H.O. Stekler Research Program on Forecasting

WORKING PAPER SERIES

How do Macroeconomic Expectations React to Extreme Weather Shocks?

Andrew B. Martinez
Office of Macroeconomic Analysis, Department of the Treasury
School of Advanced International Studies, the Johns Hopkins University
H.O. Stekler Research Program on Forecasting, the George Washington University
Climate Econometrics, Nuffield College

Working Paper No. 2025-001

January, 2025

H. O. STEKLER RESEARCH PROGRAM ON FORECASTING
Department of Economics
Columbian College of Arts & Sciences
The George Washington University
Washington, DC 20052
https://cer.columbian.gwu.edu/ho-stekler-research-program-forecasting

How do Macroeconomic Expectations React to Extreme Weather Shocks?

Andrew B. Martinez*

January 2025

Abstract

I study how extreme weather events affect macroeconomic expectations to better understand the propagation of climate shocks. I identify the immediate and dynamic effects of a Hurricane Katrina-sized shock on business economists' expectations of GDP growth, inflation, and interest rates over the past two decades. My results highlight the importance of forecast revision dynamics. A shock reduces expected growth, but the total dynamic effect is more than double the immediate effect. It is also perceived as a negative supply shock as inflation expectations rise and interest rate expectations fall. The persistence of the response supports models of delayed overshooting.

JEL: C23, C33, E66, Q54

*Office of Macroeconomic Analysis, U.S. Department of the Treasury (email: Andrew.Martinez@treasury.gov); School of Advanced International Studies, The Johns Hopkins University; H.O. Stekler Research Program on Forecasting, The George Washington University; Climate Econometrics, Nuffield College. The views expressed here are my own and do not necessarily represent those of the Treasury Department or the U.S. Government. Thanks to Wolters Kluwer and Haver Analytics for providing access to the Blue Chip forecasts. Thanks to Lenin Arango-Castillo, Neil R. Ericsson, Jennifer L. Castle, Guillaume Chevillon, Julio Ortiz, Simon Sheng, and Tara Sinclair for helpful comments on earlier drafts. I have also benefited from comments from and discussions with participants at numerous seminars and conferences. All errors are my own.

1 Introduction

The increasing frequency and widespread destruction from extreme weather events has sparked a growing interest in understanding how large climate shocks affect the macroeconomy and, consequently, how economic policy should respond. This is challenging because major natural disasters have historically been relatively rare and are often localized with drawn out effects over long horizons. Furthermore, the effects are likely exacerbated by changes in expectations which subsequently filter back into the economy through investment and other decisions. Without a clear sense of how expectations dynamics react, it is difficult to understand the full effects of a climate shock and to implement timely and targeted policies that mitigate long-term economic disruptions.

This paper investigates how extreme weather shocks, specifically hurricanes, affect macroeconomic expectations. To answer this question, I construct a new high-frequency panel by merging two monthly Blue Chip surveys of more than 50 business economists' forecasts of GDP growth, CPI inflation, and 10-year Treasury yields over the past two decades. I also generate a series of real-time hurricane damage shocks based on advance estimates from catastrophe modelers and analyze how expectations are revised in response to these shocks using a dynamic panel data model.

While the existing literature has largely focused on the immediate effects of such shocks on expectations, I argue that the total dynamic effects of a shock at a given forecast horizon may differ substantially from the initial reaction, especially when revision inefficiencies are accounted for. To address this, I calculate both the immediate and total dynamic effects of a shock and propose a new test for weaker revision inefficiency to assess the statistical significance of these differences.

I find that extreme weather events have large and persistent dynamic effects on macroeconomic expectations. A shock of the magnitude of Hurricane Katrina immediately reduces expected real GDP growth by 0.3 percentage points (annualized). The total dynamic effect is significantly larger at more than double the initial effect. Expected growth gradually returns to its pre-shock trajectory over several quarters. For comparison, it would take a 5-standard-deviation increase in the VIX or a 2-standard-deviation surprise increase in initial unemployment claims to produce similar effects on GDP growth expectations.

My results are broadly consistent with existing models of expectations formation. Comparing against actual economic outcomes, I find that private forecasters are typically slower to incorporate the effects of the shock, anticipating a more prolonged recovery than is ultimately observed. The expected effects are also less distorted when considering the Federal Reserve Board's (FRB) staff forecasts. This aligns with models of costly information and delayed overshooting, as discussed in Angeletos et al. (2021).

The effect of a hurricane shock on expectations is also consistent with a temporary negative supply shock: growth expectations decline, inflation expectations rise, and interest rate expectations fall as slower growth expectations temporarily outweigh concerns about higher inflation. Over longer horizons, expectations for economic activity and interest rates gradually return to pre-shock levels, while price expectations stabilize at a higher level.

This paper contributes to several key strands of the literature. First, it expands on the literature examining the macroeconomic effects of extreme weather and natural disasters. Previous studies present mixed results: some find limited or no macroeconomic effects (e.g. Strobl, 2011, Cavallo et al., 2013, Linder et al., 2013) while others find that any negative effects are temporary (e.g. Ludvigson et al., 2021, Natoli, 2022, Kim et al., 2024, Chavleishvili and Moench, 2025).[1] Some studies even find persistent negative effects on growth (Hsiang and Jina, 2014) while others point to positive local effects (Roth Tran and Wilson, 2020). My findings suggest that hurricanes lead to a temporary reduction in GDP, with private forecasters interpreting the event as a transitory supply shock with permanently higher prices.

Second, my results relate to recent research linking expectations and the economic effects of extreme weather. Dietrich et al. (2021) and Cantelmo (2022) propose theoretical frameworks through which the macroeconomic effects of climate change are determined via an expectations channel. Meinerding et al. (2023) shows that individuals concerned about climate change tend to have lower inflation expectations. Baker et al. (2020), the closest paper to mine, demonstrates that the speed of GDP growth revisions changes following large weather news shocks. I reaffirm this result and emphasize the importance of accounting for the full dynamic effects of a shock, illustrating that expectations react in a nonlinear fashion.

Third, this paper contributes to the literature on deviations from full-information rational expectations. This dates back to Nordhaus (1987) and saw renewed attention with Coibion and Gorodnichenko (2015)), who showed that consensus forecasts underreact to new information, while Bordalo et al. (2020) demonstrated that individual forecasters tend to overreact. My findings largely align with the latter. However, I find that these general measures of forecaster inefficiency fail to capture the dynamic effects of shocks. Instead, my results are consistent with Angeletos et al. (2021)'s model of delayed overshooting.

Fourth, this paper has implications for the literature on identifying the causal effects of monetary policy shocks on macroeconomic expectations. This strand of research, which dates back to Campbell et al. (2012, 2017) and has gained prominence in recent years (e.g. Nakamura and Steinsson, 2018, Lunsford, 2020, and

[1] The differing results led Federal Reserve Board Governor Chris Waller to conclude in 2023 that "severe weather events like hurricanes do not likely have an outsized effect on growth rates in countries like the United States". See Christopher J. Waller (2023) "Climate Change and Financial Stability", May 11, 2023, `https://www.federalreserve.gov/newsevents/speech/waller20230511a.htm` (last accessed September 25, 2023).

Bauer and Swanson, 2023), has focused exclusively on identifying the immediate effects of a shock. has focused predominantly on immediate effects. My results show that focusing on the immediate effects of a shock substantially underestimates the total effect on expectations.

Finally, my paper builds on the literature on the use of high-frequency data to identify causal effects of shocks. Ghanem and Smith (2021) argue that the utility of high-frequency data depends on how frequently the shock is measured. Jacobson et al. (2022) and Buda et al. (2023) demonstrate that high-frequency data can reveal the effects of monetary policy shocks, while Chang and Levinson (2023) and Binder et al. (2024) show that forecast revisions at high frequencies expose important dynamics. I show that high-frequency revisions can help disentangle both immediate and dynamic effects of shocks at different forecast horizons, and that these dynamics can propagate differently across variables.

The paper proceeds as follows. Section 2 describes the models and methods. Section 3 outlines the forecast data and construction of the shocks, along with additional controls. Section 4 presents the results, beginning with the GDP nowcasts in section 4.1 and 4.2, followed by a discussion in section 4.3. Longer forecast horizons are discussed in 4.4 while comparisons with actual economic effects and with Federal Reserve Board forecasts are done in 4.5 and 4.6 respectively. Section 4.7 extends the results to a system of expectations. Section 5 concludes.

2 Empirical Methods

This section describes the models used to estimate and identify the causal effects of a large shock. I start by presenting a static forecast revisions framework and then discuss how it can be extended to allow for dynamic effects. I use this to illustrate the differences between the immediate and the total dynamic effects of a shock. Finally, I propose a test of the significance of the dynamic effects.

To understand how macroeconomic expectations respond to large shocks, consider a model where forecast revisions only depend on the shock and noise

$$\Delta f_{i,w,t+h} = \beta_{0,h} \mathrm{S}_{w,t} + v_{i,w,t+h}, \tag{1}$$

where $f_{i,w,t+h}$ is a forecast made by forecaster $i \in N$ during bi-week $w \in \{1,\ldots,W\}$ of quarter $t \in \{1,\ldots,T\}$ for horizon $h \in \{0,...,H\}$ and $\Delta f_{i,w,t+h} \equiv f_{i,w,t+h} - f_{i,w-1,t+h}$ is their biweekly forecast revision.[2] $\mathrm{S}_{w,t}$ is an exogenous shock that occurs over the period between when $f_{i,w-1,t+h}$ and $f_{i,w,t+h}$ were generated, and $v_{i,w,t+h}$ includes everything else such as the unexplained residuals, fixed effects, and any control variables.

[2]If $w = 1 : \Delta f_{i,1,t+h} \equiv f_{i,1,t+h} - f_{i,W,\{t-1\}+\{h+1\}}$ uses the last forecast in the current quarter made in the last quarter.

The parameter $\beta_{0,h}$ captures the immediate effect of $S_{w,t}$ on forecast revisions for horizon h. Faust and Wright (2008)'s conditional forecasting framework states that $\beta_{0,h}$ is identified if $S_{w,t}$ is strictly exogenous. This implies that forecasters do not anticipate the effects of the shock prior to its occurrence.[3]

Variations of this formulation have been used to identify causal effects.[4] A number of studies use equation (1) to identify the information effect of monetary policy or the causal effects of quantitative easing and forward guidance; e.g. see Campbell et al. (2012), Campbell et al. (2017), Nakamura and Steinsson (2018), Lunsford (2020), and Bauer and Swanson (2023).

Casini and McCloskey (2024) discuss the necessary conditions for establishing identification of causal effects in this framework. They argue that the shock, $S_{w,t}$, can not depend on and must dominate all other shocks in the forecast revision window (i.e. separability and relative exogeneity). These conditions relax the no anticipation assumption of strict exogeneity but require that the shock of interest dominates all other unmodeled shocks. Therefore, controlling for other shocks and shrinking the window limits contamination and improves identification of the causal effects.

Focusing on the immediate effect of a shock does not necessarily characterize its total dynamic effects. For example, an extensive literature discusses how forecasters either over or under-react to new information. One of the earliest and most prominent formulations, proposed by Nordhaus (1987), models this process by regressing lagged forecast revisions on contemporaneous forecast revisions at a specific forecast horizon h

$$\Delta f_{i,w,t+h} = \alpha_{1,h}\Delta f_{i,w-1,t+h} + u_{i,w,t+h}, \tag{2}$$

where $\alpha_{1,h}$ governs the revision dynamics and $u_{i,w,t+h}$ captures everything else. If $|\alpha_{1,h}| \neq 0$, then forecast revisions are weakly inefficient such that they use past forecast information to update their current forecasts.[5] The sign of $\alpha_{1,h}$ indicates the direction of inefficiency where if $\alpha_{h,1} > 0$ then forecasts are rigid or under-react to past information, whereas if $\alpha_{1,h} < 0$, then forecasters overreact to past information. There are many variations of this model but the general finding is that consensus forecasts under-react to new information and individual forecasters overreact; e.g. see Coibion and Gorodnichenko (2015) and Bordalo et al. (2020).[6]

[3]Parameter estimates for variables that are at least predetermined are consistent when using the within groups estimator in dynamic panel models when the time-dimension is large; see Alvarez and Arellano (2003).

[4]There are several unique aspects to the formulation in (1). First, it considers individual rather than consensus forecasts. Second it has two time scales: a biweekly time scale, w, over which forecasts are updated and a quarterly time scale, t, for which the forecasts are generated. Thus I there are two types of dynamics: forecast horizons (h) across different quarterly time horizons and forecast revisions (w) within the same quarterly time horizon.

[5]Strong inefficiency is when revisions are related to all information available when the previous forecast was made.

[6]Coibion and Gorodnichenko (2015) formulate a different version of (2) wherein they regress forecast revisions on forecast errors, which has subsequently become the more common approach in the literature. Nordhaus (1987) shows a close theoretical link between these formulations while Baker et al. (2020) demonstrate that the empirical results for both approaches are aligned. I focus on the pure revisions regression here because (a) I am specifically interested in the revisions themselves, (b) the dynamic

This implies that focusing exclusively on the immediate effect of a shock, as in equation (1), does not fully characterize the dynamic effects and the differences could be both economically and statistically large.

A shock can also have a nonlinear interaction with the forecast revision dynamics. For example, Baker et al. (2020) allow for state-dependent forecast revision inefficiencies by extending (2) to include an interaction between a large shock and lagged forecast revisions

$$\Delta f_{i,w,t+h} = \alpha_{1,h}\Delta f_{i,w-1,t+h} + \alpha_{2,h}\left(\Delta f_{i,w-1,t+h} \times \mathrm{S}_{w,t}\right) + \tilde{u}_{i,w,t+h}, \tag{3}$$

where $\alpha_{2,h}$ determines the speed at which forecasters incorporate new information based on the shock $S_{w,t}$ and $\tilde{u}_{i,w,t+h}$ captures the unexplained residuals. They find that consensus forecasts become more attentive to new information following large shocks such that rigidity is attenuated; i.e. $\alpha_{1,h} + \alpha_{2,h} \approx 0$. Thus, incorporating nonlinear interactions in the forecast revision dynamics may matter for the dynamic effects.

I estimate and test for the importance of these dynamics for the causal effects of a shock by formulating a general dynamic model. To capture both the immediate and potentially nonlinear dynamic effects of a shock I combine (1) with a modified (3) so that

$$\Delta f_{i,w,t+h} = \alpha_{1,h}\Delta f_{i,w-1,t+h} + \alpha_{2,h}\left(\Delta f_{i,w-1,t+h} \times \mathrm{S}_{w-1,t}\right) + \sum_{j=0}^{1} \beta_{j,h}\mathrm{S}_{w-j,t} + \varepsilon_{i,w,t+h}, \tag{4}$$

where $\beta_{j,h}$ captures the immediate and lagged effects of the shock, $\alpha_{1,h}$ represents linear revision dynamics, $\alpha_{2,h}$ governs non-linear revision dynamics, and $\varepsilon_{i,w,t,h}$ represents everything else.

The total dynamic forecast revision effects of the shock can be characterized based on the general dynamic model in (4). Tracing the shock iteratively through the autoregressive distributed lag forecast revision dynamics implies that the total dynamic effect on expectations at forecast horizon h is

$$\frac{\beta_{0,h}\left(1 + \alpha_{2,h}\mathrm{S}_{w-1,t}\right) + \beta_{1,h}}{1 - \alpha_{1,h}}, \tag{5}$$

which is determined by both the direct effects of the shock and the forecast revision dynamics.[7] While the immediate effect is linear in (4), the total dynamic effect is nonlinear in (5).

properties have a clearer interpretation and (c) it does not make use of actual data, which is often revised. That being said, as discussed further in the Supplemental Appendices, the empirical results are generally consistent across either approach.

[7] The representation in (5) is typically referred to as the long-run. However, in this context the forecast horizon is held constant such that the total can differ from the immediate effect at every horizon. The dynamic differences over longer forecast horizons are more closely associated with what Farmer et al. (2024) refer to as learning about the long-run. The variance of (5) is estimated following Bårdsen (1989) with multivariate extensions in Doornik and Hendry (2018). If the shock is serially uncorrelated, then estimates of the total dynamic effects are consistent using a pooled estimator from a large T dynamic panel model even with heterogenous effects; see Pesaran and Smith (1995).

Allowing the immediate effect of a shock to differ from the total effect has important implications for interpreting the efficiency of forecast revisions. Forecast revisions can be considered efficient in a weaker sense than Nordhaus (1987) if the immediate and total dynamic effects of a shock are identical such that the following null hypothesis holds conditionally on the shock size

$$\mathrm{H}_0|\mathrm{S}_{w-1,t}:\ \beta_{1,h}+\beta_{0,h}\left(\alpha_{1,h}+\alpha_{2,h}\times\mathrm{S}_{w-1,t}\right)\equiv 0. \tag{6}$$

This hypothesis nests Nordhaus (1987)'s notion of strong (and weak) efficiency wherein past (forecast) information does not explain forecast revisions; i.e. $\alpha_{1,h}=\alpha_{2,h}=\beta_{1,h}=0$. However, (6) is more general where past information from the persistence of incompletely modeled shocks is not necessarily penalized if it is completely offsetting. In other words, unlike other notions of forecast efficiency, (6) allows for the possibility that forecasters react to but have not completely modeled the dynamics of new information.

Econometrically, (6) implies a common factor restriction on (4) such that it simplifies to (1) and where $v_{i,w,t+h}$ has an autoregressive lag structure; see Hendry and Mizon (1978), Mizon and Hendry (1980), and Sargan (1980). However, if (6) does not hold, then there is a strong indication that forecasters over/under-react to new information and revision dynamics matter for identifying the total causal effects of a shock. The Supplemental Appendix provides detailed derivations and simulation results illustrating the advantages of testing for 'weaker efficiency' in this context.

A failure of weak efficiency does not necessarily imply a specific behavioral mechanism. The test purely rules out the possibility that forecasters may have incomplete information about the shocks that they are facing and whether or not dynamics matter. However, the results can be compared against existing behavioral frameworks, e.g. Angeletos et al. (2021), to assess whether the predictions from those models are consistent. They can also be compared across different types of forecasters, for different variables and against the actual economic effects of a shock.

The rest of the paper uses these methods to estimate and test for differences between the immediate and total effects of a large extreme weather shock on macroeconomics.

3 Data

This section describes most of the data and the forecasts used in the paper. Subsection 4.1 presents the surveys of Blue Chip forecasters and some properties of their forecast revisions. Subsection 4.2 discusses the extreme weather shocks and how they are constructed. Finally, subsection 4.3 describes additional controls including macroeconomic news announcement surprises.

3.1 Surveys of Blue Chip Forecasts

I merge forecasts from business economists from two monthly Blue Chip surveys administered by Wolters Kluwer to construct a new bi-weekly panel of forecasts. The Blue Chip Economic Indicators (BCEI) surveys economists in more than 50 financial institutions, major corporations, and economic consulting firms during the first week of the month on forecasts for macroeconomic variables for each quarter out through the next calendar year. The Blue Chip Financial Forecasts (BCFF) surveys economists at around 40 financial institutions and economic consulting firms during the last week of the month on forecasts of interest rates as well as real GDP growth and inflation for each quarter out through the next five quarters.

While the sample of forecasters across the two Blue Chip surveys is not identical, there is a large overlap between them. For example, 73% of the sample surveyed in the BCFF in late-September 2019 was surveyed two weeks later in the BCEI in early-October 2019 and accounted for 63% of the respective sample in that survey. Furthermore, of the 110 unique business economists surveyed by either Blue Chip survey between 2001-2020, 61 participated in both surveys.[8]

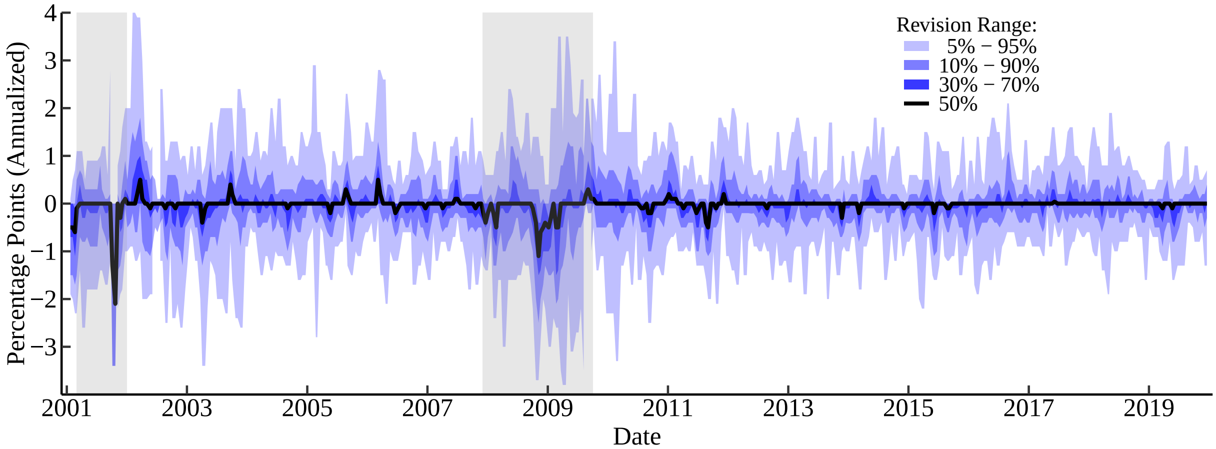
I consider the sample of 54 forecasters that contributed at least 40 biweekly GDP forecasts to these surveys. I observe between 41-477 GDP forecasts per individual with a median (mean) of 324 (297).[9] More than two-thirds of the sample is in the financial services industry (69%), just over half is located in the New York City metropolitan statistical area (54%), more than half are in publicly traded firms (54%), and around a third are in banks that are primary dealers with the Federal Reserve Bank of New York (35%).

There is a partial overlap of variables in the surveys. The BCFF primarily includes forecasts of financial variables and interest rates that are conditioned on predictions of output and inflation. The BCEI includes contains forecasts of macroeconomic variables without any conditioning assumptions. Both surveys include forecasts of real GDP growth, CPI inflation, the yield on 3-month Treasury bills, and the yield on 10-year Treasury notes. I exclude forecasts of the yield on the 3-month Treasury bills since for more than one third of the sample they are at or near the effective zero lower bound which could induce a censoring bias.

I pinpoint the information available to forecasters using official survey schedules. While the survey

[8]In a few cases I track individual forecasters across firms. However, I generally treat firms and forecasters interchangeable since the surveys typically refer to firms rather than individuals. For example, over the sample period Goldman Sachs had several Chief Economists who were nominally responsible for the forecasts. However, the surveys treat these forecasts as if from the same individual. Furthermore, most of the economists surveyed submit their institution's forecasts, which are produced by a team rather than an individual forecaster. I also confirmed through personal correspondence with several Blue Chip survey participants that the forecasts they submitted to the BCEI and the BCFF were identical except for any new information.

[9]Not all forecasters submit all of the horizons or variables in every survey. Thus, the number of current quarter GDP growth forecast observations is effectively an upper bound for other variables and horizons. I fill in occasional gaps in the BCEI survey data with other surveys such as the WSJ and Bloomberg Forecaster Surveys when their survey dates align. These account for a very small number of observations and do not materially alter the results. Despite this, the BCEI surveys for May and June 2001 and April 2002 are completely missing for all forecasters in the sample.



Notes: Smoothed using a one month rolling window. Shaded rectangles denote NBER recessions. Three BCEI surveys are missing in May 2001, June 2001, and April 2002.

Figure 3.1: Biweekly Blue Chip GDP Nowcast Revisions (2001-2019)

release dates have remained fixed, survey collection dates have varied. Official survey schedules since 2005 show the exact dates during which the surveys were open and closed.[10] Survey windows are typically open for two days and there is, on average, a 14 day gap between the two Blue Chip survey windows. Thus, the combined survey frequency is roughly every two weeks. The gap ranges from 6 to 23 days where the largest typically occurs in December / January due to schedule adjustments to circumvent holidays or in November 2013 when the BCEI survey was delayed for a week due to a delay in the release of GDP after the federal government shutdown.

The individual survey forecasts and their revisions exhibit several important properties. Figure 3.1 plots how the individual bi-weekly GDP growth current-quarter nowcast revisions evolved between 2001 - 2019. The typical range is ± 2 percentage points over any given quarter and the median revision is zero. The largest changes occur around major macroeconomic events such as at the onset / end of recessions, and the September 11 2001 terrorist attacks.

Blue Chip participants revise their forecasts more often than a monthly frequency. Table 3.1 presents the range of frequencies of any non-zero revision across both variables and horizons. The typical participant revises their GDP nowcast just above a monthly frequency at 56 percent of the sample. This means that low frequency surveys induce information loss by aggregating the dynamics, whereas using a higher revision frequency I can pinpoint when revisions actually occur.

[10] I extend the survey dates back through 2001 using additional external information.

Table 3.1: Revision Frequency by Variable and Horizon (in percent of available sample)

	GDP Growth			CPI Inflation			10-Yr T-Note Yield		
h	**Min**	**Median**	**Max**	**Min**	**Median**	**Max**	**Min**	**Median**	**Max**
0	15.1	56.0	88.2	23.5	63.7	93.4	36.1	57.3	79.7
1	9.2	48.2	87.0	14.8	53.2	83.8	32.3	54.9	81.8
2	7.1	42.6	83.6	12.5	47.4	86.8	24.0	50.7	82.5
3	7.6	37.0	83.5	9.0	43.5	85.5	17.3	48.7	86.1
4	8.7	36.4	91.4	3.0	42.7	88.4	12.9	45.7	84.0

Notes: Calculated as the number of times a revision was non-zero as a percent of each forecaster's available sample from December 2000 through December 2019.

There is considerable heterogeneity across economists. The frequency of forecast revisions ranges from once a quarter (15 percent) to once every 2.3 weeks (88 percent). Across variables, CPI inflation and Treasury yield forecast revisions are generally more frequent but are also heterogenous. The frequency of revisions typically declines across forecast horizons, indicating that forecasts are more likely to be anchored.

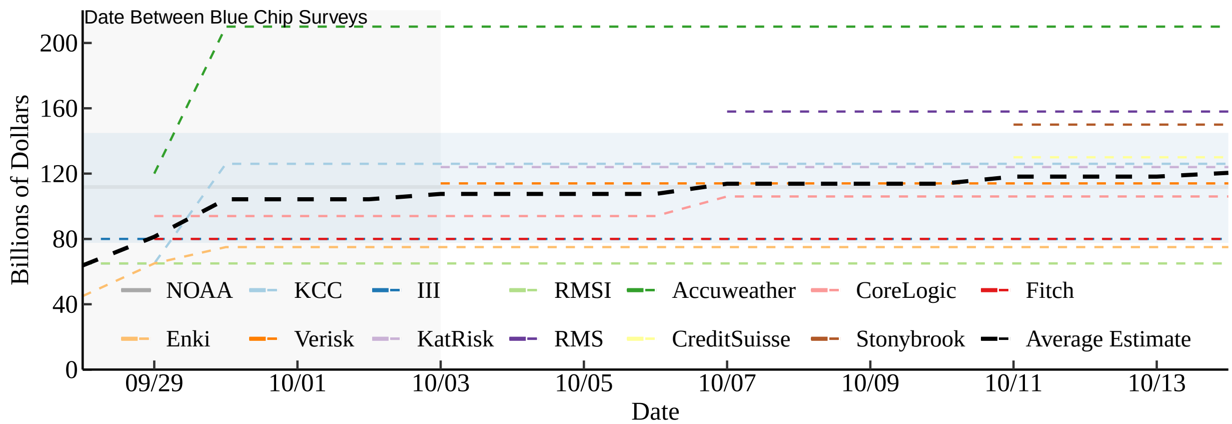
3.2 Hurricane Damage as an Extreme Weather Shock

There are many types of extreme weather events but hurricanes are among the most destructive in the United States. The National Ocean and Atmospheric Administration (NOAA)'s Billion-Dollar Weather and Climate Disasters database includes droughts, floods, freezes, severe storms, hurricanes, wildfires, and winter storms. These events are spatially and temporally heterogeneous lasting anywhere from a single day to over a year. Focusing only on extreme weather that lasted for less than two weeks between 2001 and 2020, there were 173 events that caused over 1.2 trillion dollars in damages and killed more than 7,600 people in the United States.[11] Hurricanes were the most destructive and deadly causing more than 73% of the inflation adjusted damages and 80% of the fatalities despite representing less than 20% of the events.

Hurricanes also play a prominent role in individual perceptions of disaster risks and are closely followed by economic forecasters. Dietrich et al. (2021) show that the occurrence of hurricanes in the past and the risk of their future occurrence are among the most significant drivers of individual perceptions of disasters. This is especially true since they are associated with both wind and flood risks. Hurricanes have also been cited as an explicit cause of forecast revisions with 40 percent of the November 2012 BCEI survey respondents indicating that they had trimmed their GDP growth forecasts by an average of 0.2 percentage points following Hurricane Sandy. Forecasters have also explicitly linked more recent hurricanes to their forecast revisions; e.g. see Herzon and Prakken (2016, 2017, 2018a,b), Hill (2017), and Walker (2024).[12]

[11] This represents 81% of the total real damages and 90% of the deaths from all extreme weather events.

[12] Hurricane damages do not translate directly into GDP. Hurricane damages are associated with the destruction of physical



Notes: Dotted lines represent different estimates from private modelers. Average is the average of all available estimates on that date. Solid grey line and shading around it represents the ex-ante unknown official NOAA damage estimate and its 95% confidence interval

Figure 3.2: Preliminary Damage Estimates for Hurricane Ian in 2022

I construct a measure of hurricane damage shocks by compiling direct damages from every storm that made landfall in the continental United States between 2001-2020 from the National Hurricane Center.[13] I obtain economically consistent shocks by normalizing the damage estimates with the latest estimate of the end-of-previous year's level of nominal GDP. This follows a similar approach as the normalization procedures proposed by Barthel and Neumayer (2012) and Grinsted et al. (2019) and expresses the hurricane damage shock directly in terms of its relative macroeconomic importance at the time.

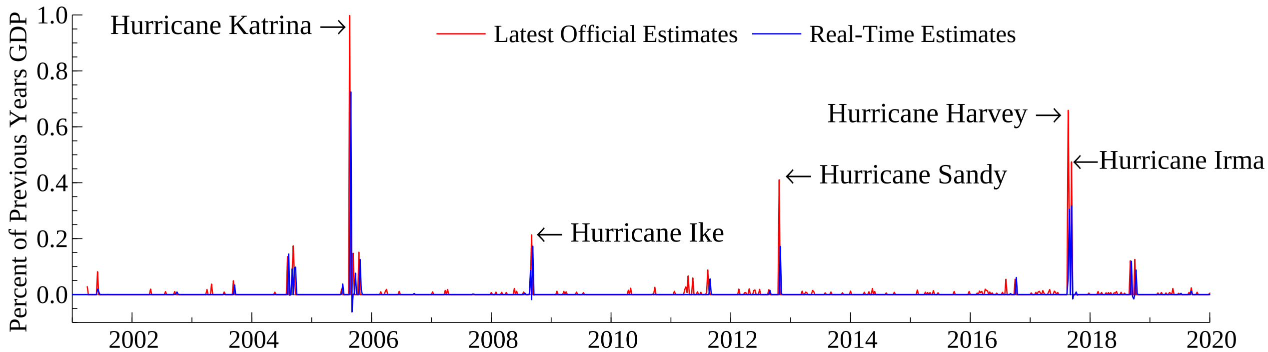
I also construct a real-time measure of damage shocks to align with forecasters information sets. Official damage estimates are typically released several months after the hurricane and are not available to forecasters in real-time. To circumvent this limitation, I construct a database of publicly available real-time damage estimates from catastrophe modeling firms for all hurricanes since 2001. I collect these estimates from news releases and newspaper articles for up to a month after each hurricane's occurrence.[14] The final database contains more than 354 damage estimates for 47 hurricanes with an average of 8 estimates per hurricane. The earliest estimate is the day of landfall while almost all estimates are available in the 30 day window.

Figure 3.2 illustrates the evolution of these estimates for Hurricane Ian which made landfall in Florida on August 28th 2022. Estimates of damages started after landfall and accumulated over the next several weeks.

structures and equipment. While this implies a loss of wealth, it does not imply a loss of income as measured by GDP. A GDP loss would occur if consumers spend less than they otherwise would or if a business is forced to close and cannot sell its products or services. Furthermore, while the reconstruction of damaged assets and insured losses imply a change in income, only expected insurance losses are included in GDP; see Chen and Fixler (2003).

[13] Every hurricane is included rather than just the billion dollar events recorded in NOAA's Billion-Dollar Weather and Climate Disasters database to ensure that relevant events are not censored.

[14] I used LexisNexis to search major newspapers. Estimates are typically provided as insured losses, so I multiple them by 2 to account for incomplete insurance coverage and obtain estimates of total damages; see Smith and Katz (2013). See Martinez (2025) for a detailed description of these estimates and their performance.



Notes: Official sample includes all 89 hurricanes that made landfall in the U.S. over the period while the real-time sample includes 47 storms. Official estimates obtained from NOAA while real-time estimates are constructed from averages of early estimates. Since early estimates can be revised down, the real-time estimates are occasionally negative. GDP is either the latest vintage or real-time year-end nominal values obtained from the Bureau of Economic Analysis.

Figure 3.3: Weekly Hurricane Damage Shocks (2001-2019)

As the figure shows, early estimates were initially too low, however, by the time the BCEI forecast window opened on October 3rd, the average damage estimate was in-line with the estimate that was eventually produced by NOAA several months later, albeit with a larger range from \$70 billion to over \$200 billion.

To construct the real-time damage shock, I use the average of latest available damage estimates the day the Blue Chip window opens and divide it by the real-time vintage of the previous year's estimate of GDP from the Bureau of Economic Analysis so that

$$\mathrm{S}_{w,t} = \frac{1}{M_w} \sum_{j=1}^{M_w} \Delta \mathrm{D}_{j,w,t} / \mathrm{GDP}_{w,t-4} \times 100, \tag{7}$$

where $\Delta D_{j,w,t}$ is the change in damage in billions of \$ that was estimated to have occurred in time period t by catastrophe model j in the sample of models (M_w) available during bi-week w, $GDP_{w,t-4}$ is the value of GDP in billions of \$ the prior year based on the vintage the was available during w. This refines Baker et al. (2020) who use the number of news articles associated with an event interacted with the latest damage estimate. The supplemental appendices consider other measures including the spread or disagreement.

Hurricane Katrina dominates other damage shocks. Figure 3.3 shows that the largest shock is Hurricane Katrina at almost 1 percent of GDP or 0.4 percent of the physical capital stock at the time.[15] Katrina first made landfall in Florida on August 25, 2005 one day after the BCFF survey for September closed and then made landfall again in Louisiana three days before the BCEI survey for September opened. Following

[15] This only includes direct damages. Gallagher and Hartley (2017) and Deryugina et al. (2018) show that the total economic costs were substantially higher. Hurricane Katrina is both the largest shock in my sample and is one of the most destructive hurricanes ever to strike the United States; see Martinez (2020b). Projections suggest that a Katrina-sized event may be more likely in the future due to changing climate risks and increasing wealth in vulnerable areas; see Martinez and Wilson (2024).

Hurricane Katrina, several forecasters explicitly revised their macroeconomic outlook as a result of the expected economic effects; see Hatzius (2005), Kasman and Mellman (2005), and Varvares (2005).

Other well known hurricanes also feature prominently. The second largest shock is Hurricane Harvey in 2017, which made landfall one day after the BCFF survey for September closed and eleven days before the BCEI survey opened, at around 0.75 percent of GDP. Hurricane Sandy in 2012 also stands out. Other substantial shocks include Hurricane Ike in 2008 as well as clusters of activity in 2004, 2011, and 2018.

The real-time estimates are generally smaller than the official estimates. This is because early damage estimates tend to underestimate total hurricane damages, especially following large storms with a large component of flood damages . Figure 3.3 also shows that while there are occasionally negative real-time shocks due to downward revisions in the expected damage estimates, these never exceed 0.1 percent of GDP.

3.3 Macroeconomic News

Figure 3.1 illustrates that forecasts are systematically revised around major economic events. Not capturing this major source of variation could leave a large degree of unexplained noise and limit the ability to identify the causal effects of extreme weather shocks. However, the literature is mixed about whether macroeconomic news releases are important for forecast revisions. For example, Clements (2012) finds that data surprises do not explain forecast revisions.

Some high frequency information may be difficult to separate from the shock of interest. For example, Aaronson et al. (2020) show that google searches for unemployment and initial unemployment insurance claims typically spike immediately following major hurricane strikes. Alternatively, Kruttli et al. (2021) find that financial markets respond to forecasts of storms while Davis and Ng (2023) find that at a monthly frequency, damages from large disasters are endogenously determined with initial unemployment insurance claims and financial market uncertainty. To avoid these concerns I focus on a set of macroeconomic news controls based on information that is predetermined with respect to the shock.

I use data announcement surprises to control for important macroeconomic news releases. I construct these as the difference between the data release and the available Bloomberg forecasts aggregated over the window between the Blue Chip survey dates; e.g. see Altavilla et al. (2017). There is a large number of data announcement surprises to chose from and I only include those that satisfy the following criteria: (1) investors pay close attention to the releases, see Bok et al. (2018); (2) they are available over the full sample; (3) the data are predetermined with respect to the hurricane damage shock; (4) the release matters for the GDP forecast. The data announcements surprises that satisfy this criteria are: continuing jobless claims, durable goods orders, the monthly budget statement, the Philadelphia Fed Manufacturing Business outlook, new single-family home sales, advanced retail sales, and the ISM Manufacturing Report.[16] Several other releases satisfy my criteria including total non-farm payrolls, construction spending, the trade balance, and wholesale and retail inventories but they were not significant and just added noise.

I also control for advance GDP release surprises using each forecaster's last available backcast from the BCEI. While the other data announcement surprises control for common surprises affect all forecasters, i.e common correlated effects as in Chudik and Pesaran (2015), individual GDP forecast errors capture how data surprises manifest differently for individual forecasters. Finally, I include a dummy variable for the September 11th 2001 attacks.

4 Empirical Results

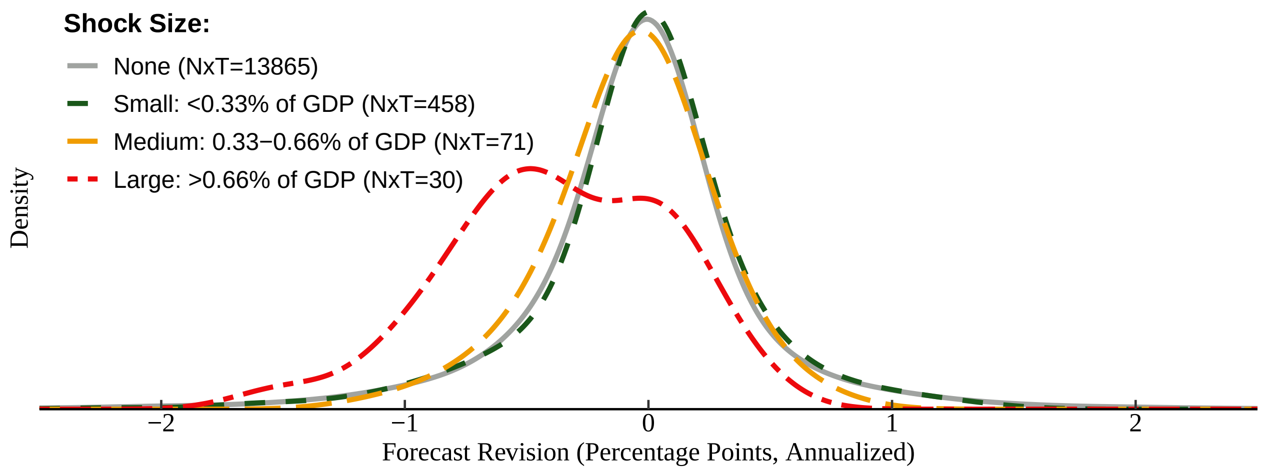
This section presents the results. Subsection 4.1 previews the main results by showing how forecast revision densities change following a shock. Subsection 4.2 presents the main results while subsection 4.3 interprets the results against other shocks. In subsection 4.4 I examine how the shock propagates across forecast horizons. Subsection 4.5 compares how expectations differ from the actual economic effects and subsection 4.6 examines how Blue Chip forecasters compare to the Federal Reserve Board staff forecasts. Finally, subsection 4.7 considers how the shock propagates through a system of macroeconomic expectations.

4.1 Forecast Revision Density Response to a Hurricane Damage Shock

Before proceeding with the analysis, I preview the results by presenting estimates of the GDP growth nowcast revision densities by shock size in Figure 4.1. The unconditional forecast revision density is centered around zero with tails extending out past ± 2. Small shocks leave the forecast revision density unchanged. After medium-sized shocks (i.e. Sandy and Harvey) there is more mass to the left of the unconditional density and a shorter upper tail. This is consistent with only 40 percent of the BCEI sample indicating that they revised their forecasts after Hurricane Sandy.

Following a Hurricane Katrina-sized shock the entire density shifts leftward such that the median revision is -0.4 percentage points . The density becomes more diffuse with two peaks at around -0.5 and 0. This is unchanged if low frequency updaters are excluded, meaning that forecasters perceive the effects of the shock differently. Overall, despite the variation in individual forecast revisions, there is a clear response to a large hurricane damage shock.

[16] Continuing jobless claims are reported with a three week lag and so are unlikely to be contemporaneously affected.



Notes: Forecast revision densities estimated non-parametrically using a Gaussian kernel with a bandwidth of 0.2 percentage points across all shock sizes. Observations are truncated at ±2.5 percentage points.

Figure 4.1: Current Quarter GDP Growth Forecast Revision Densities by Shock Size

4.2 Main Regression Results

I now proceed with the main analysis. I first consider the static model. Next, I discuss how the results change as I extend the model to allow for forecast revision dynamics. Finally, I discuss the results from the general dynamic model that allows for both a linear and non-linear lag forecast revision structure.

A shock of 1 percent of GDP, equivalent to Hurricane Katrina, reduces expected real GDP growth in the quarter in it occurs by 0.33 percentage points (annualized). The result, based on equation (1), is shown in Column (1) of Table 4.1. The estimated standard error is 0.19 so that the estimate is significantly different from zero with more than 90% confidence. The magnitude of the estimate is consistent with the November 2012 BCEI survey results following Hurricane Sandy and with Figure 4.1.

Table 4.1: Effects of a Hurricane Katrina Shock on Real GDP Growth Nowcasts

	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		−0.27 (0.02)	−0.27 (0.02)	−0.27 (0.02)	−0.27 (0.02)
Lagged Revision × Lagged Shock:				0.36 (0.16)	0.19 (0.18)
Immediate Effect:	−0.33 (0.19)		−0.47 (0.17)		−0.46 (0.17)
Lagged Effect:			−0.38 (0.13)		−0.32 (0.14)
Total Effect:	−0.33 (0.19)	0	−0.67 (0.16)	0	−0.69 (0.18)
Tests of Efficiency, $\chi^2(1)$:	n.a.	126.7 [0.000]	3.18 [0.074]	0.28 [0.596]	4.09 [0.043]
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Observations (N×T):	13,747	13,747	13,747	13,747	13,747
Forecasters/Firms (N):	54	54	54	54	54
$\hat{\sigma}$:	0.45	0.43	0.43	0.43	0.43
R^2 :	0.23	0.29	0.29	0.29	0.29

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by firm and time following Thompson (2011) and Cameron et al. (2011).

Forecasts are over-revised with respect to past forecast information, which shows that the immediate effect of the shock, as estimated using a static equation, may not convey the total effect. Column (2) in Table 4.1 shows the results for equation (2). The lagged forecast revision is statistically significant with a t-ratio of over 10 and a p-value far less than 1%. The negative coefficient indicates that forecast revisions are weakly inefficient in a Nordhaus (1987) sense and represent an over-reaction to past forecast information. This result is also consistent with Bordalo et al. (2020) using a higher frequency sample.[17]

Even though the dynamics indicate a general overreaction to past information, expectations under-react immediately following a Katrina-sized shock such that the total effect is nearly double the immediate effect.

[17] Performing this regression for each forecaster independently and averaging the estimates also gives similar results.

Column (2b) of Table 4.1 augments equation (2) with the shock and its lags and shows that the immediate response to the shock is a downward revision in the GDP nowcast by 0.47 percentage points. The lagged effect implies a further downward revision of 0.38 percentage points. The total effect, after accounting for the immediate and lagged effects as well as the dynamic overreaction, is a total downward revision of 0.67 percentage points. This contrasts with the estimates in column (1) which are less than half the size of the total effect in column (2b). The common factor restriction is weakly rejected at a 90% confidence level. Thus, the immediate and total effects are not identical and forecast revisions are not weakly efficient.

Nonlinear lag dynamics indicate that while forecasts are over-revised immediately in response to new information, following a large shock the inefficiency declines. Column (3) of Table 4.1 presents the results for equation (3). It shows that both the lagged forecast revision and its interaction term are statistically significant with roughly offsetting coefficients. Tests of forecast efficiency, conditional on a Katrina-sized shock where $H_0 : \alpha_1 = -\alpha_2$, are not rejected at any level of statistical significance. These effects imply that forecast revision inefficiency is ameliorated following large shocks and is consistent with the model and findings in Baker et al. (2020).

Allowing for both the shock and non-linear lag dynamics confirms that the total response to the shock is significantly larger than the immediate revision. The results in column (4) of Table 4.1 are based on the general dynamic model in equation (4). While the offsetting effect of the lagged revisions and interaction term is retained when including the direct effects of the shock, it is smaller and no longer statistically significant. The immediate and lagged effects of the shock are roughly the same magnitude and significance as in column (2b). The total effect is also roughly the same magnitude as in column (2b) and helps confirm that the total revision is larger than the immediate response. Furthermore, while the non-linear term is not statistically significant, its inclusion improves the power of the test for weaker efficiency.[18]

The results are generally robust to a range of alternative specifications. In the supplemental appendices I consider a number of specifications including different survey sub-samples, consensus forecasts, removing outliers, allowing for forecaster disagreement, and forecaster heterogeneity. Overall, the results remain consistent across all specifications with the main differences being that (a) the power of the tests generally declines in smaller samples and (b) the non-linearities become insignificant when removing outliers.

There are important differences across subsamples of forecasters. Forecasters in large or publicly traded firms and forecasters who are closer to the hurricane strike have larger responses to a Katrina-sized shock,

[18]The test of 'weaker efficiency' depends on the size of the shock. Although the common factor restriction implied by the null hypothesis of forecaster efficiency is rejected with a confidence level greater than 95%, this is conditional on a Hurricane Katrina-sized shock of 1 percent of GDP. This does not hold for all values of the shock. It is only rejected with 90% confidence level if the shock is 0.5 and 95% confidence level if the shock is >0.9.

whereas forecasters in the financial services industry are significantly more likely to revise their forecasts more efficiently in response to a shock. These results suggest that obtaining timely information about the shock is costly to forecasters such that only those with resources or a vested interest do so; e.g. Sims (2003).

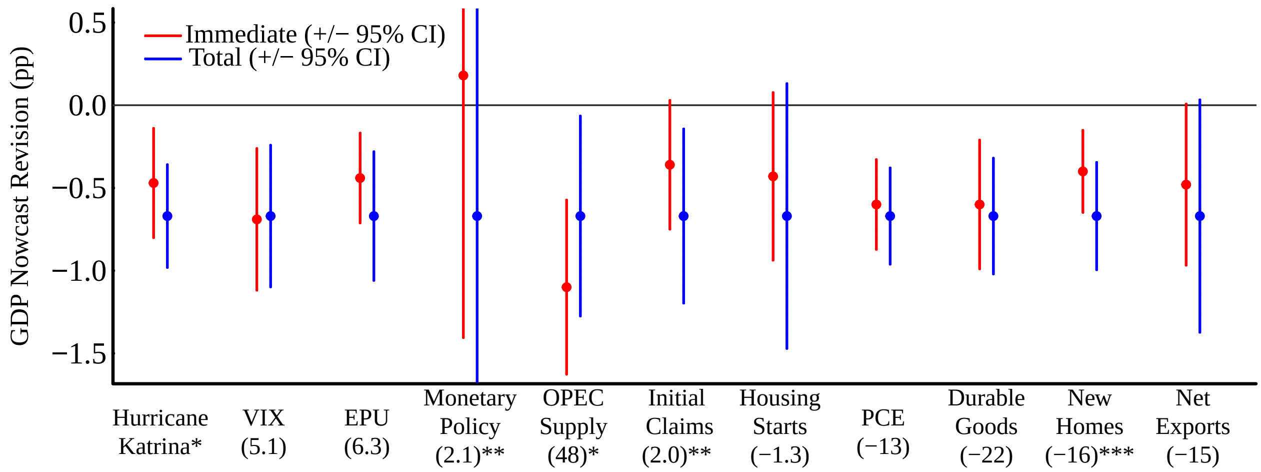
Overall, modeling the revision dynamics together with the shock provides a clearer picture of the response of macroeconomic expectations to large shocks. While it is possible to estimate the immediate effect using a static model, as is common in the literature, these estimates do not capture the total effect of the shock when forecast revisions are inefficient. For hurricane damage shocks, the differences between the immediate and the total effects are significant and roughly double what the static model implies. Furthermore, focusing on whether forecasters generally over-react to past informatioyean is not helpful for estimating these differences. Instead, including lagged forecast revision and shock dynamics provides a complete picture of the dynamic effects and allow us to test for their importance.

4.3 Interpreting the Estimates

This subsection compares the response to hurricane damage shocks with the response to other macroeconomic news shocks. For this exercise I use a restricted version of equation (4) where $\alpha_2 \equiv 0$ such that there are no nonlinearities. This specification is robust across alternative specifications and easier to interpret than the non-linear specification. I generalize $S_{w,t}$ in (4) to represent any number of shocks including economic policy uncertainty from Baker et al. (2016), monetary policy shocks from Nakamura and Steinsson (2018), OPEC supply shocks from Känzig (2021), and macroeconomic news release surprises. In each case I rescale the shock such that the total dynamic effect is the same magnitude as I obtained for the the Hurricane Katrina shock in Column (2b) of Table 4.1. This allows me to compare the magnitude of the shocks required in order to achieve the same effect on expectations.

The immediate effect of a Katrina-sized shock is large relative to other macroeconomic news surprises. As Figure 4.2 shows, a 5 s.d. increase in the VIX is required for forecasters to revise their current quarter forecasts by the same magnitude as a Hurricane Katrina shock. Alternatively, it takes a 2 s.d. surprise increase in initial unemployment insurance claims or about a 1 s.d. surprise decline in housing starts. Thus, a Katrina-sized shock has a large effect on expectations about current quarter GDP compared to other macroeconomic news shocks.

The total dynamic effects are larger than the immediate effect for most shocks. While the total effects in Figure 4.2 are all normalized to have the same size, the immediate effects are not. 80% of the shocks considered have total effects that are estimated to be slightly larger than their immediate effects. Differences are especially large and significant for hurricane damages, monetary policy, initial jobless claims, and new



Notes: The immediate effects are all scaled to match the Hurricane Katrina shock. The number in parentheses denotes the size of the shock in standard deviations required to match that of Hurricane Katrina. Bars capture the 95% confidence interval of the estimates. Stars done significant differences between immediate and total effects using 10% (*), 5% (**), and 1% (***) critical values.

Figure 4.2: The Immediate and Total Effects of Alternative Shocks on GDP Nowcasts

home sales.[19] Focusing on the immediate effects in these cases is misleading.

An immediate under-reaction of forecast revisions following a shock is consistent with a model of delayed overshooting. While interpreting the results in Figure 4.2 is complicated by the fact that some of the shocks may be serially correlated, the consistent pattern across multiple shocks suggests a general behavioral pattern. Angeletos et al. (2021) argue that forecasters tend to exhibit delayed overshooting wherein they immediately under-react to a shock but then overshoot at longer horizons. My results are consistent with an immediate under-reaction to a shock even when allowing for the fact that individual forecasters may generally over-react to past information. In the next sections I extend them across multiple horizons in order to assess whether there is evidence of overshooting.

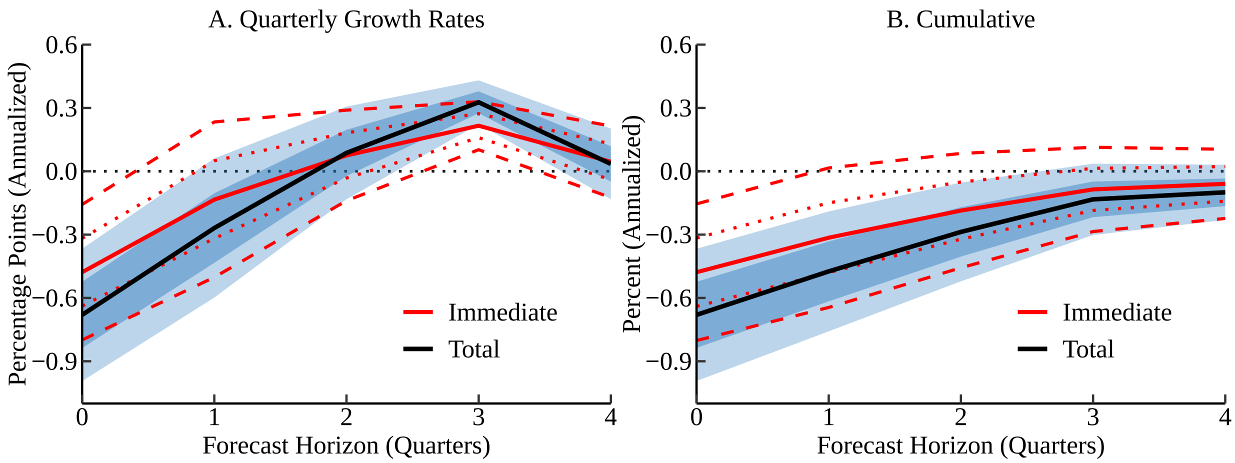
4.4 Extending the Results Across Longer-term Expectations

Having demonstrated the importance of the dynamic specification to distinguish between the immediate and total effects of a large shock, I now examine how these dynamics transmit across longer-term expectations. For this exercise I estimate a restricted version of (4) where $\alpha_2 \equiv 0$ for each forecast horizon separately out through four quarters ahead.[20]

[19] The effect of a monetary policy shock is insignificant. This is consistent with Bauer and Swanson (2023).

[20] Estimating forecast revisions separately across horizons imposes strong independence assumptions. I test this using a structural vector-autoregression of GDP growth forecast revisions with exogenous variables (SVARX) across all five forecast horizons with a Choleski identification scheme where contemporaneous feedback only flows forward across horizons. I test whether complete cross-horizon independence is a valid reduction and find that it is strongly rejected at any reasonable level of significance with a chi-square test statistic of $\chi^2(30) = 259.4$ [0.000]. However, I can impose some restrictions on the dynamics such that (a) only the last forecast horizon matters for a given horizon's contemporaneous revisions and (b) only one lead and one lag forecast horizon matters for a given horizon's lagged revision. These are not rejected with a chi-square test statistic of $\chi^2(22) = 24.3$ [0.331]. The Supplemental

An important feature of this exercise is that I consider the cumulative forecast revisions across horizons as well as the horizon-specific revisions. This allows me to track both revisions to expected growth rates and revisions in the expected level of GDP. Panel A of Figure 4.3 shows the immediate and total GDP growth rate forecast revisions at each horizon while Panel B presents the estimates of the immediate and total cumulative GDP forecast revisions in percent out through four quarters ahead.



Notes: Immediate (red) and total (black) effects of a hurricane shock. Scaled to represent a Hurricane Katrina-sized shock. Solid lines are point estimates and the shaded areas (and dashed/dotted lines) are the point-wise 68 and 95 percent confidence intervals at each horizon respectively.

Figure 4.3: Dynamic Effects of a Hurricane Katrina Shock on GDP Forecasts

Forecasters have a delayed response to the shock at longer horizons. Panel A in Figure 4.3 shows that the three-quarter-ahead growth rate is initially revised up by 0.2 percentage points but that the total upward revision is significantly larger around 0.3 percentage points. Thus, the delayed response seen in the nowcast is also observed in longer-term expectations.

Hurricanes are expected to have persistent but not permanent macroeconomic effects. Panel B in Figure 4.3 shows that hurricane shocks initially cause a shallow decline in forecasters GDP expectations with a recovery after 2-3 quarters. Overt time the total effect of the shock is expected to be larger but with an offsetting recovery that is expected be broadly complete within 3 quarters. Thus, forecasters do not expect the negative effects of the shock to have permanent effects on GDP but instead expect there to be persistent business cycle effects.[21]

Appendix shows that the dynamic effects are smoother but otherwise similar to the estimates under total independence. Thus, while the independence assumptions are rejected, the empirical differences are relatively minor.

[21]Note that I do not disentangle how forecasters anticipate the semi-automatic response of fiscal policy through the Federal Emergency Management Agency and the Small Business Administration in response to the shock. Therefore I am estimating a total effect of what forecasters expect the effect of the shock and any policy response to be.

4.5 Comparing with the Estimated Economic Effects of Hurricane Damage

This subsection estimates the actual economic effects from a hurricane damage shock and compares how they differ from the expected macroeconomic effects. For this exercise I estimate a model using local projection methods following Jordà (2005) such that

$$y_{t+h} = c + \zeta t + \eta_h \mathrm{S}_t + \sum_{j=1}^{L} \gamma_{j,h} y_{t-j} + e_{t+h}, \tag{8}$$

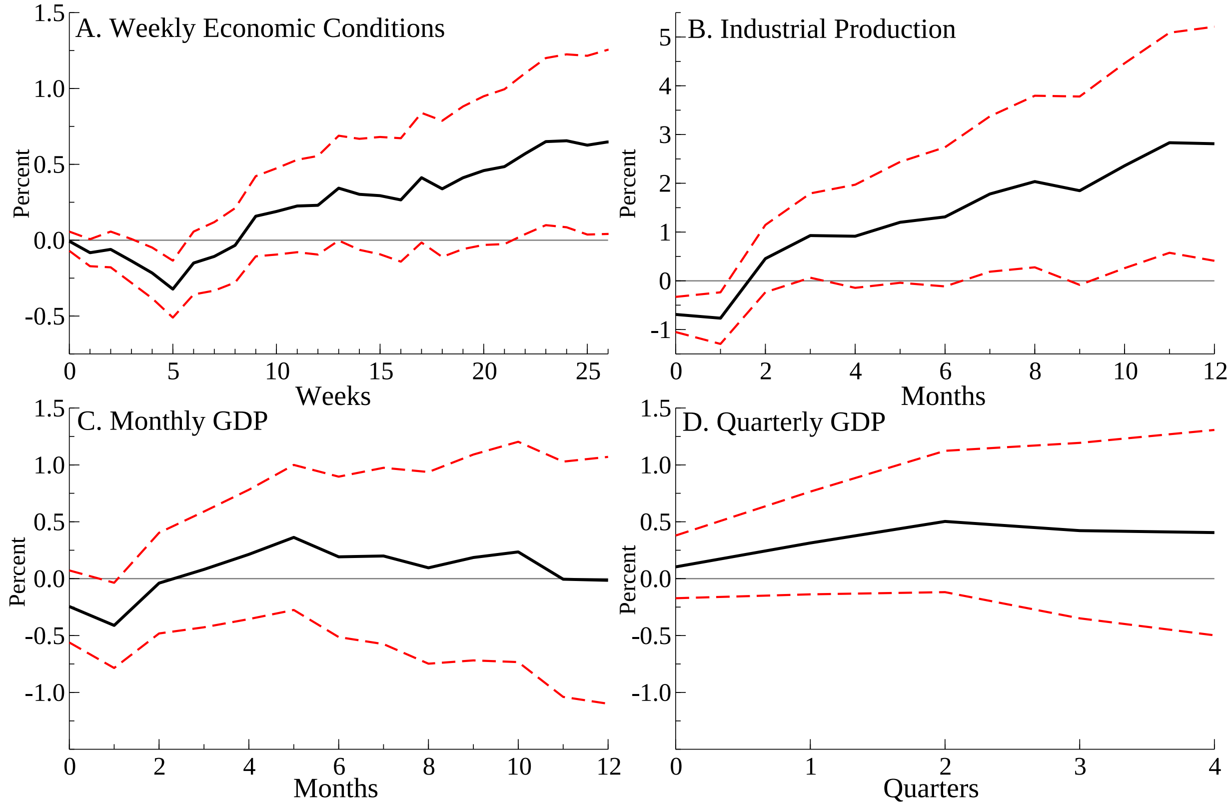
where y_t is a measure of economic activity at time t, S_t is the official measure of the damage shock as discussed above in section 3.2 that occurs over time t, η_h captures the cumulative effect of the shock on economic activity through horizon h, L is number of lags used as explanatory variables. I set L equal to the frequency of the data to ensure robustness following Montiel Olea and Plagborg-Møller (2021) such that for quarterly data $L = 4$, for monthly data $L = 12$ and for weekly data $L = 52$, and e_t is the unexplained residual. I estimate (8) for each measure from 1990 through 2019 including a constant, a trend, and seasonal dummy variables using standard methods.

I consider several measures of economic activity at different time frequencies including (a) the national weekly economic conditions index from Baumeister et al. (2024), (b) monthly industrial production from the Federal Reserve Board, (c) monthly real GDP as estimated by Stock and Watson (2014) and extended using estimates from S&P Global[22], and (d) quarterly real GDP from the Bureau of Economic Analysis. I transform each measure (except for the weekly index which is already scaled to match year-over-year percent changes in real GDP) into their log-levels and multiply by 100 such that my estimates correspond to percent changes. The estimated effects following a Hurricane Katrina damage shock for each of these measures are shown in Figure 4.4.

The differences between actual and expected economic effects of a hurricane shock depend on the frequency of economic activity. At a weekly frequency economic activity (panel A) reaches a trough of -0.3 percent five weeks after the shock. It then recovers and is slightly above trend for the next 6 months. At a monthly frequency, economic activity declines both during the month of the shock and the following month to a trough of about -0.5 percentage points (not annualized) before recovering. Industrial production (panel B) exhibits above trend growth for the rest of the year while monthly GDP (panel C) returns to and effectively remains at its pre-shock trend. However, at a quarterly frequency there is little evidence that GDP is affected by the shock (panel D), which is consistent with the findings of Linder et al. (2013). Thus, from a

[22]Downloaded on October 11, 2024 from `https://www.spglobal.com/marketintelligence/en/mi/products/us-monthly-gdp-index.html`.

quarterly perspective the results suggest that forecasters' response to a hurricane shock is pure overreaction whereas at a monthly or weekly frequency the results indicate that forecaster's downward revisions are in line with or less than the actual economic effects immediately following the shock.



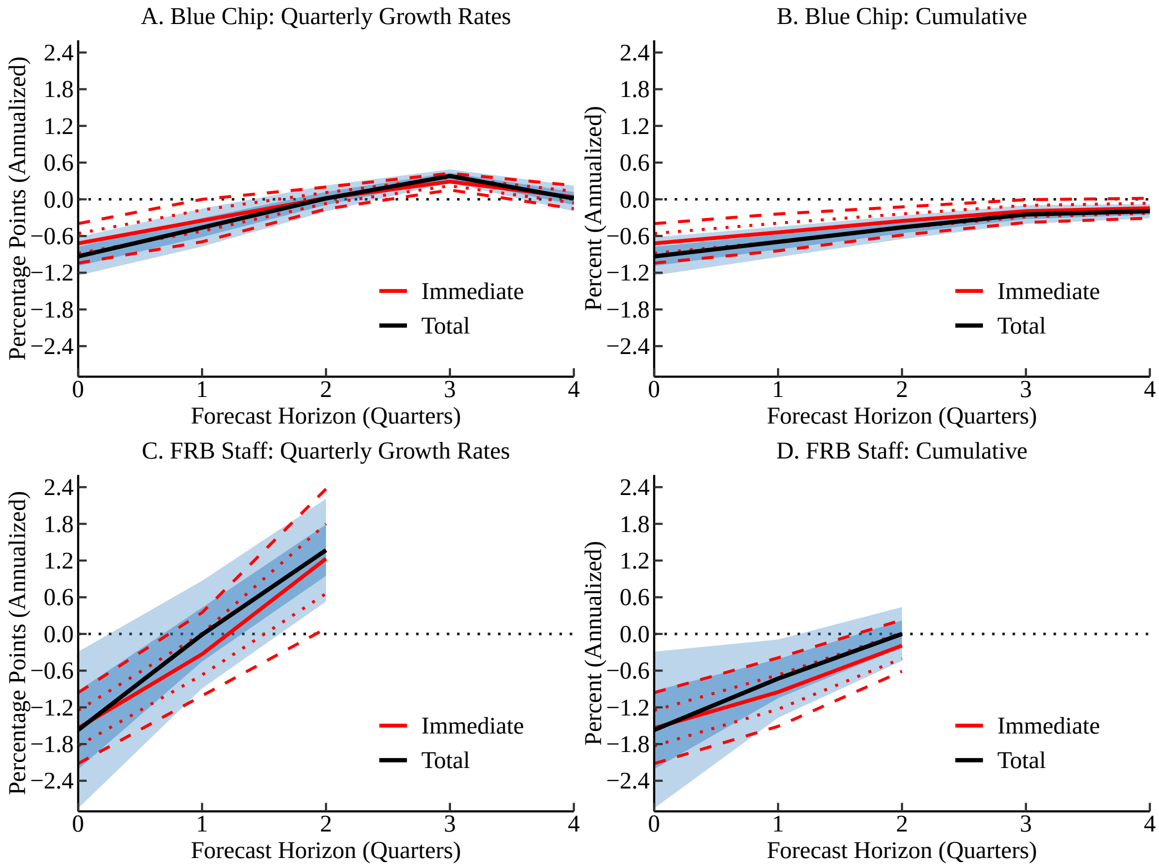
Notes: Estimated using a sample from 1990-2019. Dashed red lines denote the 68% confidence interval.

Figure 4.4: Estimated Effects of a Hurricane Katrina Shock on Measures of Economic Activity

Forecasters believe that the effects of a hurricane shock will persist for longer than it actually does. While forecasters expect the real GDP to only return to its pre-shock growth path after at least 2-3 quarters, see panel B in Figure 4.3, the actual effects in Figure 4.4 indicate that regardless of the measure considered, recovery in economic activity is faster than anticipated with a return to the pre-trend baseline within 2 months. This evidence is consistent with the theory of delayed overshooting from Angeletos et al. (2021) where Blue Chip forecasters are effectively overshooting how long they expect the recovery to take following a major negative shock.

4.6 Comparing with Federal Reserve Board Staff Forecasts

In this subsection I compare the Blue Chip forecasts with the Federal Reserve Board (FRB) staff forecasts. For this exercise I use data from Chang and Levinson (2023) who compile FRB staff forecasts on a quasi-



Notes: See Notes for Figure 4.3. Estimated using a sample from 2001-2011. The confidence intervals for FRB staff forecasts are derived from estimates of heteroskedasticity corrected standard errors following White (1980).

Figure 4.5: Effects of a Hurricane Katrina Shock on Blue Chip and FRB Staff GDP Forecasts

weekly basis for real GDP growth and core PCE inflation from 2001-2011. While the sample of inflation forecasts is too sparse to be used here, I align the dates that the FRB staff generate their forecasts with the Blue Chip survey dates and estimate a single equation version of equation (4) with $\alpha_2 \equiv 0$ for each forecast horizon.[23] I also re-estimate the Blue Chip results over this shorter sample which captures the very active 2004 and 2005 hurricane seasons but excludes Hurricane Sandy in 2012 and the 2017 hurricane season.

The effect of the shock is earlier and more pronounced for the FRB staff's forecast than the Blue Chip forecasts. Panels C and D of Figure 4.5 show that the FRB staff forecasts have a large initial response to the shock with a downward revision in the GDP nowcast which is more than double that of the Blue Chip forecasters. Tests of weaker efficiency and the implied common factor restriction are not rejected at any forecast horizon for FRB staff forecasts such that the immediate and total responses to the shock at a given

[23] There is some sensitivity in how this alignment is done. If the dates are chosen such that only FRB staff forecasts made on the Blue Chip survey dates are included, then there are many missing values. Allowing for a wider range of dates implies less precise identification of the response to the shock. I balance these trade-offs by slightly expanding the date range to include 3 days before or after over which the Federal Reserve staff forecasts are generated. This ensures there is a sufficient sample without diluting the ability to identify a response to the shock.

forecast horizon are statistically indistinguishable. This is consistent with the fact discussed above in section 4.2 that Blue Chip forecasters in the financial services industry also exhibit more efficient forecast revisions.

The FRB staff expect a quicker recovery following the shock. In particular, FRB staff expect a full recovery in GDP within two quarters after the shock whereas Blue Chip forecasters only expect a full recovery after three to four quarters. These differences could be driven by differences in assumptions about supplemental fiscal packages as well as the fact that FRB staff typically only generate their forecasts up through three quarters ahead. However, the FRB Staff forecasts are more consistent with the actual effects as seen in Figure 4.4. This suggests that unlike the Blue Chip forecasters, the FRB staff forecasts do not show evidence of delayed overshooting. This supports previous evidence on the FRB staff information advantage; see Romer and Romer (2000).

Differences between Blue Chip and FRB staff forecasts could have important implications when interpreted through the lens of monetary policy. Several weeks after Hurricane Katrina's landfall in 2005, the Federal Open Market Committee (FOMC) met to decide whether to continue raising interest rates. Prior to the meeting, news outlets and markets speculated that the FOMC might pause because of the damage caused by Katrina and the added uncertainty to the outlook.[24] According to the published transcripts, the staff presented their baseline outlook in which they estimated that while Katrina was expected to have a negative effect on GDP growth, a recovery would quickly take hold in large part due to an expected fiscal aid package. Despite this, the transcripts also indicate that several participants were concerned about the outlook. One participant, Governor Mark Olson, voted to pause the increase in interest rates and dissented from the FOMC statement because of concerns about the effects from Hurricane Katrina. It is possible the outcome may have been different if FOMC participants used the Blue Chip forecasts instead.

4.7 Extending to a System of Macroeconomic Expectations

This subsection examines how a hurricane shock dynamically effects expectations of GDP, inflation, and interest rates. I draw from recent analyses monetary policy shocks, e.g. see Gertler and Karadi (2015) and Miranda-Agrippino and Ricco (2021), and formulate a structural vector-autoregressive model of forecast revisions of GDP growth, CPI inflation, and 10-year Treasury yields with an exogenous shock variable

[24] See Paul R. La Monica (2005) "Will Katrina make Greenspan pause? The Fed may need to stop raising interest rates due to the damage from Hurricane Katrina", CNN/Money Special Report: Fed Focus, September 2, 2005, `https://money.cnn.com/2005/09/01/news/economy/fed_katrina/index.htm` (last accessed September 25, 2022).

(SVARX). It is loosely based on equation (4) without non-linear terms and three lags

$$\mathbf{A}_h \Delta \mathbf{F}_{i,w,t+h} = \sum_{k=1}^{3} \Gamma_{1,k,h} \Delta \mathbf{F}_{i,w-k,t+h} + \sum_{j=0}^{1} \beta_{h,j} \mathrm{S}_{w-j,t} + \mathbf{e}_{i,w,t+h}, \tag{9}$$

where bold terms are vectors and $\mathbf{A}_h$ and $\Gamma_{1,k,h}$ are matrices. $\mathbf{F}_{i,w,t+h} = \{ \ \mathrm{GDP}_{i,w,t+h} \quad \mathrm{CPI}_{i,w,t+h} \quad \mathrm{T10}_{i,w,t+h} \ \}'$ is a 3×1 vector of forecasts of real GDP growth, CPI inflation, and the 10-year Treasury yield made by forecaster $i \in N$ during bi-week $w \in$\{1,...,W\} of quarter $t \in \{1, \ldots, T\}$ for horizon $h \in \{0, \ldots, H\}$. Thus, $\Delta \mathbf{F}_{i,w,t+h} = \mathbf{F}_{i,w,t+h} - \mathbf{F}_{i,w-1,t+h}$ is the vector of forecast revisions. To keep the notation simple, control variables or fixed effects are included in the vector $\mathbf{e}_{i,w,t+h}$ along with the unexplained residuals.

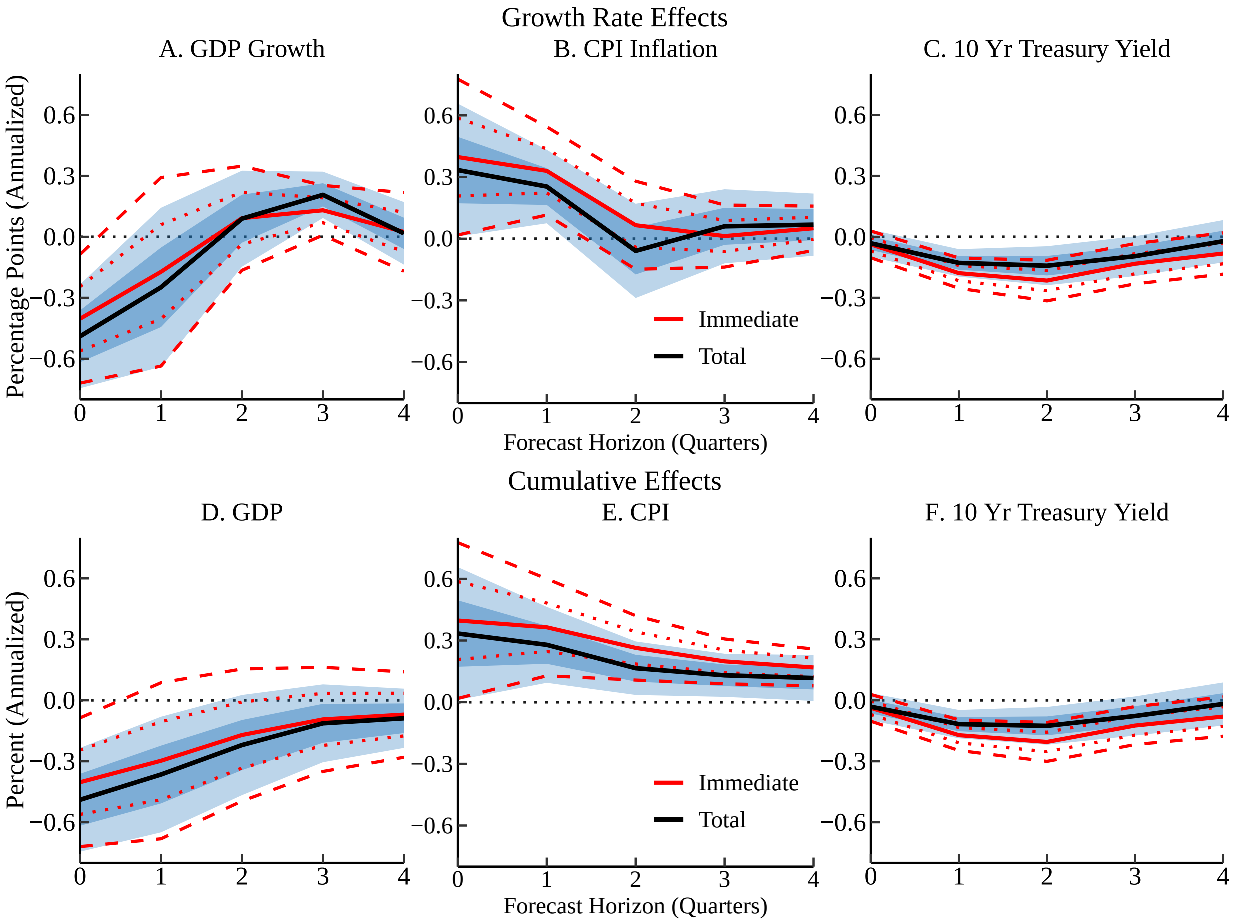
I impose several restrictions to simplify the system. First, I assume a recursive ordering for $\mathbf{A}_h$ where CPI inflation and 10-year Treasury yields are allowed to react to GDP growth revisions contemporaneously and Treasury yields can respond to contemporaneous revisions in CPI inflation. This imposes a quasi-Phillips curve / Okun's law relationship between GDP growth and CPI inflation and a quasi-Taylor rule relationship between Treasury yields, CPI inflation, and GDP growth. It is also consistent with the conditioning assumptions in the BCFF survey. As a result, the residuals have a diagonal covariance matrix such that each equation is estimated independently without a loss of information.[25] Second, I set the off-diagonal elements of $\Gamma_{1,k,h}$ to zero such that dynamics are determined exclusively by a variable's own lagged revisions and cross-equation linkages only occur contemporaneously through $\mathbf{A}_h$.

Figure 4.6 traces out the effect of a Katrina-sized shock on the system of forecast revisions. It extends the results for GDP from Figure 4.3 to a system of expectations. Panels A-C show the responses in growth rates and panels D-F present the cumulative effects. I focus on the results for inflation and interest rate expectations and compare them against the previously discussed results for GDP growth.

Inflation and interest rate expectations show an immediate over-reaction to hurricane shocks across multiple horizons. The shock immediately raises inflation expectations by 0.4 percentage points at the current and one-quarter-ahead forecast horizons (panels B and E) while there is a smaller total dynamic effect on inflation expectations around 0.3 percentage points. The shock also causes an immediate reduction of interest rate expectations at around 25 basis points up to two-quarters-ahead (panels C and F) with a total dynamic effect thats is noticeably smaller.

The effect of a hurricane shock on macroeconomic expectations are consistent with a temporary negative supply shock. Figure 4.6 shows that real GDP growth expectations fall, inflation expectations rise, and in-

[25]To ensure that the results remain consistent I only consider those forecasters that have forecasts for all horizons and variables. The results are robust to alternative recursive orderings for $\mathbf{A}_h$.



Notes: See Notes for Figure 4.3.

Figure 4.6: Dynamic Effects of a Hurricane Katrina Shock on a System of Forecasts

terest rate expectations fall as expectations of slower growth temporarily dominate those of higher inflation. At longer horizons, growth expectations normalize and the expected price level stabilizes at a higher level. These results are consistent with what others have found for the actual macroeconomic effects of extreme weather events and natural disasters; e.g. see Parker (2018), Heinen et al. (2019), and Kim et al. (2024).

The results are robust to a number of alternative specifications. First, I get similar results when I estimate each variable separately, albeit there is less evidence of over-reaction for inflation and interest rates. This implies that the overreaction may be propagated through growth expectations. Second, the results remain broadly unchanged when the model is expanded to control for changes in oil price and interest rate shocks. This suggests that hurricane shocks are not proxies for other important economic shocks.[26] Third, the results are robust to considering other measures of extreme weather shocks such as (a) google searches for 'natural disasters' as in Dietrich et al. (2021) and (b) real-time model-based hurricane damage shocks from Martinez

[26] Major hurricane strikes along have had substantial impact on oil production and distribution and some have previously been identified as oil supply shocks; e.g. Caldara et al. (2019).

(2020a). See the Supplementary Appendices for details on these and other results.

The system results illustrate that revision dynamics matter for interpreting the causal effects of hurricane damage shocks. The revision dynamics interact differently across variables and horizons but the total effects suggest a temporary negative supply shock. They dynamics for growth expectations are consistent with models of delayed overshooting whereas inflation and interest rate expectations indicate pure overshooting. Future work will be need to disentangle whether this is a general behavioral pattern.

5 Conclusion

This paper asks how extreme weather shocks affect macroeconomic expectations. To answers this, I construct a new high frequency database by merging together two monthly Blue Chip surveys of more than 50 business economists forecasts of GDP growth, CPI inflation, and 10-year Treasury yields over the last two decades. Next, I generate a real-time series of shocks from hurricanes, which are the most destructive short-duration extreme weather events in the U. S., that reflect the information available to forecasters. I model the causal effects of how expectations are revised in response to a hurricane using methods established in the applied macroeconomics literature.

While the literature has focused exclusively on identifying the immediate effect of a shock on expectations, I argue that the total dynamic effects of a shock at a given forecast horizon could differ substantially from the immediate effect when forecast revision inefficiencies are appropriately accounted for. Therefore, I calculate both the immediate and the dynamic effects of the shock and propose a new test of weaker revision inefficiency to assess the significance of these differences.

I find that hurricanes have large and persistent dynamic effects on macroeconomic expectations. A Hurricane Katrina-sized shock immediately reduces expected real GDP growth by 0.3 percentage points (annualized). However, the immediate effect does not capture the full effect of the shock on expectations. Accounting for revision dynamics I show that the total dynamic effect on expectations is significantly larger than the immediate effect at around 0.7 percentage points.

The effect of a hurricane shock on expectations is large. For comparison, it would require almost a 5 standard deviation increase in the VIX or a 2 standard deviation surprise increase in initial unemployment insurance claims to have the same total effect on GDP growth expectations as Hurricane Katrina. This illustrates that private forecasters pay attention to these shocks and they have a substantial effect on forecasters expectations formation, especially in the near-term.

Hurricanes have a persistent but not permanent effect on expectations. These effects are generally consistent with models of costly information and delayed overshooting. Comparing against actual economic effects depends on the frequency at which economic activity is measured but generally shows that private forecasters are slower to incorporate the the shock and expect a slower recovery than is observed. The expected effects are less distorted when considering the Federal Reserve Board (FRB) staff forecasts or when looking at subsets of private forecasters such as those in the financial services industry, closer to the hurricane strike, and in larger publicly traded firms. These results is consistent with models of costly information and delayed overshooting as discussed in Angeletos et al. (2021).

The effect of a hurricane shock on expectations is also consistent with a temporary negative supply shock. After the shock, growth expectations fall, inflation expectations rise and interest rate expectations fall as slower growth expectations temporarily dominate higher inflation expectations. Both inflation and interest rate expectations show weak evidence of over-reacting to the shock. At longer forecast horizons, expectations of economic activity and interest rates gradually normalize back to their pre-shock trajectories while expected prices stabilize at a higher level.

Overall, I find that extreme weather shocks in the form of hurricanes cause statistically significant and economically meaningful, albeit temporary, declines in expectations of near-term economic growth. Accounting for the dynamics from individual forecaster revision inefficiencies provides a more complete picture of the total effects of the shock, which are substantially larger than the immediate effects. This helps to illustrate an important channel of how climate and weather shocks can impact the broader macroeconomy.

References

Aaronson, D., Brave, S. A., Butters, R. A., Sacks, D. W., and Seo, B. (2020). Using the eye of the storm to predict the wave of COVID-19 UI claims. *Covid Economics*, 9(April):59–76.

Altavilla, C., Giannone, D., and Modungo, M. (2017). Low frequency effects of macroeconomic news on government bond yields. *Journal of Monetary Economics*, 92:31–46.

Alvarez, J. and Arellano, M. (2003). The time series and cross-section asymptotics of dynamic panel data estimators. *Econometrica*, 71(4):1121–1159.

Andrade, P. and Le Bihan, H. (2013). Inattentive professional forecasters. *Journal of Monetary Economics*, 60(8):967–982.

Angeletos, G.-M., Huo, Z., and Sastry, K. (2021). Imperfect Macroeconomic Expectations: Evidence and Theory. In Eichenbaum, M. S. and Hurst, E., editors, *NBER Macroeconomics Annual*, volume 35. Chicago: University of Chicago Press.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4):1593–1636.

Baker, S. R., McElroy, T. S., and Sheng, X. S. (2020). Expectation formation following large, unexpected shocks. *Review of Economics and Statistics*, 102(2):287–303.

Bårdsen, G. (1989). Estimation of long run coefficients in error correction models. *Oxford Bulletin of Economics and Statistics*, 51(3):345–350.

Barthel, F. and Neumayer, E. (2012). A trend analysis of normalized insured damage from natural disasters. *Climatic Change*, 113(2):215–237.

Bauer, M. D. and Swanson, E. T. (2023). An Alternative Explanation for the "Fed Information Effect". *American Economic Review*, 113(3):664–700.

Baumeister, C., Leiva-León, D., and Sims, E. (2024). Tracking weekly state-level economic conditions. *Review of Economics and Statistics*, 106(2):483–504.

Binder, C., Campbell, J. R., and Ryngaert, J. (2024). Consumer inflation expectations: Daily dynamics. SSRN Working Paper. Available at: http://dx.doi.org/10.2139/ssrn.4785748, Social Science Research Network (SSRN).

Bok, B., Caratelli, D., Giannone, D., Sbordone, A. M., and Tambalotti, A. (2018). Macroeconomic nowcasting and forecasting with big data. *Annual Review of Economics*, 10:615–643.

Bordalo, P., Gennaioli, N., Ma, Y., and Shleifer, A. (2020). Over-reaction in Macroeconomic Expectations. *American Economic Review*, 110(9):2748–82.

Buda, G., Carvalho, V. M., Corsetti, G., Duarte, J. B., Hansen, S., Moura, A. S., Ortiz, A., Rodrigo, T., Rodriguez Mora, J. V., and Alves da Silva, G. (2023). Short and variable lags. Cambridge Working Papers in Economics Janeway Institute Working Papers, University of Cambridge Faculty of Economics.

Caldara, D., Cavallo, M., and Iacoviello, M. (2019). Oil price elasticities and oil price fluctuations. *Journal of Monetary Economics*, 103:1–20.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2):238–249.

Campbell, J. R., Evans, C. L., Fisher, J. D., and Justiniano, A. (2012). Macroeconomic effects of federal reserve forward guidance. *Brookings Papers on Economic Activity*, pages 1–80.

Campbell, J. R., Fisher, J. D., Justiniano, A., and Melosi, L. (2017). Forward guidance and macroeconomic outcomes since the financial crisis. *NBER Macroeconomics Annual*, 31(1):283–357.

Cantelmo, A. (2022). Rare disasters, the natural interest rate and monetary policy. *Oxford Bulletin of Economics and Statistics*, 84(3):473–496.

Casini, A. and McCloskey, A. (2024). Identification and estimation of causal effects in high-frequency event studies. ArXiv Working Paper, ArXiv.

Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5):1549–1561.

Chang, A. C. and Levinson, T. J. (2023). Raiders of the Lost High-Frequency Forecasts: New Data and Evidence on the Efficiency of the Fed's Forecasting. *Journal of Applied Econometrics*, 38(1):88–104.

Chavleishvili, S. and Moench, E. (2025). Natural disasters as macroeconomic tail risks. *Journal of Econometrics*, 247:105914.

Chen, B. and Fixler, D. J. (2003). Measuring the services of property-casualty insurance in the NIPAs. *Survey of Current Business*, 83(10):10–26.

Chudik, A. and Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2):393–420.

Clements, M. P. (2012). Do professional forecasters pay attention to data releases? *International Journal of Forecasting*, 28(2):297–308.

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

Davis, R. and Ng, S. (2023). Time series estimation of the dynamic effects of disaster-type shocks. *Journal of Econometrics*, 235(1):180–201.

Deryugina, T., Kawano, L., and Levitt, S. (2018). The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2):202–33.

Dietrich, A., Müller, G., and Schoenle, R. (2021). The expectations channel of climate change: Implications for monetary policy. CEPR Discussion Paper No. DP15866, Available at SSRN: `https://ssrn.com/abstract=3805281`, Center for Economic Policy Research, London, UK.

Doornik, J. A. and Hendry, D. F. (2018). *Modelling Dynamic Systems*, volume II of *PcGive 15*. Timberlake Consultants Ltd.

Farmer, L. E., Nakamura, E., and Steinsson, J. (2024). Learning about the long run. *Journal of Political Economy*, 132(10):3334–3377.

Faust, J. and Wright, J. H. (2008). Efficient forecast tests for conditional policy forecasts. *Journal of Econometrics*, 146(2):293–303.

Gallagher, J. and Hartley, D. (2017). Household finance after a natural disaster: The case of Hurricane Katrina. *American Economic Journal: Economic Policy*, 9(3):199–228.

Gertler, M. and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Ghanem, D. and Smith, A. (2021). What are the benefits of high-frequency data for fixed effects panel models? *Journal of the Association of Environmental and Resource Economists*, 8(2):199–234.

Grinsted, A., Ditlevsen, P., and Christensen, J. H. (2019). Normalized us hurricane damage estimates using area of total destruction, 1900- 2018. *Proceedings of the National Academy of Sciences*, 116(48):23942–23946.

Hatzius, J. (2005). Katrina, growth, and rates: Less now, more later. US Economic Analyst Issue No: 05/36, Goldman Sachs, US Economic Research Group, New York, NY.

Heinen, A., Khadan, J., and Strobl, E. (2019). The price impact of extreme weather in developing countries. *Economic Journal*, 129(619):1327–1342.

Hendry, D. F. and Mizon, G. E. (1978). Serial correlation as a convenient simplification, not a nuisance: A comment on a study of the demand for money by the Bank of England. *Economic Journal*, 88(351):549–563.

Herzon, B. and Prakken, J. (2016). Gauging the GDP Effect of Hurricane Matthew. Recently Asked Questions, Macroeconomic Advisers, St. Louis, MO.

Herzon, B. and Prakken, J. (2017). Impact of Hurricane Irma. Recently Asked Questions, Macroeconomic Advisers, St. Louis, MO.

Herzon, B. and Prakken, J. (2018a). Impact of Hurricane Florence. Recently Asked Questions, Macroeconomic Advisers, St. Louis, MO.

Herzon, B. and Prakken, J. (2018b). Impact of Hurricane Michael. Recently Asked Questions, Macroeconomic Advisers, St. Louis, MO.

Hill, S. (2017). Hurricanes Irma and Harvey to Delay but Not Derail US Growth. U.S. Daily, Goldman Sachs, Economic Research, New York, NY.

Hsiang, S. M. and Jina, A. S. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Working Paper No. 20352, National Bureau of Economic Research, Cambridge, MA.

Jacobson, M. M., Matthes, C., and Walker, T. B. (2022). Inflation measured every day keeps adverse responses away: Temporal aggregation and monetary policy transmission. Finance and Economics Discussion Series No. 2022-054, Board of Governors of the Federal Reserve System, Washington, D.C.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from OPEC announcements. *American Economic Review*, 111(4):1092–1125.

Kasman, B. and Mellman, R. (2005). Katrina's US double edge: a hurricane and an oil shock. Global Data Watch, Economic Research Note, JPMorgan Chase Bank, Economic Research, New York, NY.

Kim, H. S., Matthes, C., and Phan, T. (2024). Severe Weather and the Macroeconomy. *American Economic Journal: Macroeconomics*, Forthcoming.

Kruttli, M. S., Roth Tran, B., and Watugala, S. W. (2021). Pricing poseidon: Extreme weather uncertainty and firm return dynamics. *Available at SSRN 3284517*.

Lakdawala, A., Ryngaert, J. M., Kay, B., and Futch, M. (2023). Partisan bias in professional macroeconomic forecasts.

Linder, M. H., Peach, R., and Stein, S. (2013). The effect of Superstorm Sandy on the macroeconomy. Liberty street economics blog, Federal Reserve Bank of New York.

Ludvigson, S. C., Ma, S., and Ng, S. (2021). Covid-19 and the costs of deadly disasters. *AEA Papers and Proceedings*, 111(May 2021):366–70.

Lunsford, K. G. (2020). Policy language and information effects in the early days of Federal Reserve forward guidance. *American Economic Review*, 110(9):2899–2934.

Martinez, A. B. (2020a). Forecast accuracy matters for hurricane damage. *Econometrics*, 8(2):18.

Martinez, A. B. (2020b). Improving normalized hurricane damages. *Nature Sustainability*, 3(7):517–518.

Martinez, A. B. (2025). Real-time hurricane damage nowcasts. Unpublished working paper.

Martinez, A. B. and Wilson, A. J. (2024). Forecasting the macroeconomic effects of physical climate risk. In Clements, M. P. and Galvao, A. B., editors, *Research Methods and Applications on Macroeconomic Forecasting*, Forthcoming, chapter 15. Elgar Edwards, London, UK.

Meinerding, C., Poinelli, A., and Schüler, Y. (2023). Households' inflation expectations and concern about climate change. *European Journal of Political Economy*, page 102451.

Miranda-Agrippino, S. and Ricco, G. (2021). The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics*, 13(3):74–107.

Mizon, G. E. and Hendry, D. F. (1980). An empirical application and monte carlo analysis of tests of dynamic specification. *Review of Economic Studies*, 47(1):21–45.

Montiel Olea, J. L. and Plagborg-Møller, M. (2021). Local projection inference is simpler and more robust than you think. *Econometrica*, 89(4):1789–1823.

Nakamura, E. and Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: the information effect. *Quarterly Journal of Economics*, 133(3):1283–1330.

Natoli, F. (2022). The macroeconomic effects of temperature surprise shocks. SSRN Working Paper available at: `https://dx.doi.org/10.2139/ssrn.4160944` (last accessed September 17, 2022), SSRN.

Nordhaus, W. D. (1987). Forecasting efficiency: concepts and applications. *Review of Economics and Statistics*, pages 667–674.

Parker, M. (2018). The impact of disasters on inflation. *Economics of Disasters and Climate Change*, 2(1):21–48.

Pesaran, M. H. and Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1):79–113.

Romer, C. D. and Romer, D. H. (2000). Federal reserve information and the behavior of interest rates. *American economic review*, 90(3):429–457.

Roth Tran, B. and Wilson, D. J. (2020). The local economic impact of natural disasters. Federal Reserve Bank of San Francisco Working Paper 2020-34, Federal Reserve Bank of San Franciso, San Francisco, CA.

Sargan, J. D. (1980). Some tests of dynamic specification for a single equation. *Econometrica*, 48(4):879–897.

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

Smith, A. B. and Katz, R. W. (2013). US billion-dollar weather and climate disasters: data sources, trends, accuracy and biases. *Natural hazards*, 67(2):387–410.

Stock, J. H. and Watson, M. W. (2014). Estimating turning points using large data sets. *Journal of Econometrics*, 178:368–381.

Strobl, E. (2011). The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties. *Review of Economics and Statistics*, 93(2):575–589.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economics*, 99(1):1–10.

Varvares, C. (2005). The U.S. Economic Outlook, Katrina and Oil Shock Torque the Outlook. Presentation at Macroeconomic Advisors 15th Washington Policy Seminar, Macroeconomic Advisers, Washington, DC.

Walker, R. (2024). The Impact of Hurricanes: A Roadmap for Upcoming Data Releases. U.S. Economics Analyst, Goldman Sachs, Economic Research, New York, NY.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4):817–838.

Supplemental Appendices

A Forecast Revisions and Tests of Weaker Forecast Efficiency

Consider that individual forecasters revise their forecasts for forecast horizon h as follows

$$f_{t,i}^{h} = f_{t-1,i}^{h} + v_{t,i}^{h}, \tag{10}$$

such that the revision is a random walk subject to an idiosyncratic shock. The shock can be further decomposed into a common shock and an idiosyncratic shock

$$v_{t,i}^{h} = g_{t}^{h} + u_{t,i}^{h}. \tag{11}$$

Shocks are typically assumed to be iid; see Nordhaus (1987). However, forecasters face a large mix of shocks, some of which can persist. For example, monthly growth in non-farm payrolls exceeded the Bloomberg consensus forecast 19 out of the 24 months between May 2022 and May 2024. Suppose that both the common and the idiosyncratic shocks follow autoregressive processes with single lags such that

$$\begin{aligned} g_{t}^{h} &= \rho g_{t-1}^{h} + o_{t}^{h} \\ u_{t,i}^{h} &= \gamma u_{t-1,i}^{h} + e_{t,i}^{h} \end{aligned} \tag{12}$$

where o_{t}^{t+h} is iid $N(0, \sigma_o^2)$ and $e_{t,i}^{t+h}$ is iid $N(0, \sigma_e^2)$ and both are completely uncorrelated. Under these assumptions the original forecast revision process can be rewritten

$$\Delta f_{t,i}^{h} = \rho \Delta f_{t-1,i}^{h} + o_{t}^{h} + (\gamma - \rho) u_{t-1,i}^{h} + e_{t,i}^{h} \tag{13}$$

where the forecast revision dynamics follow directly from the dynamics of the shocks. Note that this model does not explicitly allow for forecast revision inefficiency. Allowing for inefficiency such that forecasters react to their lagged revisions gives

$$\Delta f_{t,i}^{h} = (\rho + \delta) \Delta f_{t-1,i}^{h} - \rho \delta \Delta f_{t-2,i}^{h} + o_{t}^{h} + (\gamma - \rho) u_{t-1,i}^{h} + e_{t,i}^{h} \tag{14}$$

where δ governs the degree of inefficiency. This result also holds for consensus forecast revisions where if we define $\Delta \bar{f}_{t}^{h} = \sum_{i=1}^{N} \Delta f_{t,i}^{h}$ then the resulting consensus revision process is

$$\Delta\bar{f}_t^h = (\rho+\delta)\Delta\bar{f}_{t-1}^h - \rho\delta\Delta\tilde{f}_{t-2}^h + o_t^h \tag{15}$$

where the estimates of the coefficient on the lagged revision can be non-zero in both the aggregate and individual forecaster cases even when $\delta = 0$. Furthermore, the estimated coefficient from the aggregate equation can be different from and even opposite signed as the estimated coefficient in the individual forecaster equation as long as $\gamma \neq \rho$. In fact when $\delta = 0$, while $\hat{\alpha}_{AGG} \to \rho$, $\hat{\alpha}_{IND} \to (\rho\sigma_o^2 + \gamma\sigma_e^2)/\left[\sigma_o^2/(1-\rho^2) + \sigma_e^2/(1-\gamma^2)\right]$ such that it depends on both the autocorrelation of the aggregate and idiosyncratic shocks, their respective variances, and how they differ. If $\rho > 0$ and $\gamma < 0$ then it is possible to see the sign flip when switching between individual and aggregate forecasts as in Bordalo et al. (2020). For example, if $\delta = 0$, $\sigma_e^2 = \sigma_o^2 = 1$ and $\rho = 0.3$ and $\gamma = -0.6$ then $\hat{\alpha}_{IND} \to -0.11$ vs $\hat{\alpha}_{AGG} \to 0.3$.

Thus, it is not possible to identify whether forecasters are over-reacting or under-reacting to new information based on the dependence of the forecast revisions alone when the shocks forecasters face are autocorrelated. Panel A in Figure A.1 shows that tests of forecast efficiency based on the lag revision are severely oversized under the null of no forecast revisions inefficiency ($\delta = 0$) when the shocks are autocorrelated for both consensus estimates, individual estimates, and even when controlling for common factors.

This issue can be circumvented if at least one of the shocks is independent from all other shocks and serially uncorrelated such that

$$v_{t,i}^h = g_t^h + u_{t,i}^h + \eta x_t \tag{16}$$

where x_t is common across forecasters, completely uncorrelated with other shocks, and has a variance of σ_x^2. The revision process can be rewritten as

$$\Delta f_{t,i}^h = (\rho+\delta)\Delta f_{t-1,i}^h + \eta x_t - \rho\eta x_{t-1} + (\gamma-\rho)u_{t-1,i}^h + e_{t,i}^h + o_t^h. \tag{17}$$

In the aggregate forecaster case if we only observe x_t and the forecast revisions then

$$\Delta\bar{f}_t^h = \beta_0\Delta\bar{f}_{t-1}^h + \beta_1 x_t + \beta_2 x_{t-1} + \tilde{v}_t^h, \tag{18}$$

where $\beta_{0,AGG} = \rho+\delta$, $\beta_{1,AGG} = \eta$, $\beta_{2,AGG} = -\rho\eta$, and $\tilde{v}_t^h = o_t^h$. It is possible to test for forecast revision efficiency under these assumptions using a common factor (COMFAC) restriction imposing that the short-run response to x_t is identical to the long-run. That is

$$H_0 : \beta_{1,AGG} - (\beta_{1,AGG} + \beta_{2,AGG})/(1-\beta_{0,AGG}) \equiv 0, \tag{19}$$

where if $\delta = 0$ then this restriction holds for any stationary value of ρ.

This also applies to analyses of individual forecasters, however it requires that we observe a proxy measure of the serially correlated common shocks that forecasters face such that

$$\Delta f^h_{t,i} = \beta_0 \Delta f^h_{t-1,i} + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 g^h_t + \beta_4 g^h_{t-1} + \tilde{v}^h_{t,i}, \tag{20}$$

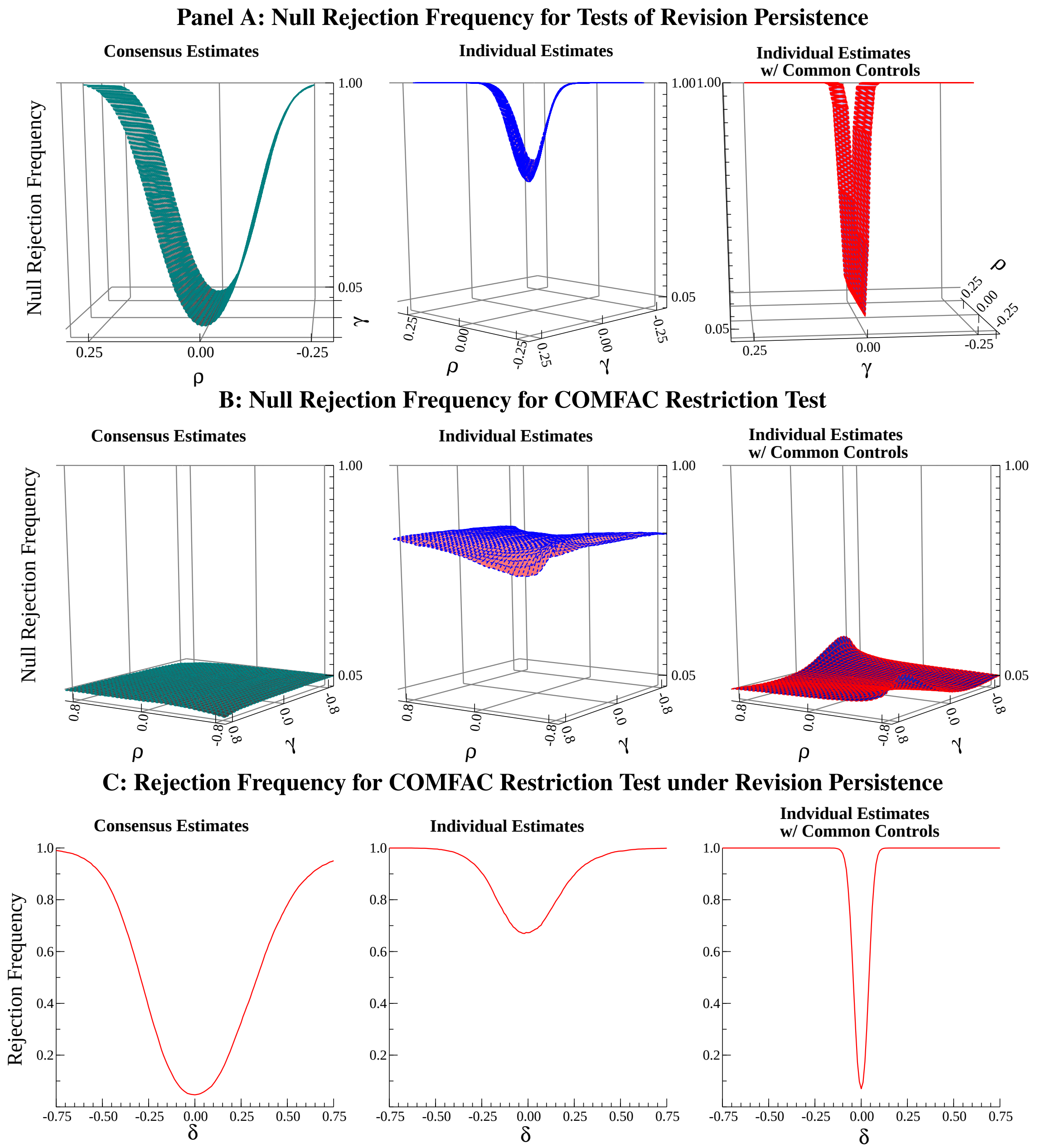
where $\beta_0 = \gamma + \delta$, $\beta_1 = \eta$, $\beta_2 = -\rho\eta$, $\beta_3 = 1$, $\beta_4 = \rho - \gamma$, and $\tilde{v}_{t,i} = o_{t,h}$ and where estimates of β_0 are not consistent if g^h_{t-1} or some proxy thereof is not observed and included in the equation. Given this equation then again a test of forecast revision efficiency using a common factor restriction

$$H_0 : \beta_{1,IND} - (\beta_{1,IND} + \beta_{2,IND})/(1 - \beta_{0,IND}) \equiv 0, \tag{21}$$

where again if $\delta = 0$ then this restriction holds for any stationary value of ρ and γ.

Panel B of Figure A.1 shows the null rejection frequency for common factor restriction tests for consensus estimates, individual estimates, and individual estimates while controlling for the common shocks. It shows that across general values of ρ and γ the null rejection frequencies are correctly sized except for the individual estimates when failing to control for the common shocks.

Panel C of Figure A.1 shows the rejection frequency when allowing for persistence in the shocks for different values of δ . It shows that while tests performed using consensus forecasts and those performed using individual forecasts with controls for common shocks both have good size and power properties, the individual estimates with common controls have a higher power curve, particularly for small values of δ and are more likely to detect rejections of the null hypothesis.



Notes: In all cases simulations were done with N=50, T=300 and 10,000 replications. In Panels A and B δ=0. In Panels B and C $\eta = -0.4$. In Panel C $\gamma = -0.6$ and $\rho = 0.3$.

Figure A.1: Simulation Results

B Robustness and Extensions

The main results are broadly robust to a range of alternative specifications. First, focusing on either the BCEI of the BCFF survey alone rather than combined gives similar results albeit with lower power to detect non-linearities and violations of weaker efficiency; see Appendix Table C.1 and C.2. Second, the results are also weakly robust to focusing on the 'consensus forecast' of the combined surveys although again there is lower power to detect differences in efficiency and non-linearities; see Appendix Table C.3. Next, I run the forecast errors and revisions specification as advocated by Coibion and Gorodnichenko (2015) and find broadly consistent results although the test of weaker efficiency does not apply here and it is difficult to interpret the sign of the estimated coefficients given that errors could have occurred following the shock either due changes in GDP, changes in the forecasts or both; see Appendix Table C.4. Finally, I rerun the results using a measure of real-time damage uncertainty / model disagreement and show that the results are broadly similar to the baseline; ; see Appendix Table C.5. Overall, this suggests that the results broadly robust albeit other specifications are likely to have less power than the baseline

A key question is whether these results apply to different groups of forecasters. To test for heterogeneity I interact the parameters of interest in equation (4) in the main papee with dummy variables for known forecaster characteristics. I consider four key characteristics: (1) forecaster size as measured by their firm's number of employees and if it is publicly traded, (2) industry type and if the forecaster is at a primary dealer for the Federal Reserve Bank of New York, (3) distance in miles from the shock, and (4) behavioral characteristics such as how long a forecaster is in the panel and how often they revise their forecasts. Other characteristics may also be important but are not considered here; e.g. see Lakdawala et al. (2023).

The results in Appendix Table C.6 broadly indicate that the results generally hold across different groups but also provide clear evidence of forecaster heterogeneity. Forecasters in larger or publicly traded firms as well as those who are closer to the location of the hurricane have a significantly larger response. Furthermore, forecasters in the financial services industry are significantly more likely to efficiently revise their forecasts in response to a shock. This suggests that obtaining timely information about the shocks is costly to forecasters such that only those with resources or who are likely to be affected incorporate the information; e.g. see Sims (2003). I also find that forecasters who have been in the sample longer or who revise their forecasts more often are more likely to respond. This is suggestive of adaptive expectations or learning by doing; e.g. see Andrade and Le Bihan (2013).

Allowing for a general measure of forecaster disagreement reduces long-run heterogeneity across forecasters. I augment equation (4) in the main paper with the lag deviation of the individual forecast from consensus. Appendix Table C.7 indicates that the results are broadly similar to those in the main paper except that forecasters "error-correct" their expectations back to consensus at a speed of approximately one fifth of the gap per period. This means that forecasters bring their forecasts back inline with consensus over the quarter. This is both highly significant, stable over time, and identical across forecasters such that much of the forecaster heterogeneity in Appendix Table C.6 is eliminated in the long-run with the exception of differences across industries, distance from the hurricane, and revision frequency.

The results are also generally robust to outliers but exhibit a gradual decline over time. Removing 1 percent of observations from each of the tails or winsorizing 5 percent of the observations in each of the tails generates similar results; see Appendix Tables C.8 and C.9. The main changes are that there is a loss of power such that the non-linear terms become statistically insignificant. Examining the stability of the results over time using an expanding window recursive analysis, indicates that there is a reduction in the response to a Hurricane Katrina shock over time such that both the immediate and total effects decline, however the gap between them remains fairly constant; see Appending Figure C.2. This suggests an interesting puzzle in that there is a dynamic under-reaction to individual shocks within a quarter but gradual downward revisions in the effect size over time.

C Additional Figures and Tables

■ OCTOBER 1, 2019

Blue Chip Financial Forecasts Panel Members

NatWest Markets
DePrince & Assoc.
Action Economics
Amherst Pierpont Securities
Bank of America Merrill Lynch
Daiwa Capital Markets America
Economist Intelligence Unit
MacroFin Analytics & Rutgers Bus School
MUFG Union Bank
Naroff Economic Advisors
RDQ Economics
The Northern Trust Company
ACIMA Private Wealth
Chan Economics
Chmura Economics & Analytics
Comerica Bank
Georgia State University
Grant Thornton/Diane Swonk
J.P. Morgan Chase
Regions Financial Corporation
S&P Global
Scotiabank Group
Swiss Re
Via Nova Investment Mgt.
Cycledata Corp.
GLC Financial Economics
High Frequency Economics
Moody's Capital Markets Group
Oxford Economics
PNC Financial Services Corp.
Societe Generale
Wells Fargo
AIG
Barclays
BMO Capital Markets
BNP Paribas Americas
Fannie Mae
Goldman Sachs & Co.
Loomis, Sayles & Company
Mizuho Research Institute
Nomura Securities, Inc.
TS Lombard
ING
Moody's Analytics

32/44=0.73

■ BLUE CHIP ECONOMIC INDICATOR
■ OCTOBER 10, 2019

OCTOBER 2019

Amherst Pierpont Securities
Action Economics
Econoclast
MUFG Union Bank
ACT Research*
Bank of America-Merrill Lynch, US**
BMO Capital Markets*
Credit Suisse
Daiwa Capital Markets America
Eaton Corporation
Fannie Mae
FedEx Corporation, US
Ford Motor Company*
General Motors Corporation, US
Goldman Sachs & Co.**
High Frequency Economics
Inforum - Univ. of Maryland
Macroeconomic Advisers by IHS Markit**
MacroFin Analytics & Rutgers Bus School
Moody's Analytics, US
Morgan Stanley, US**
Naroff Economic Advisors*
National Assn. of Home Builders
National Retail Federation
NatWest Markets
Nomura Securities, US
PNC Financial Services Group
Point72 Asset Management*
RBC Capital Markets
RDQ Economics
Regions Financial Corporation
S&P Global, US*
Societe Generale
SOM Economics, Inc.
Swiss Re
UBS
UCLA Business Forecasting Proj.*
Visa
AIG
Barclays, US*
Comerica**
Economist Intelligence Unit, UK
Georgia State University*
Grant Thorton/Diane Swonk
JP MorganChase, US
Moody's Capital Markets, US*
Northern Trust Company*
Oxford Economics, US
U.S. Chamber of Commerce
Wells Fargo, US
ACIMA Private Wealth, US

32/51=0.63

Notes: Yellow highlights denote those forecasters who are surveyed in both Blue Chip surveys.

Figure C.1: Example List of Blue Chip Forecasters in October 2019

Table C.1: Effect of a Hurricane Katrina Shock on BCEI GDP Nowcasts

	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		−0.16	−0.16	−0.16	−0.16
		(0.02)	(0.02)	(0.02)	(0.02)
Lagged Revision × Lagged Shock:				0.17	0.11
				(0.13)	(0.12)
Immediate Effect:	−0.31		−0.10		−0.10
	(0.23)		(0.22)		(0.22)
Lagged Effect:			−0.56		−0.54
			(0.29)		(0.30)
Total Effect:	−0.36	0	−0.57	0	−0.56
	(0.22)		(0.36)		(0.37)
Tests of Efficiency, $\chi^2(1)$:	n.a.	55.44	3.71	0.00	3.41
		[0.000]	[0.054]	[0.948]	[0.065]
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Observations (N×T):	8,054	8,054	8,054	8,054	8,054
Forecasters/Firms (N):	75	75	75	75	75
$\hat{\sigma}$:	0.54	0.53	0.53	0.53	0.53
R^2 :	0.35	0.37	0.37	0.37	0.37

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by firm and time following Thompson (2011) and Cameron et al. (2011).

Table C.2: Effect of a Hurricane Katrina Shock on BCFF GDP Nowcasts

	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		−0.19	−0.19	−0.19	−0.19
		(0.03)	(0.04)	(0.04)	(0.04)
Lagged Revision × Lagged Shock:				0.04	0.01
				(0.19)	(0.15)
Immediate Effect:	−0.39		−0.33		−0.33
	(0.27)		(0.24)		(0.24)
Lagged Effect:			−0.30		−0.29
			(0.16)		(0.16)
Total Effect:	−0.39	0	−0.53	0	−0.53
	(0.27)		(0.25)		(0.26)
Tests of Efficiency, $\chi^2(1)$:	n.a.	29.80	2.00	0.63	1.67
		[0.000]	[0.158]	[0.428]	[0.196]
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Observations (N×T):	7,704	7,704	7,704	7,704	7,704
Forecasters/Firms (N):	56	56	56	56	56
$\hat{\sigma}$:	0.53	0.52	0.52	0.52	0.52
R^2 :	0.33	0.36	0.37	0.37	0.37

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by firm and time following Thompson (2011) and Cameron et al. (2011).

Table C.3: Effect of a Hurricane Katrina Shock on Consensus GDP Nowcasts

	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		0.54	0.54	0.54	0.54
		(0.06)	(0.06)	(0.06)	(0.06)
Lagged Revision × Lagged Shock:				−2.31	−1.44
				(1.57)	(1.33)
Immediate Effect:	−0.27		−0.41		−0.37
	(0.35)		(0.20)		(0.22)
Lagged Effect:			0.70		0.35
			(0.53)		(0.44)
Total Effect:	−0.27	0	0.64	0	1.12
	(0.35)		(1.13)		(1.21)
Tests of Efficiency, $\chi^2(1)$:	n.a.	126.7	0.26	0.28	0.28
		[0.000]	[0.613]	[0.596]	[0.596]
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Observations (T):	468	468	468	468	468
$\hat{\sigma}$:	0.88	0.79	0.79	0.79	0.79
R^2 :	0.20	0.36	0.36	0.36	0.36

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by firm and time following Thompson (2011) and Cameron et al. (2011).

Table C.4: Effect of a Hurricane Katrina Shock on GDP Nowcast Errors

	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		−0.11	−0.11	−0.11	−0.11
		(0.02)	(0.02)	(0.02)	(0.02)
Lagged Revision × Lagged Shock:				−0.11	0.08
				(0.14)	(0.21)
Immediate Effect:	0.25		0.25		0.25
	(0.13)		(0.12)		(0.13)
Lagged Effect:			0.34		0.36
			(0.09)		(0.15)
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Observations (N×T):	13,719	13,719	13,719	13,719	13,719
Forecasters/Firms (N):	54	54	54	54	54
$\hat{\sigma}$:	0.59	0.59	0.59	0.59	0.59
R^2 :	0.84	0.84	0.84	0.84	0.84

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by firm and time following Thompson (2011) and Cameron et al. (2011).

Table C.5: Effect of a Damage Uncertainty Shock on GDP Nowcasts

	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		−0.27	−0.27	−0.27	−0.27
		(0.02)	(0.02)	(0.02)	(0.02)
Lagged Revision × Lagged Shock:				0.24	0.20
				(0.10)	(0.10)
Immediate Effect:	−0.22		−0.27		−0.26
	(0.08)		(0.08)		(0.08)
Lagged Effect:			−0.10		−0.04
			(0.10)		(0.10)
Total Effect:	−0.22	0	−0.29	0	−0.28
	(0.08)		(0.11)		(0.12)
Tests of Efficiency, $\chi^2(1)$:	n.a.	126.8	0.08	0.12	0.08
		[0.000]	[0.779]	[0.725]	[0.782]
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Observations (N×T):	13,747	13,747	13,747	13,747	13,747
Forecasters/Firms (N):	54	54	54	54	54
$\hat{\sigma}$:	0.45	0.43	0.43	0.43	0.43
R^2 :	0.23	0.29	0.29	0.29	0.29

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by firm and time following Thompson (2011) and Cameron et al. (2011).

Table C.6: Heterogenous Effect of a Hurricane Katrina Shock on GDP Nowcasts

	Publicly Traded	**>1000 Employees**	**Financial Services**	**Primary Dealers**	**Dist. (≤700mi)**	**Obs. Shr. (≥0.70)**	**Rev. Shr. (≥0.65)**
Lagged Revision:	−0.31	−0.31	−0.29	−0.30	−0.28	−0.29	−0.27
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Lagged Revision × Lagged Shock:	0.38	0.46	0.51	0.38	-0.15	0.64	-0.02
	(0.28)	(0.25)	(0.33)	(0.23)	(0.25)	(0.38)	(0.22)
Immediate Effect:	−0.29	−0.33	−0.60	−0.45	−0.42	−0.29	−0.40
	(0.15)	(0.15)	(0.18)	(0.18)	(0.18)	(0.17)	(0.19)
Lagged Effect:	−0.17	−0.20	0.01	−0.22	−0.65	−0.18	−0.37
	(0.13)	(0.13)	(0.17)	(0.15)	(0.23)	(0.19)	(0.18)
Total Effect:	−0.87	−0.81	−0.67	−0.73	−1.12	−0.83	−0.91
	(0.22)	(0.21)	(0.21)	(0.20)	(0.24)	(0.21)	(0.21)

	Other Firms	**≤1000 Employees**	**Other Industries**	**Other Firms**	**Dist (>700mi)**	**Obs. Shr. (<0.70)**	**Rev. Shr. (<0.65)**
Lagged Revision:	−0.25	−0.25	−0.26	−0.22	−0.09	−0.26	−0.28
	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)
Lagged Revision × Lagged Shock:	−0.08	−0.07	0.03	−0.31	0.19	−0.13	0.42
	(0.28)	(0.28)	(0.25)	(0.37)	(0.19)	(0.27)	(0.24)
Immediate Effect:	−0.61	−0.57	−0.38	−0.49	−0.99	−0.59	−0.62
	(0.23)	(0.22)	(0.18)	(0.20)	(0.15)	(0.25)	(0.22)
Lagged Effect:	−0.52	−0.48	−0.46	−0.55	−0.04	−0.53	−0.29
	(0.24)	(0.24)	(0.20)	(0.29)	(0.16)	(0.20)	(0.15)
Total Effect:	−0.44	−0.52	−0.70	−0.65	−0.79	−0.50	−0.60
	(0.18)	(0.18)	(0.26)	(0.20)	(0.19)	(0.23)	(0.18)
Test of Homogeneity; $\chi^2(4)$:	8.84	7.81	11.85	7.59	44.8	10.6	9.82
	[0.065]	[0.099]	[0.019]	[0.108]	[0.000]	[0.031]	[0.044]

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by firm and time following Thompson (2011) and Cameron et al. (2011). P-values in square brackets. Each column represents a single equation. The cutoff values for distance for the hurricane (Dist.), Observation share and Revision share roughly correspond to the 66th percentile.

Table C.7: Effect of a Hurricane Katrina Shock on GDP Nowcasts (Disagreement)

	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		−0.18	−0.18	−0.18	−0.18
		(0.03)	(0.03)	(0.03)	(0.03)
Lagged Revision × Lagged Shock:				0.27	0.13
				(0.15)	(0.17)
Immediate Effect:	−0.33		−0.45		−0.45
	(0.19)		(0.17)		(0.17)
Lagged Effect:			−0.30		−0.26
			(0.14)		(0.16)
Lagged Disagreement:		−0.20	−0.20	−0.20	−0.20
		(0.02)	(0.02)	(0.02)	(0.02)
Total Effect:	−0.33	0	−0.64	0	−0.65
	(0.19)		(0.17)		(0.19)
Tests of Efficiency, $\chi^2(1)$:	n.a.	48.66	2.39	0.37	2.79
		[0.000]	[0.123]	[0.541]	[0.095]
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Observations (N×T):	13,747	13,747	13,747	13,747	13,747
Forecasters/Firms (N):	54	54	54	54	54
$\hat{\sigma}$:	0.45	0.42	0.42	0.42	0.42
R^2 :	0.23	0.34	0.34	0.34	0.34

Notes: Macro News Surprises include a lag. Time fixed effects include both month-year fixed effects and week of quarter seasonal effects. Estimated standard errors in parentheses are clustered two-ways by firm and time following Thompson (2011) and Cameron et al. (2011).

Table C.8: Effect of a Hurricane Katrina Shock on GDP Nowcasts (Outliers 1%)

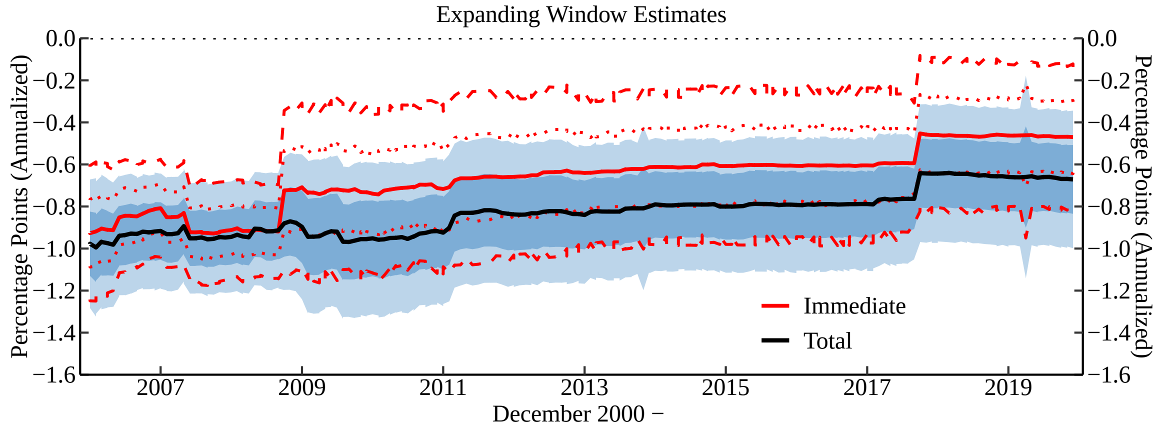
	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		−0.19	−0.19	−0.19	−0.19
		(0.02)	(0.02)	(0.02)	(0.02)
Lagged Revision × Lagged Shock:				0.03	−0.09
				(0.17)	(0.22)
Immediate Effect:	−0.37		−0.46		−0.47
	(0.15)		(0.13)		(0.13)
Lagged Effect:			−0.21		−0.25
			(0.13)		(0.15)
Total Effect:	−0.37	0	−0.57	0	−0.56
	(0.15)		(0.15)		(0.15)
Tests of Efficiency, $\chi^2(1)$:	n.a.	111.6	0.94	0.04	0.77
		[0.000]	[0.333]	[0.842]	[0.381]
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Forecaster/Firm Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Observations (N×T):	13,472	13,472	13,472	13,472	13,472
Forecasters/Firms (N):	54	54	54	54	54
$\hat{\sigma}$:	0.36	0.35	0.35	0.35	0.35
R^2 :	0.51	0.53	0.53	0.53	0.53

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by forecaster and time following Thompson (2011) and Cameron et al. (2011). Forecast revision outliers that are in the upper and lower 1 percent of the tails are excluded by including dummy variables to remove them.

Table C.9: Effect of a Hurricane Katrina Shock on GDP Nowcasts (Winsorizing 5%)

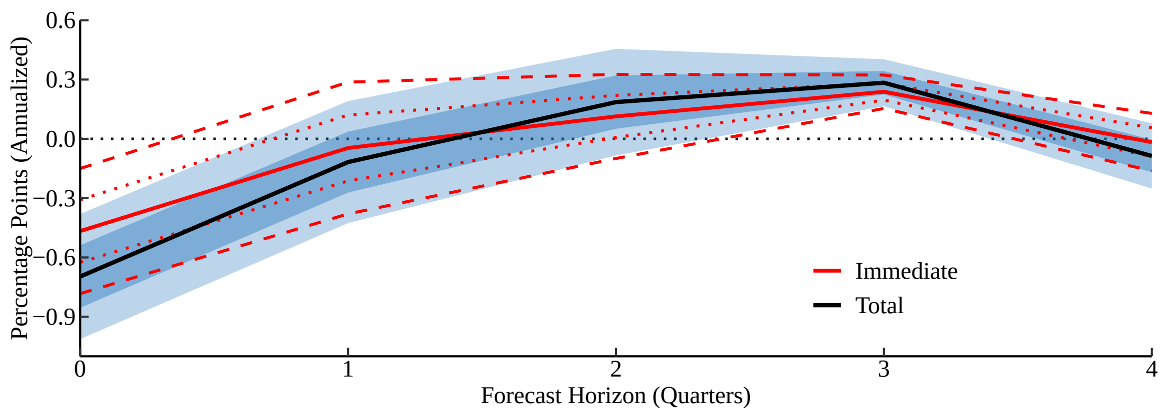
	(1)	(2)	(2b)	(3)	(4)
Lagged Revision:		−0.24	−0.24	−0.24	−0.24
		(0.02)	(0.02)	(0.02)	(0.02)
Lagged Revision × Lagged Shock:				0.15	0.01
				(0.15)	(0.06)
Immediate Effect:	−0.39		−0.48		−0.48
	(0.13)		(0.11)		(0.11)
Lagged Effect:			−0.22		−0.22
			(0.10)		(0.11)
Total Effect:	−0.39	0	−0.56	0	−0.56
	(0.13)		(0.12)		(0.13)
Tests of Efficiency, $\chi^2(1)$:	n.a.	119.2	1.04	0.35	1.00
		[0.000]	[0.308]	[0.555]	[0.318]
Macro News Surprises:	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Forecaster/Firm Fixed Effects:	Yes	Yes	Yes	Yes	Yes
Observations (N×T):	13,747	13,747	13,747	13,747	13,747
Forecasters/Firms (N):	54	54	54	54	54
$\hat{\sigma}$:	0.34	0.33	0.33	0.33	0.33
R^2 :	0.17	0.22	0.22	0.22	0.22

Notes: Macro News Surprises include a single lag. Time fixed effects includes survey month fixed effects and week of quarter fixed effects. Estimated standard errors in parentheses are clustered two-ways by forecaster and time following Thompson (2011) and Cameron et al. (2011). Forecast revisions are winsorized such that both any observation above the 95 or below the 5 percentile is censored to be equal to the respective precentiles



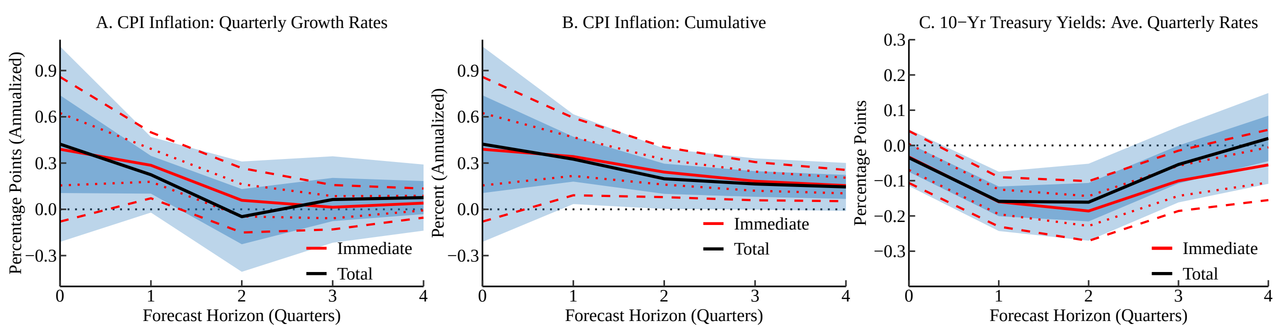
Notes: Estimates are obtained recursively using equation (13) with non-linearities set to zero. Immediate (red) and total (black) effects of a hurricane shock. Normalized to represent a Hurricane Katrina sized shock. Solid lines are point estimates and the shaded areas (and dashed/dotted lines) are 68 and 95 percent pointwise confidence bands respectively.

Figure C.2: Recursive Estimates of the Effects of a Katrina-sized Shock on GDP Nowcasts



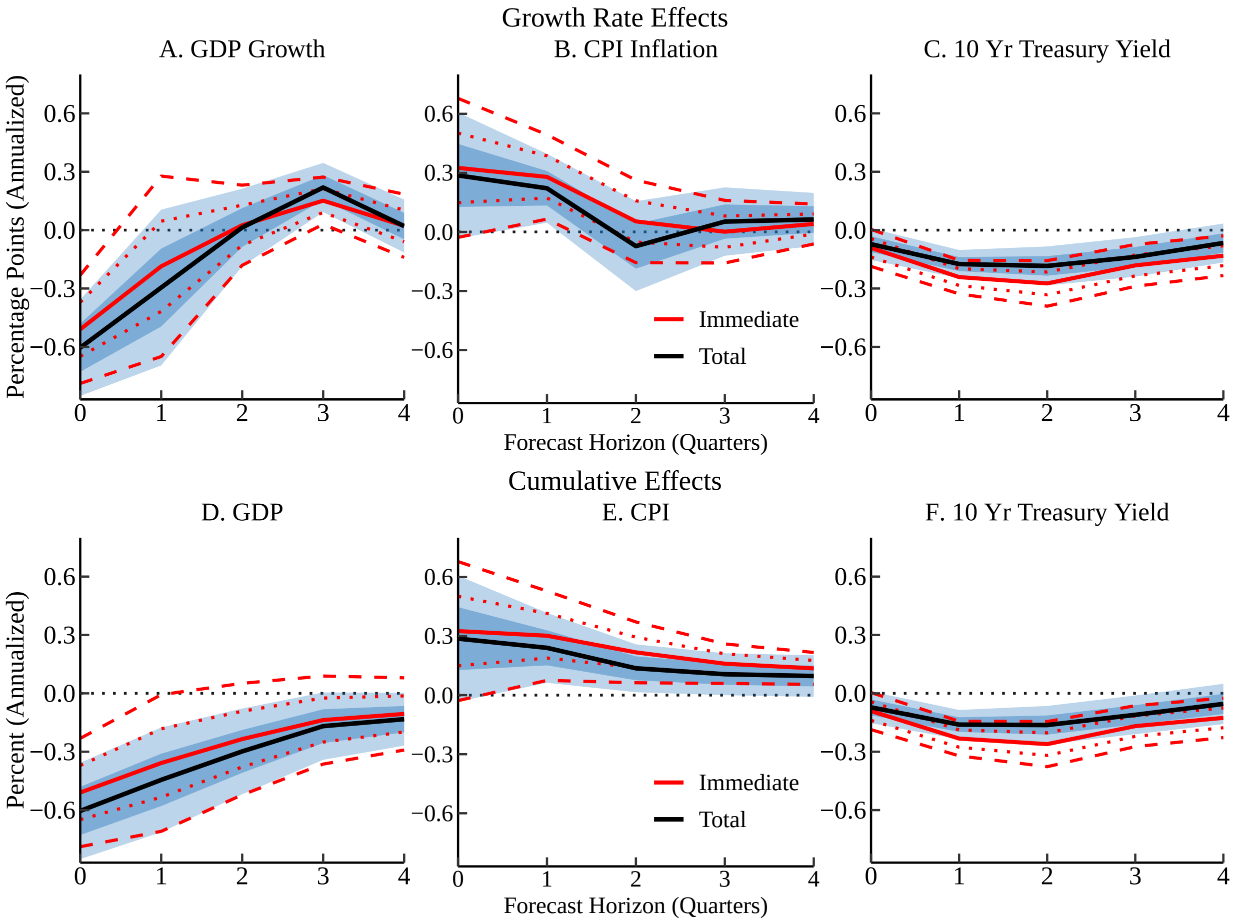
Notes: Immediate (red) and total (black) effects of a hurricane shock. Scaled to represent a Hurricane Katrina-sized shock. Solid lines are estimates and the shaded areas (and dashed/dotted lines) are the 68 and 95 percent confidence intervals at each horizon respectively. Estimated jointly based on a common sample of 11,268 observations across each horizon.

Figure C.3: Joint Dynamic Effects of a Hurricane Katrina Shock on GDP Forecasts



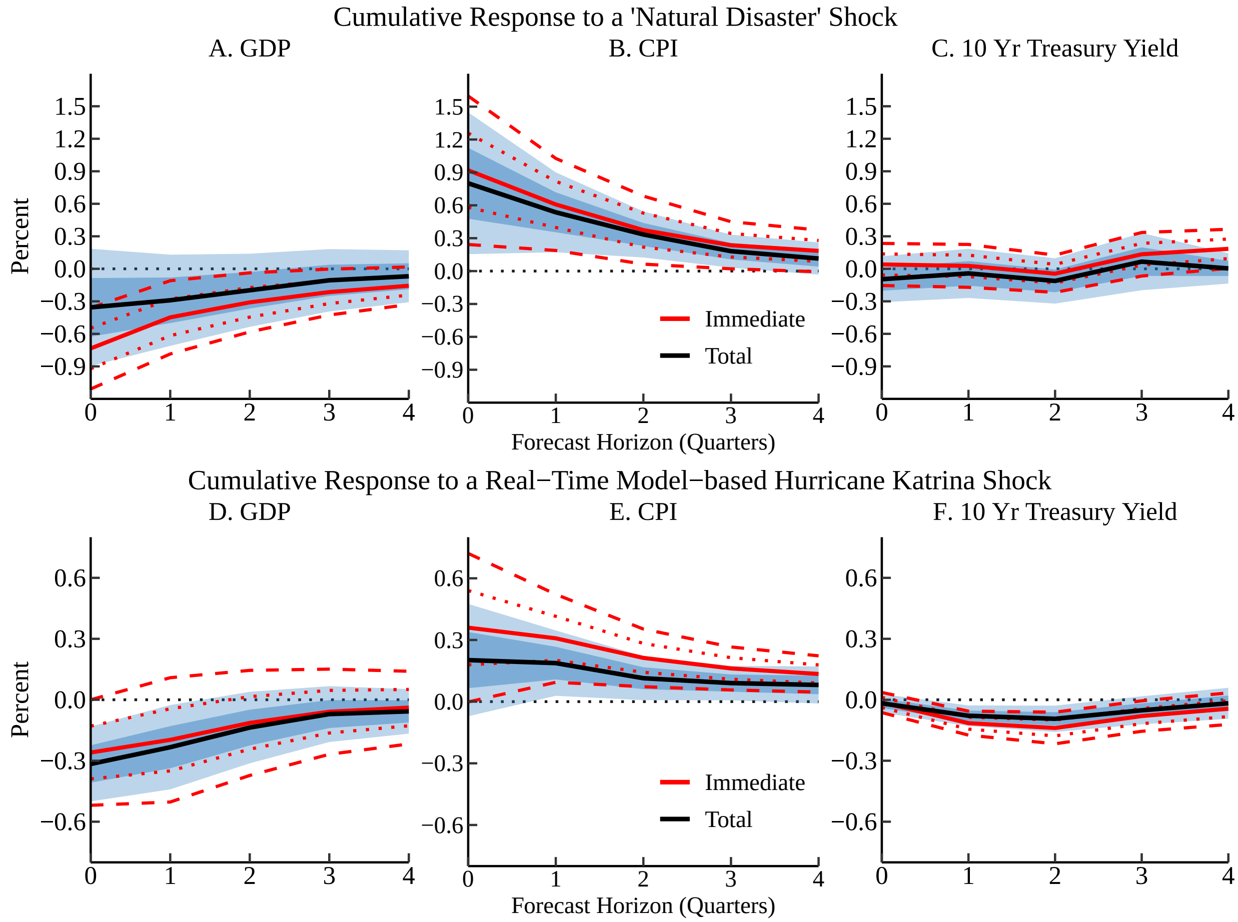
Notes: Immediate (red) and total (black) effects of a hurricane shock. Scaled to represent a Hurricane Katrina-sized shock. Solid lines are point estimates and the shaded areas (and dashed/dotted lines) are the point-wise 68 and 95 percent confidence intervals at each horizon respectively.

Figure C.4: Dynamic Forecast Revisions in CPI and Treasury Yields Following a Hurricane Katrina Shock



Notes: Immediate (red) and total (black) effects of a hurricane shock. Scaled to represent a Hurricane Katrina-sized shock. Solid lines are point estimates and the shaded areas (and dashed/dotted lines) are the point-wise 68 and 95 percent confidence intervals at each horizon respectively.. Control for OPEC shocks from Känzig (2021) and monetary policy shocks from Nakamura and Steinsson (2018).

Figure C.5: Dynamic Effects of a Hurricane Katrina Shock on a System of Forecasts after controlling for OPEC Oil Shocks and Monetary Policy Shocks



Notes: Immediate (red) and total (black) effects of a hurricane shock. Scaled to represent a Hurricane Katrina-sized shock. Solid lines are point estimates and the shaded areas (and dashed/dotted lines) are the point-wise 68 and 95 percent confidence intervals at each horizon respectively. Scaled to a Hurricane Katrina sized shock. Panels A-C are estimated using a shorter sample 2004-2019 based on daily Google searches for "natural disasters" following Dietrich et al. (2021) while Panels D-F are estimated over the full sample based on real-time estimates of damage predictions from the model in Martinez (2020a).

Figure C.6: Cumulative Dynamic Effects of Alternative Shocks on Systems of Forecasts