

EXPECTATION FORMATION FOLLOWING LARGE UNEXPECTED SHOCKS*

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March 21, 2018

Abstract

By matching a large database of individual forecaster data with the universe of sizable natural disasters across 54 countries, we identify a set of new stylized facts: (i) forecasters are persistently heterogeneous in how often they issue or revise a forecast; (ii) information rigidity declines significantly following large, unexpected natural disaster shocks; (iii) the response of forecast disagreement displays heterogeneous patterns: attentive forecasters tend to move away from the previous consensus following a disaster while the opposite is true for inattentive forecasters. We develop a learning model that captures the two channels through which natural disaster shocks affect expectation formation: attention effect – the visibly large shocks induce immediate and synchronized updating of information for inattentive agents, and uncertainty effect – the occurrence of those shocks generates increased uncertainty among attentive agents.

JEL Classification: C32, C53, D83, D84, E17, E37

Keywords: Expectation Formation, Heterogeneous Agents, Information Rigidity, Learning, Natural Disasters, Uncertainty Shock

*We thank Philippe Andrade for a valuable discussion and numerous conference and seminar participants for very helpful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of U.S. Census Bureau.

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1 Introduction

Expectations matter. Yet, how economic agents form expectations remains an open question, as evidenced by the comprehensive survey in Manski (2017). Indeed, Manski concludes, “To make progress, I urge measurement and analysis of the revisions to expectations that agents make following occurrence of unanticipated shocks.” We answer this call by matching a large database of individual forecaster data with the universe of natural disasters across 54 countries. We find that professional forecasters respond to the large unexpected shocks in consistently different ways, depending on how often they issue or revise a forecast. As a result, the overall forecast accuracy and dispersion show interesting dynamics, which has not been explored in the literature. We build a theory of information updating aimed at matching the stylized facts of expectations formation of professional forecasters.

Our theory has three key elements. (i) Agents are not interchangeable: attentive agents revise forecasts frequently and inattentive agents make revisions infrequently and non-systematically.¹ (ii) Inattentive agents update sporadically during the normal times. However, following large and unexpected shocks, the cost of not updating information is high, and accordingly the majority of inattentive agents will update their information sets and make new forecasts. (iii) Attentive agents always combine public and private signals in making their forecasts through a signal extraction process.

Our theory tells the following story about expectations formation following attention-grabbing and unexpected shocks. First, visibly large shocks induce an immediate increase in updating of information for most inattentive agents. This attention effect is particularly pronounced for those with an outdated information set, resulting in a significant decline in information rigidity. Second, for attentive agents, the occurrence of those shocks can generate increased uncertainty among them and as a result, their new forecasts resemble the previous period’s forecasts.

The ingredients of our theory are motivated by our empirical findings. Our primary database of macroeconomic forecasts comes from Consensus Economics and covers a range of macro variables across 54 countries. We focus on professional forecaster data primarily because such forecasters have a comparative advantage in allocating resources to acquire, absorb, and process information in forming expectations. As such, the degree of information rigidity found in professional forecasters likely forms a lower bound for other economic agents. Furthermore, the expectations of professional forecasters directly affect those of households (Carroll, 2003) and are used as inputs to the decisions of the representative agent (Ilut and

¹Assumed here is that the fraction of inattentive agents is exogenous and persistent, consistent with what we see in the data.

Schneider, 2014).

Moreover, we focus on a survey which has a significant amount of discretion in forecasters' action. That is, forecasters can choose to not report or not update their forecasts in any given month and a significant number of forecasters exercise this ability. The inattention channel that we study would likely be somewhat muted in surveys that require forecasters to report and/or update their forecasts for each period. A number of common survey datasets, such as the Bloomberg forecasts and the Philadelphia Fed Survey of Professional Forecasters, allow individual forecasters to not report or update their forecast in a given period. We find that forecasters are persistently heterogeneous in how often they issue or revise a forecast, with attentive agents submitting or revising forecasts every month, while inattentive agents provide and revise forecasts infrequently. This latter finding is consistent with the so-called predisposition effects in Branch (2004) that as long as there is no substantial evidence that would dramatically surprise those inattentive agents, they will not revise their previous forecasts.

Another key element of our empirical analysis is the selection and identification of large, unexpected shocks. Our natural disaster data come from the Center for Research on the Epidemiology of Disasters and contain over 15,000 natural disasters. We limit our attention to 'unpredictable' disasters like tornadoes, earthquakes, and storms rather than slower-moving disasters such as heat waves or epidemics. We further limit our focus only on significant disasters as measured by the number of people affected or killed and the monetary damages caused.²

To further address the concerns that the disaster shocks are not fully unexpected and to better measure their impact, we construct a news-based measure of coverage of the disaster across several thousand English-language newspapers from the Access World News database. Using an index of the relative change in newspaper coverage regarding the disaster, we can flexibly identify disasters that are relatively impactful and unexpected. The large, unanticipated shocks identified in our paper are different from the so-called "man-bites-dog" signals in Nimark (2014) where observing those signals would change the probability distribution of the underlying variable. By contrast, the occurrence of those shocks increases attentive agents' uncertainty and induces synchronized information updating for inattentive agents, but does not change the underlying data generating process in our framework.

By carefully matching the forecaster data with these natural disasters, we find that a large and unexpected shock induces a synchronized response and information updating among professional forecasters. Following those shocks, the overall dispersion among forecasters

²Without this limitation, nearly every country is hit by at least one small natural disaster in nearly every period of our sample, muting any identifying variation.

declines and forecast accuracy increases. These results may at first appear counter-intuitive but are in fact a natural consequence of the dominance of inattentive agents – disasters induce inattentive forecasters to update their forecasts and, in doing so, move closer to both the mean forecast and the ex-post true value of the variable.

Our paper is closely related to the theoretical literature on expectations formation with information frictions. Notable examples include the sticky information model of Mankiw and Reis (2002) and Reis (2006), the noisy information model of Sims (2003), Woodford (2003) and Maćkowiak and Wiederholt (2009), the hybrid sticky-noisy information model of Andrade and Le Bihan (2013) and Andrade, et al. (2016), and Bayesian learning model of Lahiri and Sheng (2008) and Giacomini, Skreta and Turen (2016).³

In contrast to these papers, agents in our model are persistently heterogeneous in their type – attentive and inattentive. In contrast to all previous work, we explicitly model agents' behavior following large, unexpected shocks. Our model also generalizes the noisy information model in two dimensions by allowing for (i) heterogeneous precision of private signals such that agents put different weights on private signals (relative to the same public information), and (ii) time-varying precision of public signals in order to capture the increased uncertainty among economic agents following large unanticipated shocks. These features of the model enable us to measure state-dependent information rigidity in a multivariate context.

Our empirical result that the degree of information rigidity significantly changes after the occurrence of large shocks adds to the literature relying on survey expectations to evaluate models with information frictions. Recent contributions, among many others, include Carroll (2003), Mankiw, Reis and Wolfers (2004), Branch (2007), Coibion (2010) and Coibion and Gorodnichenko (2015).⁴ The findings from all of these papers firmly establish the presence of information rigidities in expectations formation process. However, most papers treat the

³Mankiw and Reis (2002) propose the sticky information model that explains agents' rational inattention in terms of limited resources and the cost of updating information sets. Reis (2006) generalizes this basic model to allow for state-dependent setup in which the length between information update is optimally chosen as a function of shocks. Sims (2003), Woodford (2003) and Maćkowiak and Wiederholt (2009) advocate the noisy information model that emphasizes the limited ability of economic agents to process new information from noisy signals. Andrade and Le Bihan (2013) develop the hybrid sticky-noisy information model and Andrade, et al. (2016) extend the model in a multivariate context. Lahiri and Sheng (2008) develop a Bayesian learning model aimed at explaining expert forecast disagreement. Giacomini, Skreta and Turen (2016) formulate a theory of expectation updating in which agents can be inattentive but, when updating, they follow Bayes' rule and assign homogeneous weights to public information.

⁴Within the sticky information framework, Mankiw, Reis and Wolfers (2004) and Branch (2007) use the aggregate forecasts to calibrate information rigidity, while Carroll (2003) estimates the degree of inattention by matching consensus forecasts of households and professionals, and Coibion (2010) estimates the inattention degree in a sticky-information Phillips curve. Coibion and Gorodnichenko (2015) propose a new approach to test the full-information rational expectations hypothesis and quantify the underlying degree of information rigidity.

degree of inattention as a structural parameter whereas we find that the visibly large shocks induce immediate and synchronized updating of information. This result supports state-dependence in the information updating process as in Gorodnichenko (2008) and Maćkowiak and Wiederholt (2009).

Furthermore, all of these papers predict that, following large shocks, disagreement among professional forecasters either increases or does not change significantly. However, using forecasts for a variety of macroeconomic variables across many countries, we document that disagreement can decrease following large shocks that affect forecaster attention. Our model is successful in explaining this seemingly anomaly and matching other key features of the expectations formation process.

Finally, our paper makes contact with the literature on rare disasters.⁵ While the disasters utilized as shocks in our paper share some similarities to those in this literature, we turn our focus towards the effects on forecaster behavior and expectations formation rather than to any real economic effects.

The paper proceeds as follows. Section 2 describes the data used in this paper. We establish a set of new stylized facts about expectations formation following large unexpected shocks in Section 3. We introduce the information structure faced by agents in Section 4. We propose a theory of expectation updating in Section 5. Section 6 presents the simulation results and Section 7 concludes.

2 Data

2.1 Consensus Economics Forecast Data

Our database of macroeconomic forecasts comes from Consensus Economics. We utilize aggregated data from 1989-2014 covering the 54 countries for which we can obtain both forecasts and true macroeconomic data.⁶ Consensus Economics solicits the individual forecasts from professional forecasters including banks and financial firms, leading industrial companies, consulting firms, and think tanks and research groups. These forecasts cover the mean and standard deviation of individual forecasts for GDP and inflation in the current calen-

⁵For example, Barro (2006) and Gabaix (2012) explore the implications of rare disasters for asset prices. Cavallo, Cavallo, and Rigobon (2014) investigate the impact of two earthquakes in Chile and Japan on prices and supply disruptions, while Gagnon and Lopez-Salido (2014) use natural disasters to identify exogenous changes in demand. Gallagher (2014) finds that the take-up of insurance spikes immediately following a flood and then quickly declines back to baseline. Orlik and Veldkamp (2014) posit that the realizations of disasters make economic agents more uncertain. Maćkowiak and Wiederholt (2015) develop a model in which agents make state-contingent plans in a rare event subject to information constraint. Baker, Bloom and Terry (2017) study the effect of uncertainty on economic growth by using disasters of various types as natural experiments.

dar year as well as the next calendar year. For these variables, panelists are asked about calendar year predictions rather than a rolling period of 12 months. Consequently, forecasts mechanically become more accurate as forecasting horizon gets shorter. That is, forecasts for 2014 GDP will be significantly more accurate when solicited in December of 2014 than in January of 2014. Because of this feature, it is important to control for within-year variation in timing of the surveys.

In addition to this aggregated forecast data, we utilize individual forecasts from Consensus Economics. This subset of data solely covers the G7 countries: Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. The individual forecast data cover 1989 - 2014 and include forecasts for GDP, Personal Consumption, Business Investment, Corporate Profits, Industrial Production, Producer Prices, Consumer Prices, Wages, Car Sales, Housing Starts, Unemployment, Current Account Balance, Short- and Long-Term Interest Rates, and Federal Budget Balances. Not all variables are covered for all countries, though forecasts for common variables such as GDP, inflation, and investment are well-represented for the entire G7. There are 296 unique panelists across these countries, of which 225 have submitted at least 25 individual monthly forecasts to the survey.

Individual panelists are not required to submit a forecast each month and can choose the variables and countries to which they would like to respond. Additionally, panelists can submit an identical forecast from one month to the next. These features of this set of forecaster data are common across other widely used sources of forecaster data like Bloomberg forecasts and the Philadelphia Fed Survey of Professional Forecasters.

2.2 Disaster Data

Our natural disaster data has been obtained from the Center for Research on the Epidemiology of Disasters (CRED). This data contains over 15,000 extreme weather events such as, droughts, earthquakes, epidemics, floods, extreme temperatures, insect infestations, avalanches, landslides, storms, volcanoes, fires, and hurricanes from 1960 to 2014. For each disaster, we can observe the event's category, its date and location, the number of deaths, the total number of people affected by the event, and the estimated monetary cost of the event. The CRED data includes industrial and transportation accidents which we exclude in our analysis.

⁶Countries include Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russia, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, UK, US, Ukraine, and Venezuela.

For each country-month period, we give a value of one if a disaster has occurred and a zero otherwise. This means that if a country has, for example, three earthquakes in one month, it only receives a value of one. The reason for this approach is to avoid double counting recurring but linked events within a month such as an earthquake with multiple aftershocks.

Because of the large number of disasters covered in the data, we need to apply a filter to focus only on major events. With this aim, we include a shock only if it fulfills at least one of the following conditions: 1. More than 0.00001% of a country’s population dead (eg. more than 30 dead in the United States); 2. More than \$10M in damages; 3. More than 50,000 people ‘affected’ (eg. made homeless, injured, substantial financial losses). Our results are robust to modification of filters for all three characteristics, or by utilizing both relative and absolute filters. Furthermore, below we discuss a weighting system to place higher weight on larger and more unexpected disasters.

Finally, we adjust the date of a disaster if it takes place after the Consensus Economics survey date in a given month. That is, if the June Consensus Economics forecast has already taken place, we attribute any further disasters in June to the month of July.

2.3 Newspaper Data

Two potential concerns are that the disaster shocks that we utilize are not fully unexpected or are relatively small in magnitude. In order to help alleviate both of these potential problems, we turn to a measure of unexpectedness and impact derived from news article mentions.

Using a database of newspapers from Access World News, we construct an index that measures the amount of news about a given country in the days surrounding each event.⁷ For each individual disaster, we search the newspaper archive for articles that mention the country where the disaster took place. For each of the 5 days leading up to the disaster and 5 days following it, we measure this count of articles and take the ratio of the post-disaster article count to the pre-disaster article count. Figure 1 shows an average of this series where each event’s coverage has been normalized to 1 in the 15 days prior to the event. A value of 2 following time zero means that there are, on average, twice as many articles written that contain that country’s name on that day relative to the pre-disaster average.⁸

This process allows us to measure the change in attention, or at least newspaper attention, paid to a country following a disaster. This will enable us to flexibly distinguish between

⁷Access World News contains over 3,000 newspapers worldwide. We focus on newspapers from the US, as they make up the majority of coverage in this database. For US disasters, we look for changes in articles written that mention the state that the disaster occurs in rather than the country.

⁸All results are robust to using different news coverage windows up through 15 days before and 15 days after a disaster.

disasters that are relatively unimportant from those that may be much more newsworthy. Moreover, it will help us to filter out expected disasters that may have been ‘baked in’ to previous forecasts, as only unexpected disasters should have the highest increases in news coverage. That is, if we observe a similar number of articles regarding the country before and after the event date, we can assume that the event was predicted ahead and/or it was not that important.

Our primary news-based scaling measure is the percentage increase in newspaper articles mentioning a given country in the 5 days after the event relative to the 5 days prior to the event. We use a relatively narrow window in order to minimize concerns about longer-term trends in coverage about various countries, but our results are robust to using up to 15-day windows. When using the news-weighted shocks, we use the shock with the highest jump in media citations for that category in that month.⁹

Table 1 displays some basic summary statistics regarding the indexes used to weight the disasters in our sample. We include two different scalings of the disaster index. The first is the aforementioned news-scaling. The ‘combined’ scaling refers to a combined z-score comprised of the news scaling, the monetary damages caused by the disaster, and the number of deaths caused by the disaster (mean of 1 and maximum of 4.5). The scaled disaster indexes are normalized to the same mean as the overall disaster index.

Despite the filtering and scaling that we employ, most of the disasters in our data are not large enough to significantly affect the economies of the countries that we observe, especially when considering stimulative aid or spending that follows a destructive event. That is, we do not see these natural disaster shocks as equivalent to large macroeconomic shocks (e.g. oil price shocks, changes in monetary policy, release of new and surprising macroeconomic indicators, new trade deals or government spending initiatives, etc.) that would change the direction of a national economy. The primary impact on forecasters may be an increase in attention paid to a given country and its economy with predicted growth remaining relatively stable. For larger macroeconomic shocks, uncertainty about future impacts on macro variables may be significant enough to outweigh any decrease in forecast dispersion due to changes in attention among forecasters.

⁹For example, one such included disaster is Cyclone Xynthia, which hit France and other locations in Continental Europe on February 27th, 2010. It caused over \$4 billion in damages, killed approximately 50 people, left over 1 million homes without power, and halted train and air traffic. Looking at newspaper coverage surrounding this event, we see a jump in articles after the storm hit of 53% relative to the period of 5 days before the storm.

3 Empirical Results

3.1 State-Dependent Informational Rigidities

We first test for the presence of information rigidities in our sample of macroeconomic forecast data across G7 countries. Our specification takes the form noted in Coibion and Gorodnichenko (2015), utilizing data on the average forecasts across all individual forecasters in a given country-month. That is:

$$ForecastError_{i,t} = \beta_1 ForecastRevision_{i,t} + Time_t + Country_i + \epsilon_{it}, \quad (1)$$

where $ForecastError_{i,t} = ActualValue_{i,t} - MeanForecast_{i,t}$ and $ForecastRevision_{i,t} = MeanForecast_{i,t} - MeanForecast_{i,t-1}$.

In the presence of information rigidities, β_1 would be predicted to be positive. That is, forecasters update periodically over time and thus the mean forecast converges only slowly to the full-information forecast, driving a positive relationship between forecast revisions and the forecast error of any given period relative to the truth.

In Table 2, we restrict our analysis to forecasts of next-year GDP. In the first column of Table 2, we find that the change in mean forecasts from month to month is strongly and positively related to the forecast error (Table 1 displays summary statistics for forecast errors and forecast revisions). We interpret this as strong evidence for the presence of information rigidities in macroeconomic forecasting and that updating of forecasts is predictably less than ‘complete’ in any given month. That is, because not all forecasters update in each period, the movement of the mean forecast goes only part-way to the full-information forecast that is likely closer to the ex-post true value for the period.

Columns 2-4 mirror this specification but add in interactions of $ForecastRevision_{i,t}$ with disasters and disasters that are scaled utilizing two different metrics. We find strong negative coefficients on the interaction terms, demonstrating that in the month following a natural disaster, the correlation between forecast revisions and forecast errors weakens substantially. Column 2 uses a simple indicator for whether there was a natural disaster in country i in month t . In the month of a natural disaster, the strength of the relationship between forecast revisions and forecast errors falls by approximately 50% (-0.286/0.555).

Column 3 scales the disaster by the size of the aforementioned increase in newspaper coverage surrounding the disaster. Here we see that not only do natural disasters tend to affect these informational rigidities, but they do so in a way related to the size or newsworthiness of the disaster. Given the maximum disaster ‘news scaling’ is approximately 6, these coefficients indicate that a sufficiently large disaster reduces the relationship between

forecast errors and forecast revisions to approximately 0. In contrast, a small disaster may not impact the relationship to any large degree, consistent with the idea that if a disaster does not merit a mention in a newspaper, forecasters will likely be unaware, as well.

Column 4 uses a scaling based on three factors: the number of deaths caused by a disaster, the monetary cost of the disaster, and the jump in news coverage. Each series is normalized to a standard deviation of one and then an average across all three metrics is taken. Both of the disaster scalings in columns 3 and 4 have an overall mean and standard deviation of 1 for non-zero values. Similarly to our finding with only the news-based scaling, we again find that, in general, more significant disasters drive down the relationship between forecast revisions and forecast errors. This result is consistent with the idea that professional forecasters may pay more attention to larger disasters and as a result, update forecasts more frequently.

Table 3 mirrors the earlier approach but demonstrates the correlation between forecast revisions and lagged forecast revisions, as in Nordhaus (1987). An advantage of Nordhaus' test is that it is completely independent of the 'true' values of the macroeconomic variables in question. Our findings follow a similar pattern to our earlier results. We find that forecast revisions in the current month tend to consistently and positively predict those in the following month. Again, this relationship diminishes substantially following a natural disaster. Moreover, the relationship between forecast revisions and lagged forecast revisions becomes increasingly weak as the disaster becomes larger. This again suggests that a large and unexpected shock precipitates a state-dependent response and an increase in information updating.

Tables A1 and A2 follow Tables 2 and 3, but include forecast data across all variables in the sample (eg. GDP, CPI, long- and short-run interest rates, unemployment, and consumption) and include forecast variable fixed effects. We find qualitatively similar results across all forecast variables as when restricting the analysis to GDP: all variables exhibit significant information rigidity that declines following large natural disasters.

3.2 Heterogeneous Individual Forecasters

Consensus Economics forecasts are also useful in that underlying forecast data from individual forecasters are available. So, not only can we observe how the overall mean forecast for a given country-variable changes over time, but we can also observe how individual forecasters respond. Differences in the frequency and timing of forecast updates among individual forecasters can have significant impacts for the aggregate accuracy and dispersion of aggregate forecasts. With the individual forecaster data, we investigate the extent to which persistent

heterogeneity among forecasters drives some of these differences.

We split forecasters into two groups. The ‘attentive’ group is made up of forecasters who report a forecast for a given country-variable in more than 95% of the months that they are present in the sample. The ‘inattentive’ group is made up of forecasters who report forecasts less frequently (on average, reporting forecasts for 70% of months in the sample). This corresponds with approximately the top quintile and bottom four quintiles of forecaster reporting.¹⁰

Table 4 demonstrates some of the persistent differences across these two groups, controlling for time, country, and variable fixed effects. In columns 1 and 2, ‘Attentive Forecaster’ is simply a binary indicator for being in the top quintile or bottom four quintiles of this measure of forecaster attentiveness. We measure how forecasters in these two groups are different from one another in two areas: absolute forecast error and absolute differences from the mean forecast. In both cases, we find that the more attentive forecasters have fewer persistent errors and deviations from the average forecast. Some of these errors are derived from more accurate updates in forecasts, but it also stems from inattentive forecasters failing to update for a given month and reporting ‘stale’ forecasts more often.

Columns 3 and 4 of Table 4 dispense with the binary indicator of attentiveness and simply use the average fraction of total forecasts reported for a given forecaster while they were participating in the Consensus Economics panel. Again, we see that forecasters who submit more forecasts tend to have lower forecast errors relative to the truth and also smaller deviations from the mean forecast for any given country-variable-month.

One possible concern with our analysis is that forecasters may shift between being attentive and inattentive over time. We find this type of switching to be uncommon for individual forecasters. Figure 2 plots the fraction of forecasts reported against the fraction of forecasts reported in the previous year across all forecasters. We find a high degree of persistence in the reporting frequency across years, with inattentive forecasters likely to remain so over time, and the reverse is true for attentive forecasters. This may be driven by institutional features of the forecasters’ firm, where they may be assigned to update forecasts only infrequently and so do not respond to the Consensus Economics requests until a new forecast is made by the firm. Figure 3 plots the fraction of forecasts that are changed from month to month for a given forecaster rather than the fraction of forecasts reported.

In Tables 2 and 3, we found that information rigidity, as measured through mean forecast revisions, changed significantly in response to natural disasters. Table 5 utilizes the indi-

¹⁰We have performed similar exercises by measuring attentiveness as the fraction of forecasts which are different than the previous forecast for a given forecaster (e.g. Andrade and Le Bihan (2013)) and found qualitatively similar results.

vidual forecaster data to examine the channels through which this reduction in information rigidity takes effect. In columns 1 and 2, we test the effect that natural disasters have on the individual likelihood of changing a forecast from the previous month. We include time, variable, country, and forecaster fixed effects to isolate the within-forecaster and within-variable impacts of these natural disasters. We find a significant and positive impact: natural disasters tend to increase the probability of changing an individual forecast by approximately 0.86 percentage points (on a mean likelihood of changing of approximately 50%). Column 2 demonstrates that this effect is larger for more newsworthy disasters, with disasters in the top decile driving an approximate 2.13 percentage point increase in the likelihood of a forecaster revising their previous month’s forecast.¹¹

Columns 3-6 repeat this exercise for our previously defined groups of attentive and inattentive forecasters. In columns 3 and 5, we find that the likelihood of attentive forecasters updating their forecast is unaffected by a natural disaster hitting a given country. In columns 4 and 6, we find the opposite is true for inattentive forecasters. This group drives nearly all of the combined effect we found in columns 1 and 2, with inattentive forecasters being much more likely to update their forecast following a natural disaster. Column 7 demonstrates this same phenomenon across quintiles of attentiveness, where we see that the most attentive forecasters are the least likely to change their forecast following a natural disaster.

Table 6 demonstrates the counter-intuitive result that disasters can actually decrease the dispersion of professional forecasts due to the effect that disasters have on inattentive forecasters. Here we see that, following a disaster, attentive forecasters see little change in the relationship between their own forecast and the mean forecast (if anything, they have a slight positive reaction). However, inattentive forecasters see a decline in this measure of dispersion, as they tend to update their forecasts after a natural disaster. This holds true for both the difference between an individual’s forecast and the overall mean forecast as well as the difference between the individual’s forecast and their own-attentiveness-group’s forecast.

Lastly, Table 7 estimates the impacts of disasters on forecast accuracy relative to the ex-post true values of the macroeconomic variables. We perform these tests for all forecasters, attentive forecasters, and inattentive forecasters. Again, we find that there is little impact of natural disasters on forecast errors for attentive forecasters, while there are strong negative effects for inattentive forecasters. Even conditioning on a forecaster updating his forecast, inattentive forecasters tend to report more accurately following a natural disaster than when changing their forecast without a disaster.

Overall, these results suggest that disasters induce inattentive agents to update their

¹¹These results are all robust to how we treat non-responses. That is, if we ‘fill in’ missing data with the previous month’s data for a forecaster who missed a month’s forecast or if we just exclude that month.

forecasts and, in doing so, actually moves them closer to the mean forecast and also to the ex-post true value of the variable. Given the limited economic impact of most of the disasters in our sample, it is likely that, for inattentive agents, natural disasters act mainly as an attention shock, prompting them to update stale forecasts and converge towards a newer consensus value. To match the empirical results, we develop a framework aimed at explaining the expectations formation process following natural disasters. In the next section, we introduce the information structure faced by agents and derive the state space representation. In Section 5, we explore some of the key properties of both types of agents, such as their information rigidity, forecast accuracy and dispersion.

4 Information Structure and State Space Representation

We suppose that economic agents seek to forecast a signal process $\{\pi_t\}$ that is obfuscated by noise. We envision the existence of both a public and a private channel for attentive agents. Our model assumes that the i th attentive agent ($1 \leq i \leq N$) observes the signal through the public channel contaminated by a common noise $\{\eta_t\}$, whereas the private channel provides the signal contaminated by a private noise $\{\nu_t(i)\}$. Hence the observation process for the i th agent is:

$$y_t(i) = \begin{bmatrix} A^{(i)} \\ B \end{bmatrix} \pi_t + \begin{bmatrix} \nu_t(i) \\ \eta_t \end{bmatrix}. \quad (2)$$

for $1 \leq t \leq T$. The signal process is common to all agents, but the noise processes depend on i . The matrix $A^{(i)}$ corresponds to the private manifestation of the signal; for many applications these matrices are given by an identity matrix. Inattentive agents ($N + 1 \leq i \leq N + M$) can be described through a similar framework, albeit there is no private channel and $A^{(i)}$ is null. Hence, the mathematical results derived below can be applied to the inattentive case as well, with some adjustments.

We suppose that $\{\pi_t\}$ is a stationary Markov process; principal interest focuses on the case that the signal follows a VAR(p) stochastic process of dimension m . Also we suppose that $\{\eta_t\}$ is serially uncorrelated with a stochastic covariance matrix Σ_t . This assumption is designed to reflect changing uncertainty surrounding the signal, corresponding to epochs of heightened volatility following large shocks. In contrast, the private noises $\{\nu_t(i)\}$ are each serially uncorrelated with covariance matrix $\Sigma^{(i)}$; this covariance is deterministic, yielding a homoscedastic error.

4.1 State Space Representation with Known Parameters

We here give details about the Kalman filter for processing noisy information, in the case that Σ_t and the parameters governing $\{\pi_t\}$ are known. The matrices B and $A^{(i)}$ are also assumed to be known. Of course in practice the dynamics of these processes would not be known to the forecasters. Instead, our viewpoint is that the state space model reflects the essential facets of each agent's internal process for generating forecasts. Therefore, it is sufficient for our purposes to treat all the parameters as known, although it will be convenient to generate viable examples of heteroscedastic noise via a stochastic covariance process, described in Section 4.2.

Suppose that the signal can be expressed as a component of a Markovian state vector x_t , i.e., there exists a matrix G such that $\pi_t = G x_t$. The transition equation for this state vector is:

$$x_t = \Phi x_{t-1} + \epsilon_t \quad (3)$$

for $t \geq 1$ and an initial value x_0 . Here Φ is the transition matrix, which by assumption has eigenvalues less than one in absolute value. The signal innovations $\{\epsilon_t\}$ are assumed to be uncorrelated with x_0 , so that ϵ_t is uncorrelated with x_{t-1} for $t \geq 1$. The innovations' common covariance matrix is denoted as Σ^ϵ . Let

$$\delta_t(i) = \begin{bmatrix} \nu_t^{(i)} \\ \eta_t \end{bmatrix} \quad H(i) = \begin{bmatrix} A^{(i)} \\ B \end{bmatrix} G,$$

so that combining (2) with $\pi_t = G x_t$ yields the observation equation:

$$y_t(i) = H(i) x_t + \delta_t(i). \quad (4)$$

Evidently $\{\delta_t(i)\}$ is heteroscedastic white noise, with covariance matrix S_t given by:

$$S_t = \text{Var}[\delta_t(i)] = \begin{bmatrix} \Sigma^{(i)} & 0 \\ 0 & \Sigma_t \end{bmatrix}. \quad (5)$$

Note that the only data available to the i th agent is $\{y_t(i)\}$, and so estimates of the signal are to be constructed on this basis, without reference to the data available to some other agent j . For ease of notation below, we suppress the dependence on i . Together, equations (4) and (3) describe the information structure in state space form (ssf). Then $x'_t = [\pi'_t, \pi'_{t-1}, \dots, \pi'_{t-p+1}]$ with $G = [I_m, 0, \dots]$ (and I_m is the m -dimensional identity matrix) corresponds to the

companion form, yielding a VAR(1) for the state vector, writing

$$\Phi = \begin{bmatrix} \Phi_1 & \Phi_2 & \dots & \Phi_p \\ I_m & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & I_m & 0 \end{bmatrix}.$$

We define the following quantities: the forecast of the state vector is $\hat{x}_{t+1|t} = \mathbb{E}[x_{t+1}|y_1, \dots, y_t]$, and its mean square error matrix is $P_{t+1|t} = \text{Cov}[x_{t+1} - \hat{x}_{t+1|t}]$. The residual is the data minus its forecast, namely $e_t = y_t - \hat{y}_{t|t-1}$, and its mean square error matrix is denoted V_t . The Kalman gain is by definition $K_t = \text{Cov}[x_{t+1}, e_t] \text{Var}[e_t]^{-1}$, and plays a key role in updating a signal extraction estimate given new information. Initialization of the recursive Kalman filter algorithm is given by $\hat{x}_{1|0} = 0$ and $P_{1|0} = \text{Var}[x_1]$, which are the correct quantities given a stationary state vector. In the case of a VAR(p) signal process, this initial variance can be computed directly from the companion form. Then for $1 \leq t \leq T$, we compute:

$$e_t = y_t - H \hat{x}_{t|t-1} \quad (6)$$

$$V_t = H P_{t|t-1} H' + S_t \quad (7)$$

$$K_t = \Phi P_{t|t-1} H' V_t^{-1} \quad (8)$$

$$\hat{x}_{t+1|t} = \Phi \hat{x}_{t|t-1} + K_t e_t \quad (9)$$

$$P_{t+1|t} = (\Phi - K_t H) P_{t|t-1} \Phi' + G' \Sigma^\epsilon G. \quad (10)$$

As an additional step, because the signal is a linear function of the state vector, we have

$$\hat{\pi}_{t+1|t} = G \hat{x}_{t+1|t} \quad (11)$$

$$\text{Cov}[\hat{\pi}_{t+1|t} - \pi_{t+1}] = G P_{t+1|t} G'. \quad (12)$$

Equation (8) gives a recursive formula for the Kalman gain, and its dependence on the heteroscedastic noise is clearly given through V_t in (7). Moreover, equations (9) and (10) tell us how to update our one-step ahead prediction and forecast error variance for the state vector. Again, because the Kalman gain depends upon the heteroscedastic variance Σ_t , both the state vector forecast and its uncertainty will be impacted. To understand the Kalman gain better, observe that

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + P_{t|t-1} H' V_t^{-1} e_t, \quad (13)$$

which follows by applying Φ^{-1} to (9); hence $\Phi^{-1} K_t$ tells us the factor to multiply the new

information e_t by in order to update $\hat{x}_{t|t-1}$ to the revised quantity $\hat{x}_{t|t}$. Rearranging this relationship, and utilizing (11) yields

$$\hat{\pi}_{t+1|t+1} = \left(I_m - G \Phi^{-1} K_{t+1} \begin{bmatrix} A^{(i)} \\ B \end{bmatrix} \right) \hat{\pi}_{t+1|t} + G \Phi^{-1} K_{t+1} y_{t+1}. \quad (14)$$

This can be compared with expressions in Coibion and Gorodnichenko (2012), which focused upon the homoscedastic case. Formally, the signal seems to depend on past forecasts and new information in the same way; however, the Kalman gain is different from the homoscedastic case.

4.2 Estimation with Unknown Parameters

We describe below how the signal can be optimally estimated from the observed data, given a noise process that allows for time-varying volatility – this process is designed to mimic the ways in which agents might incorporate new information into their current forecasts.

In order to effectively describe the forecasting process, it is vital to give a flexible and broad specification for the signal and noise processes. If the signal is stationary, a flexible model is given by the VAR(p) class, where p is taken sufficiently large to approximate a generic signal. However, Θ must be drawn so as to ensure the stability of the resulting VAR(p) polynomial.

A bijective reparametrization of the stable VAR(p) class is provided in Roy, McElroy and Linton (2017), where a prior distribution can be simply placed upon unrestricted Euclidean space. The bijection maps arbitrary values in Euclidean space (of appropriate dimension) to a member of the stable VAR(p) class. A simple prior is obtained by adopting a diffuse Gaussian distribution. The variance matrix Σ^ϵ is also described in this mapping. The private noise has variance matrix $\Sigma^{(i)}$, which can be parameterized in the same manner as Σ^ϵ .

Regarding the dynamics about the variance of public signal, Σ_t , there is an extant literature on its specification using stochastic volatility processes.¹² We adopt the broad framework of Cogley and Sargent (2005) and Primiceri (2005), but with some modifications suggested by Neusser (2016). Specifically, consider the Cholesky decomposition $\Sigma_t = B_t \Omega_t B_t'$, where B_t is unit lower triangular and Ω_t is diagonal. The diagonal entries of Ω_t are assumed to each follow an exponential random walk. The matrix B_t can be written as the matrix exponential of some C_t , where C_t is lower triangular with zeroes on the diagonal. Each element of C_t

¹²Chiu, Leonard and Tsui (1996) modeled Σ_t as the matrix exponential of a symmetric matrix A_t (which can take negative values), whose vech was modeled as a VAR process. Uhlig (1997) modeled Σ_t via a generalized Cholesky decomposition, wherein the diagonal factor followed a positive random walk model. A Wishart autoregressive process was studied in Gouriéroux, Jasiak and Sufana (2009).

is modeled as following an independent random walk, and $B_t = \exp\{C_t\}$. In this way the process $\{\Sigma_t\}$ can be generated.

Our own implementation of this framework utilizes the VAR(p) class with the exponential random walk model for volatility. Different user parameters dictate the priors, essentially determining the dispersion for the Gaussian prior for the VAR(p) coefficients, and the dispersion for the random walk increments in the volatility process. A temporary shock at some time index τ can be generated by scaling the diagonal entries of a single Σ_t by some $a > 0$, but without altering B_t or Ω_t , so that the effect is transitory:

$$\Sigma_t = B_t \Omega_t B_t' \cdot (1 + a 1_{\{t=\tau\}}). \quad (15)$$

This ensures that Σ_τ has values multiplied by $1 + a$, but the corresponding shock η_τ will not be large unless the random vector is generated from the right tail of the normal distribution. We proceed by generating m random variables independently from the marginal distribution $\mathbb{P}[Z > x | Z > 2] = (1 - \Phi(x))/(1 - \Phi(2))$, and multiplying the corresponding vector by $\Sigma_\tau^{1/2}$ to obtain η_τ . This modification to η_t and Σ_t at time $t = \tau$ will be designated as a temporary shock, mimicking the first-moment and second-moment shock arising from natural disasters.

5 A Framework for Expectation Formation

Our framework has three key ingredients: (i) heterogeneous forecasters, i.e., attentive versus inattentive, (ii) stochastic volatility, and (iii) Kalman filter updating. As indicated by our empirical findings, there are two types of forecasters, attentive and inattentive, who are not interchangeable. Without loss of generality, let $i = 1, \dots, N$ denote the indexes of attentive forecasters and $i = N + 1, \dots, N + M$ correspond to inattentive forecasters. The key assumption here is that the fraction $q = \frac{N}{N+M}$ is exogenous.

5.1 Modeling Expectation Formation for Attentive Agents

We first develop the case of attentive agents. As noted earlier, the i th attentive agent ($1 \leq i \leq N$) observes both public and private signals and makes the forecast through a signal extraction process. Given the data $\{y_t(i)\}$ for $1 \leq t \leq T$, for each agent i , we obtain $\hat{\pi}_{t+1|t}^A(i)$ and its error covariance $G P_{t+1|t}(i) G'$ from (11) and (12), with the superscript A denoting attentive agents. If we have interest in some linear composite of attentive agents' results, say $\sum_{i=1}^N w_i \hat{\pi}_{t+1|t}^A(i)$ for given weights w_i , then the corresponding target is $\sum_{i=1}^N w_i \pi_{t+1}$, which equals π_{t+1} when the weights sum to one. The variance of the discrepancy between such a

weighted average and π_{t+1} is the mean squared error (MSE), given by

$$MSE_{t+1|t}^A = G \sum_{i,j=1}^N w_i w_j Q_{t+1|t}^{(ij)} G', \quad (16)$$

where by definition $Q_{t+1|t}^{(ij)} = \text{Cov}[\hat{x}_{t+1|t}^A(i) - x_{t+1}, \hat{x}_{t+1|t}^A(j) - x_{t+1}]$. For $i = j$, this covariance is just $P_{t+1|t}$. Otherwise, the following recursion can be used for computation; note that the Kalman gains $K_t(i)$ and observation matrices $H(i)$ depend upon the i th Kalman filter calculation.

Proposition 1 *The covariance of prediction errors across attentive agents, $Q_{t+1|t}^{(ij)}$, can be computed recursively by*

$$Q_{t+1|t}^{(ij)} = [\Phi - K_t(i) H(i)] Q_{t|t-1}^{(ij)} [\Phi - K_t(j) H(j)]' + \Sigma^\epsilon - K_t(i) \begin{bmatrix} 0 & 0 \\ 0 & \Sigma_t \end{bmatrix} K_t(j)', \quad (17)$$

with the initialization $Q_{1|0}^{(ij)} = \text{Var}[x_1]$ for all i and j .

Proof: See the appendix.

Typically we are interested in the case that attentive agents contribute equally to the composite forecast, in which the MSE is given by (16), where $Q_{t+1|t}^{(ij)}$ is computed via equation (17) and all the weights are $w_i = 1/N$. In this case, the average forecast is defined to be

$$\bar{\pi}_{t+1|t}^A = N^{-1} \sum_{i=1}^N \hat{\pi}_{t+1|t}^A(i). \quad (18)$$

The disagreement across attentive agents is defined as the sample variability of the forecasts across forecasters, i.e.,

$$D_{t+1|t}^A = N^{-1} \sum_{i=1}^N (\hat{\pi}_{t+1|t}^A(i) - \bar{\pi}_{t+1|t}^A) (\hat{\pi}_{t+1|t}^A(i) - \bar{\pi}_{t+1|t}^A)'. \quad (19)$$

We now discuss the model implications for understanding information rigidity for attentive agents. Extending the formulation of Coibion and Gorodnichenko (2012) for the homoscedastic public noise, (14) indicates that the old forecast $\hat{\pi}_{t+1|t}$ is scaled by $I_m - R_t$, where

$$R_t = G \Phi^{-1} K_{t+1} \begin{bmatrix} A^{(i)} \\ B \end{bmatrix}. \quad (20)$$

Note that R_t is $m \times m$ dimensional. When the Kalman gain is small, little modification to

the old forecast is needed. From (7) and (8), clearly K_t is small when S_t is large – a sudden jump in Σ_t (irrespective of $\Sigma^{(i)}$) will drive up V_t , and thereby decrease R_t . In other words, shocks will have the effect that new information is received with high uncertainty, as the forecaster knows there is little signal content in the noisy data; as a result, the new forecast will closely resemble the previous period’s forecast. This is the uncertainty channel through which natural disaster shocks affect expectation formation: the occurrence of those shocks generates increased uncertainty among economic agents.

Formally, the information rigidity, defined as the sequence:

$$r_t = \text{tr} [I_m - R_t]/m, \tag{21}$$

is high when the new datum is deemed untrustworthy, i.e., when Σ_t is high. The factor of m in the definition of information rigidity normalizes for the dimension m of the signal $\{\pi_t\}$. Clearly, r_t offers a scalar normalization of the quantity $I_m - R_t$ that multiplies the old forecast.¹³ Our measure in (21) represents the average degree of information rigidity when predicting many variables. This definition is in line with the empirical evidence in Coibion and Gorodnichenko (2015) that forecast revisions of other variables have little predictive power for the forecast errors of each variable, that is, the absence of statistical evidence for the importance of off-diagonal elements of the matrix $I_m - R_t$ in our context.

We emphasize three features of this definition. First, information rigidity is defined in a multivariate context. This is important because imperfect information theories of the business cycle typically require the existence of inattention for consumers, firms, and workers, not their inattention to a single variable, such as inflation. Second, information rigidity is allowed to differ across agents to reflect differences in the weight attached on prior beliefs, e.g. Lahiri and Sheng (2008). Third, information rigidity is allowed to change over time in order to capture the increased uncertainty due to large shocks, e.g. Bloom (2009).

5.2 Modeling Expectation Formation for Inattentive Agents

We now develop the case of inattentive agents. The i th inattentive agent, $N+1 \leq i \leq N+M$, observes the signal $\{\pi_t\}$ through an observation matrix B , and obfuscated by a common noise

¹³Note that information rigidity is also a function of the private information variability; the relative strength of $\Sigma^{(i)}$ and Σ_t must play a role, as these quantities are featured in S_t and hence V_t . For example, a lower value of $\Sigma^{(j)}$ for agent j means this forecaster pays close attention to finer fluctuations in the public data source volatility, and their information rigidity adapts more readily to nuanced changes in the market. Their rigidity is lower overall, and is less susceptible to sudden spikes to public information variability than inattentive forecasters.

$\{\eta_t\}$, yielding the observation equation:

$$y_t = B \pi_t + \eta_t.$$

The matrix B represents any linear combinations of the signal that dictate how the signal is manifested publicly to the agent. During normal times, inattentive agents only update sporadically. Following Reis (2006), we let $\lambda \in [0, 1]$ denote the probability that any given inattentive agent fails to update their information set, and operates under an older vintage of information. We refer to λ as the degree of information rigidity for inattentive agents. When they update, inattentive agents face the signal extraction problem. For those who do not update, they simply set their forecasts to the ones in the previous period.

Let \mathcal{G}_t denote the sigma-field generated by $\{y_s, s \leq t\}$, i.e., the information about the process available up to time t . Then if an agent at time $t+1$ has just updated his information, he would utilize the signal extraction forecast $\mathbb{E}[\pi_{t+1}|\mathcal{G}_t]$. However, if that agent had last updated two periods ago then his forecast would be $\mathbb{E}[\pi_{t+1}|\mathcal{G}_{t-1}]$. In general, we denote such a forecast by inattentive agent i by $\widehat{\pi}_{t+1|t}^{IA}(i)$, with the notation indicating that a forecast of π_{t+1} is furnished at time t , even though with probability λ the forecast is generated with older vintages. The average of such forecasts is $M^{-1} \sum_{i=N+1}^{N+M} \widehat{\pi}_{t+1|t}^{IA}(i)$; breaking the sum into subsets of agents that last updated their forecast at time $t-k$ (with $k \geq 0$) – and with A_k denoting the number of such – we obtain

$$M^{-1} \sum_{i=N+1}^{N+M} \widehat{\pi}_{t+1|t}^{IA}(i) = M^{-1} \sum_{k=0}^{\infty} A_k \mathbb{E}[\pi_{t+1}|\mathcal{G}_{t-k}].$$

When M is large, the proportion A_k/M approximates the probability of not updating for k time periods, followed by finally updating at the next time – this probability is given by the geometric distribution, and equals $(1-\lambda)\lambda^k$. Hence an asymptotic approximation to the average forecast is

$$\bar{\pi}_{t+1|t}^{IA} = (1-\lambda) \sum_{k=0}^{\infty} \lambda^k \mathbb{E}[\pi_{t+1}|\mathcal{G}_{t-k}]. \quad (22)$$

The degree of variability across inattentive agents with respect to the group mean is called the disagreement, and is computed by averaging squared discrepancies of each $\widehat{\pi}_{t+1|t}^{IA}(i)$ with $\bar{\pi}_{t+1|t}^{IA}$. Using the same approximation for large M that was used to derive (22) yields

$$D_{t+1|t}^{IA} = (1-\lambda) \sum_{k=0}^{\infty} \lambda^k \left(\mathbb{E}[\pi_{t+1}|\mathcal{G}_{t-k}] - \bar{\pi}_{t+1|t}^{IA} \right) \left(\mathbb{E}[\pi_{t+1}|\mathcal{G}_{t-k}] - \bar{\pi}_{t+1|t}^{IA} \right)'. \quad (23)$$

In order to assess the accuracy of the group inattentive mean in an ensemble sense, we can calculate the mean squared error as follows:

$$\begin{aligned} \text{MSE}_{t+1|t}^{IA} &= \mathbb{E} \left[(\bar{\pi}_{t+1|t}^{IA} - \pi_{t+1}) (\bar{\pi}_{t+1|t}^{IA} - \pi_{t+1})' \right] \\ &= (1 - \lambda)^2 \sum_{k, \ell \geq 0} \lambda^{k+\ell} \text{Cov} (\mathbb{E}[\pi_{t+1} | \mathcal{G}_{t-k}] - \pi_{t+1}, \mathbb{E}[\pi_{t+1} | \mathcal{G}_{t-\ell}] - \pi_{t+1}). \end{aligned} \quad (24)$$

Apparently, lower values of λ indicate that more timely forecasts receive higher weight in (22), and the MSE will decrease. However, other costs (such as maintaining a database, and the resources required to do analysis) may render attractive the behavior of using a higher value of λ during normal times. In contrast, following large and unexpected shocks, the cost of not updating the information vintage is very high, and accordingly the majority of inattentive agents will update their information and make new forecasts. This is the attention channel through which natural disaster shocks affect expectation formation: visibly large shocks induce immediate updating of information for most agents. This attention effect is particularly pronounced for those with an outdated information set, resulting in a significant decline in λ .

Finally, it is possible using the state space form to provide a specific formula for the signal extraction error covariance featured in equation (24), the MSE for inattentive agents. Here the formula is for a single agent, so we do not insert the i index in the notation. Replacing the conditioning on the semi-infinite sigma-field \mathcal{G}_t by projection on a finite past, the MSE is modified to the formula

$$\text{MSE}_{t+1|t}^{IA} = (1 - \lambda)^2 \sum_{k, \ell=0}^{t-1} \lambda^{k+\ell} G R_{k, \ell} G' \quad (25)$$

with $R_{k, \ell} = \text{Cov} [\hat{x}_{t+1|t-k}^{IA} - x_{t+1}, \hat{x}_{t+1|t-\ell}^{IA} - x_{t+1}]$, and the dependence of $R_{k, \ell}$ on t has been suppressed in the notation. The formula, given below, is only needed for the case of inattentive agents where no private noise is present, so the ssf quantities (such as Kalman gain) are to be interpreted accordingly by omitting $A^{(i)}$ and $\nu_t(i)$.

Proposition 2 *The covariance of prediction errors across forecast horizons, $R_{k, \ell}$, can be*

computed if $k \leq \ell$ by

$$\begin{aligned}
R_{\ell,\ell} &= \Phi^\ell P_{t+1|t} \Phi'^\ell + \sum_{j=0}^{\ell-1} \Phi^j \Sigma^\epsilon \Phi'^j \\
R_{\ell-1,\ell} &= \Phi^{\ell-1} (\Phi - K_{t+1-\ell} B) P_{t+1-\ell|t-\ell} \Phi'^\ell + \sum_{j=0}^{\ell-1} \Phi^j \Sigma^\epsilon \Phi'^j \\
R_{k,\ell} &= \Phi^k \prod_{j=k}^{\ell-1} (\Phi - K_{t-j} B) P_{t+1-\ell|t-\ell} \Phi'^\ell + \sum_{i=2}^{\ell-k} \Phi^k \prod_{j=k}^{\ell-i} (\Phi - K_{t-j} B) \Sigma^\epsilon \Phi'^{\ell-i+1} + \sum_{j=0}^k \Phi^j \Sigma^\epsilon \Phi'^j,
\end{aligned}$$

where $k \leq \ell - 2$ in the last case, and where the matrix products are computed with the lowest index matrix first, and multiplying on the right by matrices of higher index.

Proof: See the appendix.

6 Monte Carlo Simulation

6.1 Summary of Model Implications

We now summarize the model implications for understanding information rigidity, mean forecast, mean squared error and disagreement among agents. As above we set $i = 1, \dots, N$ to be the indexes of attentive agents and $i = N + 1, \dots, N + M$ correspond to inattentive agents, with $q = \frac{N}{N+M}$. Besides the individual treatment of attentive and inattentive agents, it is of interest to study the composite of these two groups.

- i. Attentive agents all form their expectations through a signal extraction process, as described in Section 4. Their information rigidity is described in equation (21), while the mean forecast is (18). The MSE is given by (16), where $Q_{t+1|t}^{(ij)}$ is defined in equation (17) and all the weights are $w_i = 1/N$. The disagreement among attentive agents is provided by (19).
- ii. Inattentive agents face a constant probability λ of not updating their information (e.g., $\lambda = 0.7$), as described in Section 5.2. We refer to λ as the degree of information rigidity for inattentive agents. When updating, they face a signal extraction problem. In periods of not updating, they simply set their forecasts to the previous ones. Their mean forecast is defined in equation (22) by assuming equal weights. Assuming that these inattentive agents update their information independently of each other, the MSE is given by (25), where the forecast error covariance is given in Proposition 2. Moreover, the disagreement among inattentive agents is provided by (23).

iii. Combining attentive and inattentive agents, the average forecast, $\bar{\pi}_{t+1|t}^{ALL}$, is defined as the average of forecasts from all $N + M$ agents, and this can be approximated (for large M) by the weighted sum:

$$\bar{\pi}_{t+1|t}^{ALL} = q N^{-1} \sum_{i=1}^N \hat{\pi}_{t+1|t}^A(i) + (1 - q) (1 - \lambda) \sum_{k=0}^{\infty} \lambda^k \mathbb{E}[\pi_{t+1} | \mathcal{G}_{t-k}]. \quad (26)$$

The exact MSE is difficult to compute, because of correlations between the attentive and inattentive forecast errors, but we can get a heuristic measure by weighting each contribution towards MSE:

$$\text{MSE}_{t+1|t}^{ALL} = q N^{-2} \sum_{i,j=1}^N G Q_{t+1|t}^{(ij)} G' + (1 - q) \text{MSE}_{t+1|t}^{IA}. \quad (27)$$

Everything else being constant, an increase in the variance of public signal following a shock leads to a larger MSE for both attentive and inattentive agents. Furthermore, a decrease in their information rigidity after a shock results in a smaller MSE for inattentive agents. The impact on inattentive agents depends on the magnitude of the shock.

Following the large, unexpected shocks, the attention effect (i.e. decrease in information rigidity) tends to dominate the uncertainty effect (i.e. increase in the variance of public signal), and thus, the MSE of inattentive agents declines. The impact of natural disaster shocks on overall MSE is determined by the proportion of inattentive agents and the average deviation of inattentive agents' mean forecast from the truth.

Finally, the overall disagreement, $D_{t+1|t}^{ALL}$ can be expressed as:

$$\begin{aligned} D_{t+1|t}^{ALL} &= q N^{-1} \sum_{i=1}^N (\hat{\pi}_{t+1|t}^A(i) - \bar{\pi}_{t+1|t}^A) (\hat{\pi}_{t+1|t}^A(i) - \bar{\pi}_{t+1|t}^A)' \\ &+ (1 - q) (1 - \lambda) \sum_{k=0}^{\infty} \lambda^k (\mathbb{E}[\pi_{t+1} | \mathcal{G}_{t-k}] - \bar{\pi}_{t+1|t}^{IA}) (\mathbb{E}[\pi_{t+1} | \mathcal{G}_{t-k}] - \bar{\pi}_{t+1|t}^{IA})' \\ &+ q (1 - q) \left\| N^{-1} \sum_{i=1}^N \hat{\pi}_{t+1|t}^A(i) - (1 - \lambda) \sum_{k=0}^{\infty} \lambda^k \mathbb{E}[\pi_{t+1} | \mathcal{G}_{t-k}] \right\|^2, \end{aligned} \quad (28)$$

where $\|\cdot\|$ denotes the ℓ_2 norm of a vector.

Clearly, overall disagreement in (28) comes from heterogeneity within attentive agents (first line), within inattentive agents (second line) and between two group mean fore-

casts (third line). The impact of natural disaster shocks on forecast disagreement displays interesting patterns. Everything else being constant, an increase in the variance of public signal following a shock has two conflicting effects for both attentive and inattentive agents: (i) differences of opinion increase due to much fuzzier public signals and (ii) disagreement decreases because agents incorporate less of noisy signals into their forecasts.

A decrease in their information rigidity after a shock results in a lower disagreement for inattentive agents, because the shock decreases the length between information updating. The overall impact on forecast disagreement depends on the magnitude of the shock. Following the large, unexpected shocks, attentive agents tend to disagree more since the uncertainty effect dominates; in contrast, inattentive agents tend to disagree less since the attention effect dominates. The impact of natural disaster shocks on overall disagreement is determined by the proportion of inattentive agents and the average deviation of inattentive agents' mean forecast from the truth.

The heterogeneous responses of disagreement across two types of agents following large shocks help reconcile the conflicting results in the literature. For example, Mankiw, Reis and Wolfers (2004) find that disagreement increases after a shock hitting the economy, while Coibion and Gorodnichenko (2012) document the absence of significant response of disagreement to structural shocks. Allowing for both heterogeneous agents and state-dependent information rigidity is a key to understanding what drives forecast disagreement.

6.2 Data Generating Process

We illustrate these assertions through the results of simulations. Our data generating process (DGP) is described as follows. We set $m = 3$, and for the signal considered a VAR(2) based upon empirical fits of industrial production, inflation, and federal funds rate data. This is merely intended to furnish a reasonable signal DGP. The coefficients are

$$\Phi_1 = \begin{bmatrix} 0.7745 & -0.1472 & -0.4292 \\ 0.0556 & 0.3139 & 0.1116 \\ 0.1066 & 0.0582 & 1.3309 \end{bmatrix} \quad \Phi_2 = \begin{bmatrix} -0.0517 & 0.0979 & 0.4708 \\ 0.0170 & 0.1813 & -0.0151 \\ -0.0054 & 0.0384 & -0.3872 \end{bmatrix},$$

and the innovation covariance was set to I_3 . Samples of size $T = 100$ were generated, with a burn-in period of 500 observations. The observation matrices $A^{(i)}$ and B were set equal to identity matrices I_3 . To generate the public noise Σ_t , the innovations of the exponential random walk Ω_t were Gaussian of standard deviation .01 for all three dimensions. A tempo-

rary shock at time $\tau = 50$ is generated in the manner described in (15) with $a = 9$ (yielding a ten-fold increase to variability).

To generate the private noise, an overall dispersion coefficient with value .01 controls the spread of entries in the covariance matrix, whereas the overall scale is determined via multiplication by $20 Y_i$, where Y_i has a χ^2 distribution of one degree of freedom, generated independently for all attentive agents. This gives some spread and variability to the private noise; the settings were determined by empirically examining various cases and studying the resulting behavior of simulations. The number of attentive agents was set to $N = 100$. For purposes of understanding the case of combining attentive and inattentive agents, we set $M = 200$ so that $q = 1/3$.

6.3 Simulation Results

Figure 4 presents the degrees of information rigidity for both types of agents. For inattentive agents, 70% do not update their information sets during the normal times. After observing a shock occurred at time $\tau = 50$, the majority of inattentive agents update information and revise their forecasts, which accordingly leads to a decline of information rigidity from 0.7 to 0.2.¹⁴ The opposite is true for attentive agents: during the normal times, they place less than 40% weight on previous forecasts relative to new information, but observing the shock significantly increases the average degree of their information rigidity to almost 70% in predicting three variables. Because the shock is temporary, information rigidity at time $t = 51$ for both types of agents returns to the pre-shock level.

The dynamics of mean squared error is shown in Figures 5, 6, and 7 for the cases of inattentive, attentive, and all agents combined. We include a “counter-factual” case for inattentive agents, whereby we compute the MSE when a shock occurs but the agents do not adjust their information rigidity downwards; from Figure 5 we see that in such a case the MSE increases more (grey line, and the black dot at time $\tau = 50$) than when they react to a shock (blue). In fact, because the impact of the shock has a lingering effect on the MSE (that is, the hump gradually declines to a steady level in the times directly following $\tau = 50$), it would be advantageous for inattentive agents to keep λ at the lower value of 0.2 for more than just one time period – especially in the third panel, it is apparent that paying more attention has decreased the MSE, but just for time point $\tau = 50$.

Figure 6 directly compares the inattentive and attentive cases of the MSE. Unsurprisingly,

¹⁴For simplicity, we assume that the probability of not updating information, λ , is the same across three variables for inattentive agents. Allowing for different levels of λ across variables (e.g. Andrade, et al. 2016) does not change the results qualitatively for the effect of a large unexpected shock on information processing of inattentive agents. In addition, we utilize a significant uncertainty shock component for illustration of the diverging responses of the attentive and inattentive forecasters.

inattentive agents make much larger forecast errors than attentive ones and as a result, the overall MSE is dominated by the former. However, agents respond differently in terms of their MSE following the shock. In particular, the MSE declines for inattentive agents (relative to the counter-factual case of unchanging λ), since the visibly large shock induces immediate and synchronized updating of information and moves their forecasts much closer to the truth. In contrast, the large unexpected shock generates increased uncertainty among attentive agents and increases their MSE. The case of mingled inattentive and attentive agents (Figure 7) follows the overall pattern of the inattentive case (a counter-factual is also displayed here, for comparison), which is due to the dominance of inattentive agents; this confirms the empirical results presented earlier.

Forecast disagreement across agents shows broadly similar findings, as shown in Figures 8, 9, and 10. In general, there exists substantial disagreement among both types of agents in predicting any of three variables. During normal times, for inattentive agents, they disagree mainly because they use different vintages of data; for attentive agents, they disagree since they receive different private signals and interpret the same public signal differently. Inattentive agents have much higher levels of disagreement and accordingly play a dominant role in the overall disagreement. Following the shock, most of inattentive agents have updated their outdated information and moved their forecasts closer to the average; as a result their forecast disagreement (blue line in Figure 8) is lower in comparison to the counter-factual case (grey line, and the black dot at time $\tau = 50$). Attentive agents, on the other hand, disagree more after observing the shock due to increased uncertainty of public information – there is a jump in the green line of Figure 9 at the shock time. The overall disagreement declines following the shock (blue-green line in Figure 10) as compared to the counter-factual case, which appears counter-intuitive but in fact is a natural consequence of the dominance of inattentive agents.

We need to point out that the effect of a large, unexpected shock on overall mean squared error and disagreement depends on the magnitude of the shock, the proportion of inattentive agents and the average deviation of inattentive agents' mean forecast from the truth. Both our empirical and simulation results show that inattentive agents tend to dominate and thus, overall mean squared error and disagreement decline following large, unexpected shocks (at least given the uncertainty component of the shock is not sufficiently large to outweigh the effects on the inattentive agents). Our model, however, has implications for different paths of overall mean squared error and disagreement following rare events.

7 Conclusion

This paper provides a new view on what drives the behavior of macroeconomic forecasters. We find that individual forecasters are persistently heterogeneous in how often they revise or even issue a forecast over time. Given that many commonly utilized macroeconomic forecasts are derived from the average forecast from a selected set of forecasters, these differences in the frequency of revision have the potential to bias average forecasts and change the dynamics of forecasts over time.

We demonstrate that there is a significant degree of information rigidity in forecasts, driven by the fact that many forecasters choose to not update their forecast in successive time periods. Matching forecasts from a panel of 54 countries to a detailed set of natural disasters, we show that this information rigidity declines significantly following natural disasters. At an individual level, this effect seems consistent with an ‘attention shock’ affecting the forecasters, where newsworthy disasters induce formerly ‘inattentive’ forecasters to update their forecasts. Moreover, following such disasters, previously inattentive forecasters move their stale forecasts closer to the mean forecast, decreasing the dispersion in forecasts. This may result in a counter-intuitive result, where shocks to countries can increase uncertainty but decrease forecaster dispersion due to the fact that inattentive forecasters may be induced to update their ‘stale’ information sets.

We model this phenomenon with a learning model that incorporates these two channels: an attention effect – the visibly large shocks induce immediate and synchronized updating of information for inattentive agents, and an uncertainty effect – the occurrence of those shocks generates increased uncertainty among attentive agents. Our theory has three key elements. (i) There are two persistent types of agents: attentive and inattentive, with attentive agents revising forecasts frequently and inattentive agents revising forecasts infrequently. (ii) Inattentive agents update sporadically during the normal times. Following large and unexpected shocks, the cost of not updating information is high, and more inattentive agents will update their information sets and make new forecasts. (iii) Attentive agents optimally combine public and private signals in making their forecasts through a signal extraction process.

Our model yields a world in which large shocks like natural disasters induce an immediate increase in updating of information for most inattentive agents. This attention effect is particularly pronounced for those with an outdated information set, resulting in a significant decline in the information rigidity. For attentive agents, the occurrence of those shocks generates increased uncertainty and as a result, their new forecasts closely resemble the previous period’s forecasts. These findings warn against treating the degree of information rigidity as a structural parameter and suggest that future research should explore state-

dependence in the information updating process. To this end, our paper moves one step forward by introducing time-varying uncertainty in expectations formation framework and accordingly proposing a measure of state-dependent information rigidity in a multivariate context.

Finally, our paper suggests that there is room to improve so-called consensus or mean forecasts. We find that many individual forecasters are persistently more inattentive and inactive than others. Accounting for this heterogeneity across forecasters can help explain both the information rigidity observed in many commonly-utilized macroeconomic forecasts and a reason why forecast dispersion may actually decline, depending on the portion of inattentive forecasters, following a national shock that increases uncertainty about future economic performance.

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Table 1: Summary Statistics

Variable	Mean	Std Dev	Min	Max
Disaster	0.159	0.366	0	1
News Shock	0.159	0.541	0	6.11
'Combined' Shock	0.159	0.441	0	4.34
Forecast Error	0.014	1.11	-4.98	4.9
Forecast Revisions	-0.016	0.354	-2.96	3.0

Notes: Disasters are indicator variables for whether there was a natural disaster (of sufficient size, as defined in the text) in a given country-month. News Shocks and 'Combined' Shocks are scaled versions of the Disaster indicators. News Shocks employ a scaling that is determined by the increase in newspaper coverage of a given country in the days after a natural disaster relative to the days leading up to the natural disaster. 'Combined' Shocks are formed from combination of the news-based scaling along with measures of how much monetary damage and how many deaths were associated with a given natural disaster. Forecast Errors are defined as the average country-month-variable level of error relative to the ex-post true value of that variable. Forecast Revisions are month-over-month changes in average forecast values for a given country-month-variable. The variables included in this table are GDP, CPI, long- and short-run interest rates, consumption, and unemployment.

Table 2. Information Rigidities Based on GDP Forecast Error

VARIABLES	(1) Forecast Error	(2) Forecast Error	(3) Forecast Error	(4) Forecast Error
Forecast Revision	0.514*** (0.0286)	0.555*** (0.0307)	0.530*** (0.0294)	0.541*** (0.0301)
Forecast Rev * Disaster		-0.286*** (0.0787)		
Disaster		-0.0339 (0.0341)		
Forecast Rev * Disaster (News Scaling)			-0.106** (0.0448)	
Disaster (News Scaling)			-0.0304 (0.0196)	
Forecast Rev * Disaster (Combined Scaling)				-0.183*** (0.0649)
Disaster (Combined Scaling)				-0.0617** (0.0282)
Observations	11,408	11,408	11,408	11,408
R^2	0.295	0.296	0.296	0.296
Time FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions performed for GDP forecasts across 54 countries. Forecast Error denotes the difference of the ex-post true GDP growth value from the mean forecast. Forecast Revision denotes the difference of the mean GDP forecast from the previous month's mean GDP forecast. 'Disaster' is an indicator variable for a disaster occurring in a particular country-month for over 1,000 natural disasters in the sample. 'News Scaling' refers to the ratio of news articles written about a country in the 5 days following a disaster to those written in the 5 days before a disaster (has a mean of 1 and a max value of 6). 'Combined Scaling' for disasters refers to a combined z-score comprised of the news scaling, the monetary damages caused by the disaster, and the number of deaths caused by the disaster (mean of 1 and maximum of 4.5).

Table 3. Information Rigidities Based on GDP Forecast Revision

VARIABLES	(1) Forecast Rev	(2) Forecast Rev	(3) Forecast Rev	(4) Forecast Rev
Lagged Forecast Revision	0.139*** (0.00924)	0.149*** (0.00988)	0.145*** (0.00949)	0.148*** (0.00972)
Lag Forecast Rev * Disaster		-0.0736*** (0.0259)		
Lagged Disaster		0.00223 (0.0115)		
Lag Forecast Rev * Disaster (News Scaling)			-0.0428*** (0.0150)	
Lagged Disaster (News Scaling)			-0.00943 (0.00661)	
Lag Forecast Rev * Disaster (Combined Scaling)				-0.0604*** (0.0214)
Lagged Disaster (Combined Scaling)				-0.00893 (0.00946)
Observations	11,444	11,444	11,444	11,444
R^2	0.106	0.107	0.107	0.107
Time FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions performed for forecasts across 54 countries (including only forecasts of GDP). Forecast Revision denotes the difference of the mean forecast from the previous month's mean forecast. 'Disaster' is an indicator variable for a disaster occurring in a particular country-month for over 1,000 natural disasters in the sample. 'News Scaling' refers to the ratio of news articles written about a country in the 5 days following a disaster to those written in the 5 days before a disaster (has a mean of 1 and a max value of 6). 'Combined Scaling' for disasters refers to a combined z-score comprised of the news scaling, the monetary damages caused by the disaster, and the number of deaths caused by the disaster (mean of 1 and maximum of 4.5).

Table 4. Individual Forecast Dispersion

VARIABLES	(1)	(2)	(3)	(4)
	Diff. From Mean	Fore. Error	Diff. From Mean	Fore. Error
Attentive Forecaster	-0.0724*** (0.00717)	-0.395*** (0.0416)		
Fraction Forecasts Reported			-0.177*** (0.0173)	-1.147*** (0.148)
Observations	292,390	176,985	292,390	176,985
R^2	0.054	0.128	0.054	0.128
Time FE	YES	YES	YES	YES
VAR FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: ‘Forecast Error’ denotes the absolute value of the difference of the individual forecast from the ex-post true value. ‘Difference from Mean’ means the absolute value of the difference between the individual forecast and the mean forecast for that country-variable-month. ‘Attentive Forecaster’ is an indicator variable that notes that a forecaster is in the top quartile of fraction of forecasts reported. Data covers 280 forecasters and 7 countries for GDP, CPI, consumption, short- and long-run interest rates, unemployment, wages, and producer prices.

Table 5. Individual Forecast Changes and Disasters

VARIABLES	(1) Change	(2) Change	(3) Change - A	(4) Change - I	(5) Change - A	(6) Change - I	(7) Change
Scaled Disaster * Attentive Quintile							-0.00285*** (0.000701)
Scaled Disaster							0.0120*** (0.00252)
Disaster	0.00857*** (0.00223)	0.00192 (0.00310)	0.00336 (0.00413)	0.0114*** (0.00259)	0.000857 (0.00541)	0.000183 (0.00373)	
Scaled Disaster		0.00576*** (0.00187)			0.00193 (0.00270)	0.0101*** (0.00241)	
Observations	292,390	292,390	64,255	228,135	64,255	228,135	292,335
R^2	0.149	0.149	0.069	0.113	0.069	0.113	0.162
Time FE	YES	YES	YES	YES	YES	YES	YES
VAR FE	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES
Forecaster FE	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: ‘Attentive Quintile’ refers to the quintile of attentiveness a forecaster belongs to in terms of fraction of new forecasts that forecaster has reported during their tenure. ‘Disaster’ is an indicator variable for a disaster occurring in a particular country-month for over 1,000 natural disasters in the sample. ‘Scaled Disaster’ refers to the ratio of news articles written about a country in the 5 days following a disaster to those written in the 5 days before a disaster (has a mean of 1 and a max value of 6). ‘Change’ is an indicator variable for whether that forecaster changed their forecast from the previous month for that country-variable. Columns 3 and 5 restrict the sample to forecasters in the top quintile of attentiveness while columns 4 and 6 restrict to the bottom 4 quintiles of attentiveness. Data covers 280 forecasters and 7 countries for GDP, CPI, consumption, short- and long-run interest rates, unemployment, wages, and producer prices.

Table 6. Dispersion Following Disasters

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Diff from Overall Mean			Diff from Attentive Group Mean		
	All Forecasters	Attentive Fore.	Inattentive Fore.	All Forecasters	Attentive Fore.	Inattentive Fore.
Scaled Disaster	-0.00612 (0.00411)	0.00129 (0.00561)	-0.00882* (0.00509)	-0.00426 (0.00504)	0.00111 (0.00635)	-0.0172** (0.00744)
Observations	284,749	60,684	224,064	284,749	60,684	224,064
R^2	0.022	0.044	0.019	0.019	0.019	0.035
Time FE	YES	YES	YES	YES	YES	YES
VAR FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Forecaster FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: ‘Attentive Forecaster’ refers to a forecaster being in the top quintile of attentiveness in terms of fraction of new forecasts that forecaster has reported during their tenure. ‘Scaled Disaster’ refers to the ratio of news articles written about a country in the 5 days following a disaster to those written in the 5 days before a disaster (has a mean of 1 and a max value of 6). ‘Difference from the Overall Mean’ refers to the difference between the individual forecast and the mean forecast across all forecasters. ‘Difference from Attentive Group Mean’ refers to the difference between the individual forecast and the mean forecast across all forecasters in their attentiveness group (eg. top quintile of attentiveness or bottom 4 quintiles of attentiveness). Data covers 280 forecasters and 7 countries for GDP, CPI, consumption, short- and long-run interest rates, unemployment, wages, and producer prices.

Table 7. Forecast Accuracy and Disasters

VARIABLES	(1) Fore. Error	(2) Fore. Error - A	(3) Fore. Error - I	(4) Fore. Error	(5) Fore. Error - A	(6) Fore. Error - I
Changed Forecast				-0.0497*** (0.00565)	-0.0343** (0.0167)	-0.0575*** (0.00601)
Scaled Disaster	-0.0252*** (0.00682)	-0.00440 (0.0175)	-0.0260*** (0.00741)	-0.0258*** (0.00682)	-0.00458 (0.0175)	-0.0265*** (0.00740)
Observations	154,274	25,350	128,923	154,274	25,350	128,923
R^2	0.085	0.110	0.088	0.085	0.110	0.089
Time FE	YES	YES	YES	YES	YES	YES
VAR FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Forecaster FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: ‘Forecast Error’ denotes the absolute value of the difference of the individual forecast from the ex-post true GDP growth value. ‘Disaster’ is an indicator variable for a disaster occurring in a particular country-month for over 1,000 natural disasters in the sample. ‘Changed Forecast’ is an indicator variable for whether that forecaster changed their forecast from the previous month for that country-variable. Columns 2 and 5 restrict the sample to forecasters in the top quintile of attentiveness while columns 3 and 6 restrict to the bottom 4 quintiles of attentiveness. Data covers 280 forecasters and 7 countries for GDP, CPI, consumption, short- and long-run interest rates, unemployment, wages, and producer prices.

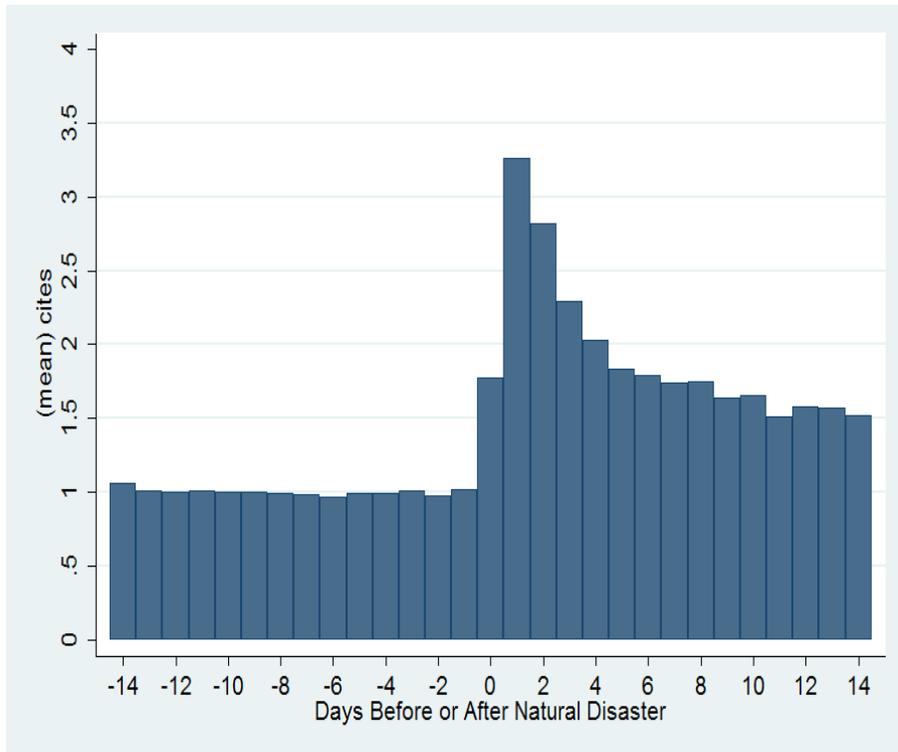


Figure 1: Changes in Newspaper Articles Regarding Affected Countries

Notes: Data obtained by searching approximately 2,500 English language newspapers on Access World News. For each natural disaster, daily article counts of the number of articles written that contain the name of the affected country. This is averaged over all natural disasters studied in the regression analysis. For graphing purposes, the series for each event is normalized such that the pre-period has a mean of one.

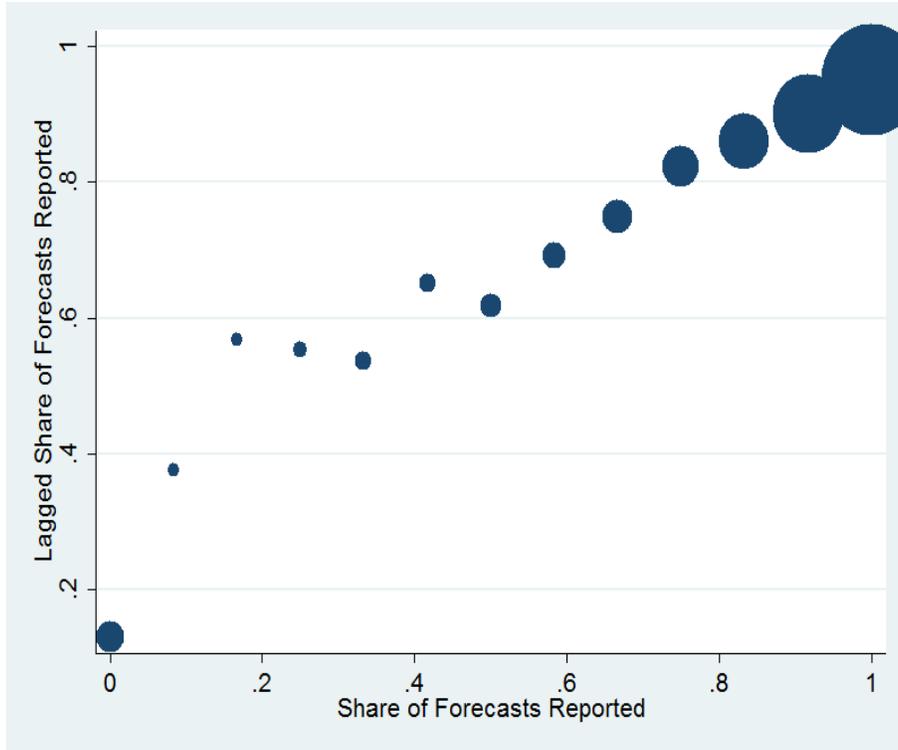


Figure 2: Persistence in Forecast Reporting

Notes: The vertical axis represents the share of eligible months that a given forecaster reported a forecast for in year $t-1$. The horizontal axis represents the share of eligible months that a given forecaster reported a forecast for in year t . Mean values of horizontal bins are plotted (each bin represents a one month out of twelve months increment). Thus, a point on the 45-degree line means that, on average, forecasters in that group reported forecasts at the same frequency as last year. Plotted points are scaled by the number of forecasters in each bin.

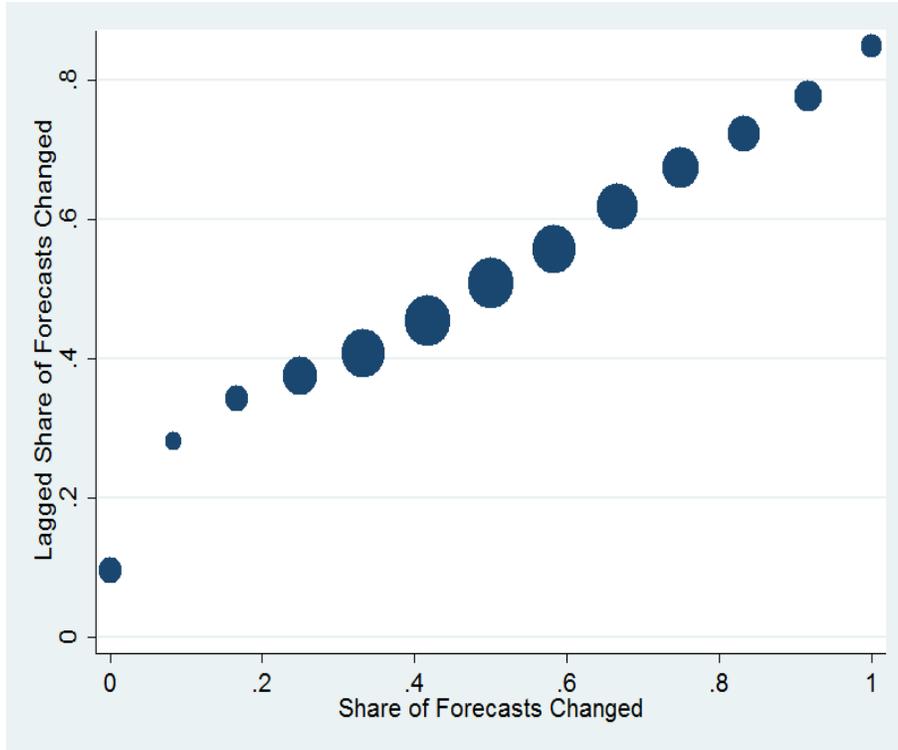
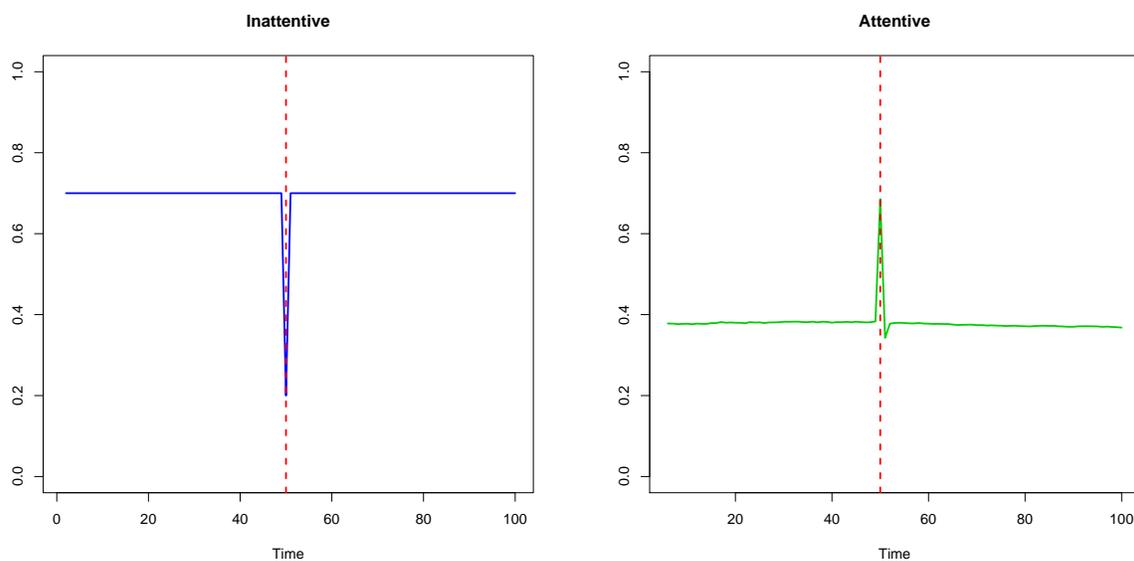


Figure 3: Persistence in Forecast Updating

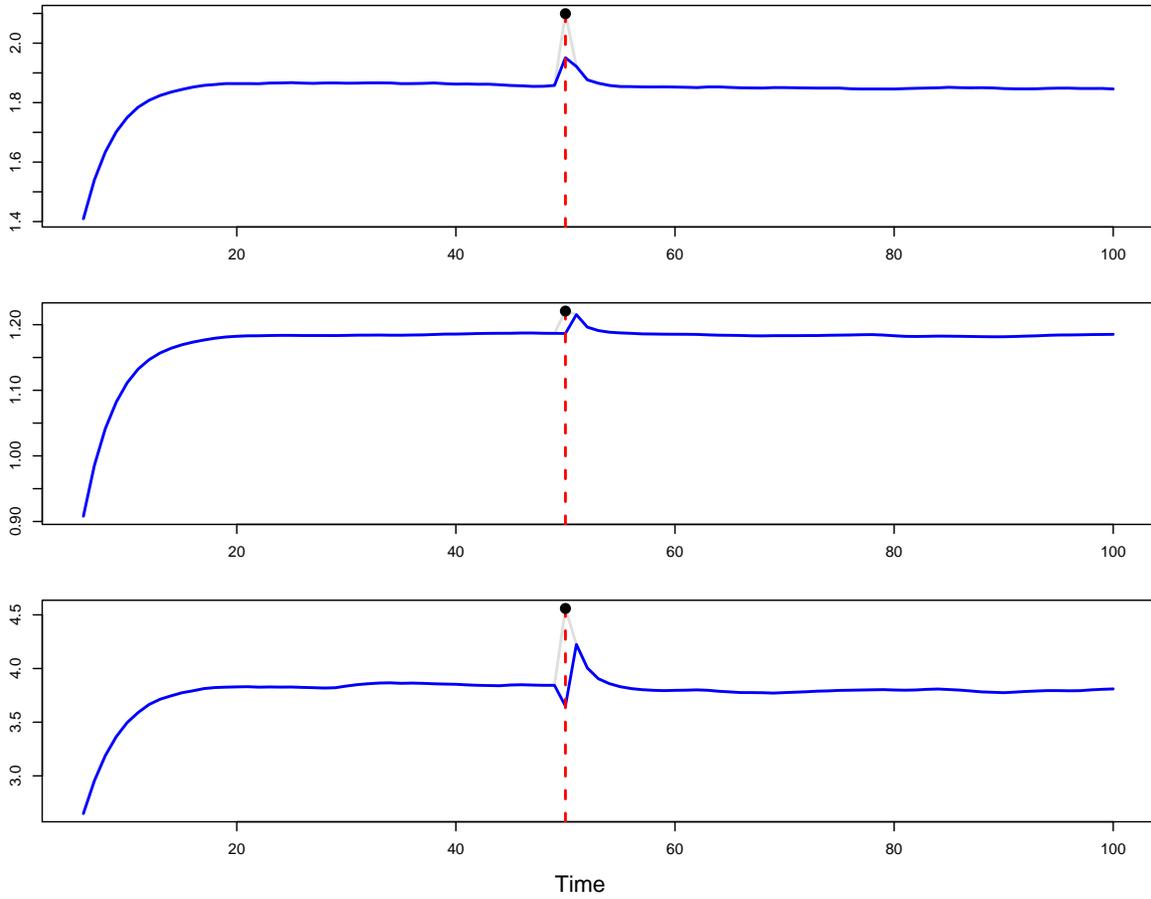
Notes: The vertical axis represents the share of eligible months where a given forecaster changed their forecast from the previous month in year $t - 1$. The horizontal axis represents the share of eligible months where a given forecaster changed their forecast from the previous month in year t . Mean values of horizontal bins are plotted (each bin represents a one month out of twelve months increment). Thus, a point on the 45-degree line means that, on average, forecasters in that group updated their forecasts at the same frequency as last year. Plotted points are scaled by the number of forecasters in each bin.

Figure 4: Information Rigidity: Inattentive vs. Attentive Agents



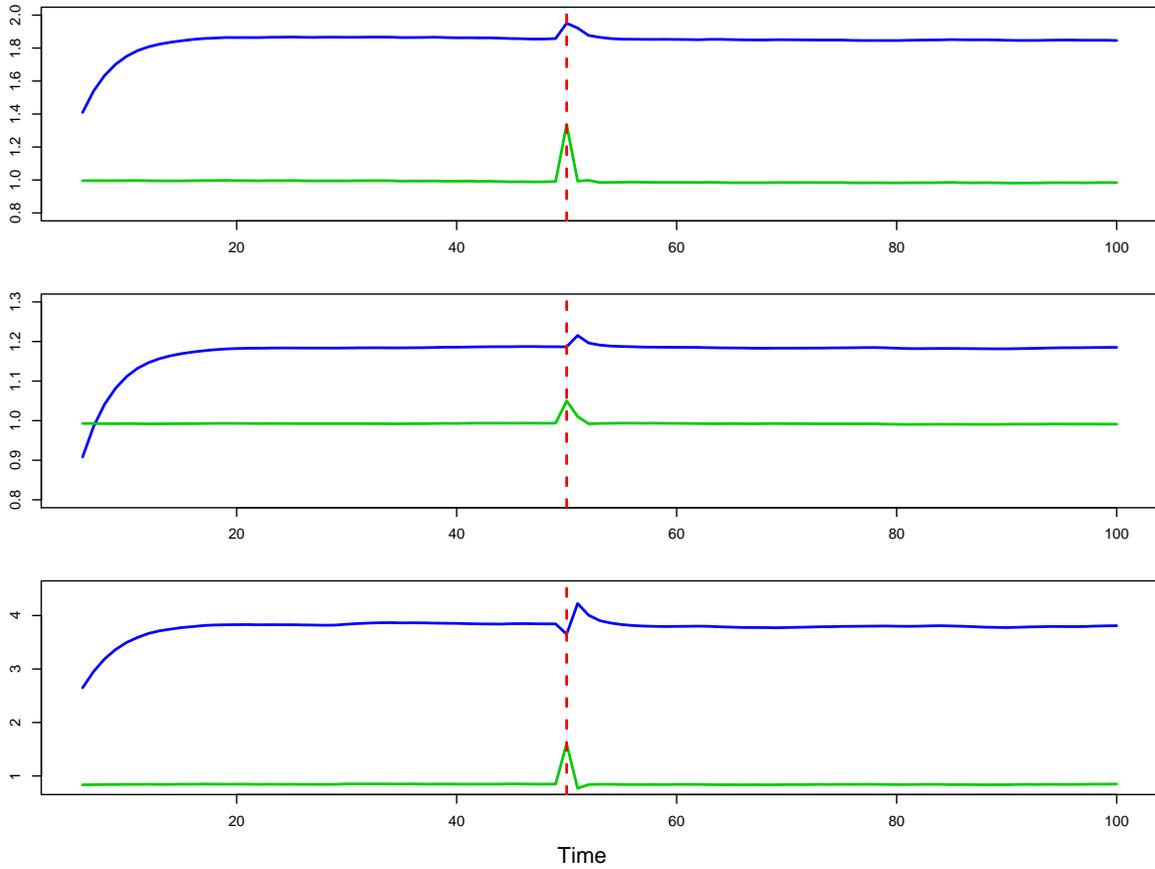
Notes: The left panel shows the degree of information rigidity for inattentive agents, measured as the percentage of agents who do not update their information sets. The right panel plots the average degree of information rigidity for attentive agents in predicting three variables, calculated as the scaled trace of the matrix of the weights attached to agent's previous forecast relative to new information.

Figure 5: Mean Squared Error: Inattentive Agents



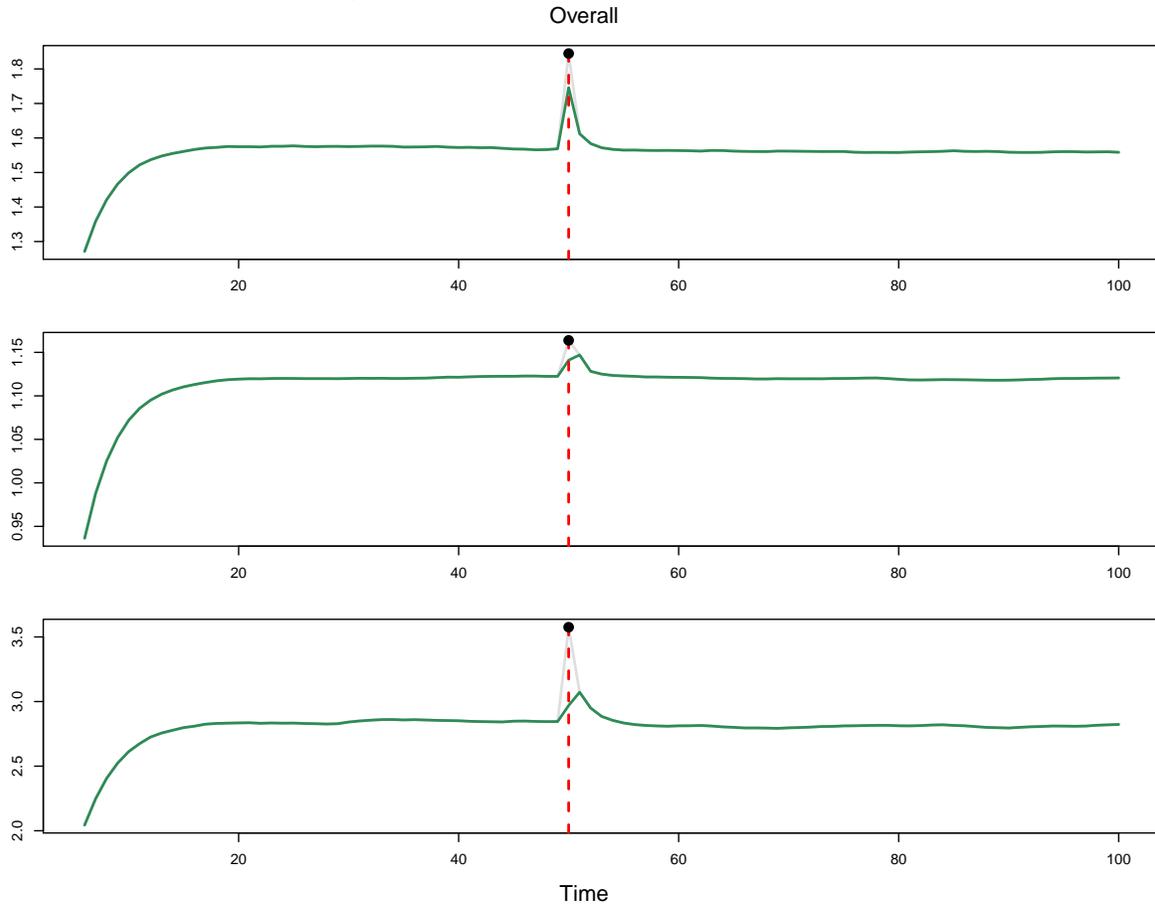
Notes: These plots show the mean squared error (MSE) in predicting three variables for inattentive agents (blue). The first (second or third) row plots the MSE in predicting the first (second or third) variable. The MSE is calculated according to (25) for inattentive agents. The counter-factual MSE (corresponding to what would have happened without a change in information rigidity) is plotted in grey scale, with a black dot at time index $\tau = 50$ (indicated by dashed red line) marking the value.

Figure 6: Mean Squared Error: Inattentive vs. Attentive Agents
 Inattentive vs. Attentive



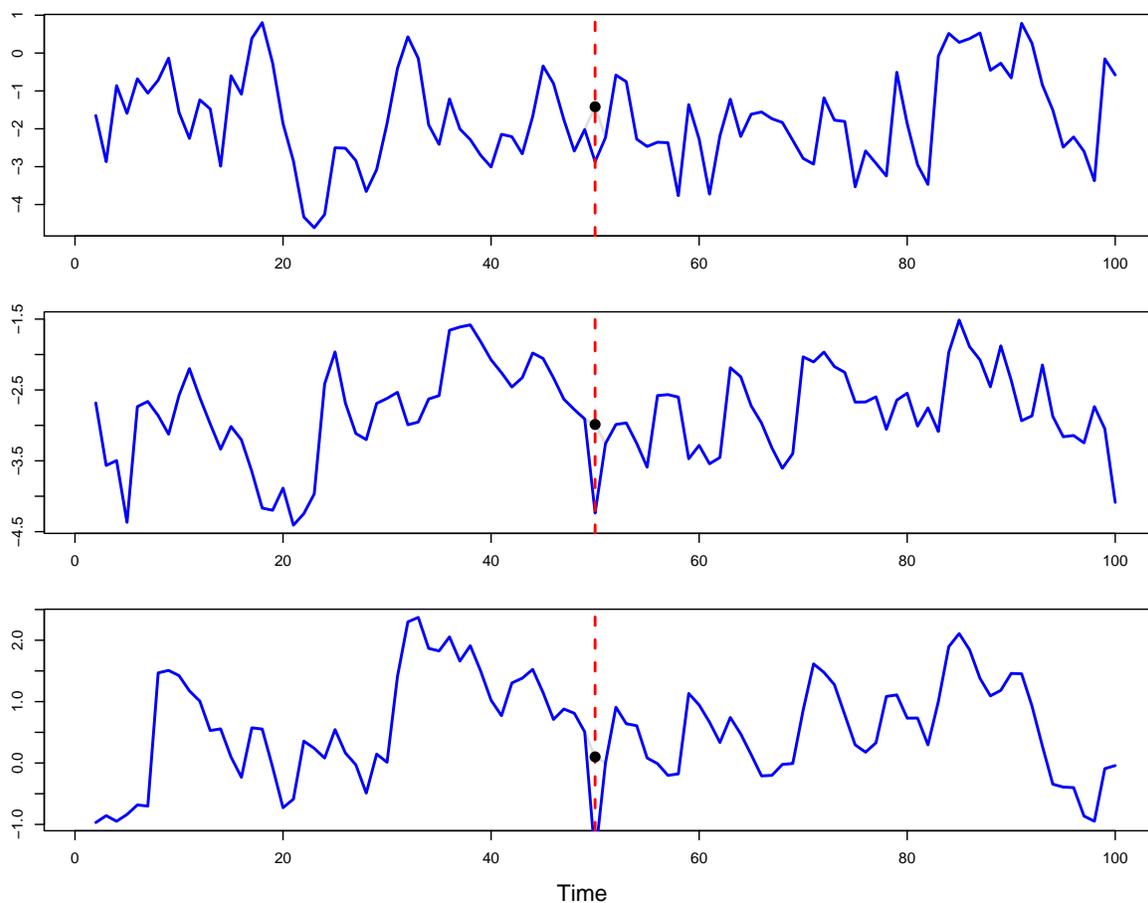
Notes: These plots show the mean squared error (MSE) in predicting three variables, for inattentive (blue) and attentive (green) agents. The first (second or third) row plots the MSE in predicting the first (second or third) variable. The MSE is calculated according to (16) for attentive agents and (25) for inattentive agents. The shock at time index $\tau = 50$ is indicated by dashed red line.

Figure 7: Mean Squared Error: Overall



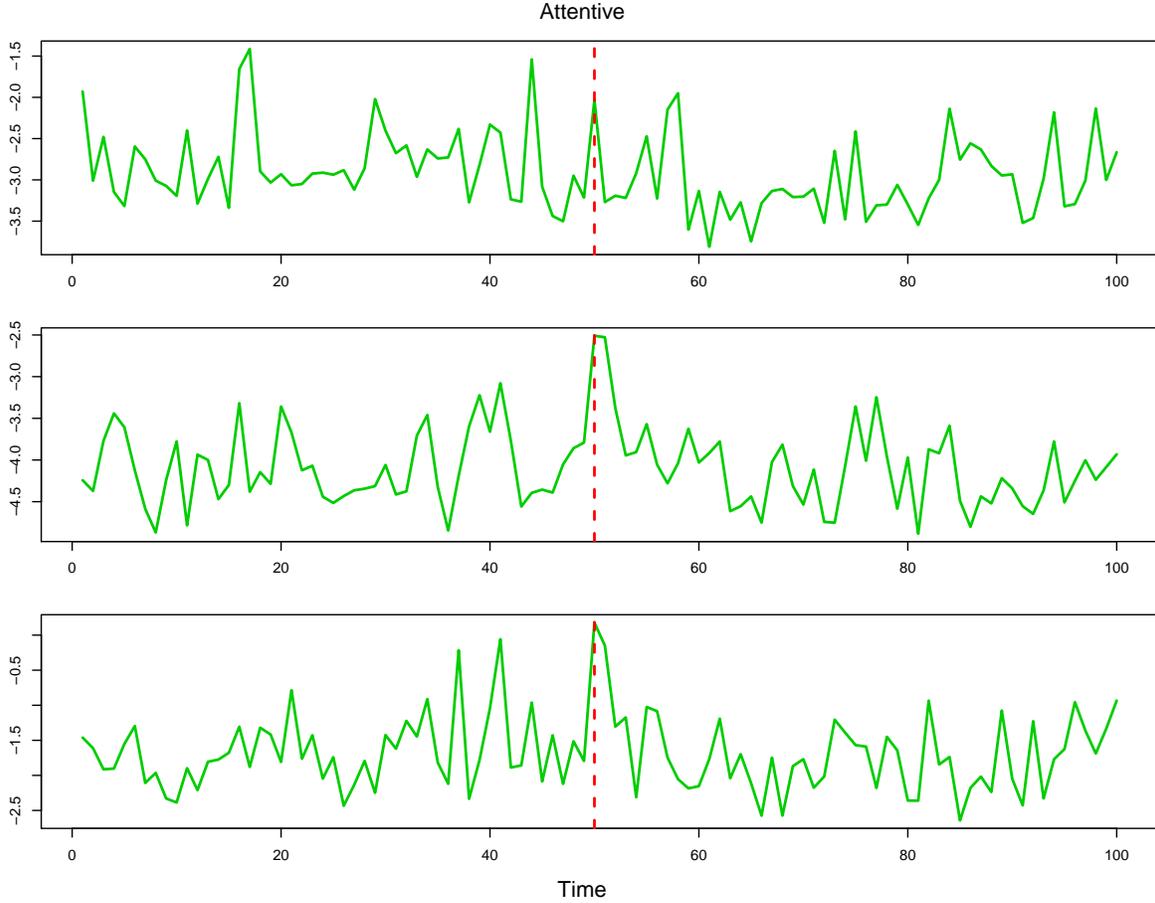
Notes: These plots show the mean squared error (MSE) in predicting three variables for all agents (blue-green). The first (second or third) row plots the MSE in predicting the first (second or third) variable. The MSE is calculated according to (27) for all agents. The counter-factual MSE (corresponding to what would have happened without a change in information rigidity in the inattentive agents) is plotted in grey scale, with a black dot at time index $\tau = 50$ (indicated by dashed red line) marking the value.

Figure 8: Forecast Disagreement: Inattentive Agents



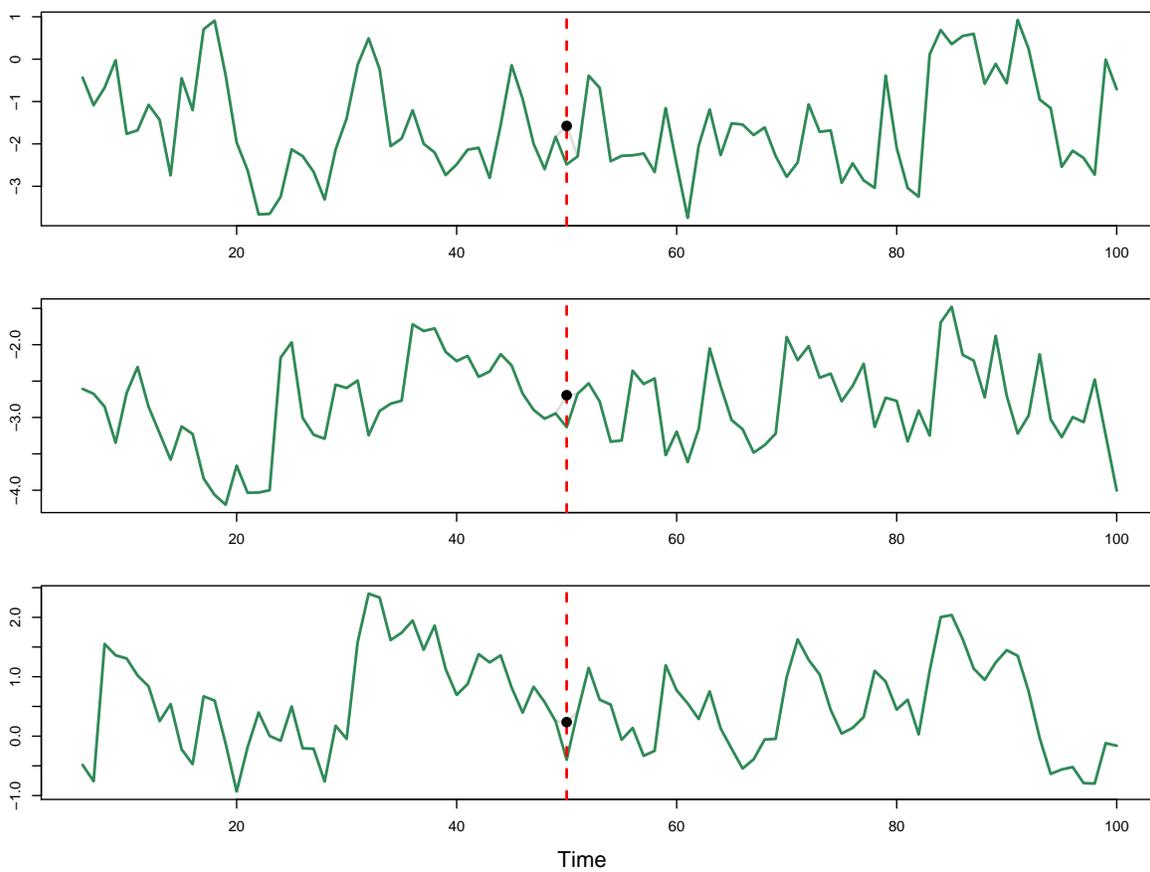
Notes: These plots show forecast disagreement in the log scale (blue) among inattentive agents in predicting three variables. The first (second or third) row plots the disagreement in predicting the first (second or third) variable. Disagreement is calculated according to (23) for inattentive agents. The counter-factual forecast disagreement (corresponding to what would have happened without a change in information rigidity) is plotted in grey scale, with a black dot at time index $\tau = 50$ (indicated by dashed red line) marking the value.

Figure 9: Forecast Disagreement: Attentive Agents



Notes: These plots show forecast disagreement in the log scale (green) among attentive agents in predicting three variables. The first (second or third) row plots the disagreement in predicting the first (second or third) variable. Disagreement is calculated according to (19) for attentive agents. The shock at time index $\tau = 50$ is indicated by dashed red line.

Figure 10: Forecast Disagreement: Overall



Notes: These plots show forecast disagreement in the log scale (blue-green) among all agents in predicting three variables. The first (second or third) row plots the disagreement in predicting the first (second or third) variable. Disagreement is calculated according to (28) for all agents. The counter-factual forecast disagreement (corresponding to what would have happened without a change in information rigidity) is plotted in grey scale, with a black dot at time index $\tau = 50$ (indicated by dashed red line) marking the value.

8 Appendix

Proof of Proposition 1. Equation (9) can be rendered with i superscripts for the i th agent, yielding

$$\begin{aligned}\widehat{x}_{t+1|t}(i) - x_{t+1} &= \Phi(\widehat{x}_{t|t-1}(i) - x_t) - \epsilon_{t+1} + K_t(i) e_t(i) \\ e_t(i) &= y_t(i) - H(i) \widehat{x}_{t|t-1}(i) = -H(i) (\widehat{x}_{t|t-1}(i) - x_t) + \delta_t(i).\end{aligned}$$

Note that $\delta_t(i)$ is orthogonal to $y_s(j)$ for all $s \leq t-1$ and all j ; moreover $\{\delta_t(i)\}$ is uncorrelated with $\{x_t\}$. Hence

$$Q_{t+1|t}^{(ij)} = \text{Cov}(\widehat{x}_{t+1|t}(i) - x_{t+1}, \widehat{x}_{t|t-1}(j) - x_t) \Phi' - \text{Cov}(\widehat{x}_{t+1|t}(i) - x_{t+1}, e_t(j)) K_t(j)' + \Sigma^\epsilon, \quad (29)$$

because ϵ_{t+1} is orthogonal to $\widehat{x}_{t+1|t}(i)$ and $\text{Cov}(x_{t+1}, \epsilon_{t+1}) = \Sigma^\epsilon$. Next,

$$\begin{aligned}\text{Cov}(\widehat{x}_{t+1|t}(i) - x_{t+1}, \widehat{x}_{t|t-1}(j) - x_t) &= \Phi Q_{t|t-1}^{(ij)} + K_t(i) \text{Cov}(e_t(i), \widehat{x}_{t|t-1}(j) - x_t) \\ &= \Phi Q_{t|t-1}^{(ij)} - K_t(i) H(i) Q_{t|t-1}^{(ij)}.\end{aligned}$$

Moreover,

$$\begin{aligned}\text{Cov}(\widehat{x}_{t+1|t}(i) - x_{t+1}, e_t(j)) &= \Phi \text{Cov}(\widehat{x}_{t|t-1}(i) - x_t, e_t(j)) + K_t(i) \text{Cov}(e_t(i), e_t(j)) \\ &= -\Phi Q_{t|t-1}^{(ij)} H(j)' + K_t(i) \left(H(i) Q_{t|t-1}^{(ij)} H(j)' + \begin{bmatrix} 0 & 0 \\ 0 & \Sigma_t \end{bmatrix} \right).\end{aligned}$$

Substituting into (29) yields

$$\begin{aligned}Q_{t+1|t}^{(ij)} &= [\Phi - K_t(i) H(i)] Q_{t|t-1}^{(ij)} \Phi' + \Sigma^\epsilon \\ &\quad + [\Phi - K_t(i) H(i)] Q_{t|t-1}^{(ij)} H(j)' K_t(j)' - K_t(i) \begin{bmatrix} 0 & 0 \\ 0 & \Sigma_t \end{bmatrix} K_t(j)',\end{aligned}$$

which simplifies to the stated formula. To initialize, we compute the $t = 0$ case, and observe that

$$Q_{1|0}^{(ij)} = \text{Cov}(\widehat{x}_{1|0}(i) - x_1, \widehat{x}_{1|0}(j) - x_1) = \text{Var}[x_1]. \quad \square$$

Proof of Proposition 2. The multi-step ahead forecasting of the state vector is straightforward: $\hat{x}_{t+1|t-k} = \Phi^k \hat{x}_{t+1-k|t-k}$. Also, iteration of (3) yields $x_{t+1} = \Phi^k x_{t+1-k} + \sum_{j=0}^{k-1} \Phi^j \epsilon_{t+1-j}$. Therefore the multi-step ahead forecasting error can be expressed in terms of one-step ahead forecasting error, via

$$\hat{x}_{t+1|t-k} - x_{t+1} = \Phi^k (\hat{x}_{t+1-k|t-k} - x_{t+1-k}) - \sum_{j=0}^{k-1} \Phi^j \epsilon_{t+1-j}.$$

We can also express the one-step ahead forecasting error in terms of prior such errors. Suppose $k \leq \ell$:

$$\begin{aligned} \hat{x}_{t+1-k|t-k} - x_{t+1-k} &= \Phi (\hat{x}_{t-k|t-k-1} - x_{t-k}) + K_{t-k} e_{t-k} - \epsilon_{t-k+1} \\ \dots &= \Phi^{\ell-k} (\hat{x}_{t+1-\ell|t-\ell} - x_{t+1-\ell}) + \sum_{j=0}^{\ell-k-1} \Phi^j (K_{t-k-j} e_{t-k-j} - \epsilon_{t+1-k-j}). \end{aligned}$$

This indicates that the multi-step ahead forecasting error is related to past one-step ahead forecasting errors as follows, when $k < \ell$:

$$\hat{x}_{t+1|t-k} - x_{t+1} = \Phi^\ell (\hat{x}_{t+1-\ell|t-\ell} - x_{t+1-\ell}) - \sum_{j=0}^{\ell-1} \Phi^j \epsilon_{t+1-j} + \sum_{j=0}^{\ell-k-1} \Phi^{j+k} K_{t-k-j} e_{t-k-j}.$$

The errors e_t have the following form (using the assumption that no private information is present):

$$e_{t-k-j} = B (x_{t-k-j} - \hat{x}_{t-k-j|t-k-j-1}) + \eta_{t-k-j}. \quad (30)$$

For $0 \leq j \leq \ell - k - 1$, η_{t-k-j} is uncorrelated with $\hat{x}_{t+1-\ell|t-\ell} - x_{t+1-\ell}$, and moreover for $0 \leq j \leq \ell - 1$, ϵ_{t+1-j} is uncorrelated with $\hat{x}_{t+1-\ell|t-\ell} - x_{t+1-\ell}$. Now using (30), we can re-express the one-step ahead forecasting errors as

$$\begin{aligned} \hat{x}_{t+1-k|t-k} - x_{t+1-k} &= (\Phi - K_{t-k} B) (\hat{x}_{t-k|t-k-1} - x_{t-k}) + K_{t-k} \eta_{t-k} - \epsilon_{t-k+1} \\ \dots &= \prod_{j=k}^{\ell-1} (\Phi - K_{t-j} B) (\hat{x}_{t-\ell+1|t-\ell} - x_{t-\ell+1}) \\ &\quad + \prod_{j=k}^{\ell-2} (\Phi - K_{t-j} B) (K_{t-\ell+1} \eta_{t-\ell+1} - \epsilon_{t-\ell+2}) \\ \dots &+ (\Phi - K_{t-k} B) (K_{t-k-1} \eta_{t-k-1} - \epsilon_{t-k}) + K_{t-k} \eta_{t-k} - \epsilon_{t-k+1}. \end{aligned}$$

The convention regarding the product symbols is as discussed in Proposition 2. Hence the multi-step ahead forecasting errors can be re-expressed as

$$\begin{aligned} \widehat{x}_{t+1|t-k} - x_{t+1} &= \Phi^k \prod_{j=k}^{\ell-1} (\Phi - K_{t-j} B) (\widehat{x}_{t-\ell+1|t-\ell} - x_{t-\ell+1}) \\ &\quad + \Phi^k \prod_{j=k}^{\ell-2} (\Phi - K_{t-j} B) (K_{t-\ell+1} \eta_{t-\ell+1} - \epsilon_{t-\ell+2}) \\ &\quad \dots + \Phi^k (\Phi - K_{t-k} B) (K_{t-k-1} \eta_{t-k-1} - \epsilon_{t-k}) + \Phi^k K_{t-k} \eta_{t-k} - \sum_{j=0}^k \Phi^j \epsilon_{t+1-j} \end{aligned} \quad (31)$$

when $k \leq \ell - 2$; when $k = \ell - 1$ the simpler formula is

$$\widehat{x}_{t+1|t-k} - x_{t+1} = \Phi^k (\Phi - K_{t-k} B) (\widehat{x}_{t-k|t-k-1} - x_{t-k}) + \Phi^k K_{t-k} \eta_{t-k} - \sum_{j=0}^k \Phi^j \epsilon_{t+1-j}.$$

From these expressions, the formulas for $R_{k,\ell}$ can now be deduced. The case $R_{\ell,\ell}$ is standard, whereas for $R_{\ell-1,\ell}$ indicates we should set $k = \ell - 1$, and together with

$$\widehat{x}_{t+1|t-\ell} - x_{t+1} = \Phi^\ell (\widehat{x}_{t+1-\ell|t-\ell} - x_{t+1-\ell}) - \sum_{j=0}^{\ell-1} \Phi^j \epsilon_{t+1-j} \quad (32)$$

we find $R_{\ell-1,\ell}$ has the stated expression. This uses the fact that $\widehat{x}_{t+1-\ell|t-\ell} - x_{t+1-\ell}$ is uncorrelated with $\eta_{t-\ell+1}$, as well as ϵ_{t+1-j} for $0 \leq j \leq \ell - 1$. Next, for $k \leq \ell - 2$ we compute $R_{k,\ell}$ using (32) together with (31). \square

Table A1. Information Rigidities Based on Forecast Error

VARIABLES	(1) Forecast Error	(2) Forecast Error	(3) Forecast Error	(4) Forecast Error
Forecast Revision	0.486*** (0.0162)	0.509*** (0.0177)	0.500*** (0.0168)	0.500*** (0.0173)
Forecast Rev * Disaster		-0.139*** (0.0425)		
Disaster		-0.00725 (0.0169)		
Forecast Rev * Disaster (News Scaling)			-0.0870*** (0.0272)	
Disaster (News Scaling)			-0.00853 (0.0106)	
Forecast Rev * Disaster (Combined Scaling)				-0.0838** (0.0353)
Disaster (Combined Scaling)				-0.0227 (0.0140)
Observations	31,981	31,981	31,981	31,981
R^2	0.141	0.141	0.141	0.141
Time FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
VAR FE	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions performed for forecasts across 54 countries (including forecasts of GDP, CPI, long- and short-run interest rates, unemployment, and consumption). Forecast Error denotes the difference of the ex-post true value from the mean forecast. Forecast Revision denotes the difference of the mean forecast from the previous month's mean forecast. 'Disaster' is an indicator variable for a disaster occurring in a particular country-month for over 1,000 natural disasters in the sample. 'News Scaling' refers to the ratio of news articles written about a country in the 5 days following a disaster to those written in the 5 days before a disaster (has a mean of 1 and a max value of 6). 'Combined Scaling' for disasters refers to a combined z-score comprised of the news scaling, the monetary damages caused by the disaster, and the number of deaths caused by the disaster (mean of 1 and maximum of 4.5).

Table A2. Information Rigidities Based on Forecast Revision

VARIABLES	(1) Forecast Rev	(2) Forecast Rev	(3) Forecast Rev	(4) Forecast Rev
Lagged Forecast Revision	0.154*** (0.00549)	0.159*** (0.00599)	0.158*** (0.00571)	0.158*** (0.00586)
Lag Forecast Rev * Disaster		-0.0332** (0.0147)		
Lagged Disaster		0.00687 (0.00593)		
Lag Forecast Rev * Disaster (News Scaling)			-0.0248*** (0.00949)	
Lagged Disaster (News Scaling)			0.000560 (0.00373)	
Lag Forecast Rev * Disaster (Combined Scaling)				-0.0293** (0.0122)
Lagged Disaster (Combined Scaling)				0.00133 (0.00490)
Observations	31,955	31,955	31,955	31,955
R^2	0.058	0.058	0.058	0.058
Time FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
VAR FE	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Regressions performed for forecasts across 54 countries (including forecasts of GDP, CPI, long- and short-run interest rates, unemployment, and consumption). Forecast Revision denotes the difference of the mean forecast from the previous month's mean forecast. 'Disaster' is an indicator variable for a disaster occurring in a particular country-month for over 1,000 natural disasters in the sample. 'News Scaling' refers to the ratio of news articles written about a country in the 5 days following a disaster to those written in the 5 days before a disaster (has a mean of 1 and a max value of 6). 'Combined Scaling' for disasters refers to a combined z-score comprised of the news scaling, the monetary damages caused by the disaster, and the number of deaths caused by the disaster (mean of 1 and maximum of 4.5).