Predicting Forecaster Inattention

By William R. Bennett *

Economic forecasters have been documented as deviating from having both full information and rational expectations. The sticky information model attempts to explain this by assuming an information rigidity: each time period a constant fraction of forecasters do not update their information sets. To explain the data, many empirical findings use calibration or follow Coibion and Gorodnichenko (2015) and estimate the fraction of non-updaters using aggregated regressions. These approaches lead to large estimates, with potentially 50% of forecasters not receiving information each quarter. Adapting Andrade and Bihan (2013) and Giacomini, Skreta and Turen (2020), I employ a different estimation strategy using data from the US survey of professional forecasters and provide evidence that the fraction is much smaller. My results imply that some other, stronger source of information rigidity must be present, and thus a model accounting for information rigidity should not use sticky information as its only mechanism. I also document novel state-dependence and show how individual and group forecast errors affect the likelihood of forecasts being sticky, with the effects being heterogeneous and nonlinear across forecast horizons.

Expectations have always had an important role in economics. Uncertainty about conditions of the future, as well as of the present and past, affects decision-making. We use the information we have at our disposal to make predictions about those conditions, and choose our decisions accordingly. Knowledge is power, and having more will likely lead to better predictions, decisions, and outcomes. However, sometimes knowledge comes at a price, perhaps literally, metaphorically, or both. In the literal sense, information can come in a form that can be bought with money. People can buy newspapers, watch a news channel by paying for a TV or phone, pay tuition and other expenses for school, or purchase data-sets from companies and government entities. In the metaphorical sense, information must be acquired and understood by exerting some kind of effort. It requires using our limited time, physical energy, and mental energy. Information, like everything else, is never truly free.

However, many macroeconomic models do not factor in the costs of information and assume that learning is frictionless. While sometimes this is be appropriate, there are many cases when this assumption is ill-founded. Perhaps the area of economics where information costs should matter most is forecasting models. Pure forecasting models don't (primarily) involve consumption/leisure trade-offs, deciding how many workers to hire, or other attributes common in macroeconomic models. Their purpose is to explain expectation formation: how do economic agents produce and change forecasts of random variables? From there the expectation formation process can be embedded in more complicated macroeconomic models.

The standard forecasting model in economics for the past half-century has been the full-information rational expectations (FIRE) paradigm. This means two distinct things. First, full-information requires agents to know all present and past conditions of their environment, and have uncertainty only about future conditions. Second, rational expectations requires agents to use all available information and not make systematically biased forecasts. Together, these assumptions produce several hypotheses, with the main one being a FIRE agent's forecast error should not be consistently predictable: no variable should be useful in predicting an individual

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forecast error because the agent should have already accounted for that variable when making their forecast.

Since its inception, researchers have tested FIRE's hypotheses in several ways and many have rejected it, with many attempting to explain and model deviations from FIRE. Two important influential contributions to this strand of literature were Mankiw and Reis (2002) and Sims (2003), which popularized forecasting models with sticky information and noisy information, respectively. Both of these models relax the full-information part of FIRE by introducing some kind of information rigidity: either having some agents not receive any information sometimes (sticky) or by having all agents always receive information, but the information itself has some uncertainty (noisy), which hearkens back to Lucas (1972)'s model with signal extraction.

From there, several papers have applied these and similar methods to more complicated macroeconomic models with a focus on the actual macro-economy, such as Mankiw, Reis and Wolfers (2007), Gorodnichenko (2008), Reis (2009), Carrillo (2012), Paciello and Wiederholt (2014), Tortorice (2018), Gelain et al. (2019), Carroll et al. (2020), Angeletos and Huo (2021), and Morales-Jiménez (2022).

Many papers specifically focused on how information rigidities could replace or augment sticky price New Keynesian models, such as Khan and Zhu (2006), Kiley (2007), Klenow and Willis (2007), Korenok (2008), Maćkowiak and Wiederholt (2009), Coibion (2010), Dupor, Kitamura and Tsuruga (2010), Knotek (2010), and L'Huillier (2020).

The other category of papers (in which this paper belongs) stays focused on the forecasting aspects of the model and places less emphasis on how to embed it into a macroeconomic model, such as Morris and Shin (2006), Branch (2007), Coibion and Gorodnichenko (2012), Andrade and Bihan (2013), Sarte (2014), Coibion and Gorodnichenko (2015), Cavallo, Cruces and Perez-Truglia (2017), Bergemann, Bonatti and Smolin (2018), Coibion, Gorodnichenko and Kumar (2018), Gaus and Sinha (2018), Kim and Kim (2019), Morikawa (2019), Bordalo et al. (2020), Giacomini, Skreta and Turen (2020), and Kohlhas and Walther (2021). These papers have shown how different information rigidities and forecaster heterogeneities can explain certain data but not others, thus providing evidence for and against the sticky information model, noisy information model, their generalizations, and other models.

This paper's main contribution to this literature is twofold: first, I provide additional evidence against the sticky information model explaining forecasters' departures from FIRE; second, conditional on sticky information still being a (now weaker) explanation of non-FIRE behavior, I novelistically yet simply show how the parameter determining the stickiness of information is state-dependent, and therefore not constant like the basic model assumes.

My first contribution involves showing that the literature's estimates of the stickiness parameter using the US survey of professional forecasters (SPF) may be inflated upward. Many of the above papers estimate this parameter, and their estimation strategies can broadly be separated into two groups. Before the influential work of Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015), the parameter was usually calibrated to match some moments of the paper's macroeconomic model. Then Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015) constructed ways to estimate various information rigidities, including information stickiness, using regressions with aggregated variables, and since then papers less interested in the macroeconomic model aspect have used this approach.

However, using an approach similar to Andrade and Bihan (2013) and Giacomini, Skreta and Turen (2020) I employ a simpler estimation strategy comparable to calibration without a formal macroeconomic model. This approach involves counting the number of times forecasts were unchanged, with the fraction of times a forecaster's predictions were unchanged being the measure of stickiness. Andrade and Bihan (2013) and to a lesser extent Giacomini, Skreta and Turen (2020) use this micro-estimate approach to analyze SPFs (from the European Central Bank and Bloomberg, respectively), and I follow by analyzing the US SPF. I argue that this is a better approach than Coibion and Gorodnichenko (2015)'s regression, which produces larger standard errors and allows for other conflicting interpretations. Also, both calibration and a Coibion and Gorodnichenko (2015) regression are model dependent and possibly suffer from omitted variable bias.

My second contribution involves predicting if a forecaster makes a sticky forecast. The sticky information model assumes a constant stickiness parameter such that the probability of not having an information set update is always the same in each time period for each forecaster for each variable being forecasted for each horizon forecasted. While I only analyze inflation in this paper and thus cannot comment on the "for each variable" part, I find evidence that the rest is untrue. While multiple papers mentioned above have also found evidence of this, I do so in a different way. Previous research involved sub-setting their data-sets into different groups of time periods–usually something like before, during, and after the Great Moderation and finding that information rigidity was lower before and after the Great Moderation and higher during. The interpretation is that in times of unusual economic activity, such as inflation being relatively high/low or volatile, people pay more attention and/or care more, leading them to update their information more and change their predictions more.

I instead estimate a distributed lag model and regress the stickiness indicator variable of each forecaster each period (for each horizon) on variables directly related to the forecaster. Specifically, I analyze how previous individual forecast errors, previous average forecast errors, and previous levels of the forecasted variable can change the likelihood of an individual not changing their forecast(s). I find that these variables impact stickiness in ways that support the general intuition of the previous literature's similar findings.

The rest of this paper is organized as follows. Section I describes the sticky information model, derives the model's predictions and implications, discusses estimates of the stickiness parameter in the literature, and proposes a different estimation strategy. Section II describes the data used and explains the construction of the stickiness variables. Section III contains my empirical results, including my various estimates for a constant stickiness and my estimates of state-dependence for a nonconstant stickiness. Section IV concludes.

I. The Sticky Information Model

Sticky information assumes that in each time period, each forecaster updates their information (relative to the previous period) with constant probability $(1 - \lambda)$. By updating, the forecaster acts as a FIRE agent, while forecasters who don't update receive no information (useful for the forecast) yet still make a rational forecast based off their limited information set.

The combination of forecasters who updated this period and those who last updated at an earlier time creates disagreement. The mean forecast across individuals at time t of the forecasted variable at time $t + h$ is given by

$$F_t x_{t+h} = (1 - \lambda) E_t x_{t+h} + \lambda F_{t-1} x_{t+h} \tag{1}$$

that is, those who updated at time t, $E_t x_{t+h}$, plus the forecast from $t - 1$, $F_{t-1} x_{t+h}$, weighted $(1 - \lambda)$ and λ respectively. Full information rational expectations are such that

$$E_t x_{t+h} = x_{t+h} - \nu_{t+h,t} \tag{2}$$

where $\nu_{t+h,t}$ is the FIRE error and is therefore uncorrelated with information from period t or earlier. Combining (1) and (2) yields the predicted relationship between the ex post mean forecast error and the ex ante mean forecast revision

$$x_{t+h} - F_t x_{t+h} = \frac{\lambda}{1 - \lambda}(F_t x_{t+h} - F_{t-1} x_{t+h}) + \nu_{t+h,t}. \tag{3}$$

Importantly, the coefficient on the forecast revision depends only on the degree of information rigidity λ. In the special case of no information frictions, $\lambda = 0$ and the specification reduces to equation (2), i.e., the average forecast error is unpredictable using information from period t or earlier. This predictability in mean forecast errors reflects the slow updating of information by some agents ($\lambda > 0$). While those who update their information immediately switch to the full information rational expectations belief, other agents do not change their information at all. This anchors the mean forecast to the previous period's, leading to a gradual adjustment of mean forecasts.

This canonical sticky information model implies a single rate of information acquisition, thus equation (3) holds for any macroeconomic variable and any forecasting horizon, including horizons of multiple periods. In addition, this specification holds regardless of the structure of the rest of the model. However, it is worth noting that the model can easily be adapted to have heterogeneous stickiness parameters by specifying what information is gathered when a forecaster updates. For example, suppose variables x and y are both being forecasted. In each period, agents update their information: with probability $(1 - \lambda_x)$ an agent learns information relevant to forecasting x, and with probability $(1 - \lambda_y)$ that agents learns information relevant to forecasting y. Therefore, papers that find heterogeneous stickiness parameters across different variables and conclude that this is evidence against the sticky information model in favor of another model that allows for heterogeneity (such as the noisy information model) may want to drop this piece of evidence when evaluating the merits of the models being compared.

My empirical work in this paper will focus on one forecasted variable (inflation) across multiple horizons, but future research can incorporate additional variables. I will discuss this more in the conclusion.

As previously mentioned, equation (3) can be estimated for a given macroeconomic variable x, mean forecasts across agents Fx, and forecasting horizon h using the following empirical specification:

$$x_{t+h} - F_t x_{t+h} = c + \beta(F_t x_{t+h} - F_{t-1} x_{t+h}) + error_t. \tag{4}$$

This allows a mapping of estimates of β to λ. Using data from the US SPF, Coibion and Gorodnichenko (2015) estimate equation (4) with inflation as the variable of interest and horizon $h = 3$ (at the quarterly frequency) and get $\hat{\beta} = 1.193$ (s.e. $= 0.497$), implying $\hat{\lambda} \approx 0.544$. After estimating the regression four more times with an additional control variable in each, their estimates barely change, with a low of $\hat{\beta} = 1.062$, s.e. $= 0.47$, $\hat{\lambda} \approx 0.515$ and a high of $\hat{\beta} = 1.196$, s.e. $= 0.504$, $\hat{\lambda} \approx 0.545$.

From there, they estimate equation (4) using the Livingston Survey with inflation as the variable of interest and horizon $h = 1$ (at the semi-annual frequency). When using all forecasters, they get $\hat{\beta} = 1.063$ (s.e. $= 0.251$), $\hat{\lambda} \approx 0.515$. When using the academic institutions subset, they get $\hat{\beta} = 0.476$ (s.e. $= 0.242$), $\hat{\lambda} \approx 0.322$. When using the commercial banks subset, they get $\hat{\beta} = 0.935$ (s.e. $= 0.197$), $\hat{\lambda} \approx 0.483$. Finally, when using the nonfinancial businesses subset, they get $\hat{\beta} = 0.572$ (s.e. $= 0.251$), $\hat{\lambda} \approx 0.364$.

They also use the Michigan Survey of Consumers, getting $\hat{\beta} = 0.705$ (s.e. $= 0.260$), $\hat{\lambda} \approx 0.413$, as well as financial markets inflation expectations, constructed using a method developed in Haubrich, Pennacchi and Ritchken (2008) and data from the Cleveland Fed, getting $\hat{\beta} = 1.495$ (s.e. $= 0.833$), $\hat{\lambda} \approx 0.599$ (both at the annual frequency). For these two results, they slightly change the regression equation due to a data limitation, but it remains comparable to equation (4). Note that all results listed above are significant at at least the ten percent level, with all but two being significant at the five percent level.

From there, Coibion and Gorodnichenko (2015) continue to estimate (using the US SPF) numerous more regressions similar to equation (3) but extended to include multiple horizons and multiple forecasted variables. These results are comparable to the estimates previously stated. Interestingly, Coibion and Gorodnichenko (2015) find that they can reject the null hypothesis that the estimated $\hat{\beta}$'s for the different variables are equal (finding multiple statistically insignificant variables), but cannot reject the null hypothesis that the estimated $\hat{\beta}$'s for the different horizons are equal (and find the horizon of 3 quarters insignificant and smaller than the shorter horizons). Later I will show that my estimates indicate that the horizons are significantly different.

I will briefly state some additional λ estimates from relevant papers. The seminal Mankiw and Reis (2002) calibrate λ to match their macroeconomic model and calculate a value of $\hat{\lambda} = 0.73$ when their monthly data is adjusted to a quarterly frequency. Andrade and Bihan (2013) use the European Central Bank's Survey of Professional Forecasters to estimate stickiness for inflation, unemployment, and GDP growth and get values of 0.28, 0.25, and 0.2 respectively. Finally, Giacomini, Skreta and Turen (2020) construct a forecasting model with elements of noise and stickiness. Using the "Economic Forecasts ECFC" survey of professional forecasters conducted by Bloomberg, they analyze monthly updates of US annual year-on-year CPI inflation forecasts. Something unique about this data-set is the forecasters in the Bloomberg survey are only making one forecast of inflation each period, specifically the forecast of the year-on-year inflation at the end of the current year (or next year, depending on the month), and for eighteen months leading up to the end of the year they forecast that same period's value. However, this difference does not affect the interpretation of λ. For the purposes of their model, they calculate a stickiness parameter for every month of their data, with most of their values being between 0.4 and 0.8. This implies that an approximate conversion of this range to fit quarterly data would give a range of 0.064 and 0.512, comparable to the estimates in Coibion and Gorodnichenko (2015).

Contrary to the calibration methods as in Mankiw and Reis (2002) and the aggregated regressions as in Coibion and Gorodnichenko (2015), Andrade and Bihan (2013) and Giacomini, Skreta and Turen (2020)'s calculations of λ involve constructing an indicator variable capturing whether an agent updates their previous forecast, i.e. 1 if yes and 0 if no. In the empirical work that follows, I use the indicator variable approach to measure the amount of sticky information in the SPF. This will allow me to investigate if sticky information has micro-level state-dependence.

II. Data Source and Variables

I use forecasts of US inflation from the Survey of Professional Forecasters. I focus on inflation forecasts for three reasons. First, because expectations about future inflation play a central role in the economy as determinants of output, consumption, and asset prices. Second, because inflation expectations are important for monetary policy and measuring real interest rates. Third, because data on inflation forecasts are available for a longer time-span than forecasts of most other variables.

The SPF is a rolling, unbalanced panel survey of between 20 and 100 professional forecasters that is conducted quarterly by the Federal Reserve Bank of Philadelphia. GDP/GNP deflator inflation forecasts are available from 1968:IV at horizons ranging from the current quarter to four quarters ahead. I focus on forecasts of quarter-on-quarter annual inflation as calculated using the SPF documentation:

$$\pi_t = 100\left(\left(\frac{PGDP_t}{PGDP_{t-1}}\right)^4 - 1\right) \tag{5}$$

where $PGDP$ is the seasonally adjusted chain-weighted GDP price index (the actual variable being forecasted). All variables are measured using real-time data to prevent reclassifications and redefinitions from affecting estimation since final values are not directly observable to the agents at the time of their forecast creation.

Table 1: Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
S_{it0}	6,127	0.0446	0.206	0	1
S_{it1}	6,123	0.0639	0.245	0	1
S_{it2}	6,103	0.0657	0.248	0	1
S_{it3}	5,830	0.0614	0.240	0	1
S_{it}^D	6,128	0.0295	0.169	0	1
S_{it}^A	6,128	0.0930	0.290	0	1
S_{it}^M	6,128	0.0601	0.209	0	1
AFE_{it-1}	6,115	1.170	1.157	0	17.45
AFE_{it-2}	5,919	1.180	1.182	0	17.45
$MAFE_{t-1}$	8,375	1.206	0.637	0.370	3.693
$MAFE_{t-2}$	8,276	1.218	0.650	0.274	3.703
π_{t-1}	8,498	3.440	2.579	-1.829	13.69
π_{t-2}	8,498	3.474	2.606	-1.829	13.69

In each time period t, forecaster i makes 5 (inflation) forecasts for 5 different horizons: $\{f_{it}\pi_t, \dots, f_{it}\pi_{t+4}\}$. I denote a forecast as sticky if it didn't change from the previous time period, i.e. if $f_{it}\pi_{t+h} = f_{it-1}\pi_{t+h}$. Similar to Giacomini, Skreta and Turen (2020), I construct an indicator variable that captures this:

$$S_{ith} = \begin{cases} 1 & \text{if } f_{it}\pi_{t+h} = f_{it-1}\pi_{t+h} \\ 0 & \text{if } f_{it}\pi_{t+h} \neq f_{it-1}\pi_{t+h} \end{cases}. \tag{6}$$

A caveat to this variable is if $f_{it}\pi_{t+h}$ is missing from the dataset but $f_{it-1}\pi_{t+h}$ is not, than I let $S_{ith} = 1$. This is because I assume if a forecaster made a forecast last period but didn't make it this period it is because they received no new information warranting them to update. My results are robust to this assumption, but I still have it so that the variables using the horizon $h = 4$ have a comparable number of observations to the other horizons. A possible extension of this work would be to jointly model sticky and missing forecasts, including the case where a forecaster gives no forecasts for any horizons (which I currently treat as unusable observations) as both represent a form of inattention, but I leave that to future research. Also note that there is no S_{it4}, because this period wasn't forecasted in $t-1$.

The sticky information model says that the forecasters who are sticky don't update their forecasts because they receive no new/useful information relating to inflation. Therefore, to estimate λ we need to construct another indicator variable that represents no updating of any forecasts:

$$S_{it}^D = \begin{cases} 1 & \text{if } S_{ith} = 1 \ \forall h \\ 0 & \text{if } S_{ith} \neq 1 \ \forall h \end{cases}. \tag{7}$$

This "dichotomous" stickiness variable is the main variable of interest to analyze the standard sticky information model, however it will be useful to have two additional variables for robustness. The first indicates if any of an individual's forecasts are sticky:

$$S_{it}^A = \begin{cases} 1 & \text{if } \exists h \ s.t. \ S_{ith} = 1 \\ 0 & \text{if } \nexists h \ s.t. \ S_{ith} = 1 \end{cases}. \tag{8}$$

and the second is an average of $\{f_{it}\pi_t, \ldots, f_{it}\pi_{t+3}\}$, excluding missing ones:

$$S_{it}^M = \frac{\sum_{h=0}^3 S_{ith}}{\#\{S_{ith}\}_{h=0}^3 \text{ not missing}}. \tag{9}$$

Note that all of these stickiness variables are upper bounds: though unlikely, it may be that some forecasters do receive new, relevant information and make updated forecasts, but the optimal forecast to which they updated just happens to be their previous forecast. Relevant summary statistics for these constructed stickiness variables are in Table 1. Also included are the state-dependence variables used later: AFE, the absolute individual forecast error; $MAFE$, the mean absolute individual forecast error; and inflation.

III. Empirical Results

Table 2: Forecast Errors Affecting Dichotomous Stickiness

VARIABLES	(1) OLS	(2) FE	(3) FE	(4) FE Logit	(5) FE Logit
AFE_{it-1}		-0.0045*	-0.0032	-0.1563	-0.1084
		(0.0025)	(0.0022)	(0.0974)	(0.0865)
AFE_{it-2}			0.0056		0.1257**
			(0.0041)		(0.0612)
$MAFE_{t-1}$		-0.0062	-0.0075	-0.2550	-0.3474
		(0.0044)	(0.0048)	(0.1859)	(0.2314)
$MAFE_{t-2}$			-0.0017		0.0336
			(0.0062)		(0.1951)
π_{t-1}		-0.0017	0.0001	-0.0322	0.0459
		(0.0015)	(0.0017)	(0.0485)	(0.0690)
π_{t-2}			-0.0030**		-0.1031*
			(0.0014)		(0.0546)
Constant	0.0295***	0.0476***	0.0428***		
	(0.0022)	(0.0058)	(0.0071)		
Observations	6,128	6,115	4,929	3,111	2,179
R-squared	0.0000	0.0025	0.0040		
Number of id		285	252		

Cluster-robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

To estimate λ, I simply calculate the average of S_{it}^D across individuals and time periods. I do this by regressing the variable on a constant,

$$S_{it}^D = \lambda + \varepsilon_{it}, \tag{10}$$

and get $\hat{\lambda} = 0.0295$ (se = 0.0022) as shown in column 1 of Table 2. Compared to the previous estimates (for inflation) in the literature discussed previously, this is very small. Recall that Coibion and Gorodnichenko (2015)'s main estimate is $\hat{\lambda} \approx 0.544$. Their regression was created in such a way that their coefficient could be interpreted by the sticky information model as well as the noisy information model. My finding provides additional evidence favoring noisy information as the better explanation of non-FIRE in forecasters: the regression must have substantial omitted variable bias if one wishes to interpret and estimate stickiness from it. However, my finding does not contradict the noisy information model's interpretation. Under the assumptions of the noisy information model, a relatively large β can be consistent with a small λ.

Table 3: Forecast Errors Affecting Any Stickiness

VARIABLES	(1) OLS	(2) FE	(3) FE	(4) FE Logit	(5) FE Logit
AFE_{it-1}		-0.0135***	-0.0032	-0.1442***	-0.1346**
		(0.0045)	(0.0022)	(0.0552)	(0.0595)
AFE_{it-2}			0.0056		0.1048**
			(0.0041)		(0.0507)
$MAFE_{t-1}$		-0.0224***	-0.0075	-0.3745***	-0.5264***
		(0.0074)	(0.0048)	(0.1131)	(0.1392)
$MAFE_{t-2}$			-0.0017		-0.0182
			(0.0062)		(0.1130)
π_{t-1}		-0.0084***	0.0001	-0.0712**	-0.0207
		(0.0023)	(0.0017)	(0.0289)	(0.0453)
π_{t-2}			-0.0030**		-0.0384
			(0.0014)		(0.0408)
Constant	0.0930***	0.1618***	0.0428***		
	(0.0037)	(0.0094)	(0.0071)		
Observations	6,128	6,115	4,929	4,583	3,526
R-squared	0.0000	0.0117	0.0040		
Number of id		285	252		

Cluster-robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

It may be that requiring every forecast made by an individual to be non-updated to be considered sticky is too restrictive. Despite that being necessary for a strict interpretation of the sticky information model, perhaps capturing the "essence" of the model can suffice to explain an information rigidity level of $\hat{\beta} = 1.193$ and its implied stickiness of $\hat{\lambda} \approx 0.544$. Maybe if only some or any of an individual's forecasts being non-updated would suffice. Therefore, for robustness I also regress S^A and S^M on a constant, the results of which are given in Table 3 and Table 4, respectively.

Using S^A I get $\hat{\lambda} = 0.0930$ (se = 0.0037) and using S^M I get $\hat{\lambda} = 0.0601$ (se = 0.0027). Only using the most liberal meaning of stickiness, S^A_{it} is the estimate somewhat close to the lower bound of the literature. Furthermore, recalling that all of these stickiness variables are upper bounds for the true value increases the gap.

I now transition from comparing my estimates of stickiness to the literature and discuss models of state-dependence. The standard sticky information model assumes a constant λ, however some rational inattention models discussed in the introduction document information rigidities, including potentially stickiness depending on the interpretation of the regressions, varying over time. Specifically, Coibion and Gorodnichenko (2015) applies models by McConnell and Perez-Quiros (2000) and Gorodnichenko (2008) and find that information rigidities have an inverse relationship with the standard deviation of the GDP growth rate over time, and finds information rigidities decrease after a recession starts before returning to its baseline.

I do a similar exercise. The sticky information model requires a parameter that is invariant over time, so I test this by expanding equation (10) to include three simple time-varying variables I a priori believe may affect a forecaster's stickiness:

$$S_{it} = \alpha_i + \beta_1 AFE_{it-1} + \beta_2 MAFE_{t-1} + \beta_3 \pi_{t-1} + \varepsilon_{it} \tag{11}$$

where S_{it} is one of the aggregated stickiness variables (either D, A, or M), α_i are individual level fixed effects, $AFE_{it-1} = |\pi_{t-1} - f_{it-1}\pi_{t-1}|$ is the absolute value of the individual's forecast error last period, $MAFE_{t-1} = \frac{1}{n_t}\sum_{i=1}^{n_t} AFE_{it-1}$ is the mean absolute forecast error last period, and π_{t-1} is inflation last period. The results of these regressions, as well as robustness extensions that include another set of lags and a logit model (not applicable for S^M), are found in Tables 2-4.

Table 4: Forecast Errors Affecting Mean Stickiness

VARIABLES	(1) OLS	(2) FE	(3) FE
AFE_{it-1}		-0.0094***	-0.0081***
		(0.0032)	(0.0030)
AFE_{it-2}			0.0081*
			(0.0042)
$MAFE_{t-2}$		-0.0149***	-0.0186***
		(0.0054)	(0.0059)
$MAFE_{t-2}$			-0.0018
			(0.0061)
π_{t-1}		-0.0055***	-0.0029
		(0.0017)	(0.0022)
π_{t-2}			-0.0025
			(0.0018)
Constant	0.0601***	0.1064***	0.0941***
	(0.0027)	(0.0068)	(0.0082)
Observations	6,128	6,115	4,929
R-squared	0.0000	0.0101	0.0110
Number of id		285	252

Cluster-robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

The results of equation (11) are fairly consistent across the tables: all coefficients in column (2) are negative, with the S^A and S^M estimates all being significant at the 1 percent level, while only the individual forecast error is significant, at the 10 percent level, for S^D. These results imply that an increase in a forecaster's previous absolute forecast error, an increase in the previous mean absolute forecast error, and an increase in inflation last period all decrease the likelihood of the forecaster not updating some subset of their forecasts.

These findings are intuitive. The worse your forecast was last time, the more likely you are to pay attention and exert more effort in making a better forecast. Perhaps you're disturbed by how poorly you did, and thus will more thoroughly investigate what you did wrong and how you can do better. Therefore, you will probably not stick to your previous forecast, thus you update. Similarly, if everyone's forecast was very bad last time, you may feel shaken by the poor performances, and feel a need to devote extra time and energy in preparing your own forecasts. Finally, as inflation increases, the economy might be in trouble. In times of high inflation, such as in the 1970s and early 1980s in the US, the economy is very turbulent, people are scared and angry about their eroding purchasing power, and there is a great deal of concern about price levels. Therefore, again, extra time and energy are spent because the forecasts matter more, and there is likely more (and more volatile) information being put forth that must be processed.

The reason that S^D's significance levels are lower is likely because it is the most restrictive dependent variable: it is relatively difficult, in a sense, for an individual to have all their forecasts in a period be sticky. For example, suppose, ceteris paribus, that AFE_{it-1}decreases. If this marginally increases the likelihood that one more of your forecasts will be sticky, it would have the biggest effect on S^A, which would switch from 0 to 1 if the decrease makes any of the forecasts sticky; it would have a medium effect on S^M, which increases slightly by another forecast becoming sticky; and it would have the smallest effect on S^D, because one more forecast becoming sticky is not enough to change S^D from 0 to 1 unless all the others become sticky too.

Going past the significance levels, we can see that the coefficients' point estimates seem to follow inequalities implied by the previous paragraph's logic, $\beta_1^D < \beta_1^M < \beta_1^A$, $\beta_2^D < \beta_2^M < \beta_2^A$, and $\beta_3^D < \beta_3^M < \beta_3^A$. However, actually testing these relationships results in p-values all greater than 0.1. Nevertheless, the main result–the coefficients being negative–adds additional evidence to the literature of a nonconstant λ. Further more, while previous work focused on a more macro meaning of state-dependence, I've shown that variables directly related to the individual forecaster and the group of forecasters impacts the amount of information rigidity in a way similar to how the literature has accessed deviations of forecaster behavior from FIRE.

Table 5: Forecast Errors Affecting Stickiness, Continuous Horizon, 1 Lag

	(1)	(2)	(3)	(4)	(5)
VARIABLES	OLS	FE	FE	FE Logit	FE Logit
AFE_{it-1}		-0.0087***	-0.0118***	-0.1372**	-0.1984***
		(0.0032)	(0.0031)	(0.0592)	(0.0635)
$MAFE_{t-1}$		-0.0165***	-0.0051	-0.4178***	-0.1594
		(0.0053)	(0.0052)	(0.1245)	(0.1307)
π_{t-1}		-0.0053***	-0.0068***	-0.0645**	-0.0764**
		(0.0017)	(0.0018)	(0.0325)	(0.0334)
h		0.0061***	0.0093***	0.1210***	0.2492***
		(0.0015)	(0.0024)	(0.0261)	(0.0501)
$hAFE_{it-1}$			0.0021*		0.0377*
			(0.0012)		(0.0218)
$hMAFE_{t-1}$			-0.0077***		-0.1664***
			(0.0020)		(0.0391)
$h\pi_{t-1}$			0.0010*		0.0072
			(0.0005)		(0.0097)
Constant	0.0588***	0.0963***	0.0915***		
	(0.0015)	(0.0062)	(0.0070)		
Observations	24,183	24,133	24,133	18,048	18,048
R-squared	0.0000	0.0086	0.0089		
Number of id		285	285		

Cluster-robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

For the remainder of this section, I switch from analyzing the stickiness variables (D, A, and M) that aggregate the horizons and look at horizons separately. To do this, I now treat S_{ith} as the observation level and test the following regression:

$$S_{ith} = \alpha_i + \boldsymbol{\beta X}_{it-1} + \gamma h + \boldsymbol{\delta X}_{it-1} h + \varepsilon_{ith} \tag{12}$$

where $\boldsymbol{X}_{it-1}$ is a vector of the independent variables previously used and h is the horizon. I include interaction terms to test if the effects change as the horizon changes. The results of this regression are found in Table (5), and results using additional lags are in Table (6). The main results are in column (3) and column (2), respectively.

The relatively large positive estimate for the horizon coefficient combined with the relatively small negative average marginal effect of the interaction terms indicates that a forecast associated with a horizon farther in the future is more likely to be sticky.

The relatively large negative estimate for the individual error and relatively small positive estimate for the individual error interaction term imply that, for the horizon of 0, an increase in a forecaster's previous absolute forecast error decreases the likelihood of the forecaster being sticky. However, as the horizon being forecasted increases, this negative effect of the error becomes smaller in magnitude (yet is still negative).

The insignificant estimate for the mean error and negative estimate for the mean error interaction term imply that, for the horizon of 0, an increase in the previous mean absolute forecast error does not affect the likelihood of the forecaster being sticky. However, as the horizon being forecasted increases, the effect of the mean error becomes increasingly more negative.

Table 6: Forecast Errors Affecting Stickiness, Continuous Horizon, 2 Lags

	(1)	(2)	(3)	(4)
VARIABLES	FE	FE	FE Logit	FE Logit
AFE_{it-1}	-0.0076**	-0.0109***	-0.1224**	-0.1933***
	(0.0030)	(0.0028)	(0.0573)	(0.0679)
$MAFE_{t-1}$	-0.0199***	-0.0064	-0.5639***	-0.2587
	(0.0058)	(0.0056)	(0.1509)	(0.1642)
π_{t-1}	-0.0029	-0.0036*	-0.0197	-0.0251
	(0.0022)	(0.0021)	(0.0519)	(0.0501)
AFE_{it-2}	0.0080*	0.0055	0.1025**	0.0904**
	(0.0041)	(0.0039)	(0.0466)	(0.0444)
$MAFE_{t-2}$	-0.0015	-0.0007	0.0168	0.0403
	(0.0060)	(0.0063)	(0.1172)	(0.1242)
π_{t-2}	-0.0022	-0.0033**	-0.0344	-0.0490
	(0.0018)	(0.0017)	(0.0409)	(0.0386)
h	0.0056***	0.0082***	0.1243***	0.2616***
	(0.0015)	(0.0025)	(0.0311)	(0.0590)
$hAFE_{it-1}$		0.0023*		0.0431*
		(0.0012)		(0.0226)
$hMAFE_{t-1}$		-0.0091***		-0.1970***
		(0.0022)		(0.0470)
$h\pi_{t-1}$		0.0005		0.0022
		(0.0007)		(0.0155)
Constant	0.0838***	0.0799***		
	(0.0077)	(0.0087)		
Observations	19,451	19,451	13,876	13,876
R-squared	0.0091	0.0097		
Number of id	252	252		

Cluster-robust standard errors in parentheses.
Interaction terms for second lags omitted.
* p<0.1, ** p<0.05, *** p<0.01

Finally, similarly to the individual error, the relatively large negative estimate for inflation and relatively small positive estimate for the inflation interaction term imply that, for the horizon of 0, an increase in last quarter's inflation rate decreases the likelihood of the forecaster being sticky. However, as the horizon being forecasted increases, this negative effect of inflation becomes smaller in magnitude (yet still negative).

Overall, these results match the results from the aggregated stickiness regressions; generally, an increase in the errors or inflation will decrease stickiness. They also newly show that stickiness depends on the horizon, something Coibion and Gorodnichenko (2015) rejects. Furthermore, effects are heterogeneous across horizons. For the individual error and inflation, the effect is strongest for shorter horizons and weakens for longer horizons, while for the mean error the effect is weakest for shorter horizons and strengthens for longer horizons.

To make sense of these somewhat opposite individual and mean error results, consider a forecaster who incurred a relatively high individual forecast error last period, holding the mean constant. The individual observes that they performed poorly while the group did fine. This poor individual performance makes the forecaster more likely to update all their forecasts. However, they are more likely to update the current and next quarter forecasts than the second and third quarter ahead forecasts.

I conjecture this is because the current quarter "matters" most to the forecaster, and horizons further into the future matter less the further in the future they are: given an option (somehow) of increasing their forecast error for a further horizon in exchange for decreasing their forecast error for the current period, ceteris paribus (perhaps up to some limit), the forecaster would take this option. There may be multiple reasons for this. For example, one rationale is a forecaster only has one chance to forecast the current period, while they will have h more chances to forecast horizon h.

Table 7: Forecast Errors Affecting Stickiness, Categorical Horizon, 1 Lag

VARIABLES	(1) OLS	(2) FE	(3) FE	(4) FE Logit	(5) FE Logit
AFE_{it-1}		-0.0087***	-0.0121***	-0.1375**	-0.2195***
		(0.0032)	(0.0030)	(0.0593)	(0.0686)
$MAFE_{t-1}$		-0.0166***	-0.0013	-0.4207***	-0.0292
		(0.0053)	(0.0053)	(0.1247)	(0.1404)
π_{t-1}		-0.0053***	-0.0080***	-0.0648**	-0.0896**
		(0.0017)	(0.0020)	(0.0325)	(0.0381)
h_1		0.0199***	0.0242***	0.4324***	0.7300***
		(0.0040)	(0.0067)	(0.0829)	(0.1725)
h_2		0.0219***	0.0284***	0.4695***	0.8340***
		(0.0043)	(0.0069)	(0.0853)	(0.1664)
h_3		0.0193***	0.0299***	0.4191***	0.8901***
		(0.0047)	(0.0077)	(0.0951)	(0.1933)
$h_1 AFE_{it-1}$			0.0027		0.0700
			(0.0033)		(0.0712)
$h_2 AFE_{it-1}$			0.0045		0.1030
			(0.0032)		(0.0691)
$h_3 AFE_{it-1}$			0.0063*		0.1298*
			(0.0038)		(0.0778)
$h_1 MAFE_{t-1}$			-0.0172***		-0.4241***
			(0.0061)		(0.1351)
$h_2 MAFE_{t-1}$			-0.0192***		-0.4564***
			(0.0062)		(0.1315)
$h_2 MAFE_{t-1}$			-0.0251***		-0.6184***
			(0.0065)		(0.1426)
$h_1 \pi_{t-1}$			0.0039**		0.0378
			(0.0015)		(0.0294)
$h_2 \pi_{t-1}$			0.0033**		0.0206
			(0.0015)		(0.0289)
$h_3 \pi_{t-1}$			0.0035*		0.0334
			(0.0018)		(0.0358)
Constant	0.0588***	0.0902***	0.0849***		
	(0.0015)	(0.0061)	(0.0076)		
Observations	24,183	24,133	24,133	18,048	18,048
R-squared	0.0000	0.0092	0.0097		
Number of id		285	285		

Cluster-robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Another (not mutually exclusive) possibility is that a forecaster knows they are more likely to make a relatively worse prediction for a later horizon compared to a sooner one due to the inherent nature of probabilistic dynamic systems. They potentially could exert more effort to improve their models, data, etc., but the cost of doing so may outweigh the decrease in forecast error. This is less likely to be true for the current horizon. It may be worth doing extra work to make a better prediction of today.

With those ideas in mind, one may think that the mean error should have a similar effect. However, one must remember that this is a marginal effect, and the individual error is held constant. I conjecture that, because the forecaster's own error is the same, the forecaster believes that their current individual forecasting model and data are temporarily sufficient to predict the variable in the short-run. However, the forecaster, having observed that the mean error increased and their own error did not, may believe that whatever shocks occurred are of a more persistent and permanent nature rather than of a less persistent and transitory nature. In other words, it may take more time for that shock to have an effect. Therefore, they are more likely to update their future horizons, because by then the shock's effects will have perturbed the system.

Table 8: Forecast Errors Affecting Stickiness, Categorical Horizon, 2 Lags

	(1)	(2)	(3)	(4)
VARIABLES	FE	FE	FE Logit	FE Logit
AFE_{it-1}	-0.0076**	-0.0115***	-0.1225**	-0.2368***
	(0.0030)	(0.0027)	(0.0574)	(0.0737)
$MAFE_{t-1}$	-0.0199***	0.0003	-0.5677***	-0.0516
	(0.0058)	(0.0057)	(0.1514)	(0.1757)
π_{t-1}	-0.0029	-0.0037*	-0.0206	-0.0223
	(0.0022)	(0.0022)	(0.0520)	(0.0537)
AFE_{it-2}	0.0080*	0.0033	0.1026**	0.0740
	(0.0041)	(0.0040)	(0.0467)	(0.0499)
$MAFE_{t-2}$	-0.0014	0.0006	0.0167	0.0860
	(0.0060)	(0.0067)	(0.1176)	(0.1463)
π_{t-2}	-0.0022	-0.0052***	-0.0337	-0.0872**
	(0.0018)	(0.0017)	(0.0410)	(0.0420)
h_1	0.0184***	0.0210***	0.4475***	0.8121***
	(0.0041)	(0.0074)	(0.0949)	(0.2076)
h_2	0.0208***	0.0238***	0.4986***	0.8652***
	(0.0045)	(0.0075)	(0.0989)	(0.2023)
h_3	0.0175***	0.0268***	0.4269***	0.9600***
	(0.0049)	(0.0083)	(0.1136)	(0.2307)
$h_1 AFE_{it-1}$		0.0043		0.1229*
		(0.0033)		(0.0697)
$h_2 AFE_{it-1}$		0.0038		0.1147
		(0.0033)		(0.0754)
$h_3 AFE_{it-1}$		0.0078**		0.1781**
		(0.0036)		(0.0786)
$h_1 MAFE_{t-1}$		-0.0263***		-0.6272***
		(0.0072)		(0.1719)
$h_2 MAFE_{t-1}$		-0.0234***		-0.5555***
		(0.0073)		(0.1688)
$h_3 MAFE_{t-1}$		-0.0318***		-0.7969***
		(0.0070)		(0.1743)
$h_1 \pi_{t-1}$		0.0001		-0.0150
		(0.0020)		(0.0490)
$h_2 \pi_{t-1}$		0.0019		0.0152
		(0.0021)		(0.0496)
$h_3 \pi_{t-1}$		0.0008		-0.0054
		(0.0022)		(0.0549)
Constant	0.0780***	0.0743***		
	(0.0077)	(0.0092)		
Observations	19,451	19,451	13,876	13,876
R-squared	0.0098	0.0110		
Number of id	252	252		

Cluster-robust standard errors in parentheses.
Interaction terms for second lags omitted.
* p<0.1, ** p<0.05, *** p<0.01

Moving on, equation (12) introduced horizon as one continuous variable. However, this may not be appropriate if the effects of horizon are not linear. To test this, I rewrite equation (12) to have horizon as a categorical variable:

$$S_{ith} = \alpha_i + \boldsymbol{\beta X} + \boldsymbol{\gamma H} + \boldsymbol{\delta X H} + \varepsilon_{ith} \tag{13}$$

where $\boldsymbol{h}$ is a vector of horizon (excluding $h = 0$). The results are in Table (7) and Table (8) (more lags) with the main results in column (3) and column (2), respectively.

In general, we see that the coefficients' signs are the same as equation (12). However, the coefficients in each of the four horizon dummy groups have similar magnitudes to the others in their group, so I jointly test if the three horizon dummies are different than 0, rejecting the null with $p<0.001$, and test if the three horizon dummies are equal, and fail to reject the null with $p=0.229$. These results tentatively imply that all horizons greater than 0 can be grouped together. This implies the importance of the horizon for affecting the stickiness of a forecast rests only in differentiating if the forecast is for the current period or for a future period.

I investigate this further by conducting similar tests using the interaction terms to see if the marginal effects follow the same pattern. I jointly test if the three individual error interaction terms are different than 0, and fail to reject the null with $p=0.417$, then I test if they are equal, and fail to reject the null with $p=0.530$. Next, I jointly test if the three mean error interaction terms are different than 0, and reject the null with $p=0.002$, then I test if they are equal, and fail to reject the null with $p=0.192$. Finally, I jointly test if the three inflation interaction terms are different than 0, and reject the null with $p=0.072$, then I test if they are equal, and fail to reject the null with $p=0.630$. For additional robustness, I jointly test that all four horizon dummy groups have their three coefficients equal and fail to reject the null with $p=0.347$.

These results provide stronger evidence that the importance of horizon comes from differentiating present and future, and thus the notion of linear horizon's effects is rejected. Interestingly, when horizon is switched from being continuous to categorical, the individual error interaction term switches from being significant (at the ten percent level) to insignificant for horizons one and two while remaining significant for horizon 3 (jointly insignificant, as shown before). This result contradicts the initial finding that the effect of the individual error decreases in magnitude as the horizon lengthens; an increase in an individual's absolute forecast error last period decreases the likelihood of their forecasts for all horizons equally.

IV. Conclusion

This paper investigated the sticky information forecasting model and analyzed two aspects of it. The first aspect involved my estimates of the stickiness parameter being smaller than is needed to explain the amount of information rigidity observed in the data. Some other mechanism must be included and primary. However, while the estimates I get are smaller than much of the literature's, they are still nonzero (keeping in mind that these estimates are upper bounds). This implies the sticky information model may still be useful in more complicated macroeconomic models, but less so.

This leads to the second aspect analyzed: when using a model with sticky information, a researcher should be cautious if assuming the stickiness parameter is state-independent. I find evidence that periods of lower forecast errors and lower inflation are accompanied with a higher amount of stickiness. As some of the literature has emphasized, this may have important ramifications for the macro-economy. Potentially, this may be a cyclical dynamic: lower inflation and errors make agents pay less attention, then the decrease in attention make cause agents to make decisions that lead to higher inflation and errors, which causes attention to increase, causing inflation and errors to become low again.

Future research could adapt this paper's methodology and changes its distributed lag model into a vector autoregression model to see how stickiness affects future errors and inflation. Ideally one would construct a structural macroeconomic model to do so. Before doing so, it would be wise to extend this paper's results to additional variables such as GDP growth and interest rates. This paper documents smaller stickiness for inflation, but can only speculate about the stickiness of other variables.

Finally, I found additional evidence of heterogeneity of stickiness for different horizons, and a new result of nonlinear heterogeneity of the effects of state-dependence. My estimates suggest that forecasters may "care" about their forecasts of the current period more than they care about their forecasts of later periods. Future research may try to create a structural model for a forecaster where their dynamic objective function contains utility each period coming from both current and future horizon forecast errors, their choice variables each period are their forecasts for all horizons, and they have one or more information rigidity constraints that can potentially prevent the forecaster from updating one or more forecasts to the optimal forecast. This potentially has implications for macroeconomic models that involve variables having more than one lag.

REFERENCES

Andrade, Philippe, and Hervé Le Bihan. 2013. "Inattentive Professional Forecasters." *Journal of Monetary Economics*, 60(8): 967–82.

Angeletos, George-Marios, and Zhen Huo. 2021. "Myopia and Anchoring." *American Economic Review*, 111(4): 1166–200.

Bergemann, Dirk, Alessandro Bonatti, and Alex Smolin. 2018. "The Design and Price of Information." *American Economic Review*, 108(1): 1–48.

Bordalo, Pedro, Nicola Gennalioli, Yueran Ma, and Andrei Shleifer. 2020. "Overreaction in Macroeconomic Expectations." *American Economic Review*, 110(9): 2748–82.

Branch, William A. 2007. "Sticky Information and Model Uncertainty in Survey Data on Inflation Expectations." *Journal of Economic Dynamics and Control*, 31(1): 245–76.

Carrillo, Julio A. 2012. "How Well Does Sticky Information Explain the Dynamics of Inflation, Ouput, and Real Wages?" *Journal of Economic Dynamics and Control*, 36(6): 830–50.

Carroll, Christopher D., Edmund Crawley, Jiri Slacalek, Kiichi Tokuoka, and Matthew N. White. 2020. "Sticky Expectations and Consumption Dynamics." *American Economic Journal: Macroeconomics*, 12(3): 40–76.

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

Coibion, Oliver, and Yuriy Gorodnichenko. 2012. "What Can Survey Forecasts Tell Us about Information Rigidities?" *Journal of Political Economy*, 120(1): 116–59.

Coibion, Oliver, and Yuriy Gorodnichenko. 2015. "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts." *American Economic Review*, 105(8): 2644–78.

Coibion, Olivier. 2010. "Testing the Sticky Information Phillips Curve." *Review of Economics and Statistics*, 92(1): 87–101.

Coibion, Olivier, Yuriy Gorodnichenko, and Saten Kumar. 2018. "How Do Firms Form Their Expectations? New Survey Evidence." *American Economic Review*, 108(9): 2671–713.

Dupor, Bill, Tomiyuki Kitamura, and Takayuki Tsuruga. 2010. "Integrating Sticky Information and Sticky Prices." *The Review of Economics and Statistics*, 92(3): 657–69.

Gaus, Eric, and Arunima Sinha. 2018. "What does the yield curve imply about investor expectations?" *Journal of Macroeconomics*, 57: 248–65.

Gelain, Paolo, Nikolay Iskrev, Kevin J. Lansing, and Caterina Mendicino. 2019. "Inflation dynamics and adaptive expectations in an estimated DSGE model." *Journal of Macroeconomics*, 59: 258–77.

Giacomini, Raffaella, Vasiliki Skreta, and Javier Turen. 2020. "Heterogeneity, Inattention, and Bayesian Updates." *American Economic Journal: Macroeconomics*, 12(1): 282–309.

Gorodnichenko, Yuriy. 2008. "Endogenous Information, Menu Costs and Inflation Persistence." National Bureau of Economic Research Working Paper 14184.

Haubrich, Joseph G., George Pennacchi, and Peter H. Ritchken. 2008. "Estimating Real and Nominal Term Structures Using Treasury Yields, Inflation, Inflation Forecasts, and Inflation Swap Rates." FRB of Cleveland Working Paper No. 08-10.

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

Kiley, Michael T. 2007. "A Quantitative Comparison of Sticky Price and Sticky-Information Models of Price Setting." *Journal of Money, Credit, and Banking*, 39(1): 101–25.

Kim, Insu, and Young Se Kim. 2019. "Inattentive agents and inflation forecast error dynamics: A Bayesian DSGE approach." *Journal of Macroeconomics*, 62: 103–39.

Klenow, Peter J., and Jonathan L. Willis. 2007. "Sticky Information and Sticky Prices." *Journal of Monetary Economics*, 54: 79–99.

Knotek, Edward S. 2010. "A Tale of Two Rigidities: Sticky Prices in a Sticky Information Environment." *Journal of Money, Credit, and Banking*, 42: 1543–64.

Kohlhas, Alexandre N., and Ansgar Walther. 2021. "Asymmetric Attention." *American Economic Review*, 111(9): 2879–925.

Korenok, Oleg. 2008. "Empirical Comparison of Sticky Price and Sticky Information Models." *Journal of Macroeconomics*, 30(3): 906–27.

L'Huillier, Jean-Paul. 2020. "Consumer Imperfect Information and Endogenous Price Rigidity." *American Economic Journal: Macroeconomics*, 12(2): 94–123.

Lucas, Robert E. 1972. "Expectations and the Neutrality of Money." *Journal of Economic Theory*, 4(2): 103–24.

Maćkowiak, Bartosz, and Mirko Wiederholt. 2009. "Optimal Sticky Prices under Rational Inattention." *American Economic Review*, 99(3): 769–803.

Mankiw, N. Gregory, and Ricardo Reis. 2002. "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." *The Quarterly Journal of Economics*, 117(4): 1295–328.

Mankiw, N. Gregory, Ricardo Reis, and Justin Wolfers. 2007. "Sticky Information in General Equilibrium." *Journal of the European Economic Association*, 5(2-3): 603–13.

McConnell, Margaret M., and Gabriel Perez-Quiros. 2000. "Output Fluctuations in the United States: What Has Changed since the Early 1980's?" *American Economic Review*, 90(5): 1464–76.

Morales-Jiménez, Camilo. 2022. "The Cyclical Behavior of Unemployment and Wages under Information Frictions." *American Economic Journal: Macroeconomics*, 14(1): 301–31.

Morikawa, Masayuki. 2019. "Uncertainty over production forecasts: An empirical analysis using monthly quantitative survey data." *Journal of Macroeconomics*, 60: 163–79.

Morris, Stephen, and Hyun Song Shin. 2006. "Inertia of Forward-Looking Expectations." *American Economic Review*, 96(2): 152–57.

Paciello, Luigi, and Mirko Wiederholt. 2014. "Exogenous Information, Endogenous Information, and Optimal Monetary Policy." *Review of Economic Studies*, 81(1): 356–88.

Reis, Ricardo. 2009. "Optimal Monetary Policy Rules in an Estimated Sticky-Information Model." *American economics Journal: Macroeconomics*, 1(2): 1–28.

Sarte, Pierre-Daniel. 2014. "When is Sticky Information More Information?" *Journal of Money, Credit, and Banking*, 46(7): 1345–79.

Sims, Christopher A. 2003. "Implications of rational inattention." *Journal of Monetary Economics*, 50: 665–90.

Tortorice, Daniel L. 2018. "The business cycle implications of fluctuating long run expectations." *Journal of Macroeconomics*, 58: 266–91.