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Expectation formation following pandemic events

Zidong An [a], Dingqian Liu [b], Yuzheng Wu [a,*]

[a] School of Applied Economics, Renmin University of China, China
[b] Department of Economics, American University, United States of America

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ABSTRACT

Previous studies find that the degree of information rigidity is negatively associated with natural disaster shocks, recessions, and high economic uncertainty, suggesting that the expectation formation process is state dependent. Matching a large panel data of macroeconomic forecasts to the pandemic data, this letter shows that the degree of information rigidity declines significantly following pandemic events, confirming that the expectation formation process is also driven by unexpected health shocks.

1. Introduction

Macroeconomic forecasts play a central role in economic agents' decisions and macroeconomic dynamics. Expectation formation is the key to understand how these forecasts are made, and it has long been discussed since the 1970s (e.g., Lucas, 1972). The current resurgence of interest in expectation formation process has been inspired by the mismatch between theoretical predictions and empirical evidence, and the full-information rational expectation hypothesis has been questioned specifically. Nordhaus (1987) finds that forecasters tend to slowly incorporate new information and smooth forecasts, and he argues that slow forecast revisions could occur for behavioral reasons. From the literature, two prominent models are developed to study the expectation formation process: the sticky-information model (Mankiw and Reis, 2002) explains forecast smoothing as a rational response that forecasters not updating information sets continuously; the noisy-information model (Sims, 2003; Woodford, 2003) sees forecast smoothing as a result of which forecasters are not able to distinguish information from noisy signals. Despite their differences, both models agree on the existence and importance of information rigidity in forecasters' expectation formation.

This letter builds on the empirical literature that estimates information rigidity using survey data and pays special attention to the state-dependent feature of expectation formation process. Coibion and Gorodnichenko (2015) first document the state-dependent expectation formation that the degree of information rigidity declines during recession periods. Lahiri and Zhao (2016) study the U.S. surveys of consumers and show that consumer sentiment is determined by macroeconomic conditions. Binder (2017a) finds that consumers inflation expectation uncertainty is countercyclical and is affected by volatility and Economic Policy Uncertainty. Binder (2020) surveys over 500 consumers and studies their expectations facing Covid-19 before and after informing them about the policy change. Baker et al. (2020) find that the degree of information rigidity becomes significantly lower following nature disaster shocks. They develop a novel learning model to study the two channels—attention effect and uncertainty effect—through which the shocks affect expectation formation. This letter follows the empirical literature and seeks to investigate how does pandemic, as a health shock, affect the expectation formation process.

The economic impacts of pandemic have been studied. We refer to Ma et al. (2020) for a comprehensive survey. They find that real GDP growth falls by around 3 percent after a pandemic, and output stays below pre-pandemic level for about five years. The focus of this letter is not on how pandemic events affect the economy. It studies how information shocks from these events affect the expectation formation of forecasters. Using Consensus Forecasts data, we find that forecasters' degree of information rigidity decreases substantially following pandemic events.

* Correspondence to: Renmin University of China, 59 Zhongguancun Street, Beijing, 100872, China.
E-mail address: YuzhengWu@ruc.edu.cn (Y. Wu).

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2. Pattern of forecast smoothing

We match a large panel survey forecasts data with pandemic events. We retrieve GDP growth forecasts from Consensus Forecasts. Each month, professional forecasters are surveyed about their forecasts for GDP growth in the current and next year.[1] For each forecasting target year, there is a sequence of 24 forecasts with forecast horizon getting shorter by month. We use consensus forecasts from 1990 to 2020 covering 85 countries. As of the pandemic events data, we follow Ma et al. (2020) and focus on five major pandemic events: SARS in 2003, H1N1 in 2009, MERS in 2012, Ebola in 2014, and ZIKA in 2016. We also include COVID-19 in 2019 as a global pandemic event. Aside from the COVID-19, H1N1 is the most widespread one and it affects 79 out of the 85 countries in our sample.

Fig. 1 illustrates the evolution of average GDP growth forecasts (bar charts) in pandemic years and compares them with the overall evaluation of unconditional forecasts (dashed line). We take arithmetic average of GDP growth forecasts across all countries that are affected. The first 12 periods show average forecasts made in the previous year and the subsequent 12 periods show current-year forecasts, for the same target period. The solid line shows the actual value of the target period, calculated as the average value across all pandemic years and countries.

What does Fig. 1 reveals? Unconditional forecasts show a pattern of smoothing and the forecast revisions are gradual. Similar patterns are shown in recent studies based on different surveys. For example, Binder (2017b) uses the Federal Reserve Bank of New York Survey of Consumer Expectations and shows that forecasters tend to make small forecast revisions. Lahiri and Zhao (2020) use the Blue Chip survey and show that a large portion of individual forecast revisions are zero. Forecasts for the pandemic years start out very close to the unconditional average, then converge to the actual value. Though forecast revisions are relatively larger in magnitude, they still show a pattern of smoothing.

3. Information rigidity following pandemic

Next, we test for information rigidity during normal years and pandemic years. Our first specification follows the approach proposed by Nordhaus (1987). The presence of information rigidity can be tested by regressing a series of forecast revisions on the lagged forecast revisions:

$$Rev_{i,t+1} = \gamma Rev_{i,t} + \mu_i + \sigma_{t+1} + \varepsilon_{i,t+1} \tag{1}$$

where $Rev_{it} = \overline{F}_{it} - \overline{F}_{i,t-1}$ is the forecast revision between current and past mean forecasts for the same target. A full set of country and time fixed effects denoted by μ_i and σ_t, respectively, are included to control for time-invariant characteristics and global trend in forecast revisions. Under the null hypothesis of full-information rational expectation, forecast revisions should be serially uncorrelated, and the persistency parameter γ would be statistically indifferent from zero. In the presence of information rigidity, γ would be significantly positive and a larger magnitude would indicate a relatively higher degree of information rigidity.

Our second specification follows the approach proposed by Coibion and Gorodnichenko (2015). It has been widely used to quantify the length of information rigidity in the literature. Compared to the Nordhaus (1987) test, the Coibion and Gorodnichenko (2015) approach can not only test for the presence of information rigidity but also quantify the duration between information updates or the weight forecasters allocate on old beliefs. The degree of information rigidity can be tested by regressing forecast errors against forecast revisions:

$$Err_{it} = \beta Rev_{it} + \mu_i + \sigma_t + \varepsilon_{it} \tag{2}$$

where $Err_{it} = A_{it} - \overline{F}_{it}$ is the difference between actual value and forecast. The coefficient β measures the degree of information rigidity, and it can be translated into either the fraction of forecasters who do not update information in each period (sticky-information model) or the weight forecasters put on old information (noisy-information model). A greater positive magnitude of β indicates a higher level of information rigidity.

The main interest of this letter lies in the expectation formation process facing pandemic events. On the state-dependency feature, studies find that the degree of information rigidity increases systematically after the Great Moderation (Coibion and Gorodnichenko, 2015), while it decreases during recession periods (An et al., 2018) or when volatility and economic uncertainty are high (An et al., 2020). Baker et al. (2020) use natural disaster data to prove the causal effect of an exogenous shock on the decreases in information rigidity. To further test for the extent of information rigidity following pandemic, we include a dummy variable for pandemic period and its interaction with the forecast revision into the two baseline specifications discussed above:

$$\begin{aligned} Rev_{i,t+1} &= \gamma_1 Rev_{i,t} + \gamma_2 Rev_{i,t} \times Pand_{i,t} + \gamma_3 Pand_{i,t} \\ &\quad + \mu_i + \sigma_{t+1} + \varepsilon_{i,t+1} \end{aligned} \tag{3}$$

$$\begin{aligned} Err_{it} &= \beta_1 Rev_{it} + \beta_2 Rev_{it} \times Pand_{i,t} + \beta_3 Pand_{i,t} \\ &\quad + \mu_i + \sigma_t + \varepsilon_{it} \end{aligned} \tag{4}$$

where the interaction term captures the nonlinear and state-dependent information rigidity. A negative and significant γ_2 (and β_2) indicates a relatively lower degree of information rigidity following the pandemic events. To control for horizon effect, we follow Baker et al. (2020) and restrict our analysis to the next-year forecasts. The four specifications discussed above are estimated through OLS regression with Driscoll–Kraay standards errors.

Table 1 reports the empirical results. As shown in Column 1, forecast revisions are significantly autocorrelated, with a monthly persistency parameter of 0.095. Column 2 shows that the forecast errors are positively related to forecast revisions. With the sticky-information model, the estimated coefficient of 0.605 can be explained as 38 percent of forecasters not updating information every month; while with the noisy-information model, it can be explained as forecasters putting a 38 percent weight on the old believes when forming expectations.[2] We interpret these results as strong evidence of information rigidity when forecasting GDP growth.

Columns 3 and 4 present estimates with additional terms of pandemic indicator and its interaction with forecast revisions. For both approaches, the interactions show negative and significant coefficient estimates. The persistency in forecast revisions decreases by 0.078 facing the pandemic, while the association between forecast errors and forecast revisions decreases by approximately half. Also, adding an interaction term does not have major effect on the coefficient estimates of forecast revision. These results indicate that forecasters tend to update their information sets more frequently and incorporate new information more efficiently facing pandemic events.[3] Bordalo et al. (2020) document that forecasters under-react to information at the consensus level, while over-react at the individual level. Our results

[1] The survey frequency forms a lower bound for estimated inattention; see also Binder (2017b).

[2] Information rigidity $= \beta/(1+\beta)$.

[3] We conduct robustness check taking into account that forecast revisions and errors are generally larger in absolute value during pandemics, and the results are generally robust.

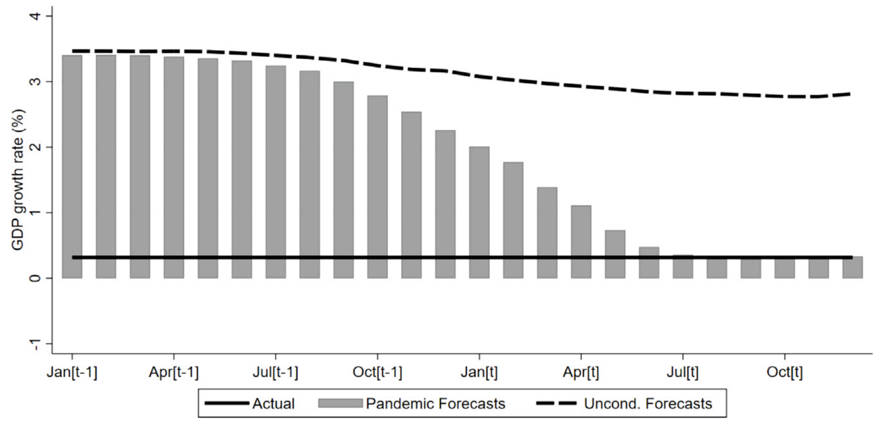

Fig. 1. Forecast Smoothing.

Table 1
State-dependent information rigidity.

	(1) Forecast rev (forward)	(2) Forecast error	(3) Forecast rev (forward)	(4) Forecast error
Forecast revision	0.095***	0.605***	0.102***	0.632***
	(0.022)	(0.097)	(0.023)	(0.106)
Forecast rev × Pandemic			−0.078**	−0.296**
			(0.033)	(0.146)
Pandemic			0.001	−0.096
			(0.012)	(0.131)
R-squared	0.20	0.28	0.20	0.28
Observations	23615	21708	23615	21708
Number of groups	85	85	85	85
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable is forward forecast revision in columns (1) and (3), and forecast error in columns (2) and (4).

are consistent with these statements and show that the pandemic events alleviate the under-reaction but do not reverse this pattern.

4. Conclusion

This letter contributes to the empirical literature that studies expectation formation process and its state-dependency feature. By matching survey forecasts of 85 countries to the pandemic events data, we show that macroeconomic forecasts feature a pattern of smoothing. For the pandemic years, forecasts are revised more aggressively, but such a pattern of forecast smoothing still holds. Formal tests show significant information rigidity in macroeconomic forecasts, and it declines substantially following pandemic events. This letter provides an alternate view of what affects forecasters' expectation formation process. Facing unexpected health shocks, forecasters tend to pay more attention to the new information, and incorporate new information more efficiently when forming expectations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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