
| $\beta_1$ $(F_{i,t-1}x_{t+2})$ | 0.393*** | 0.300*** | 0.452*** | 0.374*** | 0.422*** | 0.316*** | 0.506*** | 0.441*** |
| | (0.031) | (0.034) | (0.016) | (0.020) | (0.025) | (0.031) | (0.015) | (0.018) |
| $\beta_2$ $(x_{t+2})$ | 0.113*** | 0.105*** | 0.159*** | 0.160*** | 0.135*** | 0.130*** | 0.115*** | 0.115*** |
| | (0.017) | (0.016) | (0.025) | (0.023) | (0.021) | (0.021) | (0.012) | (0.013) |
| $\beta_3$ $(C_{t-1}x_{t+2})$ | 0.503*** | 0.588*** | 0.371*** | 0.454*** | 0.485*** | 0.604*** | 0.393*** | 0.457*** |
| | (0.048) | (0.046) | (0.035) | (0.039) | (0.051) | (0.054) | (0.021) | (0.022) |
| $\beta_4$ $(C_t x_t - C_{t-1}x_t)$ | 0.932*** | 0.930*** | 0.874*** | 0.871*** | 0.846*** | 0.838*** | 0.915*** | 0.915*** |
| | (0.047) | (0.051) | (0.044) | (0.043) | (0.066) | (0.062) | (0.037) | (0.036) |
| **Wald-Test on restriction** $\beta_1 + \beta_2 + \beta_3 = 1$ | | | | | | | | |
| $\beta_1 + \beta_2 + \beta_3 =$ | 1.010 | 0.993 | 0.982 | 0.989 | 1.042 | 1.049 | 1.014 | 1.013 |
| p-value | **0.398** | **0.698** | **0.217** | **0.615** | **0.230** | **0.120** | 0.003 | 0.001 |
| $R^2$ | 0.92 | 0.91 | 0.89 | 0.88 | 0.82 | 0.82 | 0.98 | 0.98 |
| $n$ | 5612 | 5612 | 5591 | 5591 | 5687 | 5687 | 5818 | 5818 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third digit after the comma.

The estimation results are presented in Table 3. Also, the sums of these three coefficients, $\beta_1 + \beta_2 + \beta_3$, are shown at the bottom of the table. Interestingly, these sums are surprisingly close to 1 across variables and estimation techniques, and range from 0.982 to 1.049.

Further, to conduct a formal test on our model, we use a Wald test to test whether $\beta_1 + \beta_2 + \beta_3 = 1$ can be rejected. As can be seen there, this restriction cannot be rejected by the data at the 5% significance level for inflation, Nominal GDP and real GDP. This holds for the OLS estimates as well as the fixed effects estimates. Given the large amount of observations (over 5500 for these three variables), this is a strong indication that the restriction seems to have some validity, and that our model captures some important features of the data.[5]

However, in the case of unemployment, the Wald test does reject the restriction that $\beta_1 + \beta_2 + \beta_3 = 1$. Still, the sum of the three coefficients is quite close to 1 here (1.014 for pooled OLS and 1.013 for fixed effects). Therefore, the rejection reflects even smaller standard errors rather than a clear economically significant misspecification of the model.

It can further be seen in Table 3 that the estimated values of $\beta_2$, $\beta_3$ and $\beta_4$ are close to the estimates of $\alpha_1$, $\alpha_2$ and $\alpha_3$ in Table 2 for all variables. This is further indication that the theoretical model is not rejected by the data, as these coefficients are equal to respectively $(1-\lambda)(1-\delta)$, $(1-\lambda)\delta$ and $\gamma$ in both Equation (15) and Equation (16).

### 4.3 Forecasting horizon

Now, we consider results for different forecasting horizons. That is, we estimate Equation (17) for $h = 1$ and for $h = 3$. The estimation results can be found in Tables 17 and 18, respectively, in Appendix C.

From the estimated coefficients, which are all statistically significant, we again calculate estimates of the parameters $\lambda$, $\delta$ and $\gamma$, as described in Section 4.1. In Table 4, we present the average estimates of $\lambda$, $\delta$ and $\gamma$ for the three different forecasting horizons. Further, the minimum and maximum estimates that we obtain across variables and estimation methods are given in square brackets. The numbers in the second row are those discussed in Section 4.1.

In Table 4, it can be seen that the results for $h = 1$ and $h = 3$ are qualitatively in line with those discussed in Section 4.1. However, there are quantitative differences in the estimates of $\lambda$, $\delta$ and $\gamma$. In fact, there seems to be a clear pattern, where the average estimate of $\lambda$ becomes higher the larger the forecasting horizon, and the average estimates of $\delta$ and $\gamma$ become lower the

[5] Using a (robust) F-Test for the validity of the restriction gives identical results, which is not surprising given a large number of observations and the asymptotic equivalence to the (robust) Wald-test in this case.

**Table 4:** Average Estimates of behavioral parameters for different forecasting horizons.

| | $\lambda$ | $\delta$ | $\gamma$ |
|---|---|---|---|
| SPF (h=1) | 0.33 [0.24,0.40] | 0.86 [0.81,0.89] | 0.95 [0.93,0.98] |
| SPF (h=2) | 0.40 [0.30,0.51] | 0.78 [0.71,0.85] | 0.90 [0.85,0.93] |
| SPF (h=3) | 0.50 [0.40,0.58] | 0.72 [0.62,0.81] | 0.52 [0.32,0.92] |

*Note*: In brackets are the minimum and maximum estimates across variables and estimation methods.

larger the forecasting horizon. A similar pattern arises in the minimum and maximum estimates of the three model parameters.

It is intuitive that boundedly rational extrapolation of current news to future periods becomes weaker the further these periods lie in the future. That is, a forecaster may be considerably biased in her one-quarter-ahead forecast when she is surprised by a shock or news in the current period, but her three-quarter-ahead forecast may be considerably less distorted by what is happening in the current period. A lower value of the extrapolation parameter $\gamma$ for larger forecasting horizons is, therefore, understandable. Further, our average estimate (across variables and horizons) of $\gamma$ is substantially higher than the extrapolation parameter in the simple experimental environment of Landier et al. (2019) which is estimated to be around 0.45.

The finding that expectations become more sticky ($\lambda$ higher) as the forecasting horizons increases might be explained by the fact that there is less (accurate) news available about periods that lie further in the future than about periods that lie less far in the future. Forecasters have, therefore, less reason to revise their three-period-ahead forecast than they have to revise their forecast about the next quarter. As a consequence, they may respond to this by updating even less than would be rational and have a higher stickiness parameter for larger forecasting horizons. We obtain estimates of $\lambda$ that range between 0.24 and 0.58 across variables and horizons. The literature on stickiness and expectation smoothing finds values between 0.16 and 0.65 across different measures, forecasting horizons and data sources (Fuhrer, 2018; Ma et al., 2018; Bouchaud et al., 2019; Landier et al., 2019).

On the other hand, it seems that individual forecasters are better able to efficiently use the smaller amount of information and news that is available about three quarters ahead than the larger amount of news and information that is available about the next quarter. This can be seen from the lower estimate of $\delta$ for $h = 3$. This indicates, that in the absence of stickiness and extrapolation, their forecasts are closer to an individually built rational expectations forecast and rely less on the observed past consensus forecast.

Additionally, we ran the unrestricted regression in Equation (18) for $h = 1$ and $h = 3$. We present the sum of the estimated coefficients $\beta_1$, $\beta_2$ and $\beta_3$ as well as the p-values of the Wald test on the restriction $\beta_1 + \beta_2 + \beta_3 = 1$ in Table 5. For comparison, we also summarize the results for $h = 2$ here again.

**Table 5:** Wald-Test on restriction $\beta_1 + \beta_2 + \beta_3 = 1$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| | | | | **h=1** (SPF) | | | | |
| $\beta_1 + \beta_2 + \beta_3$ | 1.010 | 0.999 | 1.003 | 1.015 | 1.036 | 1.036 | 1.007 | 1.005 |
| p-value | **0.249** | **0.950** | **0.743** | **0.190** | 0.018 | 0.008 | 0.033 | ***0.055*** |
| | | | | **h=2** (SPF) | | | | |
| $\beta_1 + \beta_2 + \beta_3$ | 1.010 | 0.993 | 0.982 | 0.989 | 1.042 | 1.049 | 1.014 | 1.013 |
| p-value | **0.398** | **0.698** | **0.217** | **0.615** | **0.230** | **0.120** | 0.003 | 0.001 |
| | | | | **h=3** (SPF) | | | | |
| $\beta_1 + \beta_2 + \beta_3$ | 1.014 | 0.985 | 0.989 | 0.956 | 1.088 | 1.109 | 1.020 | 1.021 |
| p-value | **0.336** | **0.555** | **0.656** | **0.235** | **0.116** | ***0.054*** | 0.000 | 0.000 |

*Note*: Robust Wald-Test on the restriction $\beta_1 + \beta_2 + \beta_3 = 1$ in equation (18) for $h = 1, 2, 3$ (SPF). Test Statistic is based on Driscoll and Kraay (1998) standard errors. Values are rounded to the third digit after the comma.

The results for $h = 1$ and $h = 3$ are generally in line with those of $h = 2$. The sums of coefficients are again quite close to 1, also very much so for unemployment where the Wald test rejects an exact equality to 1. Moreover, for $h = 1$ the restriction for unemployment is no longer rejected at the 5% level for the fixed effect estimation. It can, however, be seen in Table 5 that, for $h = 1$, the restriction $\beta_1 + \beta_2 + \beta_3 = 1$ is rejected for real GDP. However, the sum of 1.036 is actually closer to 1 than it is for $h = 2$. Also, this rejection should, hence, not be considered to indicate a quantitatively important misspecification of the model.

# 5 Extensions

Below, we consider several extensions of the main estimations of the previous section. These help to provide more intuition and robustness. In Section 5.1, we study how we can interpret forecasters using the past consensus. In particular, we investigate whether this finding is limited to forecasters considering the consensus of the survey that they are participating in, or that, instead, our results indicate that forecasters may use a more general consensus in the economy. That is, we consider whether the consensus that forecasters base their expectations on might also have been obtained from other sources such as a different survey. Subsequently, we study the robustness of our results by using data of individual forecasts from the Livingston survey in Section 5.2. Finally, in Section 5.3, we consider an extension of the model of expectation formation where forecasts are also partly based on lagged observations of the variables being forecast (learning).

### 5.1 Consensus forecast from Livingston survey

In Section 4, it was assumed that the lagged consensus forecasts that the SPF forecasters base their expectations on is the median of the lagged individual forecasts of the SPF. It is, therefore, not clear whether the result that forecasters use this lagged median forecast should be interpreted as participants of the survey checking the latest publications of the survey that they are participating in, or that it can be interpreted more broadly. In this section, we investigate whether similar results would be obtained if the lagged consensus forecast is *not* obtained from the same survey that forecasters are participating in.

In particular, we perform similar estimations as in Section 4, but we let the lagged consensus forecast about the period being forecast, $C_{t-1}x_{t+h}$, no longer be equal to the lagged median forecast of the SPF. Instead, we set it equal to the median forecast of a different survey: the Livingston survey.

The Livingston survey was launched in June 1946 and is today published by the Federal Reserve Bank of Philadelphia twice a year. Forecasts relevant to this paper are made in June and December about the current quarter, two quarters beyond the current quarter, and a year beyond the current quarter. Thus, only forecasts made in Q2 and in Q4 are available. This means we can only use the Livingston consensus as a lagged consensus forecast in the SPF estimations if we restrict ourselves to SPF individual forecasts made in Q1 and Q3. Moreover, forecasters in the Livingston survey are only asked to make predictions about two quarters and four quarters ahead. We can, hence, use the two-quarter-ahead consensus estimate in the SPF regression of $h = 1$ and the four-quarter-ahead consensus forecast for the SPF regression of $h = 3$ (since a *lagged* forecast in the regression must always have a horizon that is one period longer than the *current* individual forecast). For the $h = 2$ regressions, on the other hand, no suitable lagged consensus forecast is available from the Livingston survey.

A further restriction of data availability is that nowcasts are only reported from 1992 onward in the Livingston survey. For the two quarter ahead forecasts used in the $h = 1$ regression this is of no concern. However, for the $h = 3$ regressions we need to limit the sample to start in 1992, since no meaningful yearly growth rates can be calculated from a four-quarter-ahead index forecast without having a nowcast (see Appendix A for further details on how we calculate growth rates). Finally, we focus on nominal GDP, real GDP and unemployment only, as forecasts about the price deflator are not available.

To see directly the effect of replacing the lagged consensus forecast of the SPF with the lagged consensus forecast of the Livingston survey, we first re-estimate the SPF model under the same restrictions on the sample. That is, we throw out all observations with forecasts made in Q2 and Q4 and additionally limit the sample to post-1992 for $h = 3$. The estimation results of (17) for the pure SPF case with the limited samples for $h = 1$ and $h = 3$ are presented in respective Table 19 and 21 in Appendix C. Next, we replace the consensus forecast with that of the Livingston survey and estimate (17) with exactly the same samples. The estimation results of these regressions for $h = 1$ and $h = 3$ can be found in respectively Tables 20 and 22 in Appendix C.

We then calculate the values of $\lambda$, $\delta$ and $\gamma$ that are implied by these estimations. In Table 6, we present the average, minimum and maximum estimates of the three model parameters that we obtain for each of the above four cases. First, consider the cases where the Livingston consensus is used (second and fourth row of the table). It can immediately be seen that the estimates of $\delta$ are still quite large and range from 0.72 to 0.89. Moreover, when comparing the $\delta$ estimates in the second row with those in the first row, it can be seen that both the average estimate as well as the minimums and maximum estimates of $\delta$ are very close to each other. The same holds when comparing the $\delta$ estimates in the fourth row with those in the third row of Table 6. This implies that replacing the SPF lagged consensus forecast with the lagged consensus forecast from the Livingston survey only has a very marginal effect on the extent to which individual SPF forecasters use this lagged consensus rather than their own rational expectations.

Moreover, when making pairwise comparisons of the $\lambda$ and $\gamma$ estimates in case of SPF consensus and Livingston consensus for $h = 1$, it can be seen in the first two rows of Table 6 that the estimates of $\gamma$ are somewhat more affected. However, qualitatively this does not change much. Finally, for $h = 3$ the estimates of $\lambda$ and $\delta$ with the Livingston consensus are even closer to those with the SPF consensus (bottom two rows of the table).

All in all, it can, hence, be concluded that our estimation is quite robust to replacing the SPF consensus with the Livingston consensus. This is a clear indication that forecasters in the SPF are not responding to the lagged consensus from their own survey per se, but rather to a more general consensus among economic experts across the whole economy. Individual forecasters can obtain this general consensus from the lagged consensus of the SPF, but they might just as well obtain it from other sources.

**Table 6:** Average Estimates of behavioral parameters for Q1 and Q3 only, with different consensus forecasts.

| | $\lambda$ | $\delta$ | $\gamma$ |
|---|---|---|---|
| SPF consensus (h=1) | 0.36 [0.28,0.41] | 0.87 [0.84,0.92] | 0.97 [0.94,0.98] |
| Livingston consensus (h=1) | 0.39 [0.30,0.47] | 0.85 [0.82,0.89] | 0.87 [0.81,0.90] |
| SPF consensus (h=3) | 0.60 [0.50,0.69] | 0.78 [0.69,0.87] | 0.74 [0.53,1.06] |
| Livingston consensus (h=3) | 0.60 [0.51,0.68] | 0.80 [0.72,0.86] | 0.71 [0.52,1.01] |

*Note*: In brackets are the minimum and maximum estimates across variables and estimation methods. For the $h = 3$ estimates (bottom two rows), the sample was limited to post-1992.

## 5.2 Forecasts from Livingston survey

To further study the robustness of the results of Section 4, we next perform our estimations for the *individual forecasts* of the Livingston survey. As mentioned in the previous section, the survey is semi-annual, so that we only have observations of forecasts made in the second and fourth quarter. This also implies that the most recent lagged individual forecast was made two quarters ago rather than in the previous quarter. Equation (17), hence, becomes

$$\begin{aligned} F_{i,t}x_{t+h} - F_{i,t-2}x_{t+h} =& a_1(x_{t+h} - F_{i,t-2}x_{t+h}) + a_2(C_{t-1}x_{t+h} - F_{i,t-2}x_{t+h}) \\ &+ a_3(C_t x_t - C_{t-1}x_t) + e_t. \end{aligned} \tag{19}$$

As we have shown in the previous section, the estimations are robust to whether we use the lagged consensus forecast of the SPF or of the Livingston survey. We can, therefore, use the SPF lagged consensus in the above estimation equation, rather than also introducing an extra lag in the past consensus.[6] We also still proxy news with the SPF consensus revision rather than a Livingston consensus revisions, since the latter would be a revision over two quarters and would, hence, include old news in addition to current news.

Data for (19) are in the Livingston survey only available for h=2 and only from 1992 onward.[7] In order to be able to make a fair comparison between estimations based on individual forecasts of the Livingston survey with those based on individual forecasts of the SPF, we, therefore, first estimate (17) with SPF individual data for a similar sample. That is we keep only observations form the second and fourth quarter and limit the sample to post-1992. Again, we focus on nominal GDP, real GDP and the unemployment rate, as forecasts about the price deflator are not available.

The SPF estimation results for this sample can be found in Table 23 whereas the estimations of (19) with the Livingston individual forecasts are presented in Table 24 in Appendix C. The respective test results of $\beta_1 + \beta_2 + \beta_3 = 1$ in (18) (and a similar regression with a two lagged individual forecast for the Livingston case) are reported in Table 25 in Appendix C.

**Table 7:** Average Estimates of behavioral parameters for different forecasting horizons.

| | $\lambda$ | $\delta$ | $\gamma$ |
|---|---|---|---|
| SPF | 0.45 [0.41,0.48] | 0.71 [0.67,0.77] | 0.92 [0.84,0.97] |
| Livingston | 0.25 [0.19,0.32] | 0.71 [0.67,0.76] | 1.01 [0.94,1.15] |

*Note*: In brackets are the minimum and maximum estimates across variables and estimation methods.

In Table 7, we compare the resulting estimates of $\lambda$, $\delta$, and $\gamma$. Here, it can be seen that the estimates of $\gamma$ differ somewhat across the two surveys. The difference is, however, not large enough to lead to qualitatively different implications regarding the forecasting behavior of the forecasters. In both surveys, there is behavioral extrapolation of the most recent news in the economy, and in both cases, the extrapolation coefficient is quite large.

Turning to the estimates of $\delta$, it can be seen that these are remarkably stable across the two surveys. The extent to which forecasters in the Livingston survey are inclined to base their forecasts on the lagged consensus rather than trying to build their own expectations seems to be the same as for the forecasters of the SPF. Given that we included the SPF consensus in the Livingston regressions, this can also be seen as further evidence that results are not driven by

[6] The later would bias the estimation because the consensus forecast in the estimation would then not be the most recent consensus forecast available to individual forecasters.

[7] To be able to compute the lagged expected yearly growth rate for $h = 2$ implied by the level forecast of GDP, we need individual nowcasts. See also Appendix A. These nowcasts are available from 1992 only.

forecasters anchoring on the latest publication of the survey that they are participating in.

If we turn to the estimates of $\lambda$, a different picture arises. The extent to which forecasters in the Livingston survey anchor to their own lagged forecast seems to be almost 50% smaller than for the SPF forecasters. A reasonable explanation for this could lie in the fact that participants in the Livingston survey made their previous forecast two quarters ago rather than one quarter ago. This, first of all, makes their previous forecasts more outdated and less relevant, and forecasters may realize this. Secondly, if stickiness in expectations is partly caused by a confirmation bias (Nickerson, 1998), then this bias is likely to be weaker when the previous forecast was formed a longer time ago. This is because a forecaster may be more inclined to defend, and stick with, a previously formed opinion or forecast (i.e., may have a stronger confirmation bias) if she formed this opinion/forecast in the more recent past. Along these lines, Zhu et al. (2012) find, for example, that subjects in their laboratory experiment were more likely the revise their opinion in response to new information when more time had past between the moment of the possible revision and the moment that the original opinion was formed.

### 5.3 An alternative deviation from rationality

As a final extension, we consider adding an additional bias to our model of expectation formation. In addition to stickiness, extrapolation and the dependence of expectations on lagged consensus forecasts, one could imagine that forecasters also partly base their expectations on the most recent observation of the variable being forecast.

Such behavior in expectation formation is found in laboratory experiments in macroeconomic settings by, e.g., Pfajfar and Zakelj (2015) and Assenza et al. (2019). Moreover, when forecasters were using adaptive learning as in Evans and Honkapohja (2012), one would also expect to find that forecasts depend on, a.o., the lag of the variable being forecast.[8]

Furthermore, these different kinds of 'backward-looking' expectation formation processes can make expectations more persistent. Therefore, macroeconomic models that include some form of backward-looking expectation formation can improve the fit to the data compared to a specification with fully rational expectation (Branch, 2004; Milani, 2007; Slobodyan and Wouters, 2012; Cornea-Madeira et al., 2019). Based on these findings, it might be the case that basing forecasts on lagged observations is also an important deviation from full rationality that can

[8]Additionally, forecasts might then also depend on observations further in the past than the most recent lag and on lags of other variables. We have also checked for this. When adding other lags to our regressions, estimated coefficients on these lags are always very small and in most cases statistically insignificant. Also, our estimated coefficients are robust to adding these additional lags.

explain forecasting behavior in survey data.

We, therefore, add the most recent observation of the variable that is being forecast to the regression in (17). If forecasters base their decisions on this variable in addition to the components of our proposed model of expectation formation, this should be reflected in the coefficient on this additional regressor. Moreover, if persistence in survey expectations were driven by backward-looking expectations rather than by stickiness, adding the additional regressor would lead to a considerably smaller estimate of $\lambda$.

The estimation results of Equation (17) with the lagged realization as an additional regressor for $h = 1, 2, 3$ are presented in Tables 26 - 28 in Appendix C. In 18 of the 24 estimations, the coefficient on the lagged realization is not statistically significant at the 5% level. Moreover, the estimated coefficients on this regressor are always small in size and take on both positive and negative values. This is summarized in the most right column of Table 8. For each forecasting horizon, the average coefficient on the lagged realization is either 0.00 or 0.01. Meanwhile, the individual estimates range from $-0.02$ to 0.03.

**Table 8:** Average Estimates of behavioral parameters including for lagged actual for different forecasting horizons.

| | $\lambda$ | $\delta$ | $\gamma$ | actual lag |
|---|---|---|---|---|
| SPF (h=1) | 0.33 [0.24,0.40] | 0.86 [0.81, 0.89] | 0.94 [0.90, 0.98] | 0.01 [0.00,0.03] |
| SPF (h=2) | 0.40 [0.30,0.50] | 0.78 [0.71,0.85] | 0.89 [0.83,0.94] | 0.00 [-0.02,0.02] |
| SPF (h=3) | 0.50 [0.40,0.58] | 0.72 [0.62,0.80] | 0.50 [0.30,0.91] | 0.01 [0.00,0.03] |

*Note*: In brackets are the minimum and maximum estimates across variables and estimation methods.

This confirms the findings of Fuhrer (2018) that stickiness in expectations (or expectations smoothing) can better explain the persistence found in survey expectations than backward-looking adaptive expectations or adaptive learning. Landier et al. (2019) draw similar conclusions from the expectations data of their laboratory experiment.

Moreover, in the other columns of Table 8, we present the corresponding mean, minimum and maximum estimates of $\lambda$, $\delta$ and $\gamma$. Comparing these columns with Table 4, it can be seen that these are practically identical. For $\lambda$ and $\delta$, the mean estimates in both tables are exactly the same and the minimum and maximum estimates never deviate more than 0.01. For $\gamma$ differences are somewhat bigger but still very small. Our model of expectations formation, hence, is robust to adding the lagged realization as a potential additional bias.

## 6 Discussion: the (ir)rationality of using the lagged consensus forecast

In the previous sections, we found that individual forecasters, to a large extent, are not able to build their own rational expectations and instead partly base their forecasts on the lagged consensus forecast. This raises the question of how useful the lagged consensus forecast is as a source of information for individual forecasters.

Of course, the lagged consensus forecast might contain some important new information that agents should rationally take into account. Given that not all agents in the economy have rational expectations, expectations of other economic participants are an important determinant of what will happen to economic variables.

However, this does not explain the large values of $\delta$ that we have found in our estimations. If an individual forecaster was building rational expectations based on all information, including the lagged consensus, then her value of $\delta$ would be zero. After all, the rational expectation forecast efficiently incorporates all information, including the lagged consensus forecast and the lagged consensus would not show up as an additional determinant of the individual forecast. A positive value of $\delta$, hence, means that *instead* of forming rational expectations, a forecaster is partly basing her forecast on what the most recent consensus forecast is.

To get some insight into the extent to which this is a smart thing to do, we compare mean squared forecast error (MSFE) of the individual forecasters in the surveys with the corresponding MSFE of the *lagged* consensus forecast. Thus, for each individual $i$ we take the MSFE, Mean $(F_{i,t}x_{t+h} - x_{t+h})^2$, over all periods for which she was in the panel. We then compare this with the MFSE of the *lagged* consensus forecast, Mean $(C_{t-1}x_{t+h} - x_{t+h})^2$, about *the same* periods. This gives an indication of how well the individual performed relative to the lagged consensus forecast.

In particular, when the MSFE of the individual is larger than that of the lagged consensus forecast, then the individual was outperformed by the lagged consensus. In the top rows of the different panels of Table 9 we summarize, for different forecasting horizons, for how many forecasters in the sample this was the case.

By looking at the table as a whole, it immediately stands out that the percentage of individuals that was outperformed by the lagged consensus forecast lies between 18% and 50%. This is strikingly high, as the individuals can observe this lagged consensus forecast when making

**Table 9:** Percentage of forecasters outperformed by lagged consensus forecast

| | Infl. | Nom. GDP | Real GDP | Unemp. |
|---|---|---|---|---|
| | **h=1** (SPF) | | | |
| Outperformed by $C_{t-1}x_{t+h}$ | 30% | 29% | 29% | 21% |
| Mean $(F_{i,t}x_{t+h} - x_{t+h})^2$ | 0.6 | 1.4 | 1.29 | 0.18 |
| | **h=2** (SPF) | | | |
| Outperformed by $C_{t-1}x_{t+h}$ | 34% | 37% | 30% | 25% |
| Mean $(F_{i,t}x_{t+h} - x_{t+h})^2$ | 1.23 | 2.70 | 2.58 | 0.39 |
| | **h=3** (SPF) | | | |
| Outperformed by $C_{t-1}x_{t+h}$ | 44% | 50%$'$ | 43%$'$ | 33% |
| Mean $(F_{i,t}x_{t+h} - x_{t+h})^2$ | 2.11 | 4.4 | 4.2 | 0.68 |
| | **h=2** (LIV) | | | |
| Outperformed by $C_{t-1}x_{t+h}$ | | 50% | 35% | 18% |
| Mean $(F_{i,t}x_{t+h} - x_{t+h})^2$ | | 1.76 | 1.18 | 0.38 |

*Note*: A $'$ indicates that individual forecasts are on average (across time) outperformed by the lagged consensus forecast.

their forecast. Hence, they obviously have the opportunity to use this forecast when making their own forecast. Moreover, in the previous sections, we found evidence that they indeed, for a considerable part, do base their forecasts on the past consensus forecast. However, many forecasters are apparently still outperformed by this forecast.

The strong performance of the lagged consensus forecast relative to individual forecasts first of all confirms that using the consensus forecast as an alternative to rational expectations is a good choice for an individual with cognitive limitations that is not able to fully build a rational expectations forecast by herself. The cognitive bias of Section 2.3 should, therefore, really be interpreted in this way, and not as irrational overweighting of the past consensus forecast.

This becomes even more clear when we consider the following. For many individuals, the lagged consensus forecast has a better forecasting performance than the individual forecasts that are made one period later. If such an "outperformed" forecaster would have decided to abandon all attempts to build her own forecast and instead always blindly submitted the observed past consensus forecast (for example from the SPF website), then her forecasting performance would on average have been *better*. In other words, individual biases such as stickiness and extrapolation seem, for a considerable portion of individuals, to cause any attempt to build an own individual rational forecast to fail. Even if this attempt partly uses the information from the past consensus, their resulting forecast is on average still worse than this past consensus forecast.

Considering Table 9 in some more detail, it can be seen that the larger the forecasting horizon, the more individuals would have been better off by always blindly copying the lagged consensus forecast. This indicates that the more difficult the forecasting task, the larger individual errors might become and the worse the performance of individuals relative to the lagged consensus forecast. The bottom rows of the first three panels confirm that the MSFE across individuals *and* time periods indeed increases considerably as the forecasting horizon increases. This holds for all variables. While the MSFE of the consensus forecast also increases as the horizons increases, it does so to a lesser extent, so that more individuals are outperformed by the lagged consensus forecast.

Moreover, for nominal GDP and real GDP, for a forecasting horizon of three periods (marked with a $'$), we even find that, when we compare the MSFE of *all* individuals and *all* time periods with the MSFE of the corresponding lagged consensus forecasts, the individual forecasts are, on average, outperformed by the lagged consensus forecasts.

Finally, turn to the bottom panel of Table 9 that displays the results for the Livingston survey for a forecasting horizon of $h = 2$. The MSFE in the Livingston survey (bottom row) are smaller than those of the SPF (bottom row of the second panel). This is because the sample starts in 1992 where all variables were generally more stable and better forecastable. However, even in these more stable times, even more forecasters of the Livingston survey would have been better off by always copying the lagged (SPF) consensus nominal and real GDP forecasts than the forecasters in the SPF for the same forecasting horizon.

# 7 Conclusion

We have constructed a theoretical model of expectation formation and confronted it with survey expectations. We consider forecasting data of four important macroeconomics variables: inflation, nominal GDP, real GDP and the unemployment rate. We confirm that forecasters in the survey of professional forecasters and the Livingston survey have stickiness in their expectations in the sense that their forecasts are biased to their own past forecast. Moreover, we find that forecasters overly extrapolate news (surprises) about the current period into the future, which further biases their forecasts.

Also, we find that forecasters are not able to come up with their own rational forecasts but, instead, rely to a large extent on the most recent consensus forecast about the period that they are forecasting. They can observe this consensus of economic experts from the website of their survey, but could also get it from other sources. In particular, we have shown that they are not basing their forecast on the survey that they are participating in per se, but that the past consensus forecast rather is a more general public signal that can also be obtained from, e.g., a different survey.

According to our proposed model of expectation formation, the sum of the coefficients in front of an individual's lagged own forecast, the lagged consensus forecast and the lagged realization of the variable being forecast should be equal to 1. When we estimate an over-identified specification of our model, the sum of these coefficients always lies close to 1. Moreover, the null hypothesis that the sum is equal to 1 can, in most cases, not be rejected. This gives support to the validity of the proposed model.

We also obtained estimates of the behavioral parameters in our model with a revision regression that is not over-identified. For the SPF, we find stickiness estimates between 0.24 and 0.58, depending on the forecasting horizon. Larger forecasting horizons seem to imply more stickiness in expectations.

For shorter forecasting horizons (one or two quarters) we find estimates of the coefficient of extrapolation of current news between 0.85 and 0.98, which can be considered quite large. For three quarter ahead forecasts we find quite diverse, but generally smaller extrapolation coefficients that range from 0.32 to 0.92.

Regarding the lagged consensus forecast, we find that forecasters put weights between 0.62 and 0.89 on the most recently observed consensus forecast rather than on a rational expectations forecast that they would have to build themselves. It, therefore, seems that individual forecasters have a hard time processing all available information and news and building a rational expectations forecast. This seems to be especially the case for shorter forecasting horizons.

We find, however, that using the lagged consensus forecast to form expectations is not a stupid thing to do for a boundedly rational forecaster that is not able to come up with a rational expectations forecast by herself. In fact, depending on the forecasting horizon and the variable being forecast, up to 50% of the forecasters in the survey would have been better of in terms of forecasting performance if they would have abandoned all attempts to build their own forecast and instead blindly submitted the most recently observed consensus forecast in every period.

For the Livingston survey we find similar estimates of extrapolation and of the use of the lagged consensus forecast as in the SPF. However, the estimates of the stickiness parameter lie between 0.19 and 0.32, which is considerably smaller than the stickiness found in the SPF for the same forecasting horizon. This can be explained by the fact that the survey is semi-annual so that the previous forecast that a forecaster made was half a year ago rather than one quarter ago. This could make this previous forecast more outdated and could reduce the magnitude of a confirmation bias.

Finally, we find that lagged realizations of variables being forecast have only very little explanatory power for forecasts and revision and are often statistically insignificant when added to our model. This indicates that the biases in our proposed model can better explain individual survey expectations than adaptive learning or other forms of backward-looking expectations.

## References


Assenza, T., Heemeijer, P., Hommes, C., and Massaro, D. (2019). Managing self-organization of expectations through monetary policy: a macro experiment. *Journal of Monetary Economics*.

Bordalo, P., Gennaioli, N., Ma, Y., and Shleifer, A. (2018a). Over-reaction in macroeconomic expectations. Technical report, National Bureau of Economic Research.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2018b). Diagnostic expectations and credit cycles. *The Journal of Finance*, 73(1):199–227.

Bouchaud, J.-P., Krueger, P., Landier, A., and Thesmar, D. (2019). Sticky expectations and the profitability anomaly. *The Journal of Finance*, 74(2):639–674.

Branch, W. A. (2004). The theory of rationally heterogeneous expectations: evidence from survey data on inflation expectations. *The Economic Journal*, 114(497):592–621.

Branch, W. A. and McGough, B. (2010). Dynamic predictor selection in a new keynesian model with heterogeneous expectations. *Journal of Economic Dynamics and Control*, 34(8):1492–1508.

Carlson, J. A. (1977). A study of price forecasts. In *Annals of Economic and Social Measurement, Volume 6, number 1*, pages 27–56. NBER.

Coibion, O. and Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, 105(8):2644–78.

Cornea-Madeira, A., Hommes, C., and Massaro, D. (2019). Behavioral heterogeneity in us inflation dynamics. *Journal of Business & Economic Statistics*, 37(2):288–300.

Croushore, D., Stark, T., et al. (2019). Fifty years of the survey of professional forecasters. *Economic Insights*, 4(4):1–11.

Davis-Stober, C. P., Budescu, D. V., Dana, J., and Broomell, S. B. (2014). When is a crowd wise? *Decision*, 1(2):79.

De Grauwe, P. (2012). *Lectures on behavioral macroeconomics*. Princeton University Press.

Driscoll, J. C. and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of economics and statistics*, 80(4):549–560.

Ehrbeck, T. and Waldmann, R. (1996). Why are professional forecasters biased? agency versus behavioral explanations. *The Quarterly Journal of Economics*, 111(1):21–40.

Evans, G. W. and Honkapohja, S. (2012). *Learning and expectations in macroeconomics*. Princeton University Press.

Fildes, R. and Stekler, H. (2002). The state of macroeconomic forecasting. *Journal of macroeconomics*, 24(4):435–468.

Fuhrer, J. (2017). Expectations as a source of macroeconomic persistence: Evidence from survey expectations in a dynamic macro model. *Journal of Monetary Economics*, 86:22–35.

Fuhrer, J. C. (2018). Intrinsic expectations persistence: evidence from professional and household survey expectations.

Gabaix, X. (2016). A behavioral new keynesian model. Technical report, National Bureau of Economic Research.

Hjalmarsson, E. (2008). The stambaugh bias in panel predictive regressions. *Finance Research Letters*, 5(1):47–58.

Hommes, C. and Lustenhouwer, J. (2019). Inflation targeting and liquidity traps under endogenous credibility. *Journal of Monetary Economics*, 107:48–62.

Kahneman, D. and Tversky, A. (1973). On the psychology of prediction. *Psychological review*, 80(4):237.

Landier, A., Ma, Y., and Thesmar, D. (2019). Biases in expectations: Experimental evidence. *Available at SSRN 3046955*.

Loungani, P. (2001). How accurate are private sector forecasts? cross-country evidence from consensus forecasts of output growth. *International journal of forecasting*, 17(3):419–432.

Lovell, M. C. (1986). Tests of the rational expectations hypothesis. *The American Economic Review*, 76(1):110–124.

Ma, Y., Ropele, T., Sraer, D., and Thesmar, D. (2018). Do managerial forecasting biases matter. Technical report, Working paper.

Mackowiak, B. and Wiederholt, M. (2009). Optimal sticky prices under rational inattention. *American Economic Review*, 99(3):769–803.

Mankiw, N. G. and Reis, R. (2002). Sticky information versus sticky prices: a proposal to replace the new keynesian phillips curve. *The Quarterly Journal of Economics*, 117(4):1295–1328.

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

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the econometric society*, pages 1417–1426.

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of general psychology*, 2(2):175–220.

Pfajfar, D. and Zakelj, B. (2015). Inflation expectations and monetary policy design: Evidence from the laboratory.

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

Slobodyan, S. and Wouters, R. (2012). Learning in a medium-scale dsge model with expectations based on small forecasting models. *American Economic Journal: Macroeconomics*, 4(2):65–101.

Surowiecki, J. (2004). *The Wisdom of Crowds: Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economies, Societies, and Nations.* Little, Brown, London.

Woodford, M. (2003). Imperfect common knowledge and the effects of monetary policy. *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, page 25.

Zhu, H., Huberman, B., and Luon, Y. (2012). To switch or not to switch: understanding social influence in online choices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 2257–2266.

# A Variable Construction

For the price deflator, nominal GDP and real GDP, the data is about levels (indexes), and we turn these into growth rates. To construct yearly growth rates of actual realizations, we take the first vintages of the level and divide it by the corresponding lag (four quarters earlier) of the *same vintage*. For individual forecasts, we divide the forecast by the actual realization four quarters before the period that is being forecast. Here, we use the most up-to-date vintage at the time the forecast was made, to be as close as possible to the information sets of forecasters. For four-quarter-ahead forecasts, the actual realization of the corresponding lag is not available yet at the time the forecast was made. For that case, we divide the individual's forecast by her nowcast. Below, we give detailed formulas for all cases.

## A.1 SPF

- Constructing growth rates $x$ for $y \in$ {Price Deflator, Nominal GDP, Real GDP}
  - actual realizations in $t+h$ for $h=-1,1,2,3$: $x_{t+h} = \frac{y_{t+h|t+h+1}}{y_{t+h-4|t+h+1}} - 1$
  - individual forecast in $t$ for $h=1,2,3$: $F_{i,t}x_{t+h} = \frac{F_{i,t}y_{t+h}}{y_{t+h-4|t}} - 1$
  - individual forecast in $t-1$ for $h=1,2$: $F_{i,t-1}x_{t+h} = \frac{F_{i,t-1}y_{t+h}}{y_{t+h-4|t-1}} - 1$
  - individual forecast in $t-1$ for $h=3$: $F_{i,t-1}x_{t+3} = \frac{F_{i,t-1}y_{t+3}}{F_{i,t-1}y_{t-1}} - 1$
  - consensus forecast in $t-1$ for $h=1,2$: $C_{t-1}x_{t+h} = \frac{C_{t-1}y_{t+h}}{y_{t+h-4|t-1}} - 1$
  - consensus forecast in $t-1$ for $h=3$: $C_{t-1}x_{t+3} = \frac{C_{t-1}y_{t+3}}{C_{t-1}y_{t-1}} - 1$

– consensus nowcast revision: $C_t x_t - C_{t-1}x_t = \frac{C_t y_t}{y_{t-4|t}} - \frac{C_{t-1} y_t}{y_{t-4|t-1}}$

- Unemployment

  – actuals in $t+h$ for $h = -1, 1, 2, 3$: $x_{t+h|t+h+1}$

  – for $h = 1, 2, 3$: $F_{i,t}x_{t+h}$, $F_{i,t-1}x_{t+h}$, $C_{t-1}x_{t+h}$, $C_t x_t - C_{t-1}x_t$

### A.2 Livingston

- Constructing growth rates $x$ for $y \in \{\text{Nominal GDP, Real GDP}\}$

  – actuals: $x_{t+2} = \frac{y_{t+2|t+3}}{y_{t-2|t+3}} - 1$

  – individual forecast in $t$: $F_{i,t}x_{t+2} = \frac{F_{i,t}y_{t+2}}{y_{t-2|t}} - 1$

  – individual forecast in $t-2$: $F_{i,t-2}x_{t+2} = \frac{F_{i,t-2}y_{t+2}}{F_{i,t-2}y_{t-2}} - 1$

  – consensus forecasts in $t-1$ used in regressions with individual SPF forecasts: $C^{LIV}_{t-1}x_{t+1} = \frac{C^{LIV}_{t-1}y_{t+1}}{y_{t-3|t-1}} - 1$, $C^{LIV}_{t-1}x_{t+3} = \frac{C^{LIV}_{t-1}y_{t+3}}{C^{LIV}_{t-1}y_{t-1}} - 1$

- Unemployment

  – actuals: $x_{t+2|t+3}$

  – individual forecasts: $F_{i,t}x_{t+2}$, $F_{i,t-1}x_{t+2}$

  – consensus forecasts used in regressions with individual SPF forecasts: $C^{LIV}_{t-1}x_{t+1}$, $C^{LIV}_{t-1}x_{t+3}$

## B Robustness checks

### B.1 News and Consensus Nowcast Regressions

In Section 3, we argue that the latest news, $E_t x_t - E_{t-1}x_t$, can be approximated by the consensus nowcast revision, $C_t x_t - C_{t-1}x_t$. We draw this conclusion from the results given in Table 10. For two out of four cases, the estimation shows that the consensus nowcast is unbiased, and the bias for the remaining two cases is rather small, relative to the estimates of Coibion and Gorodnichenko (2015) for the three quarter ahead consensus forecast which range from 1.02 to 1.23 for inflation.

We also provide estimations based on calculating the news term as in (13) for $h = 2$, where we infer $\tilde{\lambda}$ from the estimations in Table 10. Table 11 shows that the estimates for $\lambda$ and $\delta$

**Table 10:** SPF Consensus Nowcast Regressions
Dependent Var.: $x_t - C_t x_t$

| | Inflation | Nominal GDP | Real GDP | Unemp. Rate |
|---|---|---|---|---|
| constant | 0.000 | 0.000 | 0.000 | -0.034*** |
| | (0.000) | (0.000) | (0.000) | (0.009) |
| $C_t x_t - C_{t-1} x_t$ | 0.056 | 0.030 | 0.165** | 0.23*** |
| | (0.098) | (0.083) | (0.074) | (0.031) |
| $R^2$ | 0.006 | 0.002 | 0.046 | 0.17 |
| $n$ | 204 | 204 | 204 | 205 |

*Note*: OLS estimation of equation (11) including a constant. Newey-West standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimates are rounded to the third decimal.

are hardly affected. The estimate of $\gamma$ is somewhat affected, but not in qualitative sense. The summary given in Table 11 is based on the estimates shown in Table 12.

These results carry over to the cases of $h = 1$ and $h = 3$ in general. Also, the restriction discussed in Section 4.2 is either not rejected or close to being not rejected when using this alternative measure of news. We do not report these results here, but they are available upon request.

**Table 11:** Average Estimates of behavioral parameters for regression with news as in (13) and $h = 2$.

| | $\lambda$ | $\delta$ | $\gamma$ |
|---|---|---|---|
| Baseline | 0.40 [0.30,0.51] | 0.78 [0.71,0.85] | 0.90 [0.85,0.93] |
| News as in (13) | 0.40 [0.30,0.51] | 0.76 [0.71,0.84] | 0.80 [0.73,0.87] |

*Note*: In brackets are the minimum and maximum estimates across variables and estimation methods.

**Table 12:** Regression with $h = 2$ and News as in (13) based on SPF
Dependent Var.: $F_{i,t}x_{t+2} - F_{i,t-1}x_{t+2}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | -0.0002* | | -0.001*** | | -0.001** | | 0.052*** | |
| | (0.000) | | (0.000) | | (0.000) | | (0.010) | |
| $x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.127*** | 0.115*** | 0.159*** | 0.161*** | 0.148*** | 0.145*** | 0.132*** | 0.131*** |
| | (0.016) | (0.017) | (0.026) | (0.024) | (0.017) | (0.018) | (0.013) | (0.014) |
| $C_{t-1}x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.481*** | 0.585*** | 0.385*** | 0.463*** | 0.432*** | 0.542*** | 0.362*** | 0.427*** |
| | (0.043) | (0.046) | (0.033) | (0.032) | (0.032) | (0.039) | (0.022) | (0.023) |
| $E_t x_t - E_{t-1}x_t$ | 0.870*** | 0.867*** | 0.849*** | 0.848*** | 0.736*** | 0.729*** | 0.754*** | 0.751*** |
| | (0.050) | (0.050) | (0.043) | (0.042) | (0.062) | (0.065) | (0.042) | (0.042) |
| $R^2$ | 0.58 | 0.57 | 0.57 | 0.57 | 0.55 | 0.54 | 0.66 | 0.66 |
| $n$ | 5612 | 5612 | 5591 | 5591 | 5687 | 5687 | 5818 | 5818 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third digit after the comma (except for the point estimates of the intercept for inflation).

## B.2 post-1984

In this Appendix, we consider the question of whether behavioral biases in expectation formation are different in a more stable economic environment. In particular, we investigate whether the estimates of our model parameters are different if we limit the sample to the post-1984, i.e., after the Great Moderation started.

Table 14 presents the estimation results of (17) for $h = 2$ when we limit the sample to start at 1984Q1. In Table 13 the resulting average, minimum and maximum estimates of $\lambda$, $\delta$ and $\gamma$ are compared with those of the full sample.

**Table 13:** Average Estimates of behavioral parameters for different time samples.

| | $\lambda$ | $\delta$ | $\gamma$ |
|---|---|---|---|
| Full sample | 0.40 [0.30,0.51] | 0.78 [0.71,0.85] | 0.90 [0.85,0.93] |
| post-1984 | 0.42 [0.35,0.50] | 0.79 [0.76,0.83] | 0.92 [0.86,1.00] |

*Note*: In brackets are the minimum and maximum estimates across variables and estimation methods.

In Table 13, it can be seen that the estimates of our model parameters are close to those obtained under the full sample. Hence, there is no reason to suspect that forecasters make qualitatively different forecasts in the more stable environment of the great moderation.

**Table 14:** Regression of Equation (17) with $h = 2$ based on SPF, post-1984
Dependent Var.: $F_{i,t}x_{t+2} - F_{i,t-1}x_{t+2}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | -0.000*** | | -0.001*** | | -0.001** | | 0.042*** | |
| | (0.000) | | (0.000) | | (0.000) | | (0.009) | |
| $x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.105*** | 0.110*** | 0.137*** | 0.139*** | 0.134*** | 0.139*** | 0.098*** | 0.100*** |
| | (0.025) | (0.023) | (0.031) | (0.033) | (0.027) | (0.027) | (0.018) | (0.018) |
| $C_{t-1}x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.454*** | 0.541*** | 0.436*** | 0.495*** | 0.413*** | 0.460*** | 0.406*** | 0.487*** |
| | (0.038) | (0.042) | (0.043) | (0.045) | (0.057) | (0.057) | (0.024) | (0.026) |
| $C_t x_t - C_{t-1}x_t$ | 0.897*** | 0.899*** | 0.940*** | 0.935*** | 0.864*** | 0.861*** | 0.998*** | 0.998*** |
| | (0.051) | (0.053) | (0.054) | (0.052) | (0.053) | (0.055) | (0.055) | (0.054) |
| $R^2$ | 0.55 | 0.56 | 0.60 | 0.61 | 0.64 | 0.65 | 0.70 | 0.71 |
| $n$ | 3953 | 3953 | 3936 | 3936 | 4044 | 4044 | 4124 | 4124 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third digit after the comma (except for the point estimates of the intercept for inflation).

## B.3 Small samples

Next, we consider to what extent our estimation results would differ if we would focus only on forecasters that have at least 40 time observations in our sample. This is a relevant issue for the fixed effect estimates which may potentially be subject to small sample biases. These small sample biases are well understood in the context of dynamic panel models (Nickell, 1981) and predictive panel regressions (Hjalmarsson, 2008).

We focus on the post-1984 subsample for this robustness exercise, as forecasters with a larger amount of time periods are generally found in this subsample. Table 16 reproduces the estimation results of Table 14, but with a limited sample where all individuals that have less than 40 observations are excluded. Note that we already found in Appendix B.2 that restricting the sample to post-1984 does hardly affect the result relative to the full sample.

By comparing the OLS estimates with the corresponding fixed effects estimates in both tables, it can be seen that the OLS estimate and fixed effect estimate generally lie somewhat closer together in the sample where we only consider individuals with more than 40 time observations compared to the sample that also includes individuals with fewer time observations. This difference is, however, not very large, suggesting that small sample biases are of minor quantitative importance. Most importantly, if we compare the implied estimates of our model parameters for the cases with and without individuals with less than 40 observations, differences are small. This can be seen in Table 15, where we compare the average, minimum and maximum estimates of $\lambda$, $\delta$ and $\gamma$ from Table 16 with those of Table 14.

**Table 15:** Average Estimates of behavioral parameters post-1984, when excluding individuals wiht less than 40 observations.

| | $\lambda$ | $\delta$ | $\gamma$ |
|---|---|---|---|
| All individuals | 0.42 [0.35,0.50] | 0.79 [0.76,0.83] | 0.92 [0.86,1.00] |
| Individuals with $\geq$ 40 obs. | 0.45 [0.41,0.51] | 0.77 [0.75,0.82] | 0.92 [0.85,1.01] |

*Note*: In brackets are the minimum and maximum estimates across variables and estimation methods.

We can, hence, conclude that a small sample bias does not qualitatively affect our results and is always of minor importance quantitatively. It further follows from the above exercise that participants that have been in the survey for a long time (and, hence, may have gained more forecasting experience) do not form their forecasts in a qualitatively different way than other forecasters of the SPF.

**Table 16:** Regression of Equation (17) with $h = 2$ based on SPF, post-1984,w/o small samples
Dependent Var.: $F_{i,t}x_{t+2} - F_{i,t-1}x_{t+2}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | -0.001*** | | -0.001*** | | -0.001* | | 0.047*** | |
| | (0.000) | | (0.000) | | (0.000) | | (0.008) | |
| $x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.122*** | 0.124*** | 0.131*** | 0.136*** | 0.137*** | 0.139*** | 0.099*** | 0.102*** |
| | (0.026) | (0.025) | (0.034) | (0.034) | (0.030) | (0.030) | (0.017) | (0.017) |
| $C_{t-1}x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.403*** | 0.470*** | 0.397*** | 0.431*** | 0.406*** | 0.450*** | 0.395*** | 0.452*** |
| | (0.039) | (0.039) | (0.056) | (0.057) | (0.073) | (0.073) | (0.025) | (0.027) |
| $C_t x_t - C_{t-1}x_t$ | 0.851*** | 0.855*** | 0.942*** | 0.938*** | 0.868*** | 0.867*** | 1.011*** | 1.006*** |
| | (0.051) | (0.052) | (0.056) | (0.055) | (0.060) | (0.061) | (0.051) | (0.051) |
| $R^2$ | 0.55 | 0.55 | 0.63 | 0.63 | 0.65 | 0.65 | 0.72 | 0.73 |
| $n$ | 2503 | 2503 | 2543 | 2543 | 2616 | 2616 | 2600 | 2600 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

## C Additional Tables

**Table 17:** Regression of Equation (17) with $h = 1$ based on SPF
Dependent Var.: $F_{i,t}x_{t+1} - F_{i,t-1}x_{t+1}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | 0.000 | | 0.000 | | 0.000 | | 0.034*** | |
| | (0.001) | | (0.000) | | (0.000) | | (0.006) | |
| $x_{t+1} - F_{i,t-1}x_{t+1}$ | 0.097*** | 0.085*** | 0.117*** | 0.116*** | 0.110*** | 0.108*** | 0.067*** | 0.069*** |
| | (0.015) | (0.017) | (0.022) | (0.022) | (0.021) | (0.019) | (0.020) | (0.019) |
| $C_{t-1}x_{t+1} - F_{i,t-1}x_{t+1}$ | 0.571*** | 0.671*** | 0.512*** | 0.581*** | 0.538*** | 0.627*** | 0.531*** | 0.582*** |
| | (0.035) | (0.041) | (0.026) | (0.040) | (0.024) | (0.022) | (0.022) | (0.024) |
| $C_t x_t - C_{t-1}x_t$ | 0.980*** | 0.980*** | 0.926*** | 0.927*** | 0.931*** | 0.931*** | 0.972*** | 0.966*** |
| | (0.043) | (0.042) | (0.031) | (0.070) | (0.039) | (0.031) | (0.035) | (0.035) |
| $R^2$ | 0.67 | 0.66 | 0.69 | 0.69 | 0.68 | 0.67 | 0.75 | 0.75 |
| $n$ | 5664 | 5664 | 5669 | 5669 | 5769 | 5769 | 5872 | 5872 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 18:** Regression of Equation (17) with $h = 3$ based on SPF
Dependent Var.: $F_{i,t}x_{t+3} - F_{i,t-1}x_{t+3}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | 0.000 | | -0.001 | | -0.001** | | 0.055*** | |
| | (0.000) | | (0.001) | | (0.001) | | (0.010) | |
| $x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.173*** | 0.167*** | 0.159*** | 0.155*** | 0.136*** | 0.136*** | 0.092*** | 0.092*** |
| | (0.018) | (0.021) | (0.028) | (0.026) | (0.025) | (0.025) | (0.012) | (0.012) |
| $C_{t-1}x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.314*** | 0.413*** | 0.262*** | 0.366*** | 0.345*** | 0.465*** | 0.334*** | 0.402*** |
| | (0.051) | (0.055) | (0.040) | (0.040) | (0.033) | (0.038) | (0.022) | (0.021) |
| $C_t x_t - C_{t-1}x_t$ | 0.378*** | 0.376*** | 0.437*** | 0.438*** | 0.328*** | 0.325*** | 0.925*** | 0.925*** |
| | (0.054) | (0.055) | (0.073) | (0.070) | (0.094) | (0.093) | (0.056) | (0.056) |
| $R^2$ | 0.35 | 0.34 | 0.29 | 0.28 | 0.29 | 0.28 | 0.60 | 0.60 |
| $n$ | 5459 | 5459 | 5437 | 5437 | 5447 | 5447 | 5610 | 5610 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 19:** Regression of Equation (17) with $h = 1$ based on SPF
Dependent Var.: $F_{i,t}x_{t+1} - F_{i,t-1}x_{t+1}$
(1st & 3rd Quarter)

| | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE |
| constant | 0.000 | | 0.000 | | 0.024** | |
| | (0.000) | | (0.000) | | (0.008) | |
| $x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.092*** | 0.092*** | 0.102*** | 0.104*** | 0.048** | 0.049** |
| | (0.020) | (0.025) | (0.022) | (0.023) | (0.020) | (0.019) |
| $C_{t-1}x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.512*** | 0.568*** | 0.545*** | 0.614*** | 0.543*** | 0.583*** |
| | (0.041) | (0.040) | (0.041) | (0.040) | (0.025) | (0.028) |
| $C_t x_t - C_{t-1}x_t$ | 0.964*** | 0.970*** | 0.983*** | 0.984*** | 0.955*** | 0.941*** |
| | (0.049) | (0.051) | (0.047) | (0.044) | (0.041) | (0.040) |
| $R^2$ | 0.68 | 0.68 | 0.66 | 0.66 | 0.73 | 0.73 |
| $n$ | 2824 | 2824 | 2778 | 2778 | 2928 | 2928 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. For compatibility with Livingston consensus, our sample must be restricted to observations in 1st & 3rd quarter (see table 20). Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 20:** SPF forecasts, $h = 1$, with Livingston consensus
Dependent Var.: $F_{i,t}x_{t+1} - F_{i,t-1}x_{t+1}$
(1st & 3rd Quarter)

| | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE |
| constant | 0.000 | | 0.000 | | 0.015 | |
| | (0.000) | | (0.000) | | (0.009) | |
| $x_{t+1} - F_{i,t-1}x_{t+1}$ | 0.097*** | 0.095*** | 0.116*** | 0.120*** | 0.061*** | 0.068*** |
| | (0.024) | (0.032) | (0.027) | (0.029) | (0.015) | (0.016) |
| $C_{t-1}^{LIV}x_{t+1} - F_{i,t-1}x_{t+1}$ | 0.492*** | 0.547*** | 0.513*** | 0.576*** | 0.474*** | 0.500*** |
| | (0.042) | (0.047) | (0.043) | (0.043) | (0.036) | (0.040) |
| $C_t x_t - C_{t-1}x_t$ | 0.885*** | 0.876*** | 0.904*** | 0.893*** | 0.830*** | 0.809*** |
| | (0.055) | (0.054) | (0.053) | (0.051) | (0.040) | (0.037) |
| $R^2$ | 0.68 | 0.67 | 0.66 | 0.66 | 0.72 | 0.72 |
| $n$ | 2824 | 2824 | 2778 | 2778 | 2928 | 2928 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. For compatibility with Livingston consensus, our sample must be restricted to observations in 1st & 3rd quarter. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 21:** Regression of Equation (17), $h = 3$ based on SPF
Dependent Var.: $F_{i,t}x_{t+3} - F_{i,t-1}x_{t+3}$
(1st & 3rd Quarter & post-1992)

| | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE |
| constant | 0.000 | | 0.000 | | 0.034** | |
| | (0.000) | | (0.000) | | (0.013) | |
| $x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.087*** | 0.090*** | 0.097*** | 0.105*** | 0.060*** | 0.064*** |
| | (0.021) | (0.021) | (0.014) | (0.016) | (0.023) | (0.023) |
| $C_{t-1}x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.291*** | 0.340*** | 0.211*** | 0.239*** | 0.364*** | 0.439*** |
| | (0.036) | (0.042) | (0.047) | (0.049) | (0.025) | (0.031) |
| $C_t x_t - C_{t-1}x_t$ | 0.639*** | 0.645*** | 0.527*** | 0.527*** | 1.057*** | 1.044*** |
| | (0.144) | (0.146) | (0.127) | (0.129) | (0.118) | (0.118) |
| $R^2$ | 0.34 | 0.34 | 0.33 | 0.33 | 0.65 | 0.64 |
| $n$ | 1642 | 1642 | 1695 | 1695 | 1764 | 1764 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. For compatibility with Livingston consensus, our sample must be restricted to observations in 1st & 3rd quarter & post-1992 (see table 22). Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 22:** SPF forecasts, $h = 3$, with Livingston consensus
Dependent Var.: $F_{i,t}x_{t+3} - F_{i,t-1}x_{t+3}$
(1st & 3rd Quarter & post-1992)

| | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE |
| constant | 0.000 | | 0.000 | | 0.038*** | |
| | (0.000) | | (0.000) | | (0.011) | |
| $x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.072*** | 0.072*** | 0.089*** | 0.096*** | 0.063*** | 0.070*** |
| | (0.023) | (0.023) | (0.014) | (0.015) | (0.022) | (0.022) |
| $C^{LIV}_{t-1}x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.312*** | 0.354*** | 0.230*** | 0.261*** | 0.354*** | 0.420*** |
| | (0.045) | (0.047) | (0.043) | (0.045) | (0.025) | (0.031) |
| $C_t x_t - C_{t-1}x_t$ | 0.622*** | 0.625*** | 0.517*** | 0.516*** | 1.015*** | 0.989*** |
| | (0.139) | (0.138) | (0.123) | (0.124) | (0.118) | (0.119) |
| $R^2$ | 0.35 | 0.34 | 0.33 | 0.33 | 0.65 | 0.65 |
| $n$ | 1642 | 1642 | 1695 | 1695 | 1764 | 1764 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. For compatibility with Livingston consensus, our sample must be restricted to observations in 1st & 3rd quarter & post-1992. To construct the past consensus, we need to have data on consensus nowcasts which are available post-1992 only. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 23:** SPF forecasts, $h = 2$, with SPF consensus, $Q2\&Q4$, post-1992
Dependent Var.: $F_{i,t}x_{t+2} - F_{i,t-2}x_{t+2}$

| | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE |
| constant | -0.001** | | -0.001** | | 0.054*** | |
| | (0.000) | | (0.000) | | (0.010) | |
| $x_{t+2} - F_{i,t-2}x_{t+2}$ | 0.180*** | 0.182*** | 0.171*** | 0.176*** | 0.134*** | 0.133*** |
| | (0.052) | (0.058) | (0.051) | (0.053) | (0.023) | (0.024) |
| $C^{SPF}_{t-1}x_{t+2} - F_{i,t-2}x_{t+2}$ | 0.371*** | 0.413*** | 0.346*** | 0.383*** | 0.381*** | 0.448*** |
| | (0.079) | (0.076) | (0.078) | (0.088) | (0.033) | (0.033) |
| $C^{SPF}_{t}x_{t} - C^{SPF}_{t-1}x_{t}$ | 0.945*** | 0.929*** | 0.845*** | 0.847*** | 0.969*** | 0.968*** |
| | (0.100) | (0.101) | (0.099) | (0.102) | (0.084) | (0.083) |
| $R^2$ | 0.61 | 0.63 | 0.69 | 0.70 | 0.74 | 0.75 |
| $n$ | 1677 | 1677 | 1743 | 1743 | 1765 | 1765 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 24:** Livingston forecasts, $h = 2$, with SPF consensus
Dependent Var.: $F_{i,t}x_{t+2} - F_{i,t-2}x_{t+2}$

| | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE |
| constant | -0.001*** | | -0.001** | | 0.061*** | |
| | (0.001) | | (0.000) | | (0.015) | |
| $x_{t+2} - F_{i,t-2}x_{t+2}$ | 0.221*** | 0.236*** | 0.218*** | 0.234*** | 0.202*** | 0.192*** |
| | (0.055) | (0.060) | (0.053) | (0.053) | (0.037) | (0.034) |
| $C^{SPF}_{t-1}x_{t+2} - F_{i,t-2}x_{t+2}$ | 0.456*** | 0.541*** | 0.508*** | 0.579*** | 0.494*** | 0.616*** |
| | (0.055) | (0.065) | (0.087) | (0.083) | (0.057) | (0.066) |
| $C^{SPF}_{t}x_{t} - C^{SPF}_{t-1}x_{t}$ | 0.975*** | 0.957*** | 0.939*** | 0.936*** | 1.150*** | 1.100*** |
| | (0.134) | (0.124) | (0.115) | (0.111) | (0.116) | (0.100) |
| $R^2$ | 0.60 | 0.59 | 0.71 | 0.71 | 0.83 | 0.82 |
| $n$ | 1468 | 1468 | 1496 | 1496 | 1469 | 1469 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 25:** Wald-Test on restriction $\beta_1 + \beta_2 + \beta_3 = 1$

| | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE |
| | | | **h=2** (SPF) | | | |
| $\beta_1 + \beta_2 + \beta_3$ | 0.935 | 0.946 | 0.990 | 0.990 | 1.005 | 1.007 |
| p-value | 0.001 | 0.006 | **0.791** | **0.779** | **0.474** | **0.386** |
| | | | **h=2** (LIV) | | | |
| $\beta_1 + \beta_2 + \beta_3$ | 1.036 | 1.035 | 1.073 | 1.054 | 1.019 | 1.020 |
| p-value | **0.491** | **0.455** | **0.170** | **0.263** | 0.037 | 0.041 |

*Note*: Robust Wald-Test on the restriction $\beta_1 + \beta_2 + \beta_3 = 1$ in equation (18) for $h = 2$ SPF and Livingston. The sample is restricted to only the second and fourth quarter post-1992. Test Statistic is based on Driscoll and Kraay (1998) standard errors. Values are rounded to the third decimal.

**Table 26:** Adding lagged actual to (17) with $h = 1$ based on SPF
Dependent Var.: $F_{i,t}x_{t+1} - F_{i,t-1}x_{t+1}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | 0.000 | | 0.000 | | -0.001** | | -0.002 | |
| | (0.000) | | (0.001) | | (0.000) | | (0.020) | |
| $x_{t+1} - F_{i,t-1}x_{t+1}$ | 0.093*** | 0.085*** | 0.117*** | 0.116*** | 0.111*** | 0.110*** | 0.071*** | 0.072*** |
| | (0.015) | (0.017) | (0.022) | (0.022) | (0.022) | (0.020) | (0.021) | (0.020) |
| $C_{t-1}x_{t+1} - F_{i,t-1}x_{t+1}$ | 0.573*** | 0.671*** | 0.512*** | 0.581*** | 0.538*** | 0.626*** | 0.527*** | 0.579*** |
| | (0.035) | (0.041) | (0.027) | (0.027) | (0.025) | (0.023) | (0.023) | (0.024) |
| $C_tx_t - C_{t-1}x_t$ | 0.974*** | 0.980*** | 0.926*** | 0.924*** | 0.904*** | 0.906*** | 0.964*** | 0.960*** |
| | (0.044) | (0.045) | (0.031) | (0.031) | (0.042) | (0.041) | (0.037) | (0.036) |
| $x_{t-1}$ | 0.007 | -0.001 | 0.001 | 0.005 | 0.026** | 0.025** | 0.006* | 0.005* |
| | (0.006) | (0.008) | (0.009) | (0.010) | (0.011) | (0.010) | (0.003) | (0.003) |
| $R^2$ | 0.67 | 0.66 | 0.69 | 0.69 | 0.68 | 0.68 | 0.75 | 0.75 |
| $n$ | 5664 | 5664 | 5669 | 5669 | 5769 | 5769 | 5872 | 5872 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.

**Table 27:** Adding lagged actual to (17) with $h = 2$ based on SPF
Dependent Var.: $F_{i,t}x_{t+2} - F_{i,t-1}x_{t+2}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | -0.0004* | | 0.000 | | -0.001*** | | -0.015*** | |
| | (0.000) | | (0.000) | | (0.001) | | (0.028) | |
| $x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.114*** | 0.105*** | 0.159*** | 0.160*** | 0.139*** | 0.137*** | 0.115*** | 0.116*** |
| | (0.017) | (0.016) | (0.024) | (0.022) | (0.020) | (0.020) | (0.013) | (0.013) |
| $C_{t-1}x_{t+2} - F_{i,t-1}x_{t+2}$ | 0.493*** | 0.596*** | 0.387*** | 0.465*** | 0.443*** | 0.550*** | 0.380*** | 0.444*** |
| | (0.042) | (0.045) | (0.030) | (0.030) | (0.034) | (0.040) | (0.022) | (0.023) |
| $C_t x_t - C_{t-1}x_t$ | 0.928*** | 0.937*** | 0.886*** | 0.881*** | 0.839*** | 0.833*** | 0.914*** | 0.914*** |
| | (0.050) | (0.056) | (0.045) | (0.044) | (0.067) | (0.065) | (0.037) | (0.037) |
| $x_{t-1}$ | 0.006 | -0.009 | -0.021 | -0.018 | 0.017 | 0.017 | 0.010*** | 0.010*** |
| | (0.009) | (0.012) | (0.013) | (0.015) | (0.015) | (0.014) | (0.004) | (0.004) |
| $R^2$ | 0.58 | 0.57 | 0.57 | 0.57 | 0.55 | 0.55 | 0.66 | 0.66 |
| $n$ | 5612 | 5612 | 5591 | 5591 | 5687 | 5687 | 5818 | 5818 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third digit after the comma (except for the point estimates of the intercept for inflation).

**Table 28:** Adding lagged actual to (17) with $h = 3$ based on SPF
Dependent Var.: $F_{i,t}x_{t+3} - F_{i,t-1}x_{t+3}$

| | Inflation | | Nominal GDP | | Real GDP | | Unemp. Rate | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | OLS | FE | OLS | FE | OLS | FE |
| constant | 0.000 | | -0.001 | | -0.002** | | -0.034 | |
| | (0.000) | | (0.001) | | (0.001) | | (0.028) | |
| $x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.170*** | 0.168*** | 0.159*** | 0.155*** | 0.140*** | 0.140*** | 0.098*** | 0.099*** |
| | (0.018) | (0.021) | (0.028) | (0.026) | (0.025) | (0.025) | (0.012) | (0.012) |
| $C_{t-1}x_{t+3} - F_{i,t-1}x_{t+3}$ | 0.315*** | 0.411*** | 0.262*** | 0.366*** | 0.342*** | 0.462*** | 0.329*** | 0.396*** |
| | (0.052) | (0.055) | (0.039) | (0.040) | (0.034) | (0.039) | (0.021) | (0.021) |
| $C_t x_t - C_{t-1}x_t$ | 0.367*** | 0.371*** | 0.437*** | 0.430*** | 0.298*** | 0.298*** | 0.910*** | 0.910*** |
| | (0.057) | (0.062) | (0.071) | (0.071) | (0.010) | (0.099) | (0.055) | (0.055) |
| $x_{t-1}$ | 0.015 | 0.006 | -0.001 | -0.003 | 0.031* | 0.030* | 0.014*** | 0.015*** |
| | (0.011) | (0.020) | (0.017) | (0.016) | (0.018) | (0.017) | (0.004) | (0.004) |
| $R^2$ | 0.35 | 0.34 | 0.29 | 0.28 | 0.29 | 0.28 | 0.60 | 0.60 |
| $n$ | 5459 | 5459 | 5437 | 5437 | 5447 | 5447 | 5610 | 5610 |

*Note*: *** p<0.01, ** p<0.05, * p<0.1; Driscoll and Kraay (1998) standard errors are in brackets. Standard errors are robust with respect to heteroscedasticity, autocorrelation and general forms of spatial correlation. Estimates are rounded to the third decimal.