Do Firms Adapt to Seasonal Climate Forecasts?

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Abstract

We test whether public firms across the U.S. economy adapt operations using seasonal climate forecasts issued by the U.S. National Oceanic and Atmospheric Administration. Decomposing local weather into forecasted and unexpected components, we find evidence of adaptation: forecasted variation has more favorable effects on operating profitability than unexpected shocks. If firms merely absorbed weather variation without forecast-based adjustments, these components should affect performance similarly. Adaptation is stronger when forecasts are more accurate, for nature-dependent firms, and extends beyond traditionally weather-sensitive sectors like agriculture and energy. A survey of 1,095 operational managers validates our empirical approach, provides evidence on the mechanisms of adaptation, and highlights frictions to adaptation, including informational ones. Consistent with the latter, firm-issued guidance often does not fully incorporate available forecast information.

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1. Introduction

Extreme weather ranks as the top global risk over the coming decade, with five of the ten most severe long-term risks being environmental in nature.[1] Seasonal climate variation—temperature and precipitation anomalies that unfold over months—is partially forecastable and thus seasonal forecasts represent a potential tool for firms to adapt at operational time-scales, for example, by adjusting logistics, production schedules, or inventory in advance of anticipated conditions. Recent policy discussions, however, have proposed significant cuts to forecasting technology and research. For example, proposed cuts to the National Oceanic and Atmospheric Administration's (NOAA) research budget total nearly $100 million (Science.org, 2025), while a $20 million AI institute for weather forecasting faces closure (NBC, 2025). This spending could have large payoffs: Lemoine and Kapnick (2024) estimate that seasonal forecast skill generates billions of dollars in annual value for financial markets alone. Understanding how broadly the benefits of seasonal forecasting extend across the real economy is therefore policy-relevant: if adaptation is limited to a narrow set of weather-sensitive industries, the case for continued investment differs from one where benefits accrue across sectors.

Existing evidence on adaptation to seasonal forecasts remains limited to specific industries. Shrader (2023) shows Pacific Northwest fishers adapt expeditions based on El Niño Southern Oscillation (ENSO) forecasts, Downey, Lind, and Shrader (2023) shows construction firms reschedule work around anticipated precipitation, and Burlig et al. (2024) find that Indian farmers adjust planting decisions and input use in response to early monsoon forecasts. These studies focus on industries with direct weather exposure—fishing, construction, agriculture—where the operational link to weather is mechanical. Whether firms across the broader economy systematically adapt to available forecasts,

[1] World Economic Forum, *Global Risks Report 2026*, based on the Global Risks Perception Survey of over 1,300 experts from academia, business, government, and civil society.

rather than simply absorbing weather variation as it arrives, remains an open question.

To motivate our empirical approach and establish baseline patterns, we survey over 1,000 operational managers across North American firms in the consumer cyclicals, financial, healthcare, industrial, and technology sectors. The survey reveals three key findings. First, weather variation is operationally relevant across sectors: the vast majority of managers report that weather shocks affect their operations. Second, adaptation is widespread: most managers report that their firms make operational adjustments in response to seasonal climate forecasts. Third, however, adaptation faces significant frictions: over 80% of respondents cite substantial challenges related to forecast uncertainty, supply chain complexity, or organizational constraints. These patterns motivate our archival analyses, which test whether forecast-based adaptation is detectable in firm performance data despite the frictions managers report.

Our archival analyses use data from the U.S. National Oceanic and Atmospheric Administration (NOAA) on both local weather realizations and seasonal climate outlooks for local temperature and precipitation. This approach captures the local information readily available to managers making operational decisions. NOAA's seasonal forecasts, issued by its Climate Prediction Center (CPC), are public, updated monthly, cover the continental United States, and receive media attention (El-Bawab and Golembo 2022; Washington Post 2023; Borenstein 2023).

Crucially, the data structure allows us to decompose local weather into forecast updates (revisions in CPC seasonal outlooks over the preceding quarter) and unexpected shocks (realized weather minus the forecast). This decomposition, combined with readily available financial statement data, provides a direct test for adaptation: if firms adapt, forecasted variation should have more favorable effects on performance than unexpected shocks of equivalent magnitude. This is our primary prediction.

Our main empirical tool is the local projections method (Jordà 2005). Local projections provide a flexible and easily implementable way to estimate impulse response functions with respect to climate variation. This dynamic approach allows us to capture how the operational impacts of climate variation and weather shocks evolve over time. We consider horizons of up to eight quarters.

We first establish that realized weather anomalies, defined as deviations from long-run climatological normals, significantly affect firm performance. Both precipitation and temperature anomalies have economically meaningful effects: a one-standard-deviation precipitation deviation reduces cumulative operating profitability by approximately 1%, while a one-standard-deviation temperature deviation increases it by a similar magnitude. These baseline results confirm that weather variation matters for firm performance but do not distinguish between anticipated and unanticipated variation.

Decomposing weather into forecast updates and weather shocks reveals evidence of adaptation. For precipitation, forecast updates have significantly more positive effects than shocks: while unexpected precipitation shocks reduce profitability, anticipated precipitation deviations (captured by forecast updates) have near-zero or positive effects, suggesting firms mitigate harm when conditions are forecastable. For temperature, both shocks and updates increase profitability, but updates have larger per-unit effects—more than six times larger at short horizons. These differential responses are consistent with firms using advance information to adjust operations, either mitigating adverse conditions or amplifying benefits from favorable ones.

The adaptation effects are strongest when forecast information is most valuable. During El Niño and La Niña events, when forecast accuracy increases substantially, and we find that the differential effects of updates versus shocks are amplified. This is consistent with firms being better able to adapt when forecasts are more reliable. Similarly, firms with greater nature dependence—measured by operational reliance on ecosystem services such as water provision and climate regulation—exhibit stronger responses to forecast updates, consistent with these firms having more to gain from advance information about weather conditions.

Sector-level analysis reveals substantial heterogeneity in adaptation patterns. Using an 80% threshold (the percentage of horizons where forecast updates outperform shocks), we find evidence consistent with adaptation in multiple sectors beyond those traditionally associated with weather sensitivity. For temperature, five sectors show patterns consistent with adaptation: Basic Materials, Consumer Cyclicals, Consumer Non-Cyclicals, Financials, and Healthcare. For precipitation, four sectors exhibit patterns consistent with adaptation: Consumer Non-Cyclicals, Energy, Industrials, and Communication. Notable in these lists are service-oriented sectors such as Financials, Healthcare, and Communication, suggesting the benefits of seasonal forecasts may be broader than commonly appreciated. However, a few sectors show puzzling patterns where shocks appear to affect operating profitability more than positively than forecast updates, and many sector-specific estimates lack statistical precision.

We return to our survey to provide additional insights into adaptation mechanisms and constraints. A key concern is whether our archival estimates reflect genuine operational effects or spurious patterns from specification choices. Correlating manager-reported weather impacts with our local projection estimates reveals meaningful alignment: for forecast updates, the Pearson correlation is 0.21 ($p = 0.066$) and Spearman correlation is 0.27 ($p = 0.014$); for shocks, correlations are weaker (Pearson $r = 0.03$, Spearman $\rho = 0.17$). While both survey responses and archival estimates contain noise, the positive correlations suggest our decomposition captures real operational distinctions rather than statistical artifacts.

The survey also reveals the operational channels and constraints underlying adaptation. The main reported channels through which weather affects our respondents' firms' operations are product delivery and logistics, and customer demand. Firms adapt using a range of methods: changing project timelines, adjusting product distribution, and modifying labor scheduling. However, adaptation faces significant frictions: over 80% of managers cite substantial challenges, and notably, only 50–60% report their firms are probably or definitely aware of medium-term forecasts. This lack of forecast awareness suggests informational barriers may limit adaptation even when forecasts are publicly available.

Motivated by this last survey insight, we test whether forecast information is incorporated into managerial guidance. Even if operational constraints prevent full adaptation, attentive managers should incorporate forecast information into performance expectations. We test whether CPC forecast updates available at guidance issuance predict subsequent guidance errors. If managers fully process forecast information, forecast updates should not predict errors. We find that forecast updates do predict errors in multiple weather-sensitive sectors: for temperature updates, four sectors show significant effects (Utilities, Communication, Energy, Technology); for precipitation updates, six sectors show significant effects (Consumer Cyclicals, Consumer Non-Cyclicals, Technology, Energy, Industrials, Basic Materials). These findings suggest scope for improving forecast dissemination and utilization.

We make two main contributions. First, we use financial statement data to demonstrate that adaptation to seasonal forecasts extends broadly across sectors. A growing literature documents that weather variation affects firm performance across the economy—influencing aggregate growth (Dell, Jones, and Olken 2012, 2014), state-level output (Colacito, Hoffmann, and Phan 2018), firm earnings (Addoum, Ng, and Ortiz-Bobea 2023), and supply chain propagation (Barrot and Sauvagnat 2016; Pankratz and Schiller 2024)—yet understanding of adaptation across sectors, in particular using seasonal climate forecasts, remains limited. Prior work illustrates specific adaptation mechanisms in industries with direct weather exposure: Shrader (2023) shows fishers adjust expedition timing, Downey, Lind, and Shrader (2023) shows construction firms reschedule projects, and Burlig et al. (2024) shows farmers adjust planting decisions in response to monsoon forecasts. While these studies reveal adaptation in specific settings, the economy-wide picture remains incomplete. Our financial statement approach complements this work by testing whether adaptation occurs broadly. Our findings parallel Addoum, Ng, and Ortiz-Bobea (2023), who show that temperature shocks affect earnings in approximately 40% of industries: we provide evidence that adaptation to forecasted variation is similarly widespread. While Lemoine and Kapnick (2024) show forecasts have value to investors, we show forecasts have operational value to firms themselves through adaptation. Finding evidence of adaptation in sectors such as Financials and Healthcare suggests that the economic value of seasonal forecast infrastructure extends beyond traditionally weather-sensitive industries. This breadth of benefits is directly relevant to ongoing policy debates about forecasting infrastructure investment.

Second, our management guidance tests provide evidence inattention to forecasts or cognitive limitations in mapping seasonal climate information to expected performance. These findings complement prior work documenting underreaction to climate information: Addoum, Ng, and Ortiz-Bobea (2023) and Pankratz, Bauer, and Derwall (2023) show that analysts underreact to weather shocks' effects on firm performance, while Hong, Li, and Xu (2019) show that food company stock prices underreact to long-term drought risk. This incomplete incorporation is also consistent with broader patterns of bounded rationality in guidance (Hutton, Lee, and Shu 2012; Huang et al. 2025). These findings highlight a second dimension of the policy debate: beyond the question of whether to invest in forecast production, there is scope for improving how forecasts are disseminated and presented to end-users.

The remainder of the paper proceeds as follows. Section 2 develops the background and hypotheses. Section 3 describes the data and empirical methodology. Section 4 presents local projection results. Section 5 provides survey evidence on mechanisms. Section 6 analyzes managerial guidance. Section 7 concludes.

2. Background and Hypotheses

Though seasonal climate variation is the product of a complex system with significant uncertainty, it is partially forecastable. The National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Center (CPC) issues seasonal outlooks for temperature and precipitation with lead times of up to nine months.[2] These seasonal forecasts predict deviations from climatological normals—whether the upcoming season will be warmer, cooler, wetter, or drier than average for a given region. Underlying these predictions is a continuous forecast distribution. The realized deviations from these forecasts—what we term "weather shocks"—are what ultimately affect firm operations.[3]

Evidence that firms adapt operations based on seasonal forecasts exists but remains narrow. Shrader (2023) documents that Pacific Northwest tuna harvesters modify fishing expeditions based on ENSO forecasts, reducing catch variability by 5–10%. Downey, Lind, and Shrader (2023) show that construction firms adjust work scheduling in response to anticipated precipitation. Burlig et al. (2024) demonstrate experimentally that providing Indian farmers with advance monsoon forecasts leads to significant adjustments in cultivation decisions and input spending. These studies focus on industries with obvious, direct weather exposure—fishing, construction, and agriculture. Related work shows firms also adapt to longer-run climate signals: Lin, Schmid, and Weisbach (2023) find that electric utilities increase investment in flexible generation capacity in regions experiencing more frequent extreme heat, and Pankratz and Schiller (2024) show that firms drop suppliers after unexpected climate shocks reveal higher-than-expected climate risk. Whether firms

[2] See "Climate Prediction Center: Outlook Maps," NOAA, `https://www.cpc.ncep.noaa.gov/products/predictions/long_range/`.

[3] Our terminology follows meteorological convention. The World Meteorological Organization defines "weather" as atmospheric conditions over short periods (hours to days), while "climate" refers to statistical descriptions of the atmosphere over longer periods, typically seasons or longer (World Meteorological Organization 2017). Forecasts at seasonal horizons (1–9 months ahead) are thus "seasonal forecasts" or "climate forecasts"; the CPC explicitly characterizes its products as "seasonal climate outlooks" (NOAA Climate Prediction Center 2024). See Goddard et al. (2001) for an overview of seasonal climate forecasting and Doblas-Reyes et al. (2013) for a review of forecast skill and applications.

across the various sectors in the economy incorporate seasonal forecasts into operational decisions remains unclear.

To provide a first pass at this question, we survey over 1,000 North American operational managers across five sectors (described in detail in Section 5). The responses suggest that seasonal weather variation is operationally relevant across the economy, not just in obviously exposed industries. Across all five sectors, the vast majority of respondents report that weather variation affects their operations: less than 17% reported "no effect" from weather shocks. Further, the vast majority of respondents report that their firms make operational adjustments in response to seasonal climate forecasts: less than 12% reported that their firms do not adjust.

These survey responses motivate a conceptual distinction between two ways firms can respond to weather variation. *Adaptation* refers to proactive operational adjustments made using forecast information—adjusting logistics, inventory, staffing, or production schedules before weather conditions materialize. *Absorption* refers to bearing weather variation reactively as it arrives, without forecast-based pre-positioning. If firms adapt, the performance effects of forecasted variation should be more favorable than unexpected shocks of equivalent magnitude: either mitigating harm from adverse conditions or amplifying benefits from favorable ones. If firms merely absorb weather variation, forecasted and unexpected components should affect performance similarly.

H1: *Firms adapt to forecasted weather variation rather than simply absorbing it*

Specifically, we test whether forecasted variation has more favorable performance effects than unexpected shocks. "More favorable" means either (a) less negative effects when weather conditions impose costs, or (b) more positive effects when conditions create opportunities. Because our baseline specification uses absolute values, this comparison holds regardless of weather direction (warmer vs. cooler, wetter vs. drier); we examine directional effects separately in Section 5.1. Importantly, we test H1 not only in the aggregate but also sector by sector, examining whether adaptation extends beyond industries with obvious weather exposure (agriculture, construction, energy) to sectors where weather affects operations through less direct channels.

Yet, our hypothesis is not without tension. Our survey respondents also highlight challenges to adaptation. Over 80% of respondents cite significant challenges, including not just hard economic constraints like financing challenges, but also those related to the noisiness of forecasts and organizational inertia, suggesting that even attentive managers may struggle to fully incorporate forecast information into operational decisions. These frictions make it unclear whether we will observe adaptation.

Even if we observe adaptation in operating performance (H1), an important question remains: do managers fully incorporate forecast information into their expectations? Informational frictions, distinct from operational constraints, can limit adaptation if managers fail to process available forecasts (Hirshleifer and Teoh 2003; Gabaix 2014). Even when operational adjustments are infeasible, attentive managers should incorporate forecast information into their expectations. Our survey provides suggestive evidence of partial awareness: only 50–60% of managers report their firms are “probably” or “definitely” aware of medium-term forecasts (Figure2F). If managers are unaware of or fail to process forecast information, adaptation opportunities will be missed even when operational adjustments are feasible. This motivates a test of forecast information processing:

H2: *Managers imperfectly incorporate seasonal forecast information into expectations*

We test H2 by examining whether forecast information that available when management guidance is issued predicts subsequent guidance errors (Keane and Runkle 1990). If forecast updates predict errors, managers are failing to process available information—suggesting informational constraints on adaptation beyond operational frictions. This test complements H1: while H1 asks whether firms adapt operationally, H2 asks whether a specific mechanism (managerial inattention to forecasts) limits the scope of adaptation.[4]

[4] Firms may also adapt through financial instruments such as weather derivatives or commodity hedges that provide payoffs contingent on temperature or precipitation (Pérez-González and Yun 2013). We focus on operational adaptation because it is the primary channel through which seasonal forecasts would affect

3. Empirical Design

3.1. Data

We combine two primary types of data: (1) climate datasets from NOAA, (2) firm-level fundamentals and managerial guidance. Together, we study the impact of precipitation and temperature forecasts and shocks on firm fundamentals and managerial guidance. We discuss these sources below as well as the means of aligning and merging the data.

3.1.1. Climate Data

We use two main climate-related data sets from NOAA. Our climate forecast data come from NOAA's Climate Prediction Center (CPC) at the spatial resolution of 102 U.S. climate divisions. Since 1994, the CPC has issued freely available official seasonal climate outlooks for temperature and precipitation across the United States. As of today, these forecasts incorporate forecast guidance from the North American Multi-Model Ensemble, a multi-model seasonal forecasting system that combines output from coupled climate models developed by (1) NOAA's National Centers for Environmental Prediction, (2) NOAA's Geophysical Fluid Dynamics Laboratory, (3) NASA, (4) Environment and Climate Change Canada, and (5) the National Center for Atmospheric Research (Kirtman et al. 2014).[5] At the middle of each month, CPC issues a set of forecasts with a range of lead times for upcoming three-month seasons. For example, a lead-0.5 forecast issued in mid-February predicts temperature and precipitation for the March–April–May season. Forecast leads range from 0.5 to 13.5 months. This range of forecast horizons allows us to track how climate expectations evolve over time and when firms receive updates relevant for quarterly planning.

operating profitability, our main outcome. Financial hedging, while potentially valuable for managing earnings volatility, typically appears below operating income. Moreover, effective use of weather derivatives requires the same forecast awareness we test through H2: firms that fail to incorporate forecast information into guidance are unlikely to systematically use weather derivatives to hedge forecasted conditions.

[5]The multi-model ensemble approach produces better prediction quality on average than any single model (Becker et al. 2022).

CPC forecasts show the expected deviation from normal conditions relative to a long-run baseline called a 'climatology' (e.g., 2°F above normal, 0.5 inches below normal precipitation). It is important to note that even at lead 0.5, CPC seasonal forecasts have modest accuracy. Forecast skill varies by location and season, and is generally higher during climatic events such as El Niño and La Niña.[6] We obtain CPC forecast archives covering 1995–2023. The forecasts are issued at the spatial resolution of 102 U.S. climate divisions. For each location-forecast issuance date, we extract the lead-0.5 and lead 3.5 forecasts, issued approximately two weeks and 3.5 months before their respective target season.

Next, we get realized temperature and precipitation data from NOAA's National Centers for Environmental Information (NCEI) Monthly U.S. Climate Divisional Database (nClimDiv) monthly dataset at the spatial resolution of 344 climate divisions. Since the NCEI data are reported at a finer spatial resolution of 344 climate divisions, compared to the 102 divisions used for CPC forecasts, to merge forecasts with realizations, we map the 344 NCEI climate divisions to the 102 CPC climate divisions based on the geographic centroid of each NCEI division.[7] We aggregate monthly NCEI observations into three-month seasonal averages to match the CPC forecast structure. We then compute our climate-related variables.

First, we construct realized temperature and precipitation anomalies as the difference between realized weather at a location and the climatology for that location. CPC uses a 1961–1990 climatology for forecasts issued from 1994 to mid-2001. Likewise, it uses 1971–2000, 1981–2010, and 1991-2020 climatologies for forecasts issued from mid-2001 to mid-2010, mid-2010 to mid-2020, and mid-2020 to present, respectively. Second, we construct temperature

[6] By our calculations, seasonal forecasts explain 0.6% and 0.9% of the residual variation in temperature and precipitation after controlling for the climatology and most recent (i.e., 12 month ago) realization. This accuracy has shifted to 1.44% and 0.8% since 2011. During the five most extreme El Niño and La Niña events since 1994, CPC seasonal forecasts explain 6.5% and 4.1% of the residual variation in temperature and precipitation.

[7] The mapping assigns each of the 344 NCEI divisions to the CPC division containing its centroid. This approach ensures that realized weather observations are matched to the appropriate forecast region. The mapping file was constructed with assistance from NOAA's Climate Prediction Center.

and precipitation shocks as the difference between realized weather at a location and the lead-0.5 forecast for that location. This is the surprise element of weather outcomes that firms could not have anticipated even using the most recent seasonal forecast. Third, we construct temperature and precipitation forecast updates as the change in forecasts over the preceding quarter (lead-0.5 forecast$_t$ minus lead-3.5 forecast$_{t-1}$). This captures new information about upcoming climate conditions that became available to firms during the prior quarter, providing a window for operational adjustments such as inventory management, production scheduling, or supply chain reconfiguration.

Distinguishing between weather shocks and forecast updates is key to our identification strategy. If managers ignore seasonal forecasts, both shocks and updates should have similar effects on firm performance since both get reflected in realized climate variation. However, if managers use forecasts to adapt operations, the performance impacts of forecasted climate variation should differ systematically. Specifically, forecast update variation should have a relatively more positive effect on firm performance than shocks if adaptation is effective, as firms preemptively adjust to anticipated conditions.

3.1.2. Firm-Level Data

We obtain quarterly firm fundamentals from Compustat North America covering 1995–2023. Our primary performance measure is operating profitability (revenue minus operating costs, scaled by assets). We focus on quarterly data to align with the seasonal structure of CPC forecasts.

To assign firms to climate divisions, we use a firm's headquarters ZIP code as reported in the Compustat Snapshot Names file, which tracks changes in firm headquarters over time.[8] We forward-fill and backward-fill missing ZIP codes within each firm to maximize coverage. We then geocode these ZIP codes to latitude-longitude coordinates using the SimpleMaps

[8] We use headquarters location as our primary geographic identifier following prior work on local economic conditions and firm outcomes (Addoum, Ng, and Ortiz-Bobea 2023).

U.S. ZIP codes data and spatially match these coordinates to NCEI's 344 climate divisions using geographic shapefiles.[9] This procedure assigns each firm-quarter observation to a climate division based on headquarters location at that time, allowing us to merge firm performance data with location-specific seasonal forecasts and realizations.

A potential concern is that headquarters location may be endogenous to weather exposure. However, we note that the more documented empirically-relevant drivers of headquarters relocation—tax considerations, access to talent, transportation infrastructure, and legal environments—are likely uncorrelated to the seasonal forecast variation we study.[10] Our identification relies on deviations from local normals, not cross-sectional differences in average climate, further mitigating selection concerns. A separate concern is measurement error: firms' operational footprints may differ substantially from headquarters location, particularly for large multinationals with geographically dispersed facilities, suppliers, and customers.[11]

For our analysis of managerial guidance, we obtain earnings and revenue guidance from I/B/E/S, which contains management forecasts of quarterly earnings per share and revenue with announcement dates and fiscal periods. We link IBES to Compustat using the IBES-GVKEY link table, and merge guidance announcements with CPC forecasts based on announcement month. We also merge actual reported earnings and revenue from IBES to compute guidance errors (actual minus guidance).

[9] SimpleMaps U.S. ZIP codes database available at `https://simplemaps.com/data/us-zips`.

[10] Seasonal climate-driven deviations from climatological normals vary year-to-year and are difficult to avoid through relocation, unlike long-run climate differences (e.g., average temperature) that firms could select on.

[11] To the extent that headquarters location is an imperfect proxy for operational weather exposure, classical measurement error would attenuate our estimates toward zero. This bias works against finding differential effects between shocks and forecast updates, making our adaptation estimates conservative. Similarly, if firms adapt by coordinating operations across multiple locations—shifting production or sourcing to regions with more favorable forecasted conditions—headquarters-based measurement would understate the true scope of adaptation.

3.1.3. Sample

Table 1 shows the geographic and sectoral distribution of the sample. The sample covers firms headquartered across contiguous U.S. states plus the District of Columbia. Texas (45,707 observations), California (42,341), and New York (31,015) contribute the most observations, reflecting the concentration of publicly traded firms in these states. The sectoral distribution spans all major industries, with Technology, Consumer Cyclicals, and Industrials representing the largest shares.

Table 2 presents descriptive statistics for the analysis sample. The sample comprises 328,513 firm-quarter observations. Mean operating profitability (operating profit divided by total assets) is 3.6%, with substantial variation (standard deviation of 2.8 percentage points). The distribution is right-skewed, with a median of 3.0%.

The weather variables reveal an important feature of the data: forecast updates are an order of magnitude smaller than shocks. The mean absolute temperature shock is 2.06°F (standard deviation 1.71), while the mean absolute temperature forecast update is only 0.16°F (standard deviation 0.22). Precipitation shows a similar pattern. This implies that identifying adaptation effects requires sufficient variation in forecast updates, which may limit statistical power in some specifications.

3.2. Local Projection Specification

We estimate the dynamic effects of weather variation on operating performance using local projections (Jordà 2005). Local projections estimate impulse response functions by running separate regressions at each forecast horizon, avoiding the restrictive lag structures of VARs while providing robust inference under misspecification (Plagborg-Møller and Wolf 2021). This approach is well-suited to our setting, since weather's operational impacts may accumulate as firms adjust inventories, production schedules, and supply chains.

Following Shrader (2023), we decompose weather into forecasted and unexpected components to test for adaptation. We estimate:

$$
\begin{aligned}
\text{CumOPA}_{i,t,h} = \alpha_h &+ \beta_h^{Tmp} \cdot |\text{TmpShock}_{i,t}| + \gamma_h^{Tmp} \cdot |\Delta\text{F(Tmp)}_{i,t}| \\
&+ \beta_h^{Pre} \cdot |\text{PreShock}_{i,t}| + \gamma_h^{Pre} \cdot |\Delta\text{F(Pre)}_{i,t}| \\
&+ \Gamma' X_{i,t-1} + \mu_i + \lambda_t^{Year} + \lambda_t^{Month} + \epsilon_{i,t+h}
\end{aligned} \tag{1}
$$

for horizons $h \in \{0, 1, \ldots, 8\}$ quarters, where μ_i denotes firm fixed effects. The vector $X_{i,t-1}$ includes lagged values of the climate variables to control for persistence and serial correlation in weather exposures.

The dependent variable measures cumulative operating profitability growth:

$$
\text{CumOPA}_{i,t,h} = \frac{\sum_{s=0}^{h} OP_{i,t+s} / \sum_{s=0}^{h} A_{i,t+s}}{OP_{i,t-1}/A_{i,t-1}} \tag{2}
$$

where OP is quarterly operating profit and A is total assets. The numerator sums both operating profit and assets over the horizon $[t, t+h]$, creating an average operating profitability measure that is comparable across horizons. Dividing by lagged operating profitability yields growth in operational efficiency. Economically, this measures whether a firm becomes more or less operationally efficient over the horizon relative to its baseline; a positive coefficient indicates weather variation improves operational efficiency, while a negative coefficient indicates deterioration. This construction avoids mechanical scaling with horizon length that would arise from summing flows alone. Dividing by lagged operating profitibility allows us to pool sectors that have different average levels and variances in operating profitability.

The explanatory variables decompose weather into forecasted and unexpected components. The temperature shock $\text{TmpShock}_{i,t}$ is the realized temperature at firm i's headquarters location minus the CPC seasonal forecast. The temperature forecast update $\Delta\text{F(Tmp)}_{i,t}$ is the revision in CPC's temperature forecast for the upcoming season between the current month and three months prior, capturing new information that could enable adaptation. We construct analogous measures for precipitation. We take absolute values because climatological normals represent firms' optimized baseline. A Minnesota retailer calibrated to typical winter conditions faces adjustment costs whether the season is warmer or colder than normal; a Florida utility optimized for summer cooling demand faces planning challenges whether temperatures are above or below expectations. By using absolute values, our baseline tests capture whether the magnitude of deviation from normal affects performance. We examine directional effects (warmer vs. cooler, wetter vs. drier) in Section 5.1.

Year and month fixed effects absorb aggregate time trends and seasonality. Firm fixed effects control for time-invariant heterogeneity in operating profitability growth. Identification comes from within-firm variation in weather exposures over time, combined with cross-sectional variation in weather exposures conditional on calendar time. Standard errors are clustered at the firm level to account for serial correlation.

The coefficients β_h^{Tmp} and β_h^{Pre} capture the cumulative effect of unexpected weather shocks through horizon h. The coefficients γ_h^{Tmp} and γ_h^{Pre} capture the effect of forecast updates—new information that firms could act upon. H1 predicts $\gamma > \beta$: if firms adapt, forecasted variation should yield more favorable performance effects than equivalent unexpected shocks. We test joint significance across horizons using stacked regressions with Wald F-tests that account for cross-horizon covariances (Jordà 2005).

4. Archival Analyses Results

This section presents empirical estimates from the local projections, shown primarily as figures. We first document that realized weather anomalies affect firm profitability, then decompose these effects into unexpected shocks versus forecast updates to test for adaptation.

4.1. Baseline Results

Figure 3 presents the effect of absolute realized weather anomalies—deviations from long-run climatological normals—on cumulative operating profitability growth. Both precipitation and temperature anomalies significantly affect firm performance. The joint F-test for precipitation anomalies across all horizons is 2.43 ($p = 0.009$), and for temperature is 3.96 ($p < 0.001$), rejecting the null of no effect.

The effects are economically meaningful. Precipitation anomalies reduce profitability: a one-inch deviation from normal precipitation over three months is associated with a 0.42% decrease in cumulative operating profitability at horizon 0 ($t = -3.95$) (a one-standard-deviation increase of 2.55 inches implies an effect of −1.1%). For the mean firm with operating profitability of 3.6%, the one-inch effect represents roughly a 12% decline relative to baseline. In contrast, temperature anomalies increase profitability: a one-degree Fahrenheit deviation from normal is associated with a 0.62% increase at horizon 0 ($t = 3.98$) (a one-standard-deviation increase of 1.75°F implies a 1.1% effect). The opposing signs suggest that precipitation deviations impose net costs on average, while temperature deviations, on average, benefit firms (perhaps through increased demand for heating, cooling, or seasonal goods). The effects persist through to quarter 8, though the effects become less discernible as operating profitability mean reverts.

These baseline results establish that weather variation matters for firm performance. However, they do not distinguish between weather that firms anticipated versus weather that arrived as a surprise. We turn to this decomposition next.

Figure 4 decomposes realized weather variation into unexpected shocks and forecast updates. This decomposition allows us to test whether firms adapt to forecasted variation or simply absorb weather as it arrives. If firms merely absorb weather variation, responding reactively without using forecasts, shocks and updates should have similar effects since both ultimately manifest in realized weather. However, if firms adapt by adjusting operations in advance, forecasted variation should have more favorable performance effects than unexpected shocks.

The results provide broad-sample evidence of adaptation rather than mere absorption. For precipitation, firms absorb unexpected shocks with negative consequences but adapt to forecasted variation, mitigating harm. At horizon 0, a one-inch precipitation shock, which firms absorb reactively, reduces profitability by 0.47% ($t = -4.33$), while a one-inch forecast update has no significant effect (0.09%, $t = 0.11$), suggesting firms neutralize anticipated precipitation through advance adjustments. At horizon 8, the shock effect persists at −0.20% ($t = -2.20$), while the update effect becomes positive at 1.24% ($t = 1.85$, $p = 0.064$). In standard deviation terms (SD = 2.52 inches for shocks, 0.37 inches for updates), a one-SD precipitation shock reduces profitability by 1.2% at horizon 0, while a one-SD update has no discernible effect initially but becomes positive (0.5%) by horizon 8. The joint F-tests confirm both shocks ($F = 2.78$, $p = 0.003$) and updates ($F = 4.46$, $p < 0.001$) are significant, but their opposing signs indicate adaptation.

For temperature, both absorbed shocks and adapted-to forecasts increase profitability, but adaptation amplifies the benefit. At horizon 0, firms passively absorbing a one-degree temperature shock gain 0.49% ($t = 3.06$), while firms adapting to a one-degree forecast update gain 3.30% ($t = 2.71$), nearly seven times larger. This pattern suggests firms use advance notice to position operations to exploit favorable temperature conditions, not merely react to them. By horizon 8, both effects diminish: shocks to 0.25% ($t = 1.73$) and updates to 1.34% ($t = 1.27$). In standard deviation terms (SD = 1.71°F for shocks, 0.22°F for updates), a one-SD temperature shock increases profitability by 0.8% at horizon 0, while a one-SD update increases it by 0.7%. Both are jointly significant (shocks: $F = 3.39$, $p < 0.001$; updates: $F = 3.61$, $p < 0.001$), with updates showing stronger per-unit effects.

These patterns are consistent with operational adaptation. Firms appear to mitigate the harm from anticipated precipitation deviations (the update effect is near zero or positive, versus negative for shocks) and amplify the benefits from anticipated temperature deviations (updates have larger positive effects than shocks). The differential responses suggest that advance notice enables firms to adjust operations. To contextualize economic magnitudes: for a firm with median operating profitability of 3.0%, a one-SD precipitation shock (2.52 inches) reduces cumulative profitability by 1.2 percentage points, representing a 40% decline relative to baseline—a substantial operational drag. In contrast, when precipitation deviations of similar magnitude are forecasted, firms appear to neutralize this effect entirely.

4.2. Climate Phenomenon and Exposures

We now examine two cases where we expect adaptation responses to seasonal forecasts to be more pronounced.

4.2.1. El Niño Southern Oscillation Events

During El Niño and La Niña events (collectively ENSO events), forecast accuracy increases substantially. By our calculations, CPC seasonal forecasts explain 6.5% and 4.1% of residual temperature and precipitation variation during the five most extreme ENSO events since 1994, compared to only 0.6% and 0.9% unconditionally (see Ropelewski and Halpert 1987; Trenberth et al. 1998, for the meteorological foundations of ENSO predictability)..

If firms use seasonal forecasts to make operational adjustments, the benefits of adaptation should be most apparent during strong ENSO events, when forecasts are more informative. Conversely, if we find no differential effects even during strong ENSO events—when forecast information quality is elevated—it would suggest fundamental constraints on adaptation.

We estimate Equation 1 separately for a subsample of quarters during the five largest ENSO events in our sample, defined as periods when the Niño 3.4 index has the largest absolute values.[12]

[12] The five events are the 1997–98 El Niño, 2007–08 La Niña, 2010–11 La Niña, 2015–16 El Niño, and 2020–21

Figure 5 presents results for the ENSO subsample. During these periods of elevated forecast accuracy, the differential responses to updates versus shocks are more pronounced. For temperature, forecast updates have significantly larger effects than shocks: at horizon 0, a one-degree temperature forecast update increases profitability by 8.7% ($t = 2.21$, $p = 0.027$), compared to a near-zero shock effect. The joint F-test for temperature updates is highly significant ($F = 3.41$, $p < 0.001$), while temperature shocks are marginally significant ($F = 1.97$, $p = 0.039$). For precipitation, both updates and shocks are jointly significant (updates: $F = 2.59$, $p = 0.006$; shocks: $F = 2.05$, $p = 0.031$), but the patterns differ: precipitation shocks show negative effects at early horizons, while precipitation updates show positive effects at later horizons. These amplified differential responses during strong ENSO events—when forecast accuracy is elevated and with respect to temperature in particular—provide evidence that firms adapt more effectively when forecast information is more reliable. The 8.7% effect of temperature forecast updates during ENSO events is roughly 2.6 times larger than the 3.3% effect in the full sample, consistent with firms being better able to rely on forecasts when they are more accurate.

4.2.2. Nature Dependence

The effects of adaptation should be larger when firms have greater exposure to nature. To examine this cross-sectional heterogeneity in weather sensitivity, we obtain firm-level nature dependence scores from Garel et al. (2025). These NatureDep scores measure firms' dependence on ecosystem services—such as water provision, climate regulation, and soil quality—that may be disrupted by weather variation. The scores are constructed by combining the Exploring Natural Capital Opportunities, Risks, and Exposure (ENCORE) database, which maps industries to their dependencies on specific ecosystem services, with firm-level revenue segment information. Higher scores indicate greater operational

La Niña, selected based on quarters where the absolute Niño 3.4 index exceeded 1.0. Results are similar using alternative thresholds.

reliance on nature-provided inputs that weather shocks could disrupt. Garel et al. (2025) show that NatureDep scores predict downside risk and nature-related incidents, with effects driven primarily by dependencies on water-related ecosystem services. We use these scores to test whether firms with greater nature dependence exhibit stronger performance responses to weather variation and greater benefits from adaptation.

Figure 6 presents interaction estimates for above-median nature dependence. The results show differential effects primarily for temperature forecast updates. High nature-dependent firms show significantly more positive responses to temperature forecast updates than low nature-dependent firms (joint F-test $F = 2.15$, $p = 0.022$). At horizon 1, the interaction coefficient is 0.067 ($t = 2.51$, $p = 0.012$), indicating that high nature-dependent firms experience an additional 6.7% increase in operating profitability per degree Fahrenheit of temperature forecast update. This differential response persists through medium horizons, suggesting that nature-dependent firms are better positioned to exploit anticipated temperature variation. Likewise, the precipitation forecast coefficients are generally positive, however they are not statistically significantly different from zero (joint F-test $F = 0.75$, $p = 0.667$). The patterns indicate that nature dependence amplifies the benefits of adaptation for temperature forecast updates and is suggestive of a simliar effect for precipitation updates.

4.3. Sector Heterogeneity

Figure 7 presents sector-by-sector estimates of weather shocks and forecast updates on operating profitability.[13] To summarize the patterns, we compute the percentage of horizon-specific coefficients where forecast updates have more positive (less negative) effects than shocks. We use a conservative 80% threshold to identify sectors with consistent evidence

[13] We use GICS economic sectors rather than finer industry classifications for two reasons. First, this level of aggregation provides sufficient statistical power for sector-specific local projections while maintaining economically meaningful groupings. Second, it aligns with our survey design, which sampled managers by GICS sector, enabling direct comparison between archival estimates and survey responses in Section 5.1.

of adaptation, accounting for horizon-to-horizon sampling variation.

For temperature forecasts, five sectors show evidence of adaptation (updates outperform shocks in >80% of horizons): Basic Materials, Consumer Cyclicals, Consumer Non-Cyclicals, Financials, and Healthcare. For precipitation forecasts, four sectors exhibit adaptation: Consumer Non-Cyclicals, Energy, Industrials, and Communication.

Notably, adaptation extends beyond mechanically weather-exposed industries to service sectors. Consumer sectors, Financials, Healthcare, and Communication all show adaptation to at least one forecast dimension. This suggests weather affects firms through indirect channels, such as customer demand shifts and supply chain disruptions, where advance notice still enables adjustment. Where sector overlap exists with our survey sample (Section 5), the archival patterns are consistent with managers' reported weather impacts and forecast use. The economic implication is that the value of seasonal forecast infrastructure may be broader than commonly appreciated.

Several caveats apply. First, in many of the cases described above, the joint F-test for forecast updates is not statistically significant, indicating imprecise estimates. Second, some sector-forecast combinations fall below a 20% threshold, where shocks outperform updates in most horizons: for temperature, Industrials, Real Estate, and Utilities; for precipitation, Basic Materials and Consumer Cyclicals. These patterns are puzzling because they suggest maladaptation. One interpretation is that the supply chain partners and customers of such firms might be able to use seasonal forecasts in a way that disadvantages these firms.

5. Survey Evidence: Awareness and Mechanisms

To supplement our archival evidence, we conduct a survey of managers to provide external validation and evidence on mechanisms that are difficult to identify using archival data alone. We fielded the survey on Prolific between March and July 2025, obtaining 1,535 responses from operational-level managers in the U.S. and Canada. After applying filters for managerial responsibility, tenure (≥2 years), non-remote work, and attention checks, 1,095 usable responses remained across five sectors: Industrials, Consumer Cyclicals, Financials, Healthcare, and Technology. Firm sizes span SMEs (40%), large private firms (40%), and publicly listed companies (20%). Appendix A provides implementation details.

5.1. Comparison with Archival Estimates

A natural concern with our local projection approach is whether the reduced-form estimates reflect genuine operational effects or spurious statistical artifacts. We use the survey to triangulate: if managers' reported weather impacts align with our archival estimates, this suggests both approaches capture a common underlying signal, though neither constitutes a gold standard.

Participants rated how different weather conditions—varying by temperature (cold/warm), precipitation (wet/dry), and season (January, April, July, October)—would affect their company's operating performance on a scale from −1 (hurts) to +1 (helps). We asked separately about *unexpected* weather shocks and *forecasted* weather conditions.

Table 3 reports responses about unexpected shocks. A key pattern is similarity across sectors: unexpectedly wetter and cooler conditions are viewed as harmful, while drier and warmer conditions help. Effects are largest for Industrials, consistent with direct weather exposure through construction, transportation, and outdoor operations. Winter shocks (January) have larger impacts than summer shocks (July).

Table 4 reports responses about forecasted conditions. Comparing these to shock responses reveals an asymmetry in how adaptation works. For *favorable* conditions (warm, dry), managers report similar or larger effects when conditions are forecasted versus unexpected, suggesting firms position to exploit anticipated opportunities. For *adverse* conditions (cold, wet), the pattern reverses: forecasted adverse conditions yield smaller-magnitude effects than unexpected shocks, suggesting partial mitigation when conditions are anticipated. This asymmetry is consistent with adaptation having two channels: amplifying benefits from favorable conditions and dampening harm from adverse ones.

To formally compare survey responses with our local projection estimates, we estimate a directional version of Equation 1:

$$\begin{aligned}\text{CumOPA}_{i,t,h} = \alpha_h &+ \beta_h^{Tmp+} \cdot \text{TmpShock}_{i,t}^{+} + \beta_h^{Tmp-} \cdot \text{TmpShock}_{i,t}^{-} \\ &+ \gamma_h^{Tmp+} \cdot \Delta\text{F(Tmp)}_{i,t}^{+} + \gamma_h^{Tmp-} \cdot \Delta\text{F(Tmp)}_{i,t}^{-} \\ &+ \beta_h^{Pre+} \cdot \text{PreShock}_{i,t}^{+} + \beta_h^{Pre-} \cdot \text{PreShock}_{i,t}^{-} \\ &+ \gamma_h^{Pre+} \cdot \Delta\text{F(Pre)}_{i,t}^{+} + \gamma_h^{Pre-} \cdot \Delta\text{F(Pre)}_{i,t}^{-} \\ &+ \Gamma' X_{i,t-1} + \mu_i + \lambda_t^{Year} + \lambda_t^{Month} + \epsilon_{i,t+h}\end{aligned} \tag{3}$$

where superscripts + and − denote positive (warmer/wetter than normal) and negative (cooler/drier than normal) deviations, respectively. This specification allows asymmetric effects of weather in each direction, enabling comparison with survey responses about directional climate impacts.

Table 5 presents this comparison by correlating survey responses with archival LP estimates. Both survey responses and archival estimates contain noise. For forecast updates, the Pearson correlation is 0.21 ($p = 0.066$) and the Spearman correlation is 0.27 ($p = 0.014$). The correlations for shocks are weaker (Pearson $r = 0.03$, $p = 0.78$; Spearman $\rho = 0.17$, $p = 0.13$). The positive correlations for forecast updates suggest both approaches capture a common signal, but neither is a gold standard. One interpretation is that forecast update channel is more salient to managers than unexpected shock effects, which would explain the stronger alignment for updates.

5.2. Mechanisms and Constraints

We asked managers which operational factors are significantly affected by unexpected weather shocks. Figure 2C shows that the main channels are product delivery and logistics and customer demand, with a non-trivial percentage citing labor availability and material costs. Financials and Healthcare more frequently report no effect. Notably, across all sectors, respondents selected a variety of weather impacts that affect their firms.

We also asked how firms adapt to medium-term (2–12 month) weather forecasts. Figure 2C shows that across sectors, firms use a range of adaptation methods: changing project timelines, adjusting product and service distribution, and modifying hiring and labor scheduling.

Finally, we asked about constraints on adaptation. Figure 2E shows that the most common constraint is lack of reliable forecasts, followed by difficuly in long-term planning. Again, respondents across all sectors selected a variety of constraints to adapatation.

We also probed information constraints more specifically. Only 50–60% of respondents report their firms are probably or definitely aware of medium-term forecasts (Figure 2F). This suggests expanding forecast dissemination could enhance adaptation.

6. Degree of Seasonal Forecast Information Processing

Our local projections show that forecast updates affect operating profitability differently than unexpected shocks. Yet in some sector-horizon combinations, the effects are similar, and our survey indicates that 40–50% of managers are unsure whether their firms are aware of medium-term seasonal climate forecasts. This raises the question: does the sometimes limited adaptation we observe reflect inattentiveness to these forecasts?

To operationalize attentiveness, we examine firm-issued earnings guidance. This test isolates attentiveness from operational constraints. A manager might understand the forecast but lack resources to adjust operations, limiting operational adaptation despite full awareness. Guidance reveals information sets directly. If managers are attentive to CPC forecasts, guidance should reflect forecast implications regardless of whether full operational adaptation is economically feasible. We test this by estimating:

(4)

$$\text{ERROR}_{i,t} = \alpha + \beta^{Tmp} \cdot \text{TmpShock}_{i,t} + \gamma^{Tmp} \cdot \Delta\text{F(Tmp)}_{i,t} + \beta^{Pre} \cdot \text{PreShock}_{i,t} + \gamma^{Pre} \cdot \Delta\text{F(Pre)}_{i,t} + \mu_i + \lambda_m + \epsilon_{i,t}$$

where $\text{ERROR}_{i,t} = (\text{Guidance}_{i,t} - \text{Actual}_{i,t})/|\text{Actual}_{i,t}|$ is the scaled guidance error. We include firm fixed effects μ_i and calendar month fixed effects λ_m. Standard errors are clustered by firm.

The key coefficients are γ^{Tmp} and γ^{Pre}, which measure whether forecast updates—information available to managers at the time guidance is issued—predict guidance errors. If managers fully incorporate CPC forecast information into their expectations, $\gamma = 0$: forecast updates should not predict errors because managers would have already adjusted their guidance. If $\gamma \neq 0$, managers are failing to process available forecast information. Shocks materialize after guidance is issued, so they naturally can generate guidance errors.

We match guidance announcements in month t to CPC forecasts issued in month $t-1$, which would have been publicly available. The forecast update captures the revision between the month $t-1$ forecast and the forecast from three months prior. We allow effects to differ by season (spring, summer, fall, winter) and direction (warmer/cooler, wetter/drier).

Table 6 presents full regression results by sector (Panels a–b) and joint F-tests for each sector-variable combination (Panel c). The key columns are the forecast update F-tests: if managers fully incorporate CPC information, forecast updates should not jointly predict guidance errors.

The results indicate incomplete processing in several sectors. For temperature forecast updates, four sectors show jointly significant effects: Utilities ($F = 3.75$, $p < 0.01$), Communication ($F = 3.38$, $p < 0.01$), Energy ($F = 1.98$, $p < 0.05$), and Technology ($F = 1.72$, $p < 0.10$). For precipitation forecast updates, six sectors show jointly significant effects: Consumer Cyclicals ($F = 2.72$, $p < 0.01$), Consumer Non-Cyclicals ($F = 2.39$, $p < 0.05$), Technology ($F = 2.33$, $p < 0.05$), Energy ($F = 2.28$, $p < 0.05$), Industrials ($F = 1.82$, $p < 0.10$), and Basic Materials ($F = 1.77$, $p < 0.10$). These patterns are consistent with managerial miscalibration documented in other contexts (**?**) and with survey evidence that firms imperfectly incorporate macroeconomic forecast information into expectations (**?**).

Combined with the survey evidence, these findings suggest scope for improving forecast dissemination or processing across a range of sectors.

7. Conclusion

We study whether firms adapt operations to seasonal climate forecasts issued by the U.S. National Oceanic and Atmospheric Administration's Climate Prediction Center (CPC). Decomposing local weather into unexpected shocks and forecast updates, we find evidence consistent with adaptation: temperature and precipitation forecast updates have significantly more favorable effects on operating profitability than unexpected shocks of equivalent magnitude. These differential responses are amplified during El Niño and La Niña events and for nature-dependent firms, cases during which we expect forecasts to be more useful for firms. Further, adaptation extends beyond traditionally weather-sensitive sectors—we find patterns consistent with adaptation in service-oriented sectors such as Financials, Healthcare, and Communication (however, we note that many sector-specific estimates lack statistical precision).

We complement our archival analysis with a survey of operational managers. The survey validates our empirical approach: managers' reported weather impacts correlate meaningfully with our local projection estimates, particularly for forecast updates. The survey also sheds light on mechanisms. Regarding how weather affects firms, managers cite product delivery and logistics disruptions and shifts in customer demand as primary channels. Regarding how firms adapt to forecasts, managers report adjusting project timelines and modifying labor scheduling. Regarding constraints to adaptation, unreliable forecasts and organizational inertia emerge as key barriers. Importantly, the survey also highlights considerable unawareness of seasonal forecasts among firms.

This lack of awareness motivates our final analysis. We test whether forecast updates predict guidance errors and find they do in multiple weather-sensitive sectors, suggesting incomplete processing of publicly available information. Combined with the survey evidence, these findings suggest scope for improving forecast dissemination and utilization.

Our findings have two implications. First, the economic value of seasonal forecasts may be broader than commonly appreciated, extending beyond traditionally weather-sensitive sectors. This breadth is directly relevant to ongoing policy debates about forecasting infrastructure funding: the case for continued investment strengthens if benefits accrue across the economy rather than to a narrow set of industries. Second, informational frictions appear to be a barrier to adaptation despite the public availability of forecasts. Addressing these frictions through improved forecast communication could enhance firms' ability to adapt to climate variation.

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Figures and Tables

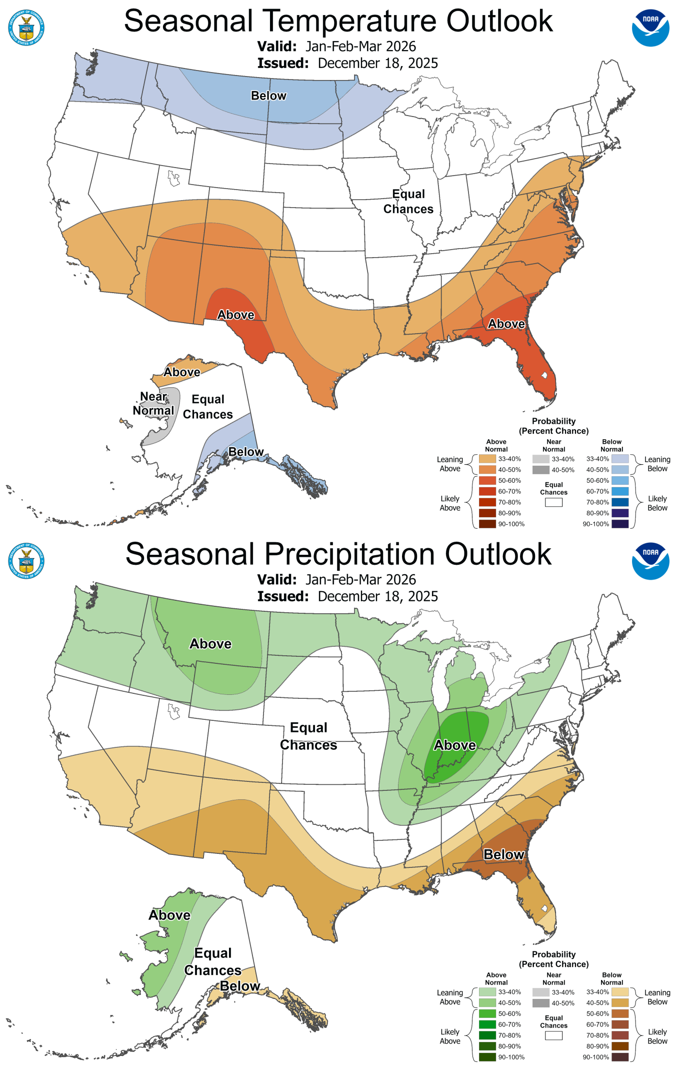
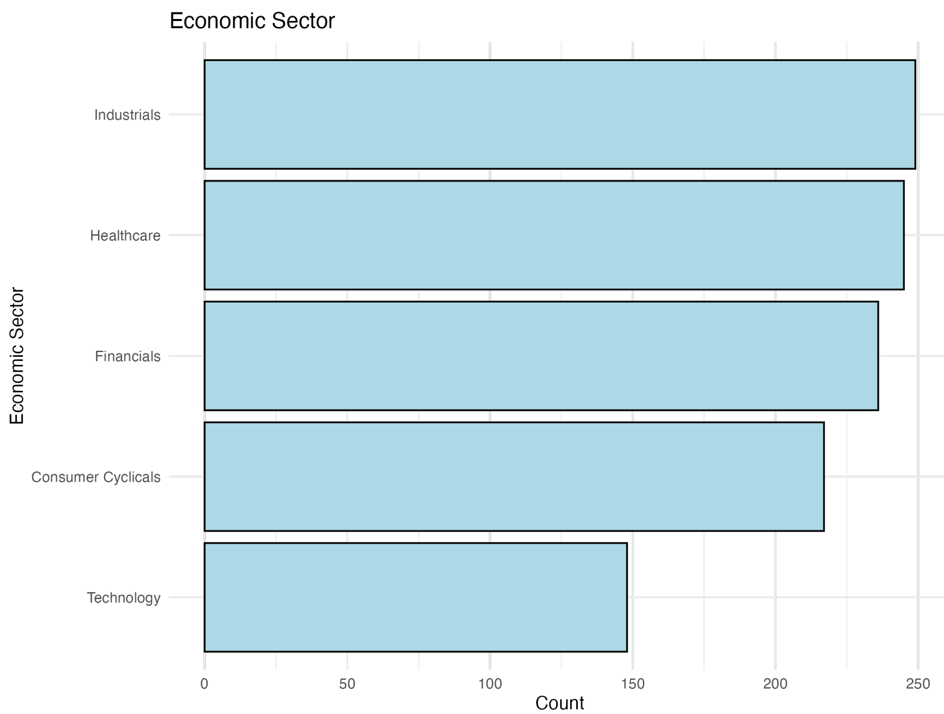


FIGURE 1. Distribution of CPC Seasonal Forecast Errors by Lead Time

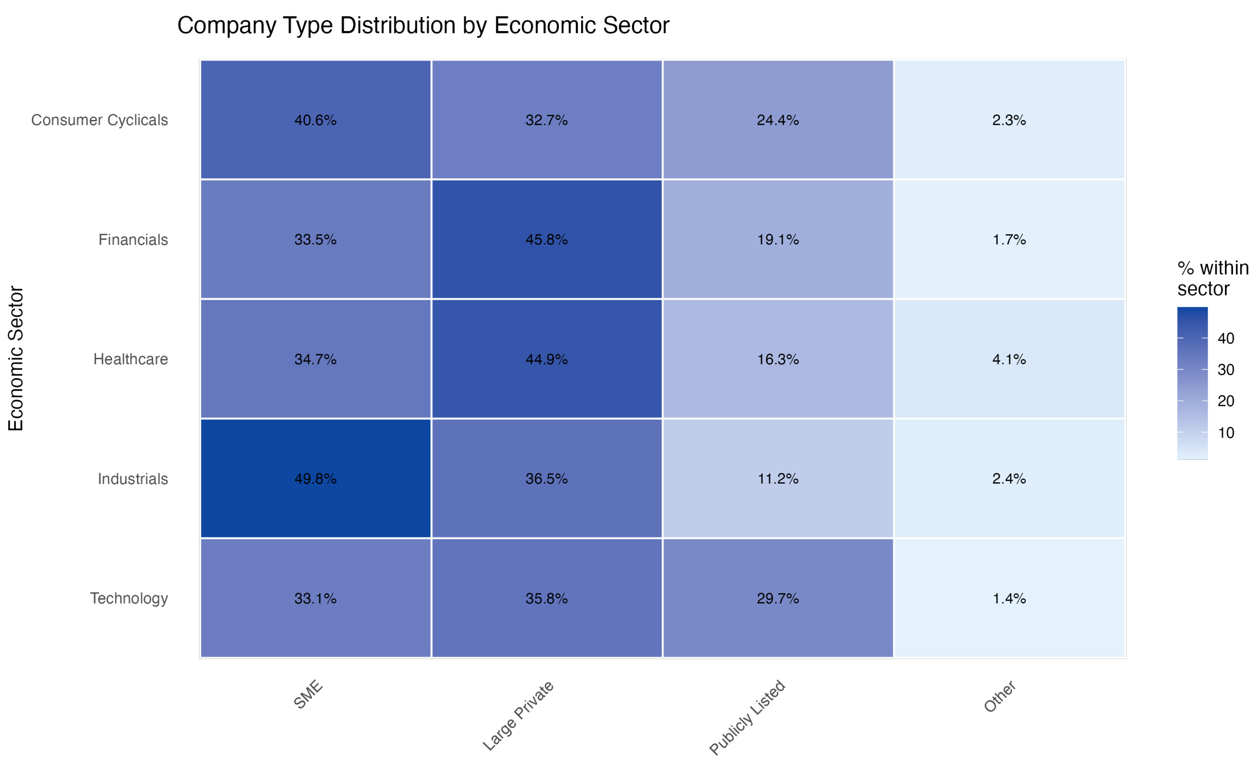
This figure presents the public-facing CPC seasonal forecast outlook for lead 0.5, issued in December 2005. That is, it shows expected deviations from normal conditions for the January-February-March 2026 season.

FIGURE 2. Survey Evidence: Sample Characteristics and Operational Impacts

A. Economic Sector Distribution

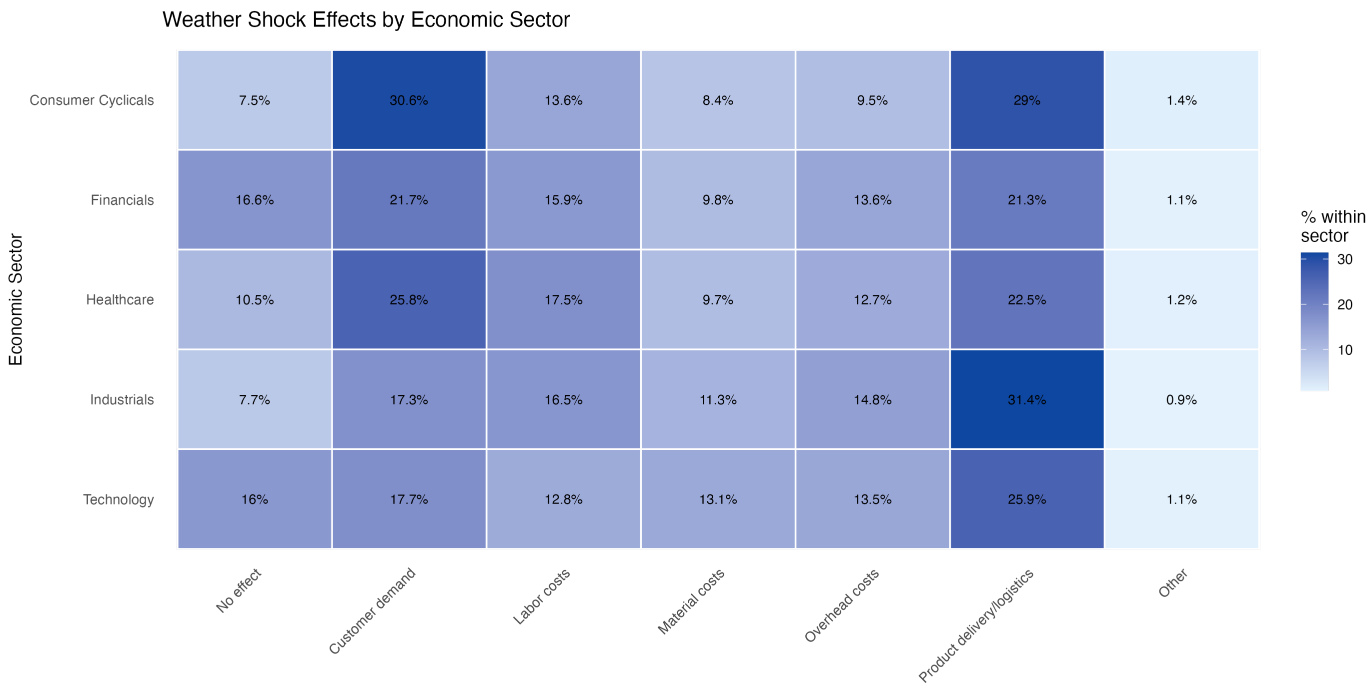


B. Company Type Distribution

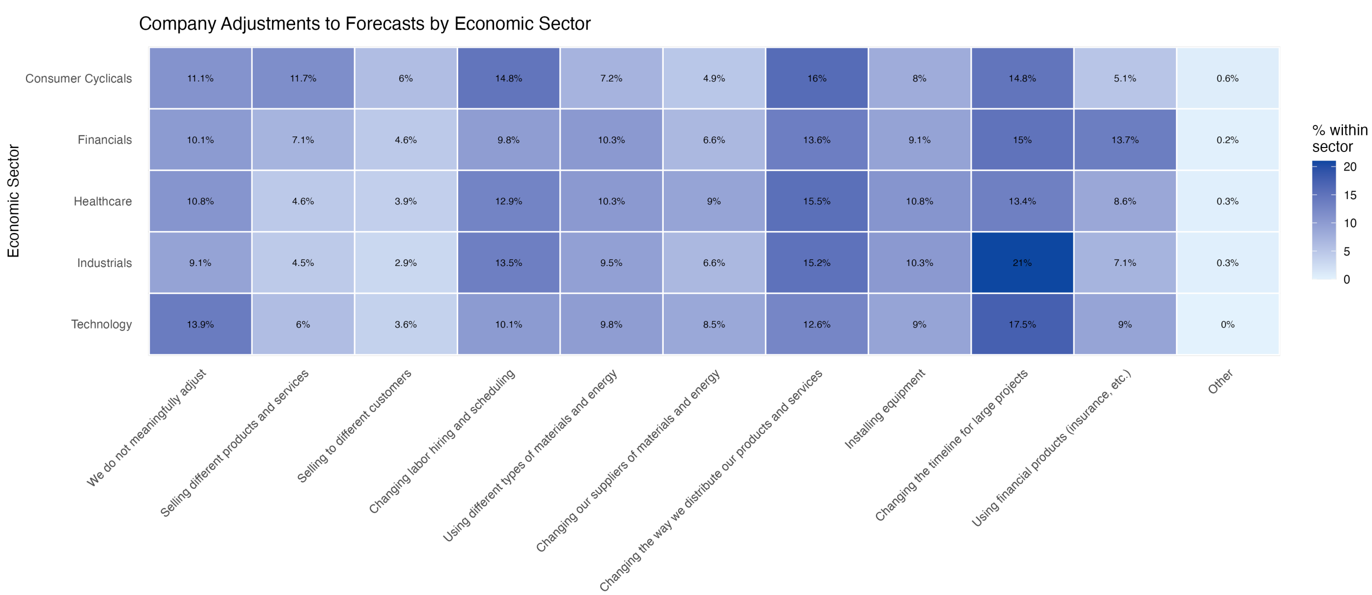


Survey Evidence: Sample Characteristics and Operational Impacts (cont.)

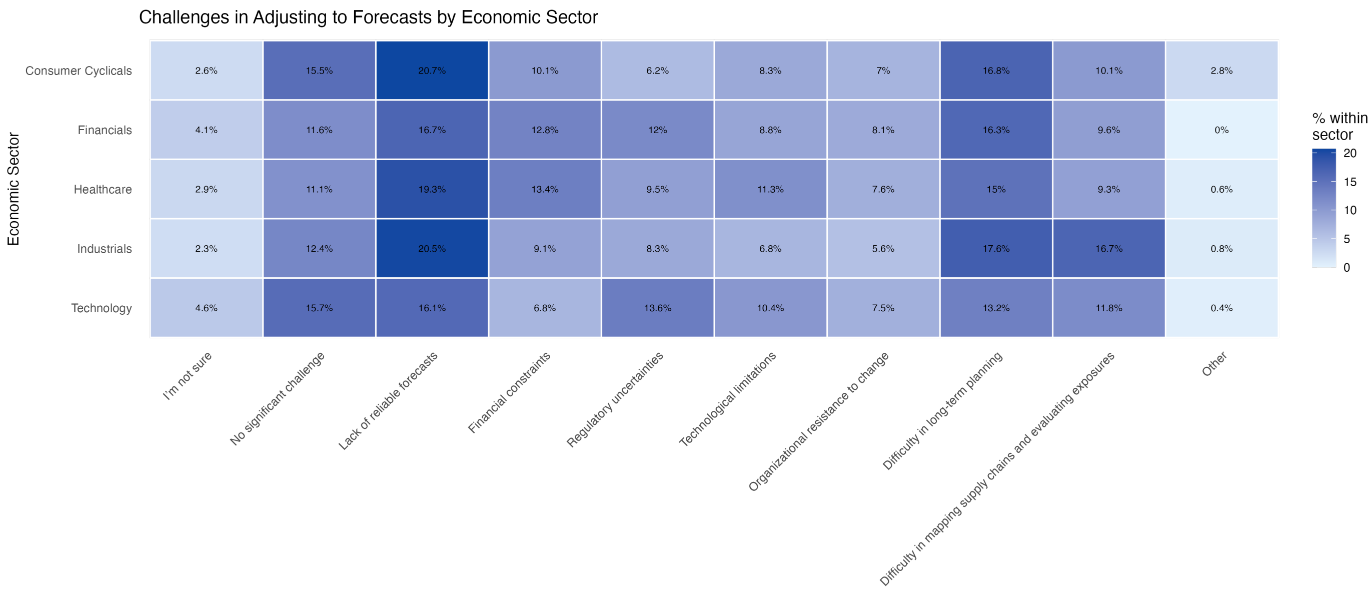
C. Weather Shock Effects



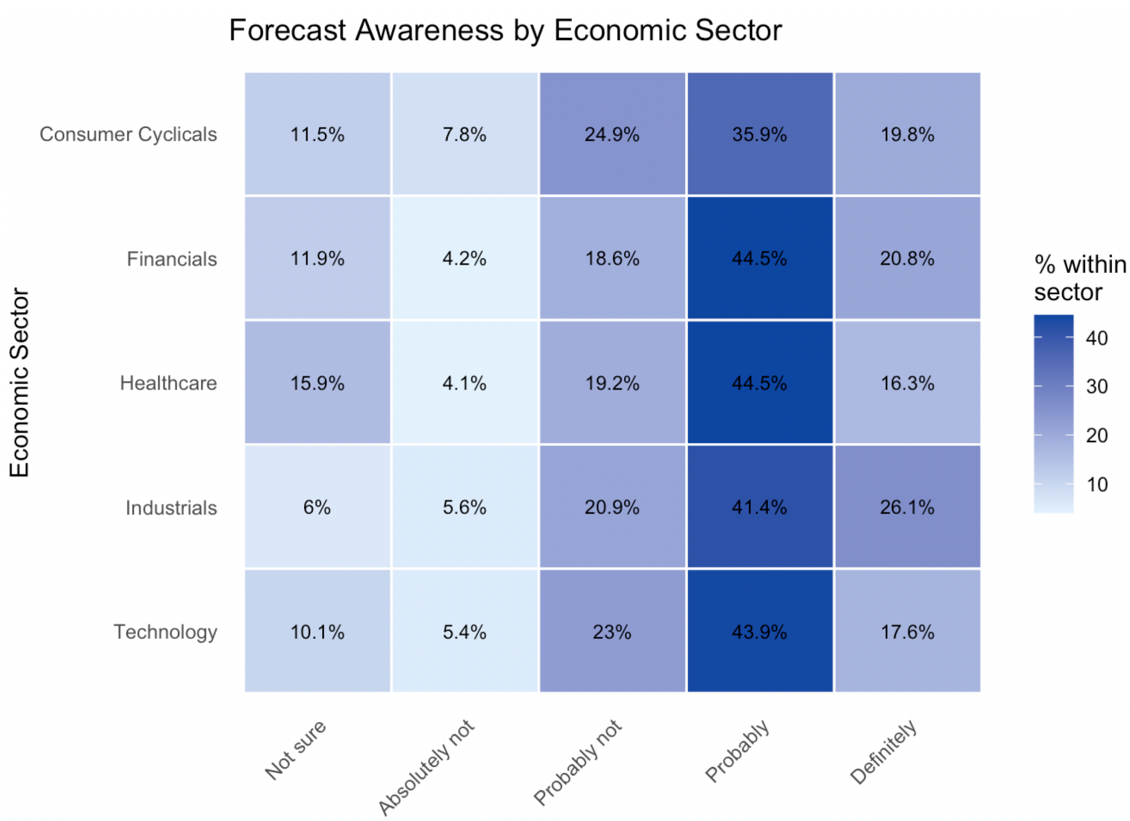
D. Company Adjustments to Forecasts



E. Challenges in Adjusting to Forecasts

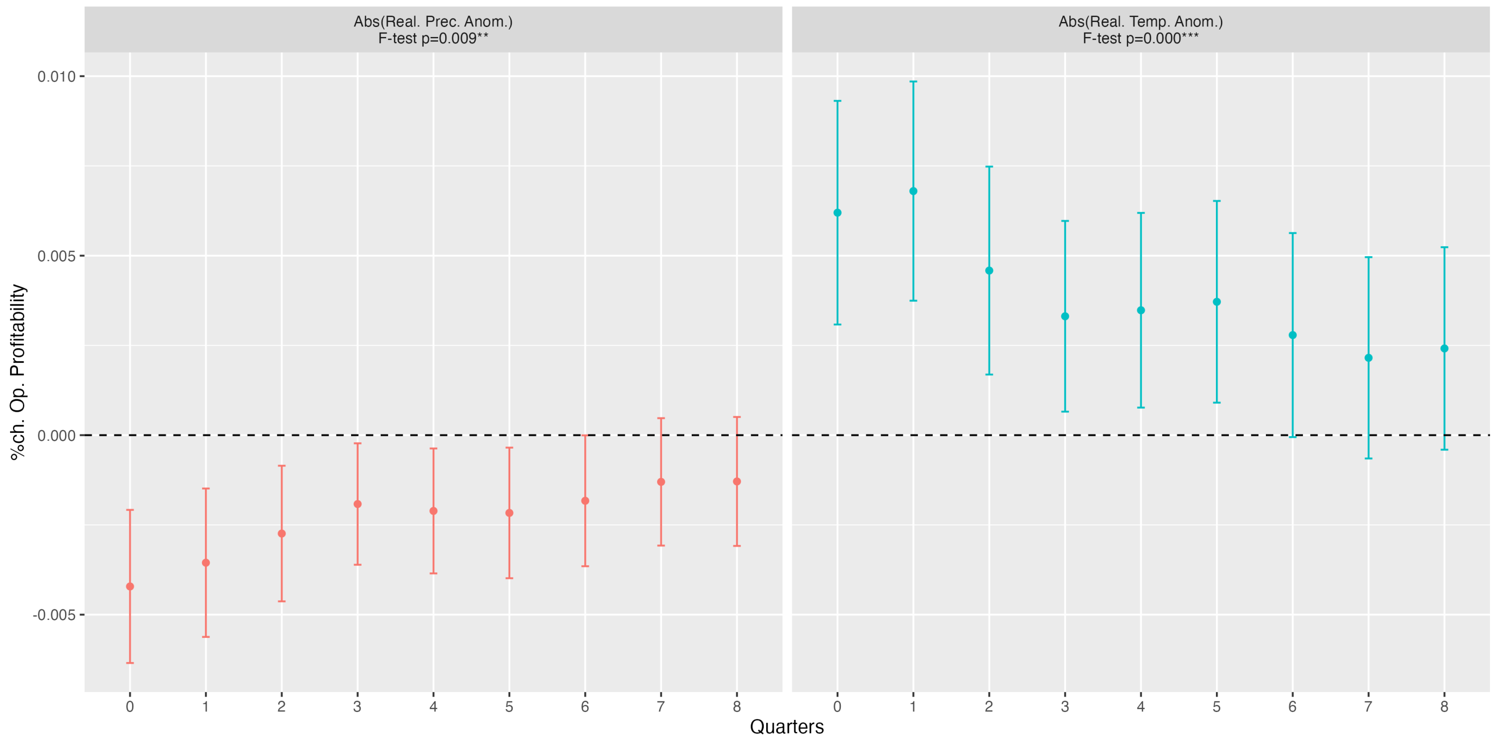


F. Forecast Awareness



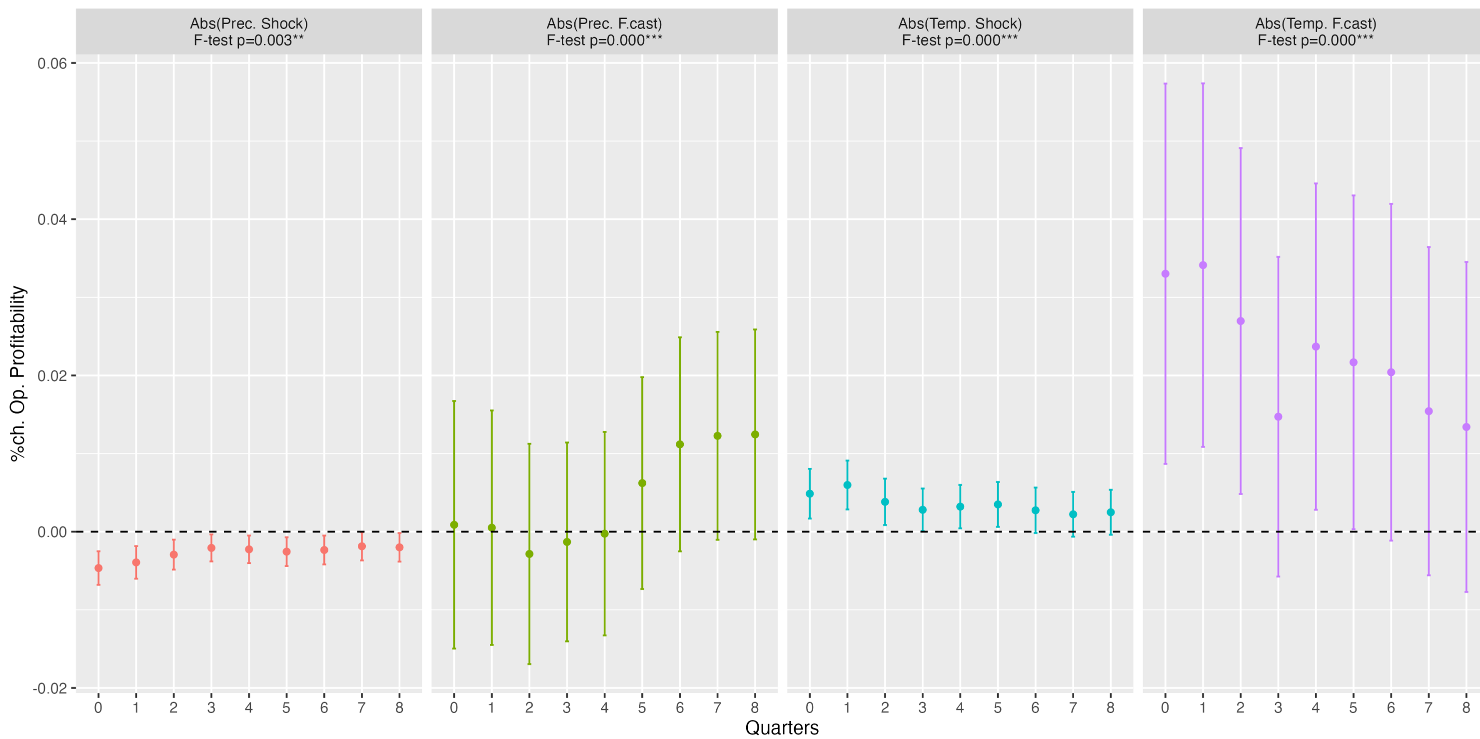
This figure presents key findings from our manager survey of 1,095 operational-level managers across Healthcare, Industrials, Financials, Consumer Cyclicals, and Technology sectors in the United States and Canada, surveyed during March-July 2025. Panel (a) shows the distribution of survey respondents across economic sectors. Panel (b) shows the distribution of company types. Panel (c) shows which operational factors managers report are significantly affected when unexpected weather shocks occur. Panel (d) shows how companies adjust operations based on weather forecasts covering the next 2-12 months. Panel (e) shows the biggest challenges companies face in adjusting to weather forecasts. Panel (f) shows managers' reported awareness of medium-term (2-12 month) weather forecasts at their firms.

FIGURE 3. Effects of Realized Weather Anomalies on Operating Profitability



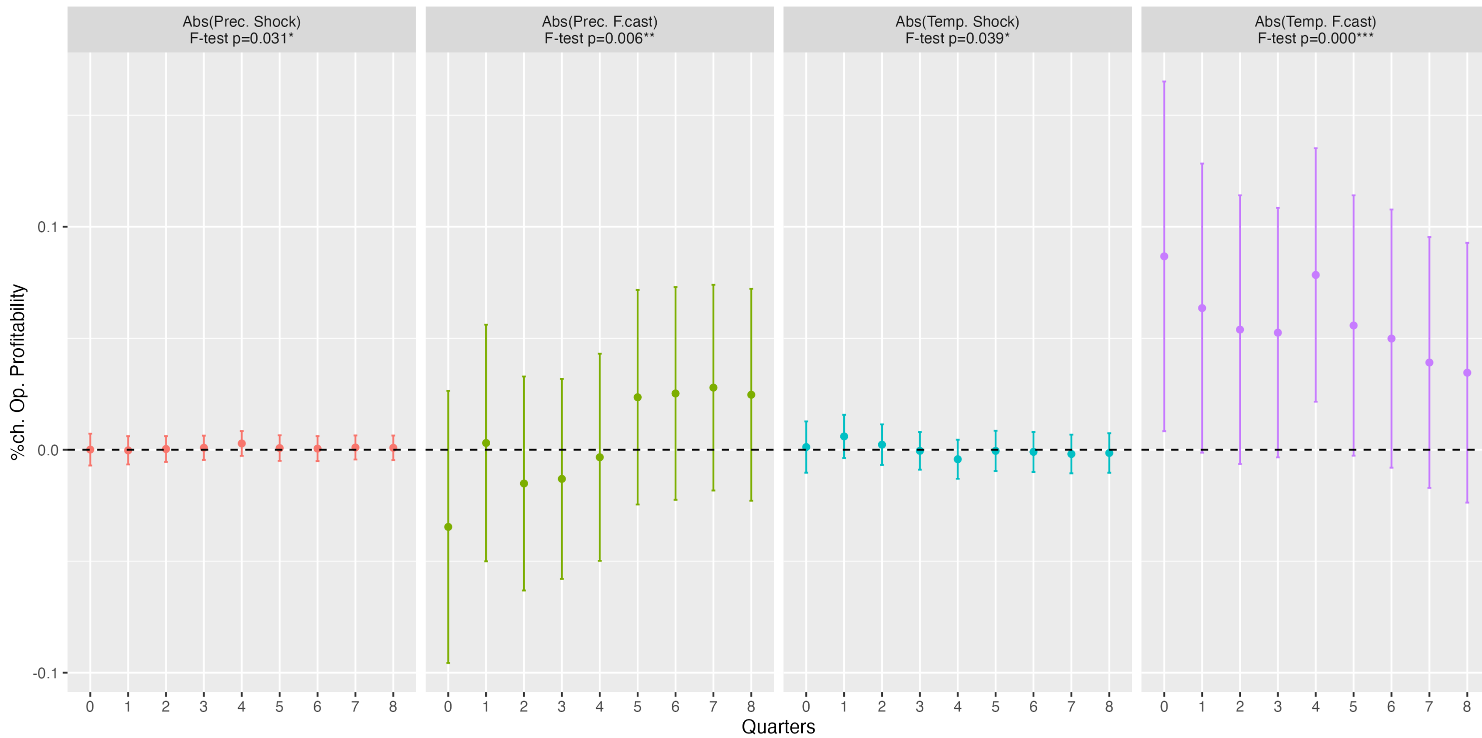
This figure presents local projection estimates of the effect of absolute realized weather anomalies (without shock/update decomposition) on cumulative operating profitability growth. The left panel shows the effect of absolute temperature anomalies and the right panel shows absolute precipitation anomalies. Points represent coefficient estimates at each horizon $h \in \{0, 1, \ldots, 8\}$ quarters, with error bars showing ± 2 standard errors clustered at the firm level. F-statistics and p-values in panel headers test joint significance across all horizons. All specifications include firm, month, and year fixed effects, plus one lag of the dependent variable. The sample comprises 328,513 firm-quarter observations from 1995-2023 (see Table 1).

FIGURE 4. Effects of Weather Shocks and Forecast Updates on Operating Profitability: Full Sample



This figure presents local projection estimates of weather shocks and forecast updates on cumulative operating profitability growth. Panels from left to right show: absolute precipitation shock, absolute precipitation forecast update, absolute temperature shock, and absolute temperature forecast update. Weather shocks are defined as realized anomaly minus the lead-0.5 forecast; forecast updates are defined as the change in forecasts over the preceding quarter (lead-0.5 minus lead-3.5). Points represent coefficient estimates at each horizon $h \in \{0, 1, \ldots, 8\}$ quarters, with error bars showing ± 2 standard errors clustered at the firm level. F-statistics and p-values in panel headers test joint significance across all horizons. All specifications include firm, month, and year fixed effects, plus one lag of the dependent variable and climate variables. The sample comprises 328,513 firm-quarter observations from 1995-2023.

FIGURE 5. Effects of Weather Shocks and Forecast Updates: ENSO Event Subsample



This figure presents local projection estimates for a subsample restricted to quarters during major El Niño and La Niña events (1997-98, 2007-08, 2010-11, 2015-16, 2023-24). Panels from left to right show: absolute precipitation shock, absolute precipitation forecast update, absolute temperature shock, and absolute temperature forecast update. Points represent coefficient estimates at each horizon $h \in \{0, 1, \ldots, 8\}$ quarters, with error bars showing ±2 standard errors clustered at the firm level. F-statistics and p-values in panel headers test joint significance across all horizons. All specifications include firm, month, and year fixed effects, plus one lag of the dependent variable and climate variables.

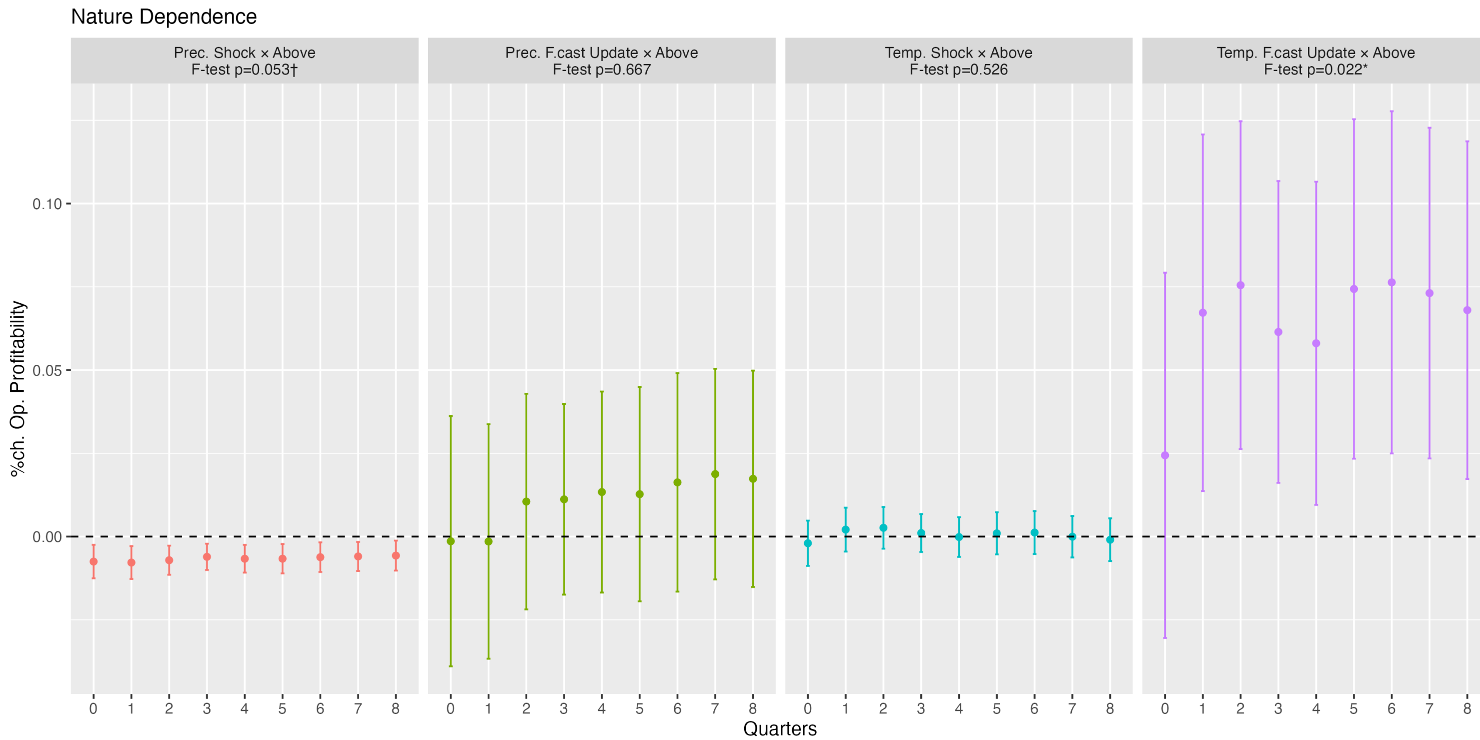
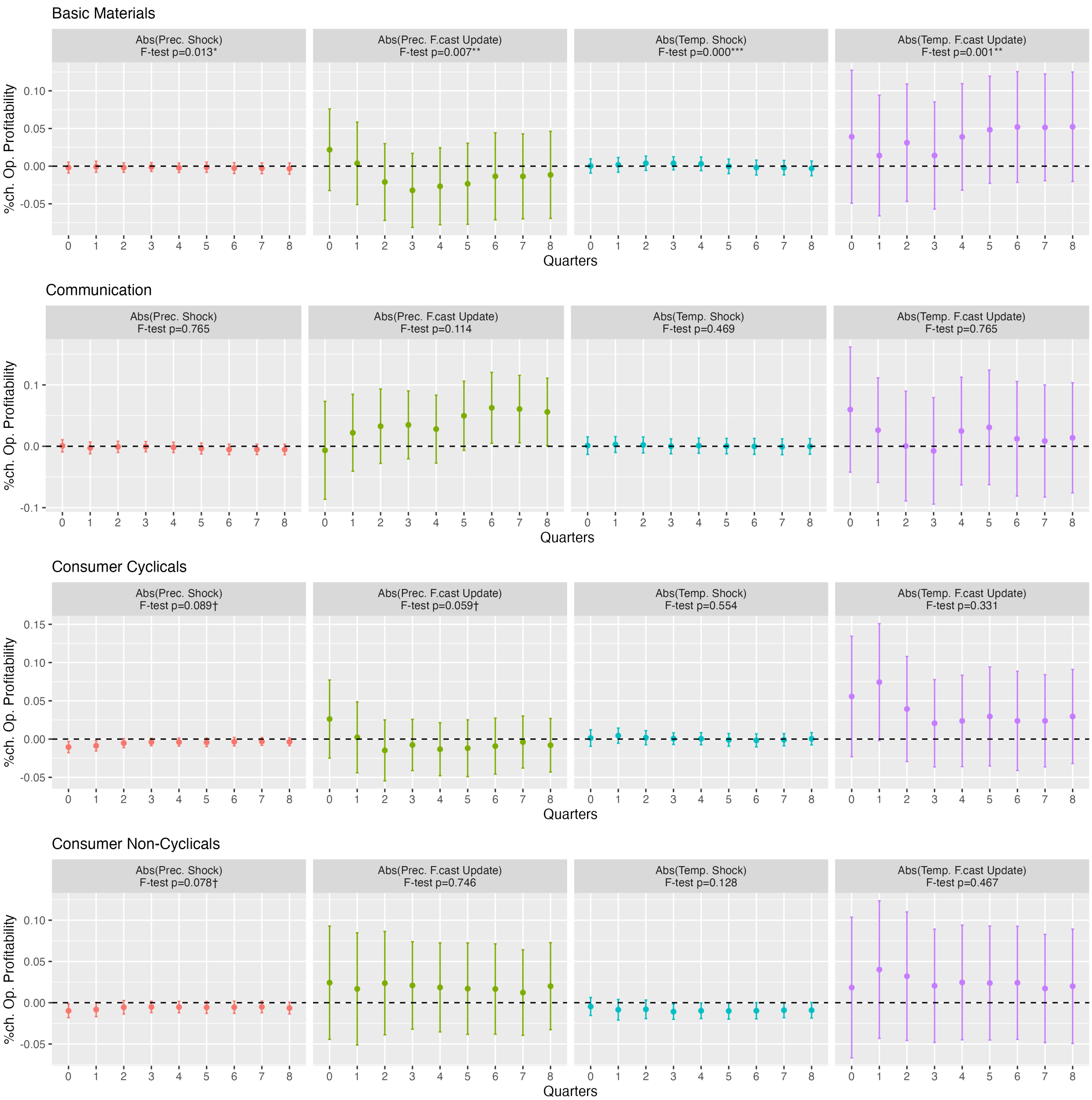


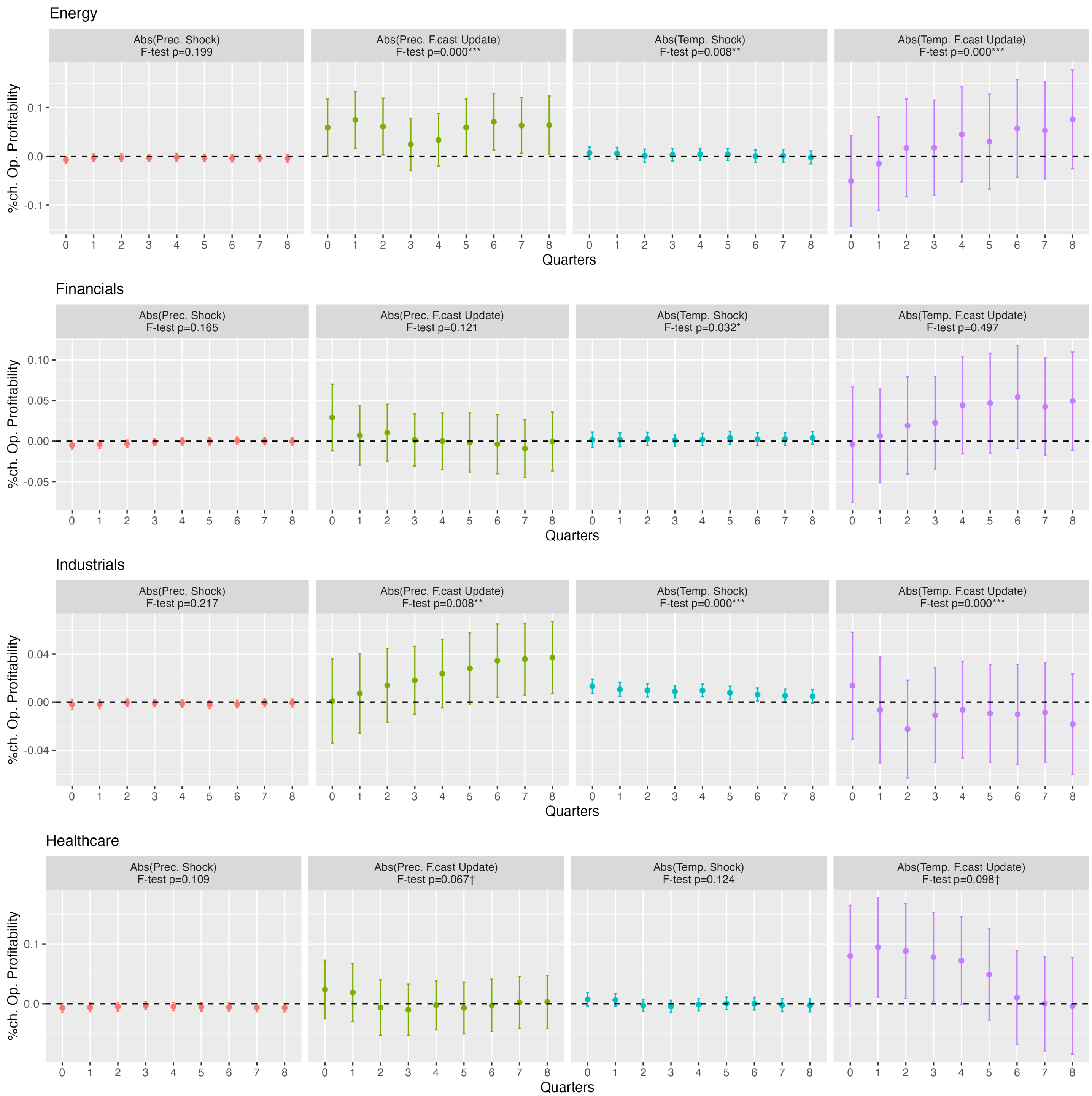
FIGURE 6. Heterogeneity by Nature Dependence

This figure presents local projection estimates with interaction terms for above-median nature dependence (measured at $t-1$). Each panel shows the coefficient on the interaction between the climate variable and the above-median indicator. Nature dependence is measured using the ENCORE database. All specifications include firm, month, and year fixed effects, plus main effects of climate variables and one lag of the dependent variable and climate variables. Points show coefficient estimates with ±2 standard errors clustered at the firm level.

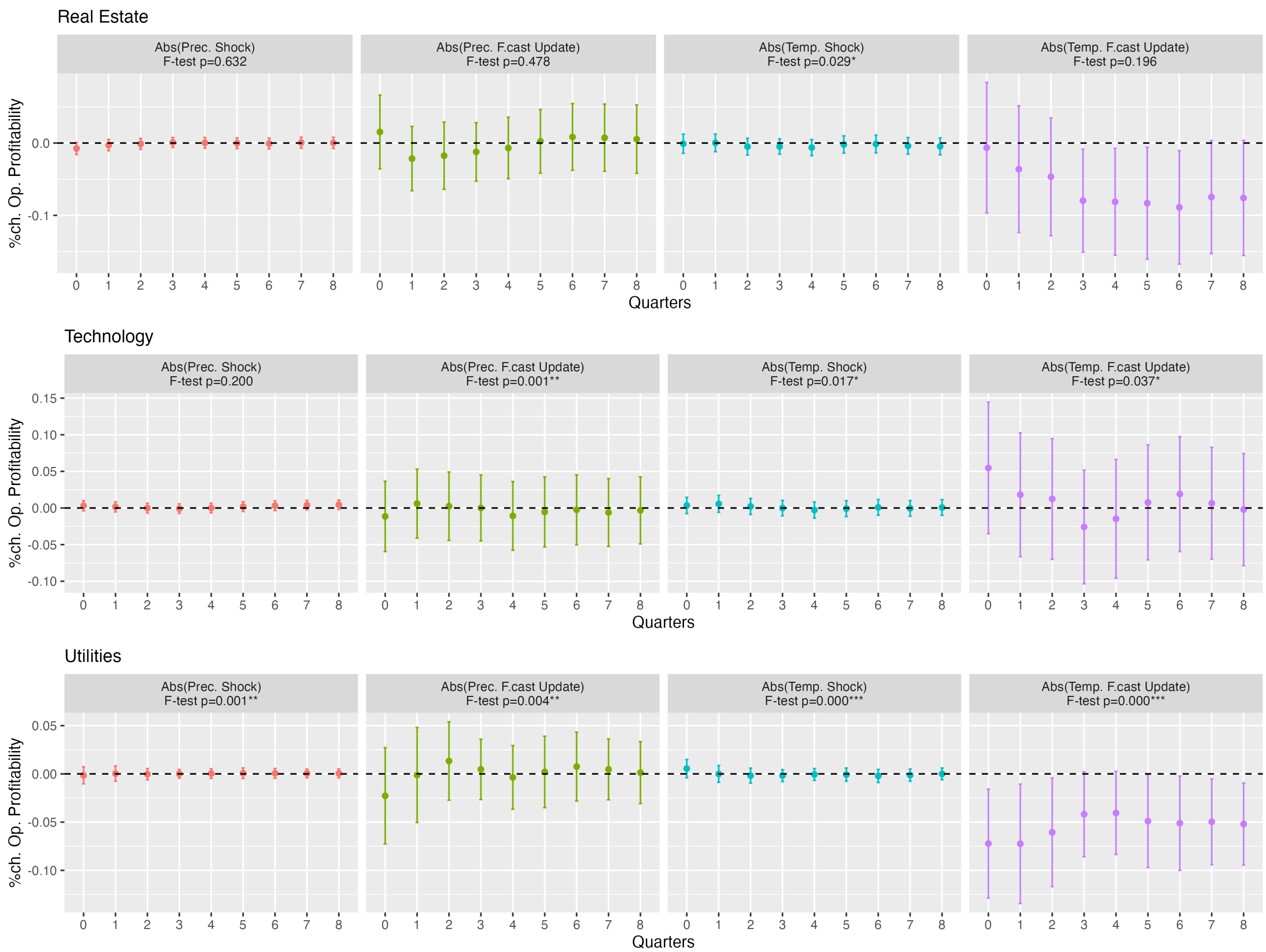
FIGURE 7. Effects of Weather Shocks and Forecast Updates by Economic Sector



Effects of Weather Shocks and Forecast Updates by Economic Sector (cont.)



Effects of Weather Shocks and Forecast Updates by Economic Sector (cont.)



This figure presents local projection estimates of weather shocks and forecast updates on cumulative operating profitability growth, separately by GICS economic sector. Each row shows one sector, with panels for: absolute precipitation shock, absolute precipitation forecast update, absolute temperature shock, and absolute temperature forecast update. Points represent coefficient estimates at each horizon $h \in \{0, 1, \ldots, 8\}$ quarters, with error bars showing ±2 standard errors clustered at the firm level. F-statistics and p-values in panel headers test joint significance across all horizons. All specifications include firm, month, and year fixed effects, plus one lag of the dependent variable and climate variables. See Table 1 for sector-specific observation counts.

TABLE 1. Observation Frequency by State and Economic Sector

State	Basic Mat.	Cons. Cycl.	Cons. Non-Cycl.	Energy	Financials	Healthcare	Industrials	Real Est.	Technology	Utilities	Total
Alabama	210	463	105	196	574	178	293	74	204	346	2,643.00
Arizona	422	1,270	184	88	176	439	1,085	152	1,770	487	6,073.00
Arkansas	77	343	235	86	0	40	610	0	63	118	1,572.00
California	380	6,821	2,133	412	3,886	5,807	3,588	1,905	16,046	1,363	42,341.00
Colorado	822	1,639	566	2,071	379	1,043	910	605	1,285	166	9,486.00
Connecticut	339	1,102	417	114	1,936	708	2,463	162	1,099	467	8,807.00
Delaware	357	212	0	85	187	200	93	0	220	434	1,788.00
District of Columbia	0	15	0	10	377	144	320	66	3	336	1,271.00
Florida	406	4,198	1,092	343	2,188	2,155	4,334	1,157	2,218	732	18,823.00
Georgia	832	2,465	346	113	1,096	1,174	2,162	334	1,767	498	10,787.00
Idaho	149	80	74	4	0	81	186	0	123	218	915.00
Illinois	1,727	2,231	1,661	12	2,340	1,305	4,320	749	2,005	920	17,270.00
Indiana	473	1,491	61	128	472	558	1,101	302	255	817	5,658.00
Iowa	41	274	133	36	605	2	521	0	18	437	2,067.00
Kansas	208	222	222	49	325	138	519	0	243	68	1,994.00
Kentucky	102	750	187	125	201	457	215	0	221	432	2,690.00
Louisiana	62	318	21	582	121	199	202	210	19	593	2,327.00
Maine	0	9	27	0	76	207	6	0	18	198	541.00
Maryland	132	608	360	109	972	738	696	1,153	908	195	5,871.00
Massachusetts	460	1,586	371	74	903	3,287	1,833	796	4,738	662	14,710.00
Michigan	302	3,009	122	86	667	371	1,239	330	627	733	7,486.00
Minnesota	637	1,796	889	100	456	1,496	1,848	9	2,046	450	9,727.00
Mississippi	12	60	210	7	1	1	37	118	23	350	819.00
Missouri	548	1,155	379	198	832	584	1,086	260	504	938	6,484.00
Montana	75	17	10	18	0	17	19	0	168	25	349.00
Nebraska	30	408	53	88	467	117	618	0	278	0	2,059.00
Nevada	75	2,330	44	5	392	129	351	55	183	476	4,040.00
New Hampshire	0	152	0	143	0	115	246	112	432	310	1,510.00
New Jersey	823	2,013	1,559	109	976	2,684	2,041	596	1,988	1,181	13,970.00
New Mexico	9	82	1	0	83	28	22	0	35	190	450.00
New York	767	5,615	1,926	292	8,556	2,142	4,143	2,477	3,933	1,164	31,015.00
North Carolina	609	2,107	715	0	659	931	2,114	255	832	638	8,860.00
North Dakota	2	7	0	80	69	0	64	81	7	118	428.00
Ohio	2,341	2,712	844	359	1,125	899	3,278	336	580	2,072	14,546.00
Oklahoma	292	338	79	2,090	4	30	489	0	128	252	3,702.00
Oregon	246	729	249	0	103	61	418	0	870	348	3,024.00
Pennsylvania	1,684	1,949	600	755	1,553	1,471	3,205	832	1,938	1,359	15,346.00
Rhode Island	2	252	187	0	36	191	189	87	203	63	1,210.00
South Carolina	214	399	8	4	330	135	168	0	373	205	1,836.00
South Dakota	0	115	31	3	0	13	102	0	100	301	665.00
Tennessee	601	1,796	217	136	635	1,515	1,262	650	45	3	6,860.00
Texas	2,319	5,585	1,328	16,509	3,909	2,340	6,478	1,463	3,796	1,980	45,707.00
Utah	233	344	512	195	331	552	359	78	369	166	3,139.00
Vermont	25	27	32	0	0	0	88	50	5	104	331.00
Virginia	608	1,794	612	149	1,408	257	2,782	708	1,617	596	10,531.00
Washington	183	1,004	187	12	441	233	1,206	337	1,257	334	5,194.00
West Virginia	41	161	0	89	0	0	68	0	26	0	385.00
Wisconsin	421	1,038	259	0	433	224	2,563	32	377	1,073	6,420.00
Wyoming	2	16	0	34	4	0	55	0	28	0	139.00

This table presents firm-quarter observation counts by U.S. state and GICS economic sector. The sample comprises Compustat North America firms with non-missing operating profitability and headquarters ZIP codes mapped to NCEI climate divisions, excluding Alaska, Hawaii, and Puerto Rico. All 50 contiguous U.S. states are shown, sorted alphabetically. The sample spans 1995-2023.

TABLE 2. Descriptive Statistics

Variable	N	Mean	SD	p10	p25	p50	p75	p90
Operating Profitability	328,499	0.036	0.028	0.009	0.018	0.030	0.046	0.069
Operating Profitability % Change (h=1)	328,513	0.026	1.314	-0.693	-0.259	-0.023	0.189	0.671
Operating Profitability % Change (h=8)	328,513	0.001	1.328	-0.756	-0.331	-0.064	0.180	0.695
abs(Realized Temp. Anomaly)	328,513	2.133	1.754	0.310	0.820	1.720	2.983	4.463
abs(Temp. Shock)	328,513	2.056	1.706	0.293	0.760	1.633	2.897	4.340
abs(Temp. Forecast Update)	328,513	0.156	0.215	0.000	0.000	0.080	0.230	0.430
abs(Realized Precip. Anomaly)	328,513	2.725	2.549	0.330	0.860	2.060	3.810	5.850
abs(Precip. Shock)	328,513	2.712	2.519	0.330	0.850	2.050	3.820	5.840
abs(Precip. Forecast Update)	328,513	0.166	0.365	0.000	0.000	0.000	0.170	0.550
Total Assets	328,513	7,067.000	65,008.000	28.000	128.000	659.000	2,904.000	10,588.000

This table presents descriptive statistics for key variables. Operating Profitability is operating profit divided by total assets. Operating Profitability % Change shows cumulative growth at horizons $h = 1$ and $h = 8$ quarters. Weather variables are in absolute values: temperature in degrees Fahrenheit, precipitation in inches. Weather shocks are defined as realized seasonal anomaly minus the lead-0.5 CPC forecast. Forecast updates are defined as the change in the lead-0.5 forecast over the preceding quarter. Total Assets are in millions of dollars. The sample comprises 328,513 firm-quarter observations from Compustat North America, spanning 1995-2023.

TABLE 3. Survey Results: Manager Responses to Unexpected Weather Shocks

	Financials	Industrials	Con. Cycl.	Technology	Healthcare
			Impact		
	(1)	(2)	(3)	(4)	(5)
January Cold	-0.305***	-0.394***	-0.281***	-0.270***	-0.290***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
January Warm	0.267***	0.378***	0.406***	0.243***	0.229***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
January Wet	-0.504***	-0.639***	-0.378***	-0.405***	-0.400***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
January Dry	0.263***	0.337***	0.304***	0.297***	0.241***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
April Cold	-0.254***	-0.241***	-0.194***	-0.088*	-0.208***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
April Warm	0.216***	0.261***	0.401***	0.162***	0.196***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
April Wet	-0.504***	-0.538***	-0.429***	-0.412***	-0.380***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
April Dry	0.237***	0.297***	0.304***	0.209***	0.171***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
July Cold	-0.178***	-0.040	0.018	0.041	-0.033
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
July Warm	0.098**	0.032	0.078*	-0.054	-0.020
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
July Wet	-0.394***	-0.450***	-0.378***	-0.270***	-0.286***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
July Dry	0.153***	0.193***	0.207***	0.216***	0.131***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
October Cold	-0.267***	-0.317***	-0.184***	-0.155***	-0.208***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
October Warm	0.280***	0.297***	0.327***	0.189***	0.127***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
October Wet	-0.475***	-0.562***	-0.369***	-0.446***	-0.429***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
October Dry	0.233***	0.237***	0.300***	0.196***	0.151***
	(0.042)	(0.040)	(0.047)	(0.053)	(0.045)
Observations	3,776	3,984	3,472	2,368	3,920
R^2	0.18019	0.24108	0.16529	0.13572	0.10439
Adjusted R^2	0.17692	0.23822	0.16167	0.13021	0.10095

This table presents regression results from a manager survey. The dependent variable is manager-reported operational impact on a scale from −1 (Hurts) to +1 (Helps), with 0 indicating no effect. Coefficients represent the average reported impact for each season-weather condition combination when weather deviates unexpectedly from forecasts. The sample comprises 1,095 operational-level managers across Healthcare, Industrials, Financials, Consumer Cyclicals, and Technology sectors in the United States and Canada, surveyed during March-July 2025 via Prolific. Standard errors in parentheses. *, **, *** denote significance at 10%, 5%, and 1% levels.

TABLE 4. Survey Results: Manager Responses to Forecasted Weather Deviations

	Financials	Industrials	Con. Cycl.	Technology	Healthcare
			Impact		
	(1)	(2)	(3)	(4)	(5)
January Cold	-0.064	-0.169***	-0.037	0.013	0.004
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
January Warm	0.381***	0.341***	0.438***	0.277***	0.322***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
January Wet	-0.216***	-0.297***	-0.120***	-0.088*	-0.131***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
January Dry	0.331***	0.313***	0.313***	0.311***	0.278***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
April Cold	0.034	-0.040	-0.018	0.108**	0.020
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
April Warm	0.314***	0.297***	0.456***	0.277***	0.306***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
April Wet	-0.123***	-0.277***	-0.147***	0×10^{-16}	-0.131***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
April Dry	0.301***	0.301***	0.332***	0.270***	0.180***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
July Cold	0.021	0.092**	0.194***	0.169***	0.090**
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
July Warm	0.284***	0.137***	0.240***	0.122**	0.163***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
July Wet	-0.157***	-0.201***	-0.111**	-0.054	-0.016
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
July Dry	0.271***	0.269***	0.327***	0.257***	0.220***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
October Cold	0.008	-0.080**	-0.009	0.095*	0.041
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
October Warm	0.335***	0.329***	0.419***	0.304***	0.286***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
October Wet	-0.157***	-0.269***	-0.184***	-0.101**	-0.078*
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
October Dry	0.288***	0.277***	0.295***	0.270***	0.237***
	(0.042)	(0.039)	(0.044)	(0.051)	(0.043)
Observations	3,776	3,984	3,472	2,368	3,920
R^2	0.09646	0.13213	0.10763	0.05127	0.04911
Adjusted R^2	0.09285	0.12885	0.10376	0.04522	0.04545

This table presents regression results from a manager survey. The dependent variable is manager-reported operational impact on a scale from −1 (Hurts) to +1 (Helps), with 0 indicating no effect. Coefficients represent the average reported impact for each season-weather condition combination when weather deviations are accurately forecasted 3 months in advance. The sample comprises 1,095 operational-level managers across Healthcare, Industrials, Financials, Consumer Cyclicals, and Technology sectors in the United States and Canada, surveyed during March-July 2025 via Prolific. Standard errors in parentheses. *, **, *** denote significance at 10%, 5%, and 1% levels.

TABLE 5. Survey Results: Correlation Between Shock and Forecast Responses

	Pearson Correlation	P-value	Spearman Rank Correlation	P-value
Shock	0.032	0.776	0.170	0.133
Update	0.207	0.066	0.273	0.014

This table presents correlations between manager-reported impacts of unexpected weather shocks and forecasted weather deviations. The sample comprises 1,095 operational-level managers across Healthcare, Industrials, Financials, Consumer Cyclicals, and Technology sectors in the United States and Canada, surveyed during March-July 2025.

TABLE 6. Managerial Guidance and CPC Forecasts

a. Sectors 1–5

	I((ERROR))					
Sector	Basic Materials (1)	Communication (2)	Consumer Cyclicals (3)	Consumer Non-Cyclicals (4)	Energy (5)	Financials (6)
Temp. Shock: Cold Fall	-0.003 (0.010)	0.007 (0.006)	0.010** (0.004)	0.003 (0.005)	0.003 (0.016)	0.001 (0.012)
Temp. Shock: Cold Spring	-0.010 (0.011)	-0.004 (0.018)	0.011 (0.008)	0.009 (0.011)	0.015 (0.016)	-0.026 (0.017)
Temp. Shock: Cold Summer	-0.007 (0.014)	0.005 (0.012)	0.006 (0.007)	0.016 (0.014)	0.032 (0.022)	-0.030* (0.017)
Temp. Shock: Cold Winter	-0.011** (0.005)	0.007* (0.004)	0.006 (0.004)	-0.009* (0.005)	0.0004 (0.023)	-0.015 (0.011)
Temp. Shock: Warm Fall	-0.0006 (0.004)	0.013 (0.017)	-0.005 (0.004)	0.001 (0.004)	-0.007 (0.011)	0.006 (0.008)
Temp. Shock: Warm Spring	-0.004 (0.009)	0.017 (0.029)	-0.010 (0.007)	0.004 (0.007)	-0.006 (0.010)	0.026 (0.021)
Temp. Shock: Warm Summer	-0.014** (0.006)	0.005 (0.012)	0.002 (0.006)	-0.004 (0.004)	-0.036 (0.030)	0.006 (0.009)
Temp. Shock: Warm Winter	0.007 (0.011)	0.024 (0.029)	-0.003 (0.004)	0.006 (0.005)	-0.025* (0.013)	0.006 (0.011)
Temp. Update: Cold Fall	-0.086 (0.063)	0.046 (0.049)	0.075 (0.052)	0.047 (0.039)	0.085 (0.153)	0.003 (0.063)
Temp. Update: Cold Spring	-0.082 (0.101)	0.041 (0.104)	-0.047 (0.073)	-0.024 (0.050)	0.164 (0.274)	-0.075 (0.112)
Temp. Update: Cold Summer	-0.100 (0.077)	0.094 (0.084)	0.041 (0.057)	0.039 (0.039)	-0.207 (0.149)	-0.147* (0.076)
Temp. Update: Cold Winter	0.046 (0.036)	-0.098 (0.138)	0.057* (0.034)	-0.037 (0.047)	-0.125 (0.108)	0.124* (0.071)
Temp. Update: Warm Fall	0.033 (0.027)	-0.195* (0.109)	-0.008 (0.035)	-0.008 (0.027)	-0.149* (0.084)	0.082 (0.057)
Temp. Update: Warm Spring	0.132 (0.080)	-0.076 (0.084)	0.044 (0.045)	-0.060* (0.034)	-0.298 (0.217)	0.006 (0.081)
Temp. Update: Warm Summer	0.009 (0.081)	-0.180 (0.148)	0.037 (0.103)	0.079 (0.078)	-0.153 (0.180)	0.120 (0.165)
Temp. Update: Warm Winter	-0.006 (0.081)	-0.097 (0.160)	0.027 (0.044)	0.004 (0.045)	-0.016 (0.081)	-0.059 (0.097)
Precip. Shock: Dry Fall	0.016** (0.007)	0.001 (0.004)	0.002 (0.003)	-0.005 (0.004)	0.021*** (0.008)	-0.001 (0.007)
Precip. Shock: Dry Spring	-0.002 (0.009)	0.015 (0.012)	-0.005 (0.005)	-0.004 (0.005)	0.004 (0.006)	-0.004 (0.010)
Precip. Shock: Dry Summer	-0.003 (0.005)	0.005 (0.006)	0.004 (0.007)	0.0002 (0.004)	-0.009 (0.021)	-0.003 (0.006)
Precip. Shock: Dry Winter	-0.004 (0.005)	0.0005 (0.008)	-0.002 (0.002)	-0.005 (0.004)	0.004 (0.006)	-0.015 (0.011)
Precip. Shock: Wet Fall	-0.006 (0.003)	0.007 (0.009)	-0.004 (0.003)	0.002 (0.004)	-0.028* (0.017)	0.002 (0.006)
Precip. Shock: Wet Spring	-0.0007 (0.003)	-0.013 (0.008)	-0.0007 (0.003)	0.003 (0.006)	-0.009* (0.005)	-0.003 (0.006)
Precip. Shock: Wet Summer	0.004 (0.003)	0.006 (0.016)	-0.002 (0.002)	0.007*** (0.002)	0.001 (0.009)	-0.007* (0.004)
Precip. Shock: Wet Winter	-0.001 (0.004)	-0.007 (0.004)	0.004 (0.004)	-0.004 (0.004)	0.009 (0.011)	0.015 (0.010)
Precip. Update: Dry Fall	-0.171 (0.112)	0.028 (0.030)	0.041* (0.022)	0.098*** (0.030)	-0.053 (0.064)	-0.035 (0.032)
Precip. Update: Dry Spring	0.135 (0.140)	0.018 (0.040)	-0.093** (0.037)	-0.008 (0.054)	-0.008 (0.107)	-0.083 (0.068)
Precip. Update: Dry Summer	0.051 (0.042)	-0.147 (0.310)	0.061** (0.025)	0.062* (0.032)	0.194** (0.075)	0.037 (0.041)
Precip. Update: Dry Winter	-0.071 (0.105)	0.035 (0.022)	0.016 (0.016)	0.012 (0.054)	0.044 (0.036)	-0.166 (0.118)
Precip. Update: Wet Fall	-0.031 (0.030)	0.014 (0.035)	0.003 (0.024)	-0.050 (0.039)	0.042 (0.059)	0.045 (0.040)
Precip. Update: Wet Spring	-0.018 (0.032)	0.099 (0.110)	0.097* (0.055)	0.011 (0.035)	0.126 (0.119)	0.005 (0.040)
Precip. Update: Wet Summer	-0.032 (0.035)	-0.083 (0.057)	0.062 (0.045)	0.036 (0.041)	-0.203** (0.090)	0.042 (0.074)
Precip. Update: Wet Winter	0.019 (0.040)	-0.002 (0.034)	-0.042 (0.027)	-0.043** (0.020)	-0.149* (0.086)	0.006 (0.043)
Observations	4,302	3,239	26,011	9,278	1,601	6,043
R^2	0.27911	0.12210	0.16429	0.19071	0.35827	0.32297
Within R^2	0.01009	0.00978	0.00274	0.00338	0.02027	0.00825
Firm fixed effects	✓	✓	✓	✓	✓	✓
Ann. Month fixed effects	✓	✓	✓	✓	✓	✓

Managerial Guidance and CPC Forecasts (cont.)

b. Sectors 6–10

Sector	Healthcare (1)	Industrials (2)	I((ERROR)) Real Estate (3)	Technology (4)	Utilities (5)
Temp. Shock: Cold Fall	0.003 (0.002)	-0.009 (0.008)	-0.006 (0.013)	-0.002 (0.007)	0.007 (0.005)
Temp. Shock: Cold Spring	-0.003 (0.006)	-0.001 (0.004)	-0.026 (0.048)	-0.0005 (0.006)	0.007 (0.010)
Temp. Shock: Cold Summer	0.014*** (0.005)	0.006 (0.006)	0.031 (0.040)	-0.001 (0.007)	0.009 (0.008)
Temp. Shock: Cold Winter	-0.0003 (0.002)	-0.002 (0.003)	0.016 (0.021)	-0.002 (0.003)	0.0005 (0.003)
Temp. Shock: Warm Fall	-0.005*** (0.002)	-0.004 (0.004)	-0.020 (0.017)	-0.001 (0.004)	-0.005 (0.003)
Temp. Shock: Warm Spring	-0.0010 (0.002)	-0.007 (0.005)	-0.007 (0.012)	0.001 (0.004)	-0.011** (0.004)
Temp. Shock: Warm Summer	-0.0009 (0.002)	-0.006* (0.003)	-0.019 (0.013)	-0.002 (0.003)	-0.005 (0.004)
Temp. Shock: Warm Winter	0.002 (0.002)	-0.0008 (0.004)	-0.025* (0.015)	5.17×10^{-5} (0.003)	-0.004 (0.003)
Temp. Update: Cold Fall	0.005 (0.026)	0.004 (0.037)	-0.160* (0.085)	-0.111 (0.072)	0.027 (0.037)
Temp. Update: Cold Spring	0.051 (0.040)	0.020 (0.042)	-0.271 (0.325)	-0.076* (0.045)	-0.048 (0.054)
Temp. Update: Cold Summer	-0.041 (0.031)	-0.016 (0.040)	-0.402 (0.317)	-0.068 (0.044)	0.095* (0.052)
Temp. Update: Cold Winter	-0.007 (0.022)	-0.024 (0.042)	-0.102 (0.403)	-0.016 (0.050)	0.016 (0.025)
Temp. Update: Warm Fall	0.007 (0.024)	-6.75×10^{-5} (0.024)	0.315 (0.239)	0.011 (0.032)	-0.009 (0.017)
Temp. Update: Warm Spring	0.002 (0.017)	-0.006 (0.051)	-0.086 (0.140)	-0.006 (0.026)	-0.066*** (0.019)
Temp. Update: Warm Summer	-0.031 (0.037)	0.043 (0.065)	0.423 (0.264)	0.105* (0.059)	-0.086** (0.040)
Temp. Update: Warm Winter	0.031 (0.031)	-0.010 (0.029)	0.167 (0.157)	0.001 (0.030)	-0.056** (0.027)
Precip. Shock: Dry Fall	0.003 (0.002)	0.008*** (0.003)	0.010 (0.010)	-5.68×10^{-5} (0.002)	0.001 (0.003)
Precip. Shock: Dry Spring	-0.0007 (0.003)	-0.003 (0.004)	-0.017 (0.015)	-0.007*** (0.002)	-0.003 (0.004)
Precip. Shock: Dry Summer	0.0006 (0.002)	0.004 (0.003)	0.004 (0.010)	0.005* (0.002)	-0.003 (0.005)
Precip. Shock: Dry Winter	-0.003 (0.003)	0.0005 (0.003)	-0.002 (0.007)	-0.006** (0.003)	-0.005 (0.006)
Precip. Shock: Wet Fall	-0.0007 (0.001)	-0.003 (0.002)	-0.003 (0.008)	0.0003 (0.002)	0.001 (0.001)
Precip. Shock: Wet Spring	0.0005 (0.002)	-0.0004 (0.002)	-0.007 (0.008)	-0.0003 (0.002)	0.002 (0.004)
Precip. Shock: Wet Summer	-0.0007 (0.0009)	0.001 (0.003)	0.008 (0.008)	-0.0006 (0.001)	0.002 (0.002)
Precip. Shock: Wet Winter	-2.47×10^{-5} (0.002)	0.008* (0.004)	0.034 (0.022)	0.003 (0.003)	0.003 (0.004)
Precip. Update: Dry Fall	0.010 (0.016)	0.034 (0.022)	-0.012 (0.061)	0.002 (0.017)	0.015 (0.014)
Precip. Update: Dry Spring	0.044 (0.029)	0.031 (0.035)	0.077 (0.081)	0.041* (0.022)	0.005 (0.028)
Precip. Update: Dry Summer	-0.008 (0.014)	0.046** (0.020)	0.024 (0.038)	-0.042 (0.035)	0.045 (0.037)
Precip. Update: Dry Winter	0.009 (0.015)	-0.002 (0.029)	-0.044 (0.087)	-0.033** (0.016)	0.004 (0.015)
Precip. Update: Wet Fall	0.007 (0.018)	-0.009 (0.023)	0.108** (0.054)	0.020 (0.031)	-0.0003 (0.014)
Precip. Update: Wet Spring	-0.0004 (0.017)	0.029 (0.025)	-0.093 (0.154)	0.058** (0.026)	0.0009 (0.019)
Precip. Update: Wet Summer	-0.025 (0.021)	-0.004 (0.036)	-0.061 (0.053)	0.018 (0.026)	-0.047 (0.032)
Precip. Update: Wet Winter	-0.020 (0.015)	-0.013 (0.017)	0.099 (0.138)	-0.013 (0.012)	-0.011 (0.023)
Observations	31,505	27,191	1,944	25,010	5,610
R^2	0.18762	0.13996	0.27659	0.18883	0.24948
Within R^2	0.00118	0.00177	0.01617	0.00190	0.00503
Firm fixed effects	✓	✓	✓	✓	✓
Ann. Month fixed effects	✓	✓	✓	✓	✓

Managerial Guidance and CPC Forecasts (cont.)

c. Joint Significance Tests

Sector	Prec. Shock	Prec. Update	Temp. Shock	Temp. Update
Basic Materials	9.76***	1.77*	1.52	1.31
	(0.000)	(0.079)	(0.143)	(0.232)
Communication	0.49	1.67	-0.64	3.38***
	(0.866)	(0.101)	(1.000)	(0.001)
Consumer Cyclicals	0.87	2.72***	1.25	1.05
	(0.539)	(0.005)	(0.263)	(0.394)
Consumer Non-Cyclicals	0.02	2.39**	1.31	0.66
	(1.000)	(0.014)	(0.234)	(0.727)
Energy	2.49**	2.28**	1.26	1.98**
	(0.011)	(0.020)	(0.263)	(0.045)
Financials	1.13	0.60	0.86	1.41
	(0.336)	(0.776)	(0.551)	(0.186)
Healthcare	0.62	0.69	2.46**	0.82
	(0.766)	(0.699)	(0.012)	(0.582)
Industrials	1.73*	1.82*	1.08	0.17
	(0.085)	(0.068)	(0.373)	(0.995)
Real Estate	3.19***	-27.22	1.20	1.01
	(0.001)	(1.000)	(0.294)	(0.424)
Technology	2.55***	2.33**	0.24	1.72*
	(0.009)	(0.017)	(0.984)	(0.088)
Utilities	0.32	0.91	1.84*	3.75***
	(0.959)	(0.504)	(0.064)	(0.000)

This table presents regression results of guidance errors on CPC seasonal forecasts by sector. The dependent variable is guidance error (guidance minus actual, scaled). Independent variables include CPC temperature and precipitation forecasts (shocks and updates) for the fiscal quarter. Panels (a) and (b) show coefficient estimates for all GICS sectors; Panel (c) reports F-statistics testing the joint significance of forecast coefficients. Each F-test cell shows the statistic for the null hypothesis that all season-condition coefficients are jointly zero, with p-values in parentheses. All specifications include firm and quarter fixed effects. Guidance data are from IBES, matched to CPC forecasts based on guidance announcement date. Standard errors clustered at the firm level in parentheses. *, **, *** denote significance at 10%, 5%, and 1% levels.

A. Survey Implementation Details

This appendix provides comprehensive documentation of our manager survey implementation, including the survey platform, timeline, participant recruitment, data quality procedures, and handling of implementation challenges.

A.1. Survey Platform and IRB Review

We administered the survey through Prolific (www.prolific.co), a research-grade crowdsourcing platform widely used in academic research. Prolific offers several advantages for our research design: (1) ability to target participants by occupation, industry, and geography; (2) high data quality through pre-screened participant pools; (3) transparent pricing and ethical compensation standards; and (4) established protocols for scientific research (Palan and Schitter 2018).

The survey instrument was developed in Qualtrics and submitted to the Southern Methodist University Institutional Review Board for review. On January 9, 2025, the SMU IRB determined that the project does not meet the federal definition of human subjects research (SMU IRB 24-163). This determination was based on the finding that the survey collects ”“factual information about business practices’ rather than ”“identifiable private information’ about individuals. Under 45 CFR 46.102, human subjects research requires both: (1) systematic investigation designed to develop generalizable knowledge (research), and (2) obtaining information about living individuals through interaction where identifiable private information is collected. Our survey meets the definition of research but not human subjects, as it focuses on organizational practices and decision-making processes rather than personal information.

This determination does not diminish our commitment to ethical research practices. All participants were provided with information about the study’s purpose and voluntary nature before beginning the survey, consistent with best practices in social science research.

A.2. Target Population and Screening Criteria

We fielded the full survey on Prolific in between March and July 2025 with pre-defined stopping rules (informed by a pilot survey power analysis) mapped to TRBC's 10-sector classification. Filters required (i) current managerial responsibility, (ii) ≥ 2 years in role or function, (iii) location in the U.S. or Canada, (iv) not fully remote, and (v) passing of attention checks. We obtained 1,535 manager responses, of which 1,095 were usable after excluding sectors that failed to meet minimum quota thresholds and respondents failing attention screens. Sectors with sufficient responses for analysis were Industrials, Consumer Cyclicals, Financials, Healthcare, and Technology.

Our target population consisted of managers with operational decision-making authority who work at physical locations where local weather conditions could affect operations. We implemented the following screening criteria through Prolific's targeting system and within-survey filters:

- **Occupation**: Participants must hold managerial or supervisory roles with responsibility for operational decisions
- **Company size**: Employed at companies with 10 or more employees (excluded micro-enterprises)
- **Work location**: Work on-site or hybrid (excluded participants working remotely more than 90% of the time)
- **Geographic coverage**: Targeted participants in North America
- **Sectoral coverage**: Mixed recruiting across primary (agriculture, mining, energy), secondary (manufacturing, construction), and tertiary (services, technology, finance) sectors

The remote work filter was critical to our research design because managers who work almost entirely remotely are less likely to experience or make decisions based on local weather conditions.

A.3. Data Quality Filters

We applied the following data quality filters to construct our final analysis sample:

a. **Missing Prolific ID**: Excluded participants with blank ”prolific_id” (indicates incomplete registration)
b. **Completion time**: Excluded participants who completed the survey in less than 170 seconds (rushed responses unlikely to be thoughtful)
c. **Survey completion**: Excluded participants with Progress < 100% (incomplete surveys)
d. **Company size**: Excluded participants working for micro-enterprises (fewer than 10 employees) based on question Q33
e. **Remote work**: Excluded participants who work remotely 90-100% of the time, as these individuals are unlikely to be exposed to location-specific weather conditions
f. **Survey condition assignment**: Excluded participants with blank values for ”Effect2” (meta-data variable indicating which experimental condition was shown; blank indicates participant did not proceed through survey)
g. **Quality check data**: Excluded data from Prolific ID ”67c18e46299a92f078c6cd7e” (belongs to our research team’s Prolific account used for quality checks)

A.4. Final Sample Composition

Figure 2A reports the number of usable respondents by sector (where we retain sufficient power to detect effects when participants evaluate the role of weather variation). Figure 2B shows the distribution of firm sizes; across sectors, the split between SMEs, large private firms, and publicly listed firms is approximately 40%/40%/20%.