The Expected Dynamic Macroeconomic Impacts of Tropical Cyclone Shocks

Andrew B. Martinez*

FIRST DRAFT: May 23, 2022

THIS DRAFT:

March 8, 2023

Abstract

We demonstrate the importance of accounting for forecast revision dynamics when analyzing the expected impacts of large shocks using a new high frequency firm-level panel of macroeconomic forecasts. We disentangle the immediate (short-run) and the total (long-run) impact of a tropical cyclone shock on real GDP growth forecasts at each horizon and show that the total impact is more than two times larger than and persists for longer than the immediate impact. We also demonstrate important heterogeneities across forecasters: large publicly traded firms anticipate larger current-quarter effects and private forecasters are more pessimistic than Federal Reserve Board staff. Expanding the analysis to a multivariate system of forecasts, we show that the expected macroeconomic impact of a tropical cyclone shock mimics that of a negative supply shock (lower GDP growth and higher inflation) and persists even after controlling for unexpected changes in key commodity prices. Looking at the cumulative impacts of a tropical cyclone shock across horizons, the total impact is expected to persist for more than a year.

Keywords: Blue Chip Forecasters, Hurricanes, Static Long-run

JEL classifications: C23, C33, C53, E27, E37, E66, Q54

*Office of Macroeconomic Analysis, U.S. Department of the Treasury, Washington DC, USA; School of Advanced International Studies, The Johns Hopkins University, Washington DC, USA; H.O. Stekler Research Program on Forecasting, The George Washington University, Washington DC, USA; Climate Econometrics, Nuffield College, Oxford, UK. 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 for providing access to the Blue Chip forecasts and to Neil R. Ericsson, Jennifer L. Castle, and Guillaume Chevillon for helpful discussions. I also benefited from participants comments at the Economic Policy Lunch Seminar, the 23rd International Symposium on Forecasting, the Climate Econometrics Seminar, and the Midwest Econometrics Group. All errors are my own. Contact: Andrew.Martinez@treasury.gov.

1 Introduction

A question of growing importance in macroeconomics is how extreme weather and climate shocks impact the macroeconomy. Over the past decade multiple records associated with extreme weather and their damages have been broken around the world as the costs associated with these events rise. There are growing efforts to understand the implications of these events for the broader macroeconomy as the risks associated with a changing climate are realized along with predictions of worse impacts to come, ; e.g. see Dell et al. (2012), Cavallo et al. (2013), Colacito et al. (2019), Kim et al. (2021), and Natoli (2022) among others.

Tropical cyclones are among the most destructive extreme weather events in the United States and globally. They account for both the largest single event losses as well as the majority of damages from all billion dollar extreme weather events in the United States over the past two decades. Tropical cyclones have also had important impacts on both monetary and fiscal policy in recent decades and their importance is expected to grow. For example, several weeks after Hurricane Katrina struck New Orleans in 2005, the Federal Reserve's Federal Open Market Committee (FOMC) debated about whether or not to pause its interest rate hiking cycle in light of the storm's uncertain impact on the macroeconomic outlook and financial markets. During that meeting, Governor Mark Olson became the last Federal Reserve Board Governor to dissent from the FOMC consensus to raise rates due to uncertainty about the recovery. Looking forward, the occurrence and intensity of tropical cyclones could more than double globally under extreme climate change scenarios, see Bloemendaal et al. (2022), while the Congressional Budget Office expects that more than a third of the projected macroeconomic impacts due to climate change in the United States will come from tropical cyclones over the next several decades; see Herrnstadt (2021).

While the macroeconomic impacts of tropical cyclones and other extreme weather events have been studied extensively, recent research by Dietrich et al. (2021) and Cantelmo (2022) argues for the importance of differentiating between the expected and actual impacts of extreme climate events. Furthermore, Dietrich et al. (2021) show that expectations about the probabilities of extreme events are determined in part by individuals experiences of tropical cyclones. They argue that when the expected probability of an extreme weather event changes, then the expectations channel implies a negative demand shock which needs to be offset by the appropriate policy response.

In this paper we test for evidence of this expectations channel following large tropical cyclone shocks. We analyze the dynamic macroeconomic impacts of tropical cyclone damage shocks using a new high frequency panel of macroeconomic expectations. We construct this panel by linking together quasi-biweekly firm-level forecasts from Blue Chip surveys for more than 50 firms across multiple variables and forecast horizons over the last two decades. We also construct a real-time measure of tropical cyclone (TC) damage shocks using a news-based measures that best reflects a forecaster's potential information set. Linking TC shocks with revisions in individual macroeconomic economic expectations allows us to assess how changes in information about TC damages altered forecasters' expectations about the macroeconomy.

Overall our results show that there is evidence of a significant impact on macroeconomic expectations across the forecast horizon. We find that a Hurricane Katrina sized shock equivalent to 1% of GDP results in an immediate downward revision in expectations of current quarter real GDP growth by half a percentage point. We also demonstrate the importance of capturing the dynamics by disentangling the immediate (short-run) and the total (long-run) expected impact of a tropical cyclone shock at each forecast horizon up through four-quarters-ahead. After accounting for these dynamic effects, the total impact on the current quarter is more than double that of the immediate. We also find that, following a large shock, private forecasters expect s slow recovery in GDP that can last up to four quarters after a shock.

We find evidence of a large amount of forecaster heterogeneity following a shock. While the typical Blue Chip forecaster agrees with Federal Reserve Board (FRB) staff about the immediate impacts of a shock, private forecasters tend to be more pessimistic at longer horizons with a slower and only partial expected recovery in GDP after three quarters in contrast with FRB staff who expect a full recovery within two quarters after a shock. Furthermore, across private forecasters, larger / publicly traded firms expect larger impacts compared to smaller and non-publicly traded firms. However, a firms industry or geographical location does not appear to matter in the formation of expectations following a large shock.

Finally, looking more broadly across a multivariate system of forecast revisions, we find that a TC shock is akin to a supply shock with an expected decline in real GDP growth, an increase in CPI inflation, and a decline in 10 year Treasury bond yields. While the Treasury bond yields are expected to recover their losses after four quarters, real GDP is only expected to recover partially while CPI inflation is not expected retrace its gains indicating an expected permanent increase in the price level. These results are robust to a range of specifications including longer lags and controlling for changes in commodity price shocks.

Our approach for identifying expected macroeconomic impacts builds on earlier approaches in the empirical macro literature by Campbell et al. (2012), Nakamura and Steinsson (2018), Lunsford (2020), and Bauer and Swanson (2021) among others to study the effects of monetary policy shocks. We show the importance of extending the typical approach to account for forecast dynamics which allows us to distinguish between the immediate (short-run) and the total (long-run) impacts at each forecast horizon. We also extend these results to individual firms and provide some of the first results on the dynamic impacts of a shock on a system of macroeconomic expectations.

Our results are also directly related to the literature on forecast efficiency and forecast revisions. We effectively replicate the findings in Bordalo et al. (2020) using our higher frequency dataset and extend the methods in Baker et al. (2020) to individual forecasters. In contrast to earlier findings, our results show that individual forecasters are more likely to under-revise rather than over-revise following a large unexpected shock. We also find that while forecaster attentiveness in the form of the frequency of revisions matters for expectations of a large shock, the size of a firm and the amount of resources it can devote appears to play to play a much more significant role in determining how much of an impact firms expect a large shock to have.

Our results are also related to recent studies on the role of high frequency data in analyzing forecasts and economic shocks. Ghanem and Smith (2021) argue that the usefulness of high frequency data for identifying causal effects depends on the on frequency with which effect of interest is measured. More recently, Jacobson et al. (2022) and Buda et al. (2023) show that higher frequency data can help to identify the true impact of monetary policy shocks. At the same time, Chang and Levinson (2022) show that high frequency forecast revisions can help uncover important dynamics. Our results add to this literature by using the difference between the frequency of the forecast updates and the frequency of the forecast horizons to disentangle the immediate and total impacts of a shock and to more precisely identify how the impacts trace out across forecast horizons.

Finally, the results in this paper provide mixed support for evidence of an expectations channel proposed by Dietrich et al. (2021) and Cantelmo (2022). While our results do confirm that TC shocks do operate through macroeconomic expectations, we find that they are viewed by firms as supply shocks with expected declines in real output and an expected increase in the price level rather than demand shocks as predicted by earlier research. Therefore, our results suggest that expectations align much more closely with actual impacts and it may not be optimal to use monetary policy to offset the expected macroeconomic impact from shocks due to climate change but rather that more targeted economic policies should be used. Future research could explore this even further by examining the differences between expectations and actual outcomes following a shock.

The rest of the paper is organized as follows. Section 2 describes the forecasts, the tropical cyclone shocks, and the macroeconomic news surprises. Section 3 describes the econometric methods. Section 4 presents the single equation results focusing on the real GDP growth forecasts and Section 5 presents the system results. Finally, Section 6 concludes.

2 Data

2.1 Surveys of Blue Chip Forecasts

We construct a new bi-weekly panel of Blue Chip forecasts by linking together forecasts from individual firms that are surveyed in two monthly Blue Chip surveys. The survey of Blue Chip Economic Indicators (BCEI) includes forecasts from more than 50 financial institutions, major corporations, and economic consulting firms submitted during the first week of the month on a number of macroeconomic variables for each quarter out through the current and next calendar years. The survey of Blue Chip Financial Forecasts (BCFF) contains forecasts from approximately 40 financial institutions and economic consulting firms submitted during the last week of the month on financial variables as well as real GDP growth and inflation for each quarter out through the next five quarters.

While the release dates for both surveys are generally fixed, survey collection dates have varied over time. To be as precise as possible, we obtain the official survey schedules available from 2005-present and use them to obtain the exact dates during which the surveys were open closed.[1] Each survey window is typically open for two days and there is, on average, a 14 day gap between the two Blue Chip survey windows. The gap between the BCEI and BCFF windows ranges from 6 to 23 days with the largest occurring in December/January due to schedule adjustments to circumvent holidays or in November 2013 when the BCEI survey was delayed by a week due to a federal government shutdown. Thus, the combined surveys have a forecast frequency of roughly every two weeks.

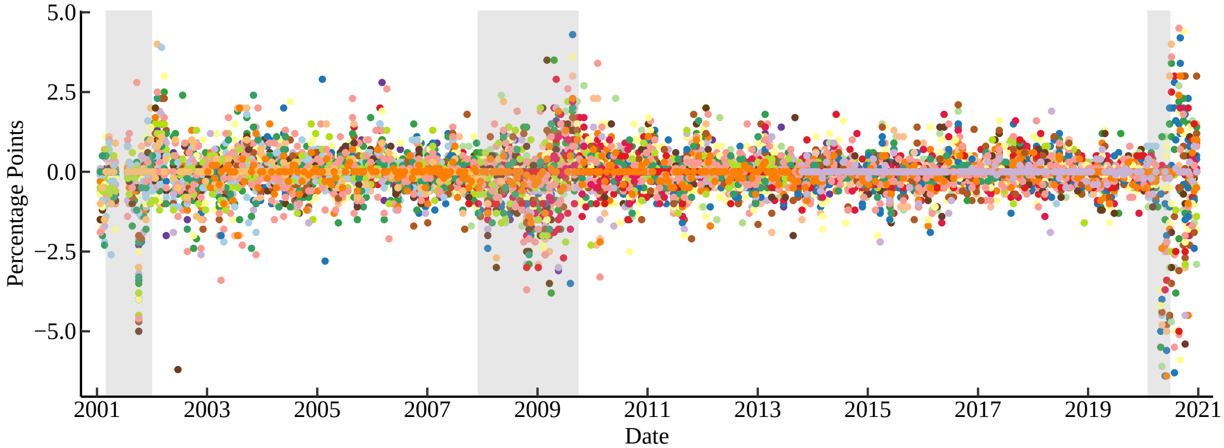
The sample of firms is not identical across the two Blue Chip surveys. However, there is a considerable overlap between the individual firms surveyed. For example, 73% of the sample surveyed in the BCFF in late September 2019 was surveyed again in the BCEI two weeks later in early October 2019 and accounted for 63% of the respective sample in that survey. Thus, while a large share of firms are captured by both surveys, it is misleading to analyze the consensus forecasts across surveys.

Of the 110 unique firms surveyed by either Blue Chip survey between 2001-2020, 61 participated in both Blue Chip surveys.[2] We focus on the sample of 54 firms that contributed at least 40 biweekly GDP forecasts. Thus, we observe between 41-477 GDP forecasts per firm with a median of 324 and an average of 297.[3] More than two-thirds of the firms in our sample are in the financial services industry (69%), just

[1] We extend the survey dates back through 2001 using additional external information.

[2] In a few cases we track individual forecasters rather than firms when it is clear that a firm only contributes to the survey because of an individual forecaster. However, for clarity of exposition we refer to the forecasters as firms.

[3] Not all firms submit forecasts for 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. We fill in ocassional gaps in the BCEI survey data with other surveys such as the WSJ and Bloomberg Surveys of Professional forecasters when their survey dates align. These account for a very small number of observations and do not materially impact the results. Despite this, the BCEI surveys for



Notes: Each color represents a different firm. The range of the y-axis is truncated from -6.5 to 4.5 percentage points to illustrate the variation in the forecast revisions prior to 2020. The shaded areas denote NBER recessions. Note that two Blue Chip surveys are completely missing in April and May of 2001.

Figure 1: Biweekly Blue Chip GDP Nowcast Revisions (2001-2020)

over half are located in the New York City metropolitan statistical area (54%), more than half are publicly traded (54%), and around a third are primary dealers with the Federal Reserve Bank of New York (35%).

There is only a partial overlap of the variables in the Blue Chip surveys. The BCFF primarily contains forecasts of financial variables and interest rates, whereas the BCEI primarily contains forecasts of macroeconomic variables. However, both surveys include nowcasts and forecasts of real GDP growth, CPI inflation, the yield on 3-month Treasury bills, and the yield on 10-year Treasury notes. We 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.

For an initial view of individual forecast revision properties we plot the bi-weekly current quarter GDP growth forecast revisions between 2001 - 2020. Figure 1 illustrates several important features about the forecast revisions. First, there is a lot of variability in the revisions over time with a typical range of ± 2 percentage points over any given quarter. The largest revisions are associated with important macroeconomic events such as the onset of the COVID-19 pandemic in 2020 which had a revision range of ± 30 percentage points (truncated in the figure), the onset of / end of NBER recessions, and the September 11th attacks. For this reason we focus our analysis on the pre-pandemic sample and control for broad range of macroeconomic surprises.

There is considerable heterogeneity in the frequency of revisions across firms. Table 1 shows that on average the typical firm revises their GDP nowcast at slightly less than a monthly frequency or about 44 percent of their available sample. However, the observed frequency of revisions ranges from once a quarter

April and May 2001 are completely missing for all forecasters in our sample.

(12.5 percent of the sample) to more than once every 2.5 weeks (80 percent). This heterogeneity is also observable at longer horizons and across the other variables in our analysis. Using a biweekly frequency allows us pinpoint when revisions actually occurred as opposed to lower frequency surveys which aggregate across the dynamics. However, it also suggests that there may be significant heterogeneity across firms.

Table 1: Revision Frequency by Variable and Horizon (in percent)

	GDP growth			**CPI inflation**			**10-yr T-Note yield**		
h	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
0	12.4	43.5	84.4	6.6	38.2	76.5	20.3	43.8	65.9
1	13.0	51.8	90.8	16.2	47.6	85.2	18.2	45.4	68.2
2	16.4	56.8	92.9	13.2	53.8	87.5	17.5	47.7	76.0
3	16.5	58.3	92.2	14.5	55.3	91.0	13.9	48.8	82.5
4	8.6	59.7	91.0	11.6	56.2	97.0	16.0	50.5	87.2

2.2 Tropical Cyclone Shocks

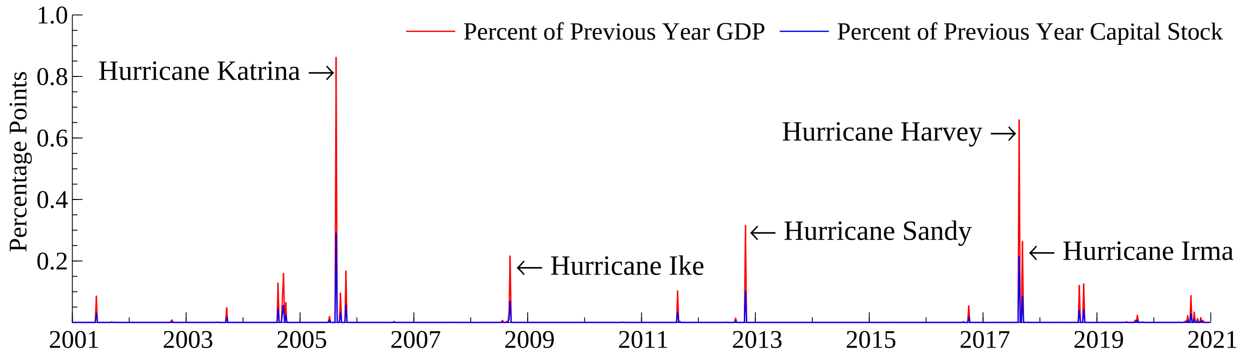
There many types of extreme weather events. The National Ocean and Atmospheric Administration (NOAA)'s Billion-Dollar Weather and Climate Disasters database includes droughts, floods, freezes, severe storms, tropical cyclones, wildfires, and winter storms.[4] These events are spatially and temporally heterogeneous lasting anywhere from a single day to more than a year. Between 2001 and 2020, 173 extreme weather events with a duration of less than two weeks caused more than 1.2 trillion dollars in real damages and killed more than 7,600 people in the United States.[5] Tropical cyclones (TCs), which include tropical depressions, tropical storms, and hurricanes, were by far the most destructive and deadly short-duration extreme weather events over this period accounting for more than 73% of the inflation adjusted damages and 80% of the fatalities despite numbering less than 20% of the total events. Thus, TCs account for the majority of damages and fatalities from extreme weather events in the United States.

In addition to having important economic and social impacts, Dietrich et al. (2021) find that both the historical occurrence of TCs and the potential risk of their occurrence in the future are among the largest and most significant drivers of individual perceptions of disaster events. This is especially true when accouting for the fact that TCs are associated with both wind and flood risks. Thus, understanding how TC shocks impact expectations about the macroeconomy is crucial for understanding broader risks due to expectations about extreme weather events and climate change.

We construct our measure of TC shocks by compiling damages from every TC that made landfall in

[4]NOAA's Storm Events database has an even more desegregated classification of extreme weather events.

[5]This accounts for roughly 81% of the total real damages over this period and 90% of the deaths.



Notes: Sample includes all 89 tropical cyclones that made landfall in the U.S. over this period. Tropical cyclone damage estimates are obtained from the National Hurricane Center. GDP and Capital Stock are year-end nominal values from the Bureau of Economic Analysis. Capital stock is calculated as the net stock of fixed assets and consumer durables excluding intellectual property products.

Figure 2: Weekly Tropical Cyclone Damage Shocks (2001-2020)

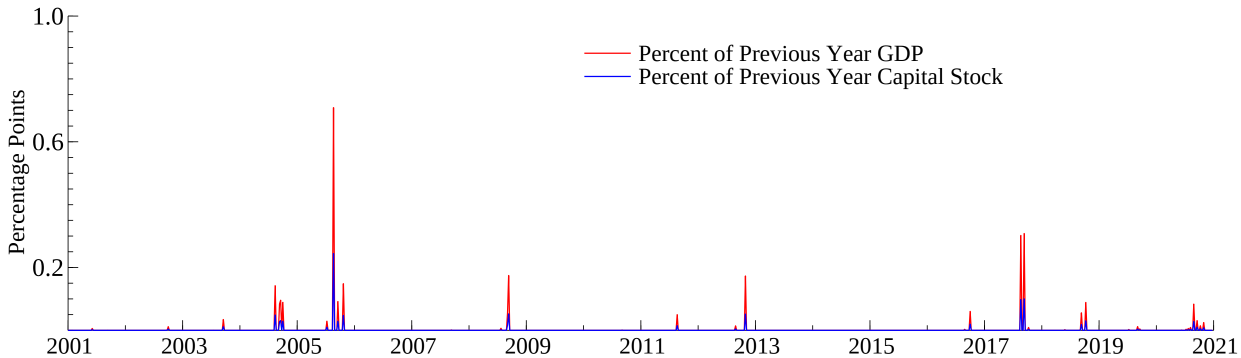
the continental United States between 2001-2020, using damage estimates in individual TC reports from the National Hurricane Center.[6] Economically consistent shocks over time are obtained by normalizing the damage estimates with the latest estimate of the end-of-previous year's level of nominal GDP or capital stock. Thus, the TC shocks are constructed similarly to the damage normalization procedures by Barthel and Neumayer (2012) and Grinsted et al. (2019). This approach circumvents many of the concerns associated with alternative damage normalization approaches and expresses the TC's impact directly in terms of its relative macroeconomic importance at the time; see Martinez (2020b) for a historical perspective.

Figure 2 presents a time series of the shocks between 2001-2020. It illustrates that the shocks are dominated by several large outliers. The largest is Hurricane Katrina, which 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 its second landfall, Hurricane Katrina caused damages equal to almost 1 percent of GDP or 0.4 percent of the physical capital stock at the time.[7] Following its strike, several prominent private forecasters explicitly revised their macroeconomic outlook as a result of Hurricane Katrina's anticipated impacts; e.g. see Hatzius (2005), Kasman and Mellman (2005), and Varvares (2005).[8] The next largest shock is associated with 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 percentage points of GDP. Superstorm Sandy in 2012 also stands out along

[6]Every tropical cyclone 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.

[7]This only includes direct damages. Note that Gallagher and Hartley (2017) and Deryugina et al. (2018) show that the total economic impact was substantially higher.

[8]Private forecasters have also explicitly revised their forecasts based on the expected macroeconomic impacts of other hurricanes; e.g. see Herzon and Prakken (2016, 2017, 2018a,b) and Hill (2017) among others.



Notes: The news-based measure includes 47 unique storms.

Figure 3: Real-Time Tropical Cyclone Damage Shocks (2001-2020)

with Hurricane Ike in 2008 and clusters of hurricane activity in 2004, 2011, and 2019. Note that plotting the normalized damage shocks for all 173 events from NOAA's Billion-Dollar Weather and Climate Disasters database whose duration was less than 2 weeks presents an almost identical picture.

An important limitation of the official TC shock measure is that official damage estimates are based on detailed assessments of the storm and its impact and are only released several months after the event. Thus, official estimates of TC damages are not available to forecasters in real-time and are therefore poor measures of a forecasters information set in real-time. In order to understand how forecasters revise their forecasts in response to the available information we need to construct a real-time measure of TC shocks.

We construct a real-time measure of shocks based on preliminary damage estimates from major catastrophe modeling firms or insurance agencies in news releases and newspaper articles up to a week after each storm's landfall.[9] For each storm we average all of the then latest available real-time estimates and scale the average estimate using real-time vintages of the previous year's estimate of real GDP or capital stock from the Bureau of Economic Analysis. This is effectively a refined version of the measure from Baker et al. (2020) who use the number of news articles associated with an event and interact it with a latest available measure of the event's damages. As a robustness exercise in the appendix we also consider an alternative real-time measure of TC shocks using the model developed in Martinez (2020a). Figure 3 presents the time series of these real-time TC shocks. It includes 47 storms and when compared against the official estimates in Figure 2 illustrates that the early estimates typically underestimate damages for the largest storms. Quantitatively, the median absolute difference between the official and real-time estimates is 30%.

[9]LexisNexis was used to search across major newspapers in the days around each storm. See Cole et al. (2010) for a comparison of popular catastrophe models. Estimates are typically provided as insured losses, so we multiple them by 2 to obtain estimates of total damages accounting for incomplete insurance coverage in line with common practice; e.g. see Blake et al. (2011).

2.3 Macroeconomic News

It is important to control for regular macroeconomic news releases and other important information in additional to TC shocks. As Figure 1 illustrates, forecasts are systematically revised around major economic events. Failing to capture this dominant source of variation in the forecast revisions could mask the importance of other sources of variation, such as TC shocks, by leaving unexplained noise. While some studies find that news releases are of limited importance to forecasters, see Clements (2012), others argue that failing to control for relevant macroeconomic releases may induce spurious correlations with the shock of interest; e.g. see Bauer and Swanson (2021).

It is also important not to over control for higher frequency economic and financial data that could mediate the expected impacts of interest. For example, Aaronson et al. (2020) show that searches for unemployment and initial unemployment insurance claims typically spike a following major hurricane strike. Alternatively, Kruttli et al. (2021) find that financial markets respond to forecasts of the storm while Davis and Ng (2022) argue that damages from large disasters are endogenously determined with initial unemployment insurance claims and financial market uncertainty. Therefore, we do not to over control for higher frequency economic and financial variables and focus instead on a subset of control variables that are unlikely to be affected by the event itself.[10]

We control for macroeconomic news releases using measures of data announcement surprises. These are constructed as the difference between the data release and the available Bloomberg forecasts aggregated over the window between Blue Chip survey dates; e.g. see Altavilla et al. (2017). There is a wide range of possible data announcement surprises to chose from. We include variables based on the following set of criteria: (1) investors pay close attention to those releases, see Bok et al. (2018); (2) they are available over the entire sample; (3) the data are predetermined with respect to the TC shock; (4) the release is likely to matter for the GDP forecast. Specifically, the data announcements surprises that we include 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 on Business.[11] We also considered several other indicators including non-farm payrolls, construction spending, the trade balance, and wholesale and retail inventories but they were not very relevant over our sample and just added noise to the estimates.

[10] As a robustness exercise we control for changes in commodity price futures to disentangle which channels a TC shock operates through.

[11] While initial jobless claims are contaminated by TC shocks since they are reported with less than a two week lag, continuing jobless claims are reported with a three week lag and so are unlikely to be impacted contemporaneously in our sample where the window is roughly two weeks.

We also include a dummy variable for the September 11th 2001 attacks and control for advance GDP release surprises using each firm's last available backcast from the BCEI. Thus, while the data announcement surprises control for how common surprises impact all forecasters, i.e common correlated effects: Chudik and Pesaran (2015), controlling for individual GDP forecast errors allows us to capture how a given data surprise may manifest itself differently for individual forecasters.

3 Methods

We are interested in the expected dynamic macroeconomic impact of a tropical cyclone shock. Thus, we start by following the empirical macroeconomic literature and formulate a simple model of the effect of an exogenous TC shock on individual forecast revisions as

$$\Delta f_{i,t_w+h} = \beta_{1,h}\mathrm{TC}_{t_w} + v_{i,t_w+h}, \tag{1}$$

where $\Delta f_{i,t_w+h} \equiv f_{i,t_w+h} - f_{i,t_{w-1}+h}$ is the forecast revision, f_{i,t_w+h} is the forecast made by firm i during week w of quarter t for horizon h where $t_w = t + \frac{w-13}{13}$ and $w \in$\{1,3,5,7,9,11\}, $t \in \{1,\dots,T\}$, and $h \in \{0,1,2,3,4\}$. TC_{t_w} is the sum of real-time TC shocks that occurred over the period between when the window for $f_{i,t_{w-1}+h}$ closed and the window for f_{i,t_w+h} opened, and v_{i,t_w+h} is the unexplained residual. The parameter $\beta_{1,h}$ represents the expected macroeconomic impact of the shock at horizon h and is identified as long as the shock is strictly exogenous.[12] The methodological basis for this setup follows the work of Faust and Wright (2008) for conditional forecasting and Ghysels and Wright (2009) when thinking about how high frequency data feeds into lower frequency forecast.[13] This framework also closely mirrors previous studies that estimate the information effect of monetary policy surprises using forecast revisions; e.g. see Campbell et al. (2012), Campbell et al. (2017), Nakamura and Steinsson (2018), Lunsford (2020), Miranda-Agrippino and Ricco (2021), and Bauer and Swanson (2021).

An important feature of the formulation in (1) is that it includes two different time scales: the biweekly time scale, w, over which forecasts are updated and the quarterly time scale, t, for which the forecasts are generated. This allows us to think about forecast dynamics in two ways: across horizons and forecast revisions. If we ignore the biweekly time scale then (1) represents a local projections framework; see Jordà

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

[13]We can think of this as a special case of the conditional forecasting framework in Faust and Wright (2008) where $TC_{tw-1} \equiv 0$ is the unconditional prediction of damages which is always observed. Thus, a key assumption is that forecasters do not already incorporate impacts prior to the storm.

(2005). However, including the biweekly time scale implies there are additional dynamics in the forecast revisions that may need to be accounted for.

Many previous studies demonstrate that forecasters' revisions have important dynamics. For example, Nordhaus (1987) formulates a model of forecast revisions based on their own lags

$$\Delta f_{i,t_w+h} = \gamma_{1,h}\Delta f_{i,t_{w-1}+h} + u_{i,t_w+h}, \tag{2}$$

where the parameter $\gamma_{1,h}$ is indicative of forecaster inefficiency or rigidity. If $\gamma_{h,1} > 0$, then forecast revisions are inefficient or rigid such that they under-react to shocks. On the other hand, if $\gamma_{h,1} < 0$, then forecasters overreact to shocks. Previous studies have found that consensus aggregates of forecasters under-react to past information but that individual forecasters overreact; e.g. see Coibion and Gorodnichenko (2015) and Bordalo et al. (2020). This implies that (1) may omit important dynamic effects.

There may be even more omitted dynamics than implied by (2) if the shock changes expectations directly and also changes how quickly expectations are revised due to past information. Baker et al. (2020) expand (2) to allow for state-dependent rigidities following large unexpected shocks by including an interaction term between the shock and lagged forecast revisions

$$\Delta f_{i,t_w+h} = \gamma_{1,h}\Delta f_{i,t_{w-l}+h} + \gamma_{2,h}\left(\Delta f_{i,t_{w-l}+h} \times \mathrm{TC}_{t_w}\right) + \tilde{u}_{i,t_w+h}, \tag{3}$$

which implies that the speed at which forecasters incorporate new information varies depending on the size of the shock. They find that following a large unexpected shock consensus forecasters revise their forecasts more quickly. This also illustrates that incorporating forecast revision dynamics can be informative about whether the initial expected impact of a shock will be revised up or down over time.

To capture both the immediate impact of a shock as well as any dynamics, we combine (1) with (3) and allow for dynamics from the shock itself thus specifying a more general model

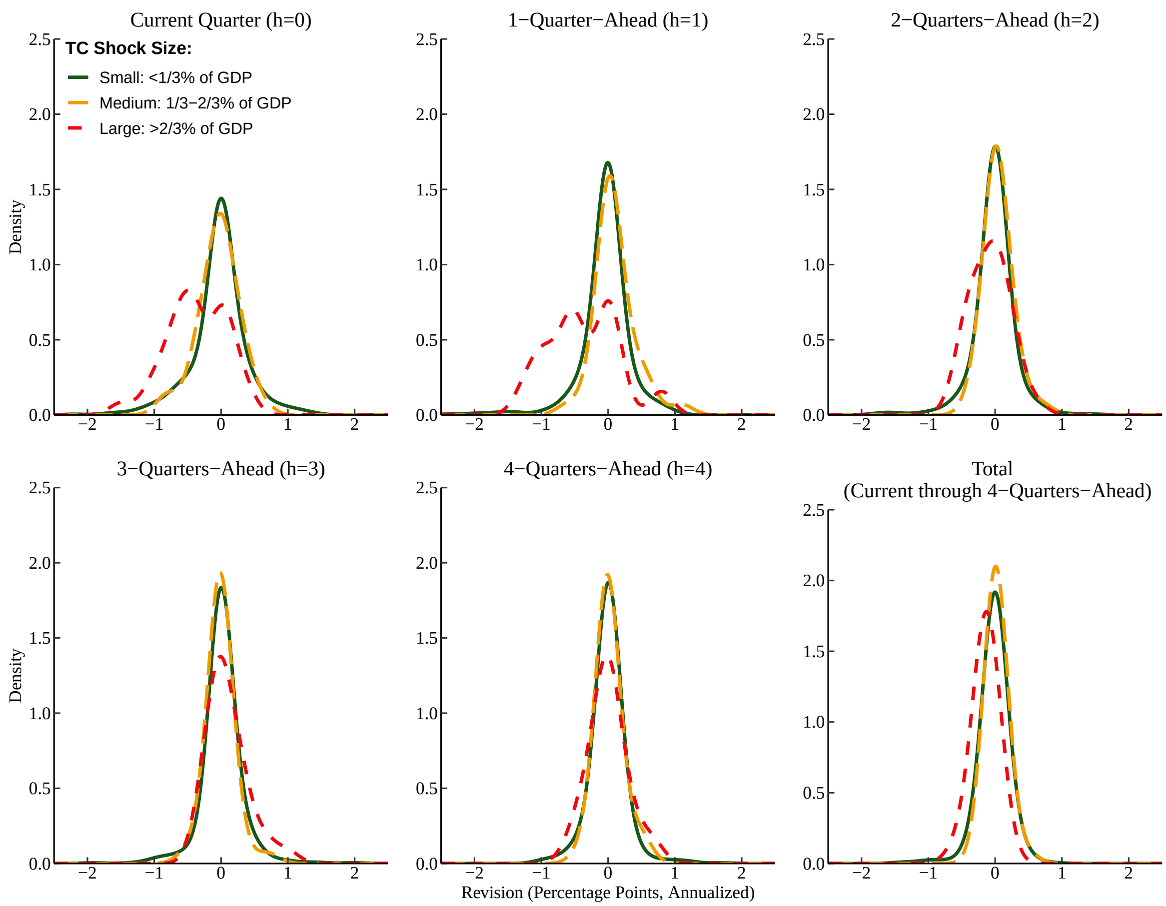
$$\Delta f_{i,t_w+h} = \gamma_{1,h}\Delta f_{i,t_{w-1}+h} + \gamma_{2,h}\left(\Delta f_{i,t_{w-l}+h} \times \mathrm{TC}_{t_w}\right) + \sum_{j=0}^{1} \beta_{j,h}\mathrm{TC}_{t_{w-j}} + \varepsilon_{i,t_w+h}. \tag{4}$$

This allows us to distinguish between the expected immediate short-run impact, captured by $\beta_{0,h}$, and the expected long-run / equilibrium impact, which is a function of the parameters in (4) such that

$$\eta_h\left(TC_{t_w}\right) = \frac{\sum_{j=0}^{1}\beta_{j,h}}{1-\gamma_{1,h}-\gamma_{2,h}\times TC_{t_w}}, \tag{5}$$

where the variance of (5) can be estimated following Bårdsen (1989) with multivariate extensions in Doornik and Hendry (2018). In general, the expected short-run and long-run impacts will only be identical if there are no dynamics and (1) is the correct model. However, there may also be offsetting dynamics such that the short-run and long-run remain relatively close.

In the following sections we use the above methods to examine how the immediate (short-run) and total (long-run) impacts of a TC shock are expected to differ across a range of specifications. In the next section we focus exclusively on the single equation results for expectations of real GDP growth. Then in section 5 we extend the results for a system of multiple equations for real GDP growth, CPI inflation, and yield on 10-year Treasury Notes. This allows us to capture economically relevant interactions between the variables and across horizons. In all cases, the equations are estimated with controls for current and lagged macro news surprises, GDP backcast errors, month-year time fixed effects, weak-of-quarter seasonal dummies, and firm fixed effects. Two-way cluster robust standard errors are used, clustering by firm and date following Thompson (2011) and Cameron et al. (2011).



Notes: Densities are estimated non-parametrically with a Gaussian Kernel and the same bandwidth across all horizons and shock sizes

Figure 4: GDP Growth Forecast Revision Densities by Shock Size and Forecast Horizon

4 Empirical Results

In this section we present the results on how firms revise their real GDP growth forecasts in response to a TC shock. Before delving into the regression results we start by presenting simple non-parametric estimates of GDP growth revision densities by TC shock size across alternative forecast horizons. Figure 4 shows clear evidence of downward forecast revisions in early quarters following a large TC shock with fat upper tails in later quarters. The near-term forecast horizons show evidence of a double peak implying forecaster heterogeneity with some revising immediately in response to the shock while others do not. There is little difference in revisions between small and medium size hurricane shocks implying most of the action in terms of GDP growth forecast revisions is associated with larger shocks such as Hurricane Katrina and Harvey. The cumulative effect across all horizons through 4-quarters-ahead is a leftward shift in the distribution implying expectations of slower growth on net over the next 5 quarters. This initial snapshot only captures the immediate revision around a TC shock date and does not control for any confounding variables or account for any additional dynamics.

We now turn to a formal analysis of this relationship. We start with the current quarter nowcasts and consider how the results vary across alternative models of forecast revisions. We then expand the analysis to see how the impacts vary across forecast horizons. We also compare the results against the Federal Reserve Board staff forecast revisions and discuss the importance of forecaster heterogeneity.

We start by looking at the current quarter nowcasts and estimate the static equation (1). Column (1) in Table 2 presents the results. It shows that a TC shock, equal to 1% of GDP or roughly the size of Hurricane Katrina, reduces expected real GDP growth in the current quarter by 0.33 percentage points. However, the estimated standard error is 0.19 such that the estimated impact is only marginally significantly different from zero at a 10% level. Since this is a static equation, the total impact is identical to the immediate impact.

Column (2) in Table 2 presents the results assessing the relevance of lag dynamics using (2). It shows that the lagged forecast revision is highly statically significant with a t-ratio of over 10 and a p-value far less than 1%. The negative autoregressive coefficient indicates that forecast revisions are inefficient as firms tend to over-revise their forecasts immediately in response to new information. This result is replicate the approach in Bordalo et al. (2020) using an alternative higher frequency sample of forecasters. It also confirms that there is a significant amount of dynamics, which is omitted from the specification in (1) and may inflate the estimated standard errors.

Table 2: Expected Impact of TC Shock on Current Quarter Real GDP Growth

	(1)	(2)	(2b)	(3)	(4)
Lagged Nowcast Revision:		-0.27^{***}	-0.27^{***}	-0.27^{***}	-0.28^{***}
		(0.02)	(0.02)	(0.02)	(0.02)
Lagged Nowcast Revision $\times$ TC:				0.39^{**}	0.49^{***}
				(0.19)	(0.17)
Immediate TC Impact:	-0.33^{*}		-0.47^{**}		-0.51^{**}
	(0.19)		(0.17)		(0.19)
Lagged TC Impact:			-0.38^{***}		-0.40^{***}
			(0.13)		(0.14)
Total TC Impact:	-0.33^{*}	0	-0.67^{***}	0	-1.16^{***}
	(0.19)		(0.16)		(0.39)
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$\times$T):	13,747	13,747	13,747	13,747	13,747
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), where * and ** and *** indicate that the estimated coefficient is statistically different from zero with a p-value of less than 10%, 5%, or 1%, respectively.*

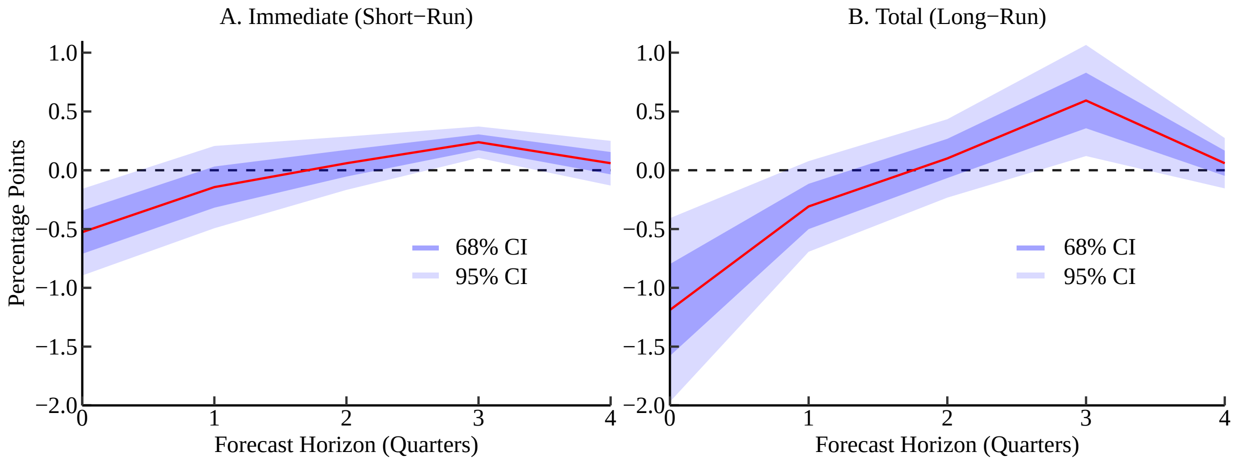
The results in column (2b) of Table 2 reestimate (2) while allowing for the shock and its lags. Again we find significant evidence that firms overreact to past information. However, we also find that forecasters revise down their nowcasts significantly in response to both contemporaneous and lagged TC shocks. Using this equation, a TC shock equal to 1% of GDP implies an immediate downward revision in the current quarter GDP nowcast of 0.47 percentage points. The lagged impact implies that the current quarter forecast is revised down an additional 0.38 percentage points. Accounting for both the immediate and lagged responses, as well as the dynamic overreaction, the expected long-run impact of a TC shock on current quarter growth implies a significant downward revision of 0.67 percentage points. This contrasts with the static estimate in column (1), which is weakly significant and less than half the size of the total impact in column (2b).

Next, we test if a TC shock induces a change in lag dynamics using (3). The results presented in column (3) of Table 2 show that both the lagged forecast revision and its interaction term are statistically significant with offsetting coefficients. While firms tend to over-revise their forecasts immediately in response to new information, following an unexpected TC shock, firms tend to under-revise their forecasts. The estimates imply that this overreaction and under-reaction are completely offset for TC shocks equal to 0.55 percent of GDP, but that the under-revision out-weighs the over-revision for all TC shocks greater than 0.55 percent of GDP. These results stand in contrast to those using aggregate consensus forecasts in Baker et al. (2020) who find that forecasters offset their under revision following large shocks as they become more attentive. One way to interpret this is that forecasters revise more slowly following large shocks as they wait for better estimates of the damage and additional supporting information. It also illustrates that moving from consensus to individual forecasters can flip the sign for both the lags and their interactions.

Finally, we estimate the unrestricted form of (4) allowing for both lagged responses to the dynamics and shocks as well as potential interactions between them. The results in column (4) of Table 2 again show that firms overreact to the average shock but under-react to TC shocks while continuing to show significant downward revisions from contemporaneous and lagged TC shocks. The immediate impact of a TC shock implies a downward revision of 0.51 percentage points, whereas the long-run impact of a TC shock implies a downward revision of 1.16 percentage points off of current quarter real GDP growth. Thus, including the interaction term does not substantially change the immediate and lagged impacts of the TC shock but substantially increases estimates of the total impact. This is because the interaction term allows for non-linearity in the response to how forecasters respond to shocks in the long-run. This highlights the importance of capturing the dynamics since it has important implications for the long-run estimates.

As a robustness exercise in the appendix we allow the parameters to change across groups of forecasters and test for evidence of forecaster heterogeneity. This exercise has several interesting findings. First, forecasters in large or publicly traded firms have significantly higher estimates of the immediate impact of a shock and are also slower at incorporating new information such that their total expected impact is more than double that of smaller firms. Second, we do not find significant differences between forecasters in firms that are close to or associated with financial markets relative to those that aren't. Nor do we find significant differences based on the forecaster's geographical location or its distance from the storm. Third, we find that firms that have been in the sample longer expect significantly higher impacts which may evidence of learning-by-doing or could be due to newer firms missing larger shocks.[14] Finally, we augment all of the results with forecaster's lagged deviation from the Blue Chip consensus forecasts and find that all forecaster groups error-correct their forecasts back to the consensus forecast such that heterogeneity in any given firm's expectations lasts only as long as they persist in their deviation from consensus.

[14]Although we do not find significant differences between firms that revise their forecasts more often and those that don't, the results qualitatively suggest that forecasters who revise more slowly, respond more slowly to larger shocks but ultimately expect impacts which are roughly double in size.



Notes: Short-run captures the immediate response and long-run includes additional dynamics. There are 11,268 observations for each horizon. All equations include controls for firm and time fixed effects as well as weekly seasonal dummies and macro news surprises and their lags. Estimated standard errors are clustered two-ways by firm and time.

Figure 5: Expected Dynamic Impacts of a TC Shock on Real GDP growth

Now that we have established the importance of a dynamic specification for our ability to distinguish between immediate and total impacts of a shock, we can examine how firms expect these dynamics to transmit across multiple forecast horizons. Specifically, we re-estimate (4) for each forecast horizon and examine both how the immediate and the total impacts of a TC shock are expected to evolve. The results for this exercise are presented in Figure 5 where Panel A presents the expected immediate impact and Panel B presents the total impact out through four-quarters-ahead. The immediate impacts suggest that following the initial expected decline in current quarter GDP growth there are no significant impacts on real GDP growth until three quarters ahead at which point there is an expected 0.25 percentage point increase in the real GDP growth rate. The total impacts indicate for exacerbated dynamics in the long-run with the current quarter real GDP growth expected to fall by 1.1 percentage points, while after three quarters growth is expected to partially recover by roughly 0.6 percentage points. Thus, firms anticipate some recovery from the shock after a year but that they also expect potential scarring effects with only a partial recovery in real GDP. These results are robust across alternative measures of TC shocks and to jointly estimating the system of revisions across all forecast horizons; see additional results in the appendix.

We can compare these results against forecasts from the Federal Reserve Board (FRB) staff. Chang and Levinson (2022) compile FRB staff forecasts on a quasi-weekly basis for real GDP growth and core PCE inflation from 2001-2011. While the sample of PCE inflation forecasts is too sparse, we are able to align the dates that the FRB staff generate their GDP forecasts with the Blue Chip survey dates.[15] We also

[15] There is some sensitivity in how this alignment is done. If the dates are chosen such that we only include FRB staff forecast made on the Blue Chip survey dates, then there is a large number of missing values. Alternatively, allowing for a wider range of dates implies less precise identification of the response to the shock. We balance these trade-offs by slightly expanding the date

re-estimate the Blue Chip results over this shorter sample which primarily captures the very active 2004 and 2005 hurricane seasons but excludes Superstorm Sandy in 2012 and the 2017 hurricane season. Thus it also provides a robustness check on how sensitive our results are to the inclusion of these later seasons.

Table 3 shows the results for both the FRB staff and the Blue Chip forecasts across all available horizons. For the FRB staff, the interaction term between the TC shock and the lagged forecast revision is never significant at any horizon but induces a large distortion to the long-run estimates such that is is excluded in order to facilitate interpretation. Despite exhibiting different forecast revision dynamics, the FRB staff's expected total impact of a TC shock is similar to the Blue Chip forecasters. Across the available forecast horizons the FRB staff forecasts exhibit a mix of both over and under reactions to news, albeit at smaller magnitudes than the Blue Chip. The FRB staff also react more strongly immediately to a TC shock with an expected decline in current quarter real GDP which is more than double that of the Blue Chip forecasters. Furthermore, unlike the Blue Chip, the FRB staff do not appear to respond to lags in the TC shock itself. However, the FRB staff's total expected impact of a TC shock in the current quarter is just below the typical Blue Chip forecasters. This illustrates that while the FRB staff incorporate the effects of a large shock much more quickly than private forecasters do, both the Blue Chip and the FRB staff appear to be in agreement about the total impacts of the shock.

The short-run differences between the Blue Chip and FRB staff also imply important differences across alternative storm types. The implied non-linearity in the Blue Chip's total response to a TC shock implies that they react more to larger storms than they do to smaller ones. On the other hand, the FRB staff have a linear response regardless of the shock size. This implies that the total impact for Blue Chip forecasters and FRB staff will be roughly identical for shocks that are roughly around 0.9% of GDP. However, for shocks less than that the Blue Chip will underestimate the total impact relative to FRB staff and will overestimate the total impact for shocks larger than 0.9%. One way of interpreting this response is that private forecasters are likely to ignore TC shocks until they become large enough to matter whereas the FRB staff pay attention to all TC shocks, regardless of the size.

FRB staff and the Blue Chip firms also differ in terms of how quickly and how much the economy is expected to recover from a shock. The results indicate that FRB staff expect a full recovery in GDP within two quarters after the shock whereas the Blue Chip firms expect further declines one-quarter after the shock and only a partial recovery in GDP within three quarters after the shock. One potential explanation for this difference is that FRB staff often explicitly assume large fiscal aid packages following a shock whereas Blue

range to include 3 days before or after over which we allow the Federal Reserve staff forecasts to be generated to ensure there is a sufficient sample without diluting our ability to identify a response to the shock.

Table 3: Expected Impact of a TC Shock on Quarterly Real GDP growth (2001-2011)

Forecast Horizon:	-1	0	1	2	3	4
Federal Reserve Board Staff						
Lagged Forecast Revision:	-0.13	0.22***	−0.20*	−0.26***		
	(0.11)	(0.08)	(0.11)	(0.08)		
Immediate TC Impact:	-0.16	−1.54***	−0.33	1.23**		
	(0.33)	(0.29)	(0.34)	(0.57)		
Lagged TC Impact:	-0.35	0.32	0.32	0.49		
	(1.73)	(0.52)	(0.54)	(0.44)		
Total TC Impact:	-0.45	−1.57**	−0.01	1.37***		
	(1.15)	(0.64)	(0.44)	(0.42)		
Observations (T):	178	210	176	166		
$\hat{\sigma}$:	0.50	0.40	0.57	0.38		
R^2:	0.18	0.26	0.27	0.21		
Blue Chip Forecasters						
Lagged Forecast Revision:		−0.29***	−0.33***	−0.33***	−0.38***	−0.42***
		(0.03)	(0.04)	(0.05)	(0.05)	(0.06)
Lagged Forecast Revision × TC:		0.60***	0.02	0.17	0.56	0.24
		(0.19)	(0.51)	(0.25)	(0.35)	(0.24)
Immediate TC Impact:		−0.73***	−0.29	0.04	0.33***	0.06
		(0.23)	(0.18)	(0.10)	(0.09)	(0.11)
Lagged TC Impact:		−0.43***	−0.24**	0.03	0.25***	−0.01
		(0.12)	(0.12)	(0.11)	(0.06)	(0.10)
Total TC Impact:		−1.70***	−0.41**	0.06	0.70**	0.04
		(0.62)	(0.21)	(0.13)	(0.34)	(0.14)
Observations (N×T):		7,335	7,320	7,279	6,929	5,883
Firms (N):		50	50	50	50	50
$\hat{\sigma}$:		0.51	0.44	0.38	0.35	0.32
R^2:		0.33	0.23	0.17	0.17	0.21

*Notes: All equations include controls for macro surprises and their lags. All equations include week of quarter fixed effects. Blue Chip forecasters include time and firm fixed effects. For FRB Staff the estimated standard errors in parentheses are heteroskedasticity corrected following White (1980) while for Blue Chip forecasters the estimated standard errors are clustered two-ways by firm and time. In all cases * and ** and *** indicate that the estimated coefficient is statistically different from zero with a p-value of less than 10%, 5%, or 1%, respectively.*

Chip firms do not. Thus, despite broad agreement on the eventual magnitude of the initial impact, private sector forecasters are more pessimistic following the initial shock with both a slower and less complete expected economic recovery.

These differences between private forecasters and the Federal Reserve have potentially important implications when interpreted through the lens of monetary policy decisions. In particular, several weeks after Hurricane Katrina's landfall in New Orleans, the Federal Reserve's Federal Open Market Committee (FOMC) met on September 20 2005 to decide whether to continue to raise interest rates. Prior to the meeting news outlets and markets speculated that the FOMC might pause due to the damage caused by Katrina and the resulting uncertain outlook.[16] The staff presented their baseline outlook in the Greenbook in which they estimated that while Katrina was expected to have a negative impact on GDP growth in the third quarter, the recovery would quickly take hold in large part due to an expected federal aid package. Despite this, the minutes from the FOMC meeting indicate that several participants were concerned about the macroeconomic outlook following Katrina. One participant, Governor Mark Olson, voted in favor to pause the rise in interest rates and ultimately dissented from the decision to raise rates as a result. It is unclear if the FRB staff's outlook had been in line with Blue Chip forecasters in expecting a slower recovery from the storm, whether the policy outcome would have been different.

Overall, the results from our analysis indicate that TC shocks can have large impacts on expectations of macroeconomic growth. We show that accounting for dynamics implies that a 1 percent of GDP shock implies an immediate downward forecast revision of current quarter GDP growth of 0.5 percentage points and a total revision which is more than double that. Forecasters at large publicly traded firms expect an even larger impact whereas there don't appear to be any significant differences across firms with more frequent revisions or that are closer to financial markets. While the negative growth impacts are not expected to last beyond the current quarter, private forecasters generally anticipate only a partial recovery in the economy within three months following a TC shock. While FRB staff generally agree with the initial impact, they tend to have a more positive view about the speed and strength of the economic recovery from a TC shock by also incorporating fiscal responses to it.

5 System Results

In this section we extend the analysis of the expected impacts of a TC shock to a system of variables. Doing so allows us to determine whether firms expect TC shocks to be supply or demand driven and also allows us to trace its expected impact dynamically across a system of variables. To our knowledge, this is the first study to jointly analyze the expected impact of a shock on a system of forecasts.[17] We focus on a three variable system of forecast revisions for real GDP growth, CPI inflation, and 10-year Treasury yields. The choice of variables in our system is determined by their availability across both Blue Chip surveys. However, the system closely resembles those typically studied in analyses of monetary policy shocks; e.g. see Gertler and Karadi (2015) and Miranda-Agrippino and Ricco (2021).

[16]For example, 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).

[17]Benhima and Poilly (2021) examine the correlation in forecast GDP and inflation forecast errors but do not formulate a dynamic model of system of errors.

We start by formulating a general dynamic system version of (4) with additional lags such that

$$\mathbf{A}_h \Delta \mathbf{F}_{i,t_w+h} = \sum_{k=1}^{3} \Gamma_{1,k,h} \Delta \mathbf{F}_{i,t_{w-k}+h} + \Gamma_{2,1,h} \left(\Delta \mathbf{F}_{i,t_{w-1}+h} \times \mathrm{TC}_{t_w} \right) + \sum_{j=0}^{1} \beta_{h,j} \mathrm{TC}_{t_{w-j}} + \mathbf{e}_{i,t_w+h}, \tag{6}$$

where bold terms are vectors and $\mathbf{A}_h$ and $\Gamma_{i,k,h}$ are matrices. $\mathbf{F}_{i,t_w+h} = \{ \ \mathrm{GDP}_{i,t_w+h} \quad \mathrm{CPI}_{i,t_w+h} \quad \mathrm{T10}_{i,t_w+h} \ \}'$ is a 3×1 vector of real GDP growth, CPI inflation, and 10 Year Treasury yield forecasts made by firm i during week w of quarter t for horizon h where $w \in \{1,3,5,7,9,11\}$ and $h \in \{0,1,2,3,4\}$. Thus, $\Delta \mathbf{F}_{i,t_w+h} = \mathbf{F}_{i,t_w+h} - \mathbf{F}_{i,t_{w-1}+h}$ is the vector of forecast revisions.

We impose some structure on (6) by assuming a recursive ordering for $\mathbf{A}_h$ such that revisions to real GDP growth contemporaneously impact revisions to CPI inflation and the 10 Year Treasury yields. This assumption allows both for a Phillips curve / Okun's law relationship between forecasts of real GDP and CPI inflation as well as a Taylor rule-type relationship between forecasts of 10-year Treasury yields, CPI inflation, and real GDP growth. However, this also assumes that the shocks are demand driven such that changes in inflation forecasts do not contemporaneously feedback into expectations of real GDP growth. This assumption also implies that the vector $\mathbf{e}_{i,t_w+h}$ has a diagonal covariance matrix such that each of the three equations can be estimated independently without loss of efficiency or information.[18]

We start with the general form of (6) at each horizon and test for restrictions on the model. In particular, we start with a more general model with 5 lags and were able to reduce it down to 3 lags. Next, we restrict the model to remove any lagged cross-equation linkages such that lagged revisions only matter for the variable being revised. This implies that we impose restrictions such that all of the off-diagonal elements of $\Gamma_{1,k,h}$ are all equal to zero. Finally, we impose restrictions such that there are no interaction effects for the CPI inflation forecasts or the 10-year Treasury Note yield forecasts. This is supported by the fact that single equation estimates for these variables, see Appendix, suggest that the interaction terms are only weakly significant at best. This implies that we impose restrictions on $\Gamma_{2,1,h}$ such that it is diagonal an only non-zero for the GDP growth equation.

Estimating the restricted form of (6) at each horizon allows us to trace out the expected dynamic macroeconomic impacts of a TC shock across all variables in our system. Figure 6 presents the results from this analysis for both the immediate short-run and the long-run estimates of a TC shock across all variables in the system. The results for the expected impact on real GDP growth in Panels A and D are similar to the earlier results in Table 2 and Figure 5 albeit with a slightly smaller long-run impact. The initial decline in

[18]To ensure that the results remain consistent we only consider those forecasts from forecasters that are available across all horizons and variables. Robustness checks using alternative recursive orderings for $\mathbf{A}_h$ indicate that the results are robust to alternative orderings.

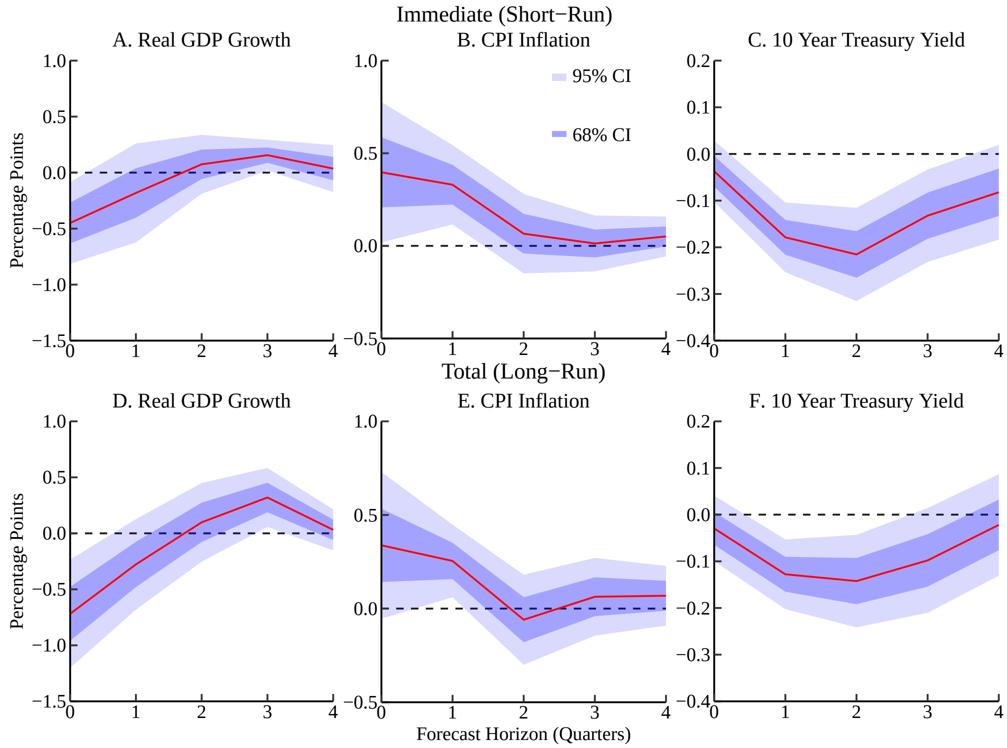
real GDP growth in the current quarter is followed by a partial recovery in real GDP after three quarters. The expected impact is somewhat larger and more precisely defined in the long-run.

The results for CPI inflation indicate that a TC shock is associated with higher inflation in the near term. Panels B and E of Figure 6 indicate that CPI inflation is expected to rise around 0.4 percentage points per quarter for the first two quarters following the shock with insignificant effects thereafter. Comparing the immediate short-run impact versus the long-run impact indicates mixed results with some effects getting magnified while others declining. However, both the short-run and long-run results consistently indicate that following a TC shock prices are expected to rise in the near term without any expected offsetting declines over the forecast horizon.

The results for forecasts of the 10-year Treasury yields indicate a transitory decline over the first three quarters following a TC shock with a recovery by the end of the forecast horizon. The results in Panels C and F of Figure 6 indicate that yields on 10 year Treasury Notes are expected to decline up to 20 basis points following TC shock with a trough occurring two quarters after the initial shock and a full recovery after four quarters. A possible explanation for this dynamic is that firms expect that there will be a flight to safe assets following a large TC shock. This interpretation is consistent with previous findings that TC shocks can have differential impacts on riskier financial assets; e.g. see Kruttli et al. (2021) and Correa et al. (2021). Comparing the immediate and total impacts indicates that in contrast to GDP, the total impact is smaller and less persistent than the immediate expected impact.

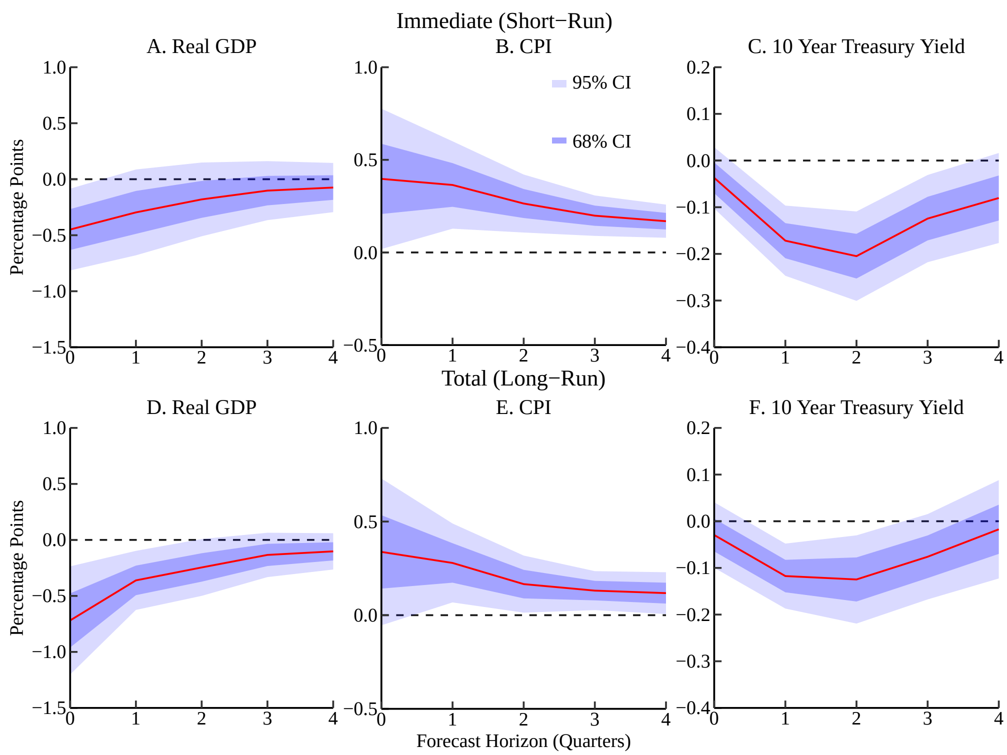
While our analysis focuses on the quarterly growth rates of GDP and CPI, it is also informative to examine the expected cumulative impacts across horizons to better understand the longer-term impacts. To do this we generate the cumulative forecast revisions across horizons for each forecaster for GDP and CPI and then re-run our analysis using the revisions to these cumulative changes instead of the revisions in the single horizon quarterly forecasts. The results are presented in Figure 7 and clearly indicate an expected slow recovery in GDP levels, particularly based on estimates of the total impact. They also suggest that CPI levels are expected to remain elevated above their pre-shock level across the entire forecast horizon. This provides clear evidence of an expected persistent negative supply shock following a tropical cyclone.

In a robustness exercise in the appendix we control for changes in key commodity prices such as oil, food, and lumber and find that the effects of a tropical cyclone shock remain. Interestingly, controlling for commodity price changes has only a limit impact on the CPI forecast results but is able explain a portion of the expected declines in GDP. Thus, while forecasters do appear to incorporate changes in key commodity prices following a TC shock, these changes do not fully explain expect macroeconomic impacts.



Notes: Estimated using 8,743 observations in each equation across all horizons. All equations include controls for firm and time fixed effects as well as weekly seasonal dummies and macro news surprises and their lags. Estimated standard errors are clustered two-ways by firm and time.

Figure 6: Expected Macroeconomic Impacts of a TC shock



Notes: See Notes for Figure 6.

Figure 7: Expected Cumulative Macroeconomic Impacts of a TC shock

Finally it is useful to contrast the expected impacts in Figures 6 and 7 against the predictions in Dietrich et al. (2021), which argues that an increase in the expected impact of an extreme weather event is akin to a demand shock where there is a fall in the natural rate, a decline in output and a decline inflation which can be offset by looser monetary policy. Our results indicate that despite a large shock occurring which may change forecasters expectations about the probability of future events, forecasters appear to predominantly incorporate expectations of a supply shock. Thus are results do not support evidence of an expectations channel for climate shocks. Our results also suggest that looser monetary policy may not be the best policy response to offset the adverse macroeconomic effects arising from a TC shock, particularly given expectations about a persistent increase in the price level following a shock.

6 Conclusion

In this paper we quantify the expected dynamic macroeconomic impacts of tropical cyclone shocks. To do so we start by constructing a new high frequency database of macroeconomic expectations by linking together quasi-biweekly Blue Chip Surveys for more than 50 firms across multiple variables and forecast horizons over the last two decades. Next, we construct new real-time measures of tropical cyclone (TC) damage shocks using a mix of model-based measures and news-based measures that reflect the information that forecasters had access to at the time. Linking the TC shocks with revisions in individual macroeconomic economic expectations allows us to assess how changes in information about TC damages altered forecasters' expectations about the macroeconomy. Extending methods which have been used in the applied macroeconomics literature, we are able to capture both the expected short-run immediate impact of a TC shock as well as the expected long-run / equilibrium impact of a TC shock over multiple quarters up through a year-ahead. Finally, we trace out the expected impact of a shock across multiple variables and test for heterogeneity across forecasters.

We demonstrate the importance of explicitly accounting for dynamics in forecast revisions when estimating the impact of shocks on expectations. This allows us to distinguish between the expected short-run immediate impact as well as the expected long-run impact which captures any dynamic effects. We find that a Hurricane Katrina sized shock results in an immediate downward revision in expectations of real GDP growth by half a percentage point. In the long-run, after accounting for dynamic effects, this downward revision is more than double the immediate impact. Furthermore, following the decline in expectations for current quarter growth, firms expect a prolonged decline in growth with only a partial recovery in real GDP after three quarters.

There is a large amount of heterogeneity across individual forecasters. While Blue Chip forecasters on aggregate agree with Federal Reserve Board staff about the initial expected impacts of a TC shock, private forecasters tend to be more pessimistic at longer horizons with a slower and only partial expected recovery in GDP in contrast with FRB staff who expect a full recovery within two quarters after a TC shock. Across individual Blue Chip forecasters there is also considerable heterogeneity about the initial impact of a shock with larger / publicly traded firms expecting larger declines in growth compared with smaller and non-publicly traded firms.

Looking more looking more broadly across a multivariate system of forecast revisions, we find that a TC shock is akin to a supply shock with an expected decline in real GDP growth, an increase in CPI inflation, and a decline in 10 year Treasury bond yields. While the Treasury bond yields are expected to recover their losses after four quarters, real GDP is only expected to recover partially while CPI inflation is not expected retrace its gains indicating an expected permanent increase in the price level. These results are robust to a wide range of specifications including longer lags and controlling changes in commodity prices.

Overall, our results provide strong evidence is support of the fact that extreme weather events such as TC shocks influence firm's expectations about the macroeconomy. Large TC shocks are expected to have prolonged negative impacts on output and result in a higher price level over the entire forecast horizon. This illustrates that private forecasters generally expect TC shocks to operate akin to supply shocks. In this context the appropriate set of short-term macroeconomic policy responses is more limited. Rather than using monetary policy to offset the expected costs of climate change, our results suggest that policymakers can manage macroeconomic expectations by reducing direct exposures and by encouraging a more resilient economy that it is less susceptible to tropical cyclone shocks.

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Appendix

Table 4: Tropical Cyclone Shocks in Historical Perspective

		Implied Shock Estimates	
	Actual Shock	Martinez (2020)	2x Air Worldwide (2017)
Great Miami Hurricane [1926]	0.09	2.79	1.37
Lake Okeechobee Hurricane [1928]	0.03	0.65	0.83
Hurricane Katrina [2005]	1.02	0.75	0.68
Fort Lauderdale Hurricane [1947]	0.02	0.21	0.66
Hurricane Betsy [1965]	0.11	0.19	0.61
Hurricane Andrew [1992]	0.44	0.70	0.60
Hurricane Donna [1960]	0.06	0.40	0.53
Great New England Hurricane [1938]	0.33	0.55	0.53
Galveston Hurricane [1900]	0.15	1.33	0.52
Galveston Hurricane [1915]	0.14	1.50	0.27

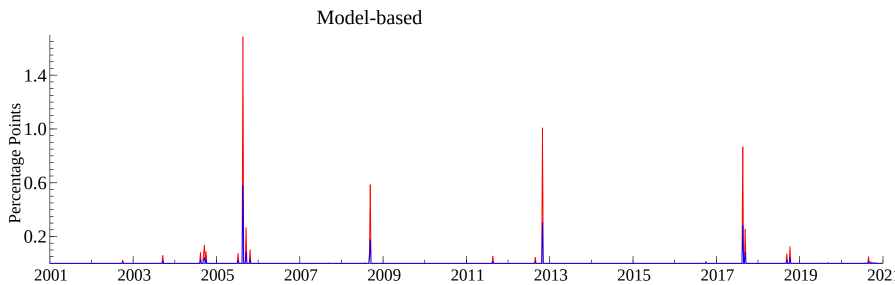
A1. Robustness to Alternative Shock Measures

We assess the robustness of the results using an alternative measure shocks. We construct a real-time model-based measure of shocks by projecting TC damages in real-time using the model from Martinez (2020a). In this model, hurricane damages are explained by measures of socio-economic vulnerabilities, the natural hazards of the storm, and the short-term forecast accuracy of the hurricane track. The model estimated using all hurricane strikes on the U.S. from 1955-2015 can be stated as

$$\begin{aligned}\widehat{dam}_n =& \underset{(38.2)}{403.0} + \underset{(0.09)}{0.27}\mathrm{hd}_n + \underset{(0.12)}{1.43}\mathrm{ih}_n + \underset{(0.09)}{0.44}\mathrm{ih}_n^2 + \underset{(0.21)}{0.57}\mathrm{rain}_n + \underset{(0.24)}{0.98}\mathrm{surge}_n \\ &+ \underset{(5.49)}{56.6}\mathrm{press}_n + \underset{(0.15)}{0.34}\mathrm{etk12}_n - \underset{(0.61)}{5.45}\mathrm{low1}_n - \underset{(0.33)}{3.44}\mathrm{low2}_n\end{aligned}$$

where all terms are in logs, $\widehat{\mathrm{dam}}_n$ is the prediction of damages for strike n, hd_n is the housing density in the area of the hurricane strike, ih_n is the income per housing unit, rain_n is the maximum recorded rainfall for the strike which captures inland flooding, surge_n is the maximum recorded storm surge which captures coastal flooding, press_n is the reciprocal of the maximum central pressure which captures wind damages, $\mathrm{etk12}_n$ is the 12-hour ahead forecast error of the strike location, and $\mathrm{low1}_n$ and $\mathrm{low2}_n$ capturing glancing strikes and measurement errors. We re-estimate the model with an expanding window in real-time to predict damages for each hurricane strike from 2001-2020.

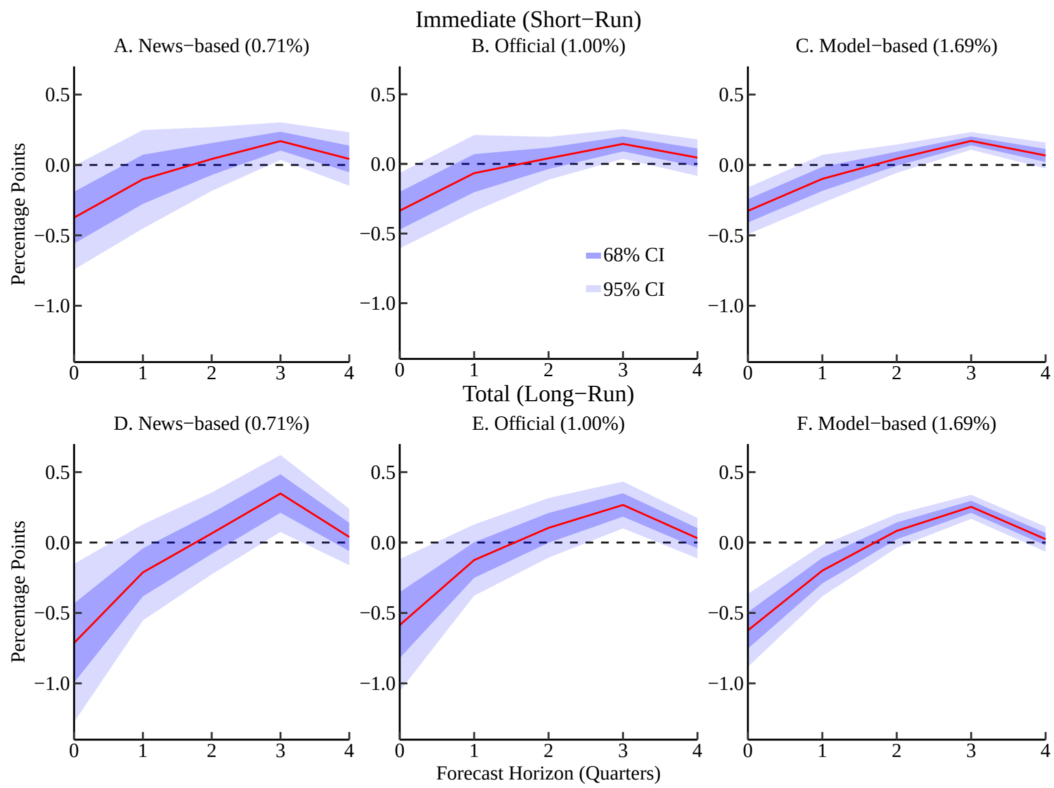
Measurements of natural the hazards and forecast accuracy are available right after landfall. Vulnerabilities are measured using real-time vintages of population and personal income from the Bureau of Economic Analysis, and housing units from the Census Bureau. The Figure presents the measures of these model-based shocks for 38 storms. In contrast with the news-based measure, this measure overestimates damages for the largest storms with a median percent error of 46%.



Notes: The model-based measure includes 38 unique storms.

Figure 8: Real-Time Model-based Tropical Cyclone Damage Shocks (2001-2020)

We compare the expected impact from a Hurricane Katarina sized shock across measures of real-time news-based, model-based, and the official TC shocks. Figure 9 shows that despite the different shocks ranging from 0.71% of GDP for the news-based measure to 1.69% of GDP for the model-based measure, all measures generate similar paths. Comparing Panel A and D in Figure 9 with Panels A and B in Figure 5 gives a sense of how forecasters react based on imperfect information about the size of the shock (i.e. 0.71% of GDP) vs. how they would have reacted if they had had perfect information about the true size of the shock at the time (1% of GDP). This suggests that the expected impact of a Hurricane Katrina sized shock is just over two thirds of what it would have been be if forecasters had perfect information about the shock.



Notes: Measures are scaled such that they are equivalent to the implied Hurricane Katrina sized shock. See Notes for Figure 5

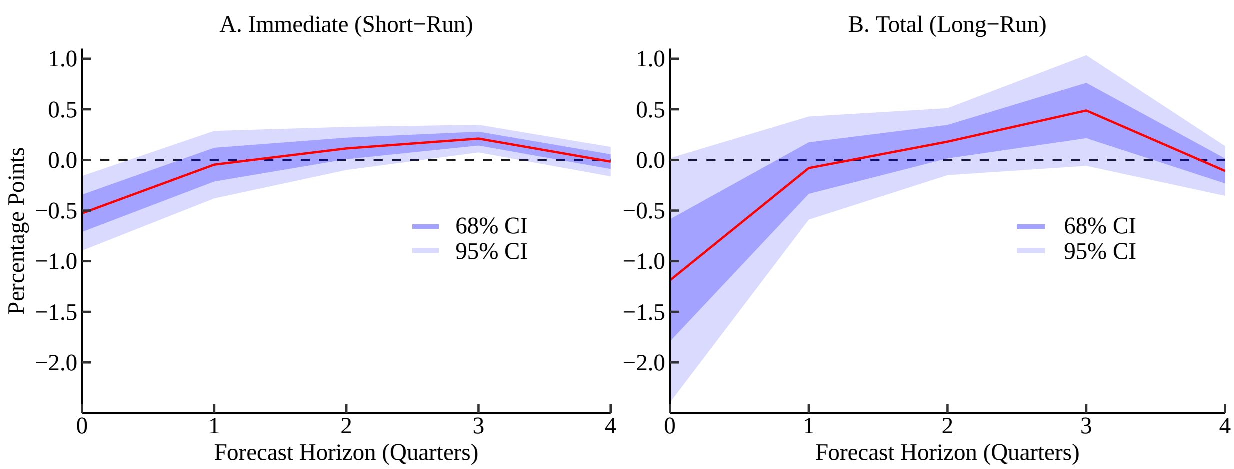
Figure 9: Expected Impact of a Hurricane Katrina-sized TC Shock Using Alternative Shock Measures

A2. Joint Analysis Across Horizons

To test for independence across the forecast horizons we can estimate a joint model across horizons

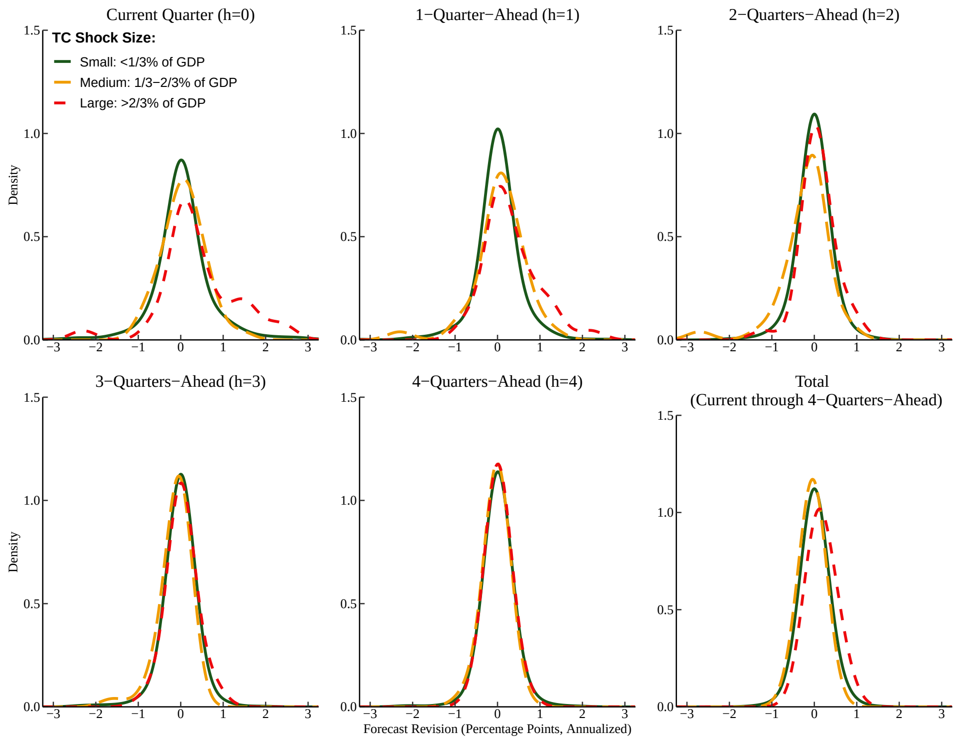
$$\mathbf{A}\Delta\mathbf{F}_{i,t_w} = \Gamma_1 \Delta\mathbf{F}_{i,t_{w-1}} + \Gamma_2 \left(\Delta\mathbf{F}_{i,t_{w-1}} \times \mathrm{TC}_{t_w}\right) + \sum_{j=0}^{1} \beta_j \mathrm{TC}_{t_{w-j}} + \mathbf{e}_{i,t_w} \tag{7}$$

where $\mathbf{F}_{i,t_w} \equiv \{\ \Delta f_{i,t_w} \ \ \ldots \ \ \Delta f_{i,t_w+4}\ \}'$ is a 5×1 vector of the forecast errors. We impose a Choleski ordering such that contemporaneous feedback only flows forward with time and not backwards. We start by estimating the joint model and then test the hypothesis of complete independence across forecast horizons. This hypothesis is strongly rejected at any reasonable level of significance with test statistics of $\chi^2(50) = 386.6\ [0.000]$. Next we test for and impose a wide range of restrictions. We are able to reduce the joint model such Γ_1 has a simple diagonal structure with one lead and lag for each equation in the off diagonals indicating some smoothing across forecast horizons. Γ_2 is simplified such that the non-linear terms are only along the diagonal and non-zero for $h = 0$ and $h = 3$. Finally we restrict the $\mathbf{A}$ matrix such that contemporaneous correlations only matter for the most recent horizon. In total this implies 40 restrictions in the VAR which are not rejected any standard level of significance with a test statistic of $\chi^2(40) = 48.6\ [0.165]$. The estimated immediate and total impacts from this joint model are generally in line with the model results which treat the data independently across horizons:



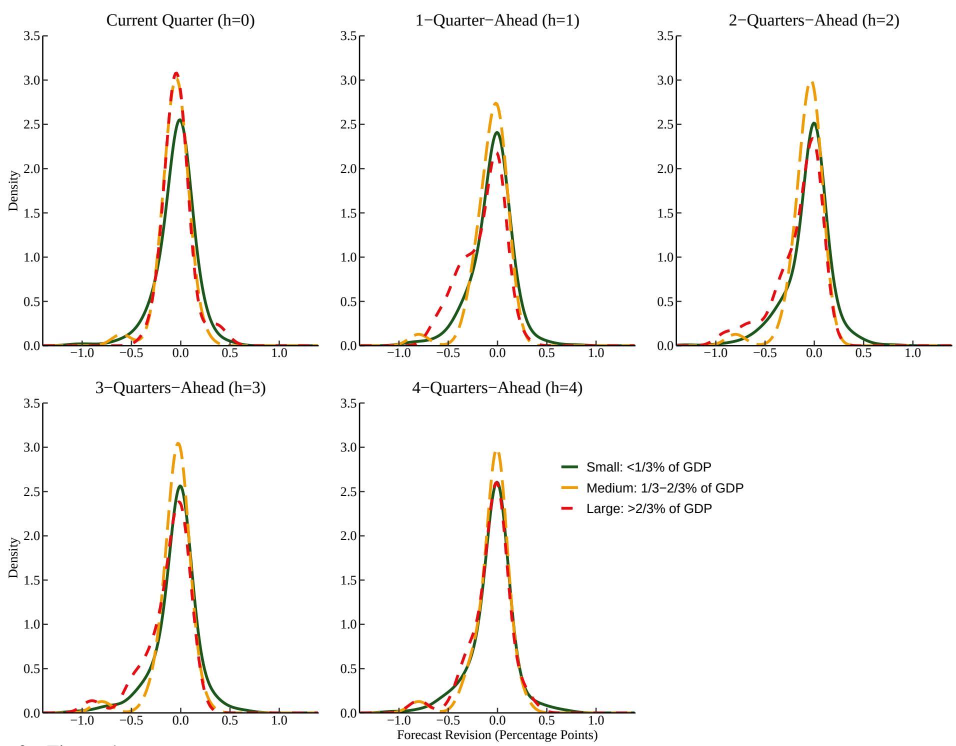
Notes: Estimated jointly based on 11,268 observations across each horizon. See Notes for Figure 5

Figure 10: Jointly Estimated Expected Dynamic Impacts of a TC Shock on Real GDP growth



Notes: See Notes for Figure 4

Figure 11: CPI Inflation Forecast Revision Densities by Shock Size and Forecast Horizon



Notes: See Notes for Figure 4

Figure 12: 10-year T-bill Yield Forecast Revision Densities by Shock Size and Forecast Horizon

Table 5: Dynamic Impacts of a TC Shock on Forecast Revisions of CPI Inflation

Forecast Horizon:	0	1	2	3	4
Lagged Forecast Revision:	-0.34^{***}	-0.40^{***}	-0.36^{***}	-0.37^{***}	-0.42^{***}
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Lagged Forecast Revision $\times$ TC:	0.15	0.92^{*}	0.43	0.64	1.75^{***}
	(0.55)	(0.50)	(0.68)	(0.45)	(0.61)
Immediate TC Impact:	0.43^{**}	0.28^{**}	0.07	0.01	0.04
	(0.20)	(0.11)	(0.11)	(0.08)	(0.08)
Lagged TC Impact:	0.19	0.07	−0.16	0.07	0.03
	(0.25)	(0.08)	(0.13)	(0.10)	(0.10)
Total TC Impact:	0.52	0.74	−0.10	0.11	−0.22
	(0.33)	(0.80)	(0.25)	(0.23)	(0.50)
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:	13,119	13,009	13,056	12,723	11,129
$\hat{\sigma}$:	0.67	0.51	0.36	0.31	0.29
R^2:	0.25	0.20	0.16	0.15	0.18

Notes: See Notes for Table 2.

Table 6: Dynamic Impacts of a TC Shock on Forecast Revisions of 10 Year Treasury Bond Yields

Forecast Horizon:	0	1	2	3	4
Lagged Forecast Revision:	-0.46^{***}	-0.44^{***}	-0.44^{***}	-0.44^{***}	-0.46^{***}
	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)
Lagged Forecast Revision $\times$ TC:	−0.08	−0.15	−0.08	0.65^{***}	0.38^{*}
	(0.19)	(0.16)	(0.16)	(0.12)	(0.19)
Immediate TC Impact:	0.01	-0.15^{***}	-0.18^{***}	−0.07	−0.03
	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
Lagged TC Impact:	−0.06	-0.08^{*}	−0.02	0.00	0.07
	(0.05)	(0.04)	(0.04)	(0.06)	(0.05)
Total TC Impact:	−0.04	-0.14^{***}	-0.15^{***}	−0.09	0.04
	(0.04)	(0.04)	(0.05)	(0.12)	(0.08)
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:	13,102	12,937	13,066	12,497	10,743
$\hat{\sigma}$:	0.15	0.17	0.19	0.20	0.21
R^2:	0.38	0.37	0.33	0.30	0.29

Notes: See Notes for Table 2.

A3. Forecaster Heterogeneity

We assess differences between alternative groups of Blue Chip forecasters by augmenting (4) to allow the estimates of $\gamma_{i,h}$ and $\beta_{i,h}$ to vary across groups of forecasters while assuming homogeneity for all other parameter estimates.[19] We consider several alternative groups based on firm characteristics including if they are publicly traded, in the financial services industry, or based in the New York City Metropolitan Statistical Area (MSA). We also consider measures of forecaster attentiveness such as forecaster participation and the frequency of forecast revisions; e.g. see Andrade and Le Bihan (2013) and Baker et al. (2020).

Table 7: Heterogeneity of Expected Impacts of a TC Shock on Current Quarter Real GDP growth

	Publicly Traded	**>1000 Employees**	**Financial Services**	**Primary Dealers**	**NYC MSA**	**Obs. Shr. (>0.72)**	**Rev. Shr. (>0.50)**
Lagged Forecast Revision:	-0.25^{***}	-0.25^{***}	-0.27^{***}	-0.23^{***}	-0.25^{***}	-0.26^{***}	-0.26^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Lagged Forecast Revision $\times$ TC:	0.55^{**}	0.55^{**}	0.46^{**}	0.50^{**}	0.44	0.50^{**}	0.15
	(0.22)	(0.22)	(0.18)	(0.20)	(0.27)	(0.20)	(0.20)
Immediate TC Impact:	-0.64^{**}	-0.63^{**}	-0.42^{**}	-0.52^{**}	-0.46^{*}	-0.65^{**}	-0.41
	(0.26)	(0.26)	(0.19)	(0.22)	(0.27)	(0.27)	(0.28)
Lagged TC Impact:	-0.51^{***}	-0.47^{***}	-0.50^{**}	-0.51^{**}	-0.34^{**}	-0.51^{***}	-0.45^{***}
	(0.16)	(0.17)	(0.24)	(0.25)	(0.15)	(0.14)	(0.16)
Total TC Impact:	-1.65^{**}	-1.57^{**}	-1.15^{***}	-1.42^{**}	-0.99^{*}	-1.53^{**}	-0.77^{*}
	(0.79)	(0.76)	(0.41)	(0.58)	(0.59)	(0.61)	(0.40)
	Other Firms	**≤1000 Employees**	**Other Industries**	**Other Firms**	**Other Places**	**Obs. Shr. (≤0.72)**	**Rev. Shr. (≤0.50)**
Lagged Forecast Revision:	-0.31^{***}	-0.31^{***}	-0.29^{***}	-0.30^{***}	-0.30^{***}	-0.29^{***}	-0.28^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Lagged Forecast Revision $\times$ TC:	0.26	0.24	0.55^{**}	0.43^{**}	0.51^{***}	0.51	0.66^{***}
	(0.34)	(0.31)	(0.22)	(0.20)	(0.18)	(0.32)	(0.22)
Immediate TC Impact:	-0.32^{**}	-0.35^{**}	-0.67^{***}	-0.49^{**}	-0.56^{***}	-0.34^{*}	-0.53^{***}
	(0.16)	(0.15)	(0.20)	(0.20)	(0.18)	(0.18)	(0.19)
Lagged TC Impact:	-0.23^{*}	-0.29^{**}	-0.20	-0.34^{**}	-0.44^{**}	-0.24	-0.37^{**}
	(0.14)	(0.13)	(0.18)	(0.13)	(0.18)	(0.18)	(0.15)
Total TC Impact:	-0.53^{**}	-0.59^{***}	-1.17^{**}	-0.96^{***}	-1.27^{***}	-0.73^{*}	-1.44^{**}
	(0.27)	(0.22)	(0.55)	(0.37)	(0.34)	(0.40)	(0.61)
Test of Homogeneity; $\chi^2(4)$:	11.98^{**}	8.05^{*}	4.86	6.64	3.09	8.33^{*}	7.16
	[0.017]	[0.090]	[0.302]	[0.156]	[0.543]	[0.080]	[0.127]

Notes: Each column represents a single equation. See additional Notes for Table 2.

Table 7 presents the results of this analysis. Each column presents the estimates for a given grouping, the alternative group and then a test of homogeneity of the estimates. For example, the first major column considers publicly versus non-publicly traded companies. The estimated long-run impact for publicly traded companies is -1.65 while the same estimate for non-traded companies is -0.53. While both estimates are

[19]Note that the use of clustered standard errors already allows for some degree of heterogeneity across forecasters. Preliminary tests of for the validity of the pooled estimates (not shown) indicate that most heterogeneity stems from the dynamic parameters.

individually statistically different from zero, we reject the null of homogeneity with a test statistic of 11.98 which can be compared to a chi-square distribution with 4 degrees of freedom and is rejected with a p-value of 1.7%. This implies that publicly traded companies expect even larger initial impacts from a TC shock compared to non-publicly trade firms. One explanation for this result is that publicly traded firms tend to be larger and are able to devote more resources to understanding the impact of non-traditional economic shocks than smaller boutique firms. This is supported by the results in column 2 where larger firms expect a significantly larger impact from a TC shock relative to smaller firms.

One possibility is that firms in the financial industry could pay more closer attention to forecasts of the storm and its impacts; e.g. see Kruttli et al. (2021). To test this hypothesis we first consider if there are any differences between firms in the financial services industry versus those that aren't. The results in Column 3 of Table 7 indicate that there are no significant differences between these firm types. Next, we also consider if some financial services firms known as primary dealers, which are vetted by the Federal Reserve Bank of New York, might have different expectations. While the estimates for these firms do to differ qualitatively, the results in column 4 indicate that we fail to reject the null hypothesis of no significant differences. As a final check we test whether firms located in the New York City MSA have significantly different expectations than firms not located in this area. Column 5 of Table 7 indicates that these differences are rejected.[20] Thus, a firms location and industry do not alter the expected impacts so that the large share of New York City based financial services firms in the sample not distortionary.

Firm attentiveness could also be important. Column 6 of Table 7 indicates that firms that have participated in the Blue Chip surveys for a longer time tend to expect a larger impact from TC shocks. These firms may have more experience with previous TC shocks and so could reflect learning by doing. Alternatively this could reflect the fact that they are more likely to have been in the sample when large TC shocks occurred. On the other hand, column 7 of Table 7 indicates that firms that are more likely to revise their forecasts on average do not have significantly different expectations about the impact of a TC shock than firms that revise their forecasts less often. Despite this there are clear qualitative differences between these firms where firms with a higher share tend to have a lower under reaction to large shocks and do expect the total shock size to be less than half that of firms with lower revision frequencies.

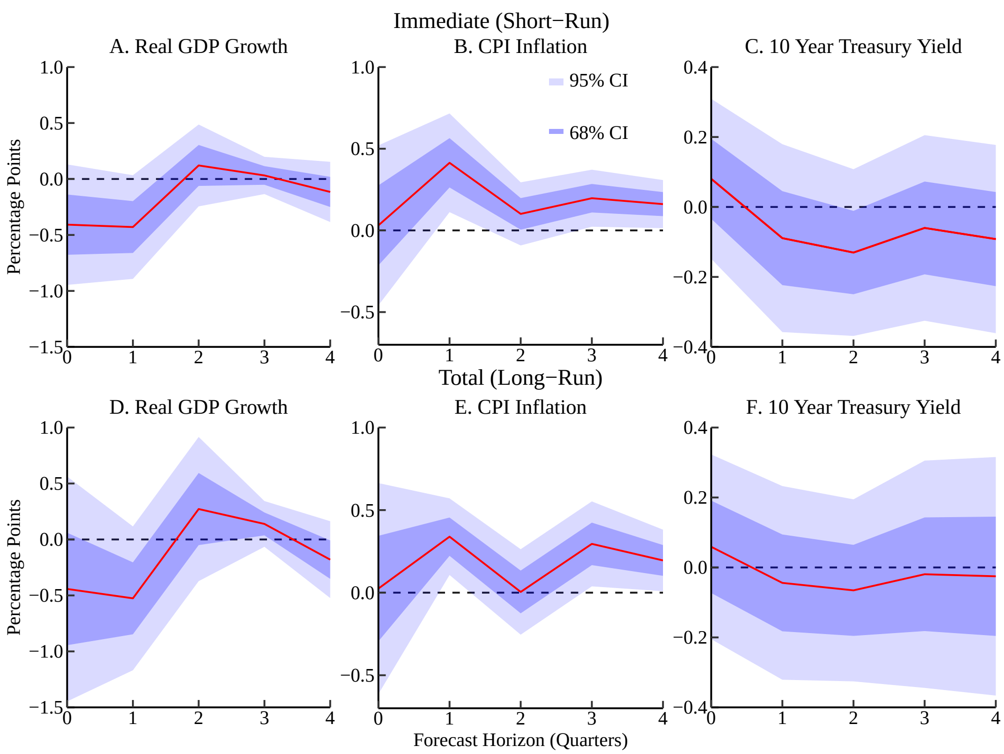
If we augment (4) to include the lagged deviation of the individual and consensus forecasts (not shown), the results show that forecasters error-correct back to the consensus at a similar speed. Thus, although we obtain heterogenous results, over the longer-term forecasters converge back to homogeneity.

[20] Additional results (not reported) indicate that a firms distance from a hurricane strike is also not an important determinant of its expected impact.

A4. Controlling for Commodity Price Changes

An important question is whether impacts are driven by expectations of an energy or food price shock. For example, major hurricane strikes along the Gulf Coast of the United States have had substantial impacts on oil production and distribution and are often associated with oil supply shocks; e.g. see Caldara et al. (2019). Other research has also shown that shocks from extreme weather events predominantly impact headline rather than core inflation; e.g. see Parker (2018) and Kim et al. (2021). Thus, the expected macroeconomic impact of a TC shock may be operating predominantly through commodity price channels.

To control for these channels we augment (6) with commodity price changes on dates during which there was a TC shock. We capture crop destruction by controlling for daily changes in agricultural and livestock price futures, energy price shocks by controlling for daily changes in crude West Texas Intermediate oil prices, and the destruction of property using lumber futures prices. The aggregate results, show in the panel of Figures below, show that changes in commodity prices can explain some of the variation in forecast revisions, they are unable to explain all of it, particularly the expected changes in inflation and output continue to show clear impacts. Thus, the revisions following a TC shock do not appear to be fully explained by commodity price changes but rather appear to reflect broader concerns about a supply shock.



Notes: See Notes for Figure 6.

Figure 13: Expected Macroeconomic Impacts of a TC shock after controlling for Commodity Price Changes