Weather Anomalies, Climate Risk, and Inflation Expectations of Households and Firms*

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Abstract

We show that locally unusual weather leaves a distinct imprint on prices, expectations, real activity, and credit. Linking the Business Tendency Survey (BTS) and the Consumer Tendency Survey (CTS) to province–day records from the Turkish State Meteorological Service, we build province–month anomaly measures and trace their effects over 2015–2024. A one–standard-deviation positive temperature anomaly raises near-term food CPI inflation for several months before mean-reverting. This salient price signal maps into beliefs: households' 12-month CPI expectations rise by about 1.5%, with larger revisions for rural, female, and lower-income respondents, who also report weaker income prospects, a darker macro outlook, lower willingness to buy durables, and higher unemployment concerns. On the food-sector firm side, 12-month CPI beliefs increase by about 0.6%, unit-cost expectations rise, and sales expectations and overall business conditions deteriorate, with stronger responses among SMEs and highly leveraged firms. Beyond prices and beliefs, real outcomes soften at monthly horizons: domestic sales fall by about 0.8%, exports by 1.2%, total purchases by 0.6%, and employment by 0.4%, with larger contractions for SMEs and high-leverage firms. Credit-registry evidence shows an access-amplified working-capital response: total outstanding credit increases by about 1.7%, driven by short-term balances alongside a decline in long-term balances, implying pronounced maturity shortening that is strongest for borrowers with better bank access, though constrained firms also tilt short. Taken together, transient but salient weather shocks raise expected inflation while depressing perceived and realized conditions and shortening debt maturity, temporarily steepening the monetary-policy trade-off and highlighting the value of climate-aware communication and adaptation policies that dampen pass-through to costs, activity, credit, and beliefs.

Keywords: Inflation Expectations, Whether Anomalies, Climate Change, Macroeconomics
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1 Introduction

The global economy is increasingly confronted with the palpable and disruptive effects of climate change, manifesting as more frequent and intense episodes of unusual weather. These phenomena are not merely environmental concerns; they are rapidly reshaping the near-term dynamics of prices, costs, and economic sentiment, posing significant challenges for macroeconomic stability and monetary policy. In economies like Türkiye, where food and energy constitute substantial portions of consumption baskets and production chains, climate anomalies function as recurrent supply shocks. These shocks can obscure monetary-policy signals, making it difficult for central banks to discern between transitory supply impulses and persistent demand pressures, while simultaneously maintaining credibility with households and firms. This paper directly addresses this critical policy problem by providing high-frequency, micro-level evidence on how localized unusual weather transmits through the economy to impact prices, inflation expectations, and, crucially, the "real side" of the economy through credit and financial vulnerability.

Our research investigates a straightforward yet profound question: Do province-level weather anomalies move realized food inflation and, through salience and information frictions, also shift the inflation expectations and economic sentiment of households and firms? If so, which groups are most affected, and along which margins (prices vs. costs vs. real activity) do firms adjust? Answering these questions matters for the design of communication and for the calibration of complementary, climate-aware policies that can dampen pass-through to costs and beliefs.

Conceptually, locally unusual heat compresses effective supply in food value chains by lowering yields, shortening shelf life, raising cooling and transport costs, and impeding logistics; it also shifts household attention toward essential prices and tightens firms' working-capital cycles. We therefore advance four testable predictions: (i) near-term food CPI rises in the wake of temperature anomalies, peaks after several months, then mean reverts; (ii) households revise 12-month CPI upward, with sharper revisions among rural, female, and lower-income respondents, while reporting weaker income prospects, a darker macro outlook, lower willingness to buy durables,

and higher unemployment concerns; (iii) managers in food-related manufacturing raise CPI and unit-cost expectations and mark down sales and overall conditions, with stronger effects for SMEs and highly leveraged firms; and (iv) firms rebalance toward short-maturity bank credit even when total outstanding credit expands, reflecting tighter cash-flow risk at monthly horizons. Our empirical strategy is designed to test these mechanisms using high-frequency microdata on beliefs, prices, real outcomes, and credit.

Direct evidence on how climate anomalies shape inflation expectations remains limited. An important recent exception is Georgarakos et al. (2025), who run a large, population-representative survey experiment in the euro area: randomly assigning respondents to hypothetical global-temperature paths, they show that a 0.5°C increase raises five-year-ahead inflation expectations by about 0.65pp, with stronger effects among more climate-aware consumers and more pessimistic views on growth and public finances. A large literature shows that households and firms react to salient food and energy signals, with consequences for spending, wage setting, and pricing; randomized information designs establish causal updating and highlight the roles of disagreement and uncertainty (Coibion and Gorodnichenko, 2015; Candia et al., 2020; Coibion et al., 2022; Altig et al., 2020). Climate shocks plausibly operate through input costs, capacity utilization, and demand reallocation—especially in food and beverage manufacturing and downstream activities reliant on temperature-sensitive logistics—so recurrent anomalies may lift short-horizon expectations, widen forecast distributions, and increase disagreement, particularly where exposure is high.[1]

Against this backdrop, we provide micro-founded evidence from Türkiye that links locally unusual weather to prices, expectations, real activity, and bank credit. We merge two high-frequency CBRT surveys—the Business Tendency Survey (firms) and the Consumer Tendency Survey (households)—with province–day meteorological records from the Turkish State Meteorological Service to construct a province–month panel aligning anomalies with agent-level beliefs and CPI components. On the firm side, we further link BTS respondents to the regulatory firm–bank credit

[1] On CPI pass-through and state dependence in weather shocks, see Parker (2018); Faccia et al. (2021); Mukherjee and Ouattara (2021); Ciccarelli et al. (2024); Moessner (2022); Cevik and Jalles (2023a).

registry (monthly stocks and new originations by contractual maturity), the Revenue Administration's firm-to-firm invoice network (domestic sales and purchases), Social Security Institution payroll records (employment and wage bills), and customs-based shipment data (exports). First, local projections show that a one–standard-deviation positive temperature anomaly raises near-term food CPI, peaking around months 4–6 before mean reversion. Second, households' 12-month CPI expectations rise by about 1.5% while income prospects, macro outlook, durable-purchase intentions, and unemployment perceptions worsen, with larger effects for rural, female, and lower-income respondents. Third, in food-related manufacturing, managers' 12-month CPI expectations increase by about 0.6% and unit-cost expectations rise, while sales expectations and overall conditions deteriorate, especially for SMEs and highly leveraged firms. Fourth, real outcomes contract at monthly horizons—domestic sales by about 0.8%, exports by 1.2%, input purchases by 0.6%, and employment by 0.4%—with sharper declines for SMEs and high leverage. Fifth, credit adjusts along maturity: total outstanding credit increases by 1.7%, driven by short-term balances (+3.6%) alongside a decline in long-term balances (1.0%), implying pronounced maturity shortening that is stronger for borrowers with better bank access. Placebo tests in non-food manufacturing and alternative anomaly standardizations support interpretation and robustness.

The remainder of the paper is organized as follows: Section 2 surveys research on weather/climate shocks, inflation, and expectations, emphasizing supply channels and heterogeneous exposure. Section 3 describes the survey datasets and construction of province–month anomalies. Section 4 reports (i) local-projection pass-through from anomalies to food CPI, (ii) household belief and sentiment responses, and (iii) food-sector firm expectations on prices, costs, sales, and economic outlook. Section 5 offers robustness checks, and Section 6 concludes the paper.

2 Related Literature

Understanding the link between climate anomalies and macroeconomic outcomes has become increasingly urgent, particularly as the economic risks associated with climate change intensify. Growing evidence links anomalous temperature volatility to inflation and output fluctuations, operating primarily through supply chains, agriculture, energy, and labor productivity. Bayesian time-varying parameter estimates suggest that increases in temperature-anomaly volatility raise both inflation and real volatility (Alessandri and Mumtaz, 2021); structural uncertainty further amplifies macro-financial risk (Barnett et al., 2022). Weather surprises tighten fiscal space by lifting spending and eroding tax revenues (Pintus et al., 2024). At a global scale, temperature shocks reduce output and productivity and put upward pressure on prices, with stronger effects in commodity importers and warmer climates (Bilal and Känzig, 2024); model-based analyses similarly find that higher climate volatility is inflationary via food and energy channels (Donadelli et al., 2021).

Narrative evidence on "temperature surprise shocks" shows persistent price-level effects, especially when agricultural or energy bottlenecks bind (Natoli, 2023). Firm- and market-based studies indicate that managers revise earnings down and cost expectations up after anomalous months (e.g., retail, construction, agriculture; see Hugon and Law, 2019), and that weather derivatives embed inflation premia as forward-looking anomalies become more probable (Schlenker and Taylor, 2021). These patterns dovetail with a broad micro literature documenting climate impacts on labor productivity, agriculture, energy demand, and health, which cumulate into aggregate damages and non-linear macro responses (Dasgupta et al., 2021; de Lima et al., 2021; Moore et al., 2017a,b; Auffhammer et al., 2017; Wenz et al., 2017; Guo et al., 2016; Song et al., 2017; Burke et al., 2015; Dell et al., 2012a; Kalkuhl and Wenz, 2020; Kotz et al., 2021, 2022). Prospective welfare losses under continued warming are sizable (Bressler, 2021; Moore and Diaz, 2015; Rode et al., 2021; Burke et al., 2018).

Because volatile or elevated prices carry substantial welfare costs and social risks (Chu and

Lai, 2013; Dotsey and Ireland, 1996; Gazdar and Mallah, 2013; Nord et al., 2014; Abaidoo and Agyapong, 2022)—as underscored by the 2022 cost-of-living surge (Molina et al., 2022; Lagarde, 2022)—understanding climate–inflation links is central to monetary policy design and communication (Bolton et al., 2020; Boneva et al., 2021; Drudi et al., 2021). Empirically, disasters and hot seasons tend to lift inflation in the short run, with persistence beyond seasonal windows and stronger pass-through in warmer economies; precipitation shocks are non-linear; and disaster exposure raises both inflation and macro volatility (Parker, 2018; Faccia et al., 2021; Mukherjee and Ouattara, 2021; Ciccarelli et al., 2024; Moessner, 2022; Cevik and Jalles, 2023a).[2]

Building on these insights and gaps, we merge province–day TSMS weather with two high-frequency CBRT surveys (CTS and BTS) to construct standardized province–month anomalies for 2015–2024 and link them to respondent-level beliefs. Our contribution is threefold. *First*, we establish a dynamic first stage from local temperature anomalies to food CPI using local projections. *Second*, we provide novel evidence on the *expectations channel of climate change* that goes beyond GDP growth expectations—quantifying short-horizon CPI and unit-cost beliefs and broader sentiment for both households and firms, with systematic heterogeneity by exposure and constraints. *Third*, and distinct in the literature, we match the BTS panel to administrative registries (firm–bank credit with contractual maturities, inter-firm invoices, payroll, and customs) to show that weather shocks depress real activity and induce borrower-specific maturity shortening of bank credit at monthly horizons. Identification relies on saturated panels with rich fixed effects, and the setting—an inflationary emerging market with high food salience—offers an externally relevant laboratory for policy.

[2]Foundations in IAMs and macro-empirical work relate climate to damages and growth (Nordhaus, 1991, 1992; Cline, 1992; Gallup et al., 1999; Nordhaus, 2006; Burke et al., 2015). Long-run, non-linear, and heterogeneous growth impacts of anomalies are well documented (Acevedo et al., 2022; Burke and Tanutama, 2019; Kahn et al., 2021; Akyapı et al., 2025). Disasters affect growth, public finances, human capital, and external balances (Loayza et al., 2012; Noy, 2009; Raddatz, 2009; Skidmore and Toya, 2002; Cuaresma, 2010; Gassebner et al., 2006). Climate vulnerability is priced in sovereign and private markets (Cevik and Jalles, 2023b, 2021, 2022; Bansal et al., 2016; International Monetary Fund, 2020; Bernstein et al., 2019; Painter, 2020).

3 Survey Data and Whether Anomaly Construction

We combine multiple complementary data sources. First, the *Business Tendency Survey* (BTS) provides monthly firm-level expectations and assessments for manufacturing. Second, the *Consumer Tendency Survey* (CTS) supplies monthly household beliefs on prices, finances, and spending plans from a nationally representative sample. Third, we compile province-level daily meteorological observations from the Turkish State Meteorological Service (TSMS), aggregate them to province–month, and construct standardized weather-anomaly exposures using pre-sample moments. We then match BTS firm respondents to administrative firm outcomes using unique firm identifiers shared across sources under strict confidentiality, linking to: (i) Revenue Administration (RA) firm-level *financial statements* for non-financial private-sector firms; (ii) RA *firm-to-firm invoice transactions* that map buyer–supplier links and monthly sales/purchases; (iii) Social Security Institution (SSI) *employment records* that track firm size and formal employment dynamics; and (iv) the national *Credit Registry* covering monthly firm–bank relationships. Aligning BTS/CTS responses with TSMS weather at the province–month level, and the administrative records at the firm–month level, yields a unified panel to study how locally unusual weather maps into beliefs across agents and transmits into firms' real and financial outcomes.

3.1 Bussiness and Consumer Tendency Surveys

The BTS is a high-frequency panel of roughly 1,800–2,200 manufacturing firms surveyed monthly. It tracks firms' assessments of operating conditions and near-term plans across core margins—capacity utilization, order books, inventories, and production constraints—eliciting both retrospective changes over the past three months (improved / unchanged / deteriorated) and expectations for the next three months. The questionnaire also collects numerical 12-month-ahead inflation expectations. In this paper, we restrict attention to food-related manufacturing (NACE Rev. 2 divisions C10–C12: food products, beverages, tobacco), a sector directly exposed to salient cost and demand shocks.[3]

[3] For the complete BTS questionnaire, see Appendix-A.

The CTS is a monthly survey of 4,884 households designed to gauge sentiment about personal finances, the broader economy, and near-term spending plans. It organizes responses along three pillars—financial situation, economic outlook, and consumption—capturing both backward-looking assessments and forward-looking expectations on inflation, wages, unemployment, borrowing conditions, and major purchases (e.g., durables, housing, automobiles), as well as intended outlays on semi-durables and home improvements. One adult (16+) per household is interviewed, providing a timely cross-section of household beliefs and planned behavior.[4]

3.2 Microdata on Firm Outcomes, Credits and Networks

The RA provides annual balance sheets and income statements for the population of Turkish firms—incorporated entities and unlimited-liability businesses that surpass statutory size thresholds—compiled under Türkiye's Tax Procedure Law and available from 2009 through 2024. These statements include detailed asset and liability sub-accounts, enabling the construction of leverage, liquidity, and related financial-constraint measures; unless noted otherwise, annual controls are taken from 2023, the latest pre-treatment year.[5] In addition, the RA supplies invoice-level domestic firm-to-firm transaction data for invoices above 5,000 TL (roughly 150 USD in 2024). We aggregate these records to the firm–month level to obtain total domestic sales.

Our primary source of bank credit information is the regulatory credit registry administered by the Banking Regulation and Supervision Agency (BRSA). The registry, reported by all regulated banks at a monthly frequency, is maintained at the bank–firm relationship level. For each bank–firm pair and month, it records (i) end-of-month outstanding credit stocks and (ii) flows of newly originated cash and non-cash loans, together with core contract attributes—contractual maturity, the interest rate at origination, and currency denomination. We use these micro-records to assemble a bank–firm–month panel that serves as our baseline unit of observation. From this

[4] Since 2012, the CTS has been part of the European Union Harmonized Business and Consumer Surveys Common Programme and, since May 2015, has received co-financing from the European Commission.

[5] Incorporated firms must file balance sheets and income statements under the Tax Procedure Law. Unlimited firms, taxed under the personal income tax regime, file conditional on exceeding regulatory size thresholds. Our annual control set references 2023 unless otherwise stated.

panel, we (a) classify borrowing into short- versus long-term using a 12-month maturity threshold and (b) construct borrowing-cost measures by weighting origination interest rates with contemporaneous origination amounts where appropriate.

Finally, SSI's matched employer–employee records provide monthly headcounts and wage bills for firms subject to the balance-sheet principle. We define monthly employment as the total number of individuals on a firm's payroll in that month and compute the average wage as the total monthly wage bill divided by employment. Linking these sources via the CBRT firm ID yields a comprehensive, internally consistent panel that integrates financial statements, transactional sales, credit positions and flows (with currency denomination), and labor-market outcomes at high frequency.

Table 1: Descriptive Statistics

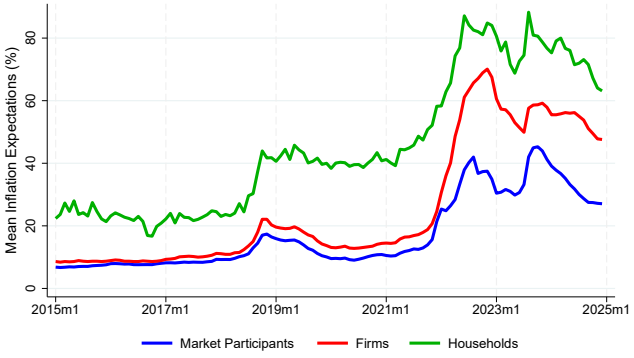
	Mean	SD
Panel A: Household Expectations		
12-Months Ahead CPI Expectations	51.24	44.98
Income Expectations	2.01	0.98
Durable Purchase Expectations	1.89	0.79
Macro Outlook	1.91	1.09
Unemployment Expectations	2.13	1.09
Urban Share (%)	0.89	0.31
Male Share (%)	0.51	0.50
Bottom Income Group Share (%)	0.38	0.49
Top Income Group Share (%)	0.15	0.36
Panel B: Firm Expectations		
Firm's Expectations		
12-Months Ahead CPI Expectations	19.02	18.95
Unit Cost Expectations	2.37	0.79
Economic Outlook	1.82	0.73
Sales Expectations	2.17	0.77
Firm's Real Outcomes		
Sales	1.01	1.48
Employment	661.45	1039.73
Leverage	0.63	0.95
Exports	0.22	0.71
Assets	0.89	1.88
SME Share (%)	0.36	0.48
High Leverage Share (%)	0.49	0.50

Notes: Entries report sample means and standard deviations. Household variables are defined as follows: CPI Expectations are 12-month-ahead inflation beliefs (percent); Income, Durable Purchases, Macro Outlook, and Unemployment Expectations are qualitative indices on a 1–3 scale (1 = pessimistic, 2 = no change, 3 = optimistic). Household shares (Rural, Male, Bottom/Top income) are fractions in $[0,1]$. Household statistics use survey sampling weights. Firm variables are defined as follows: CPI Expectations are 12-month-ahead inflation beliefs (percent); Unit Cost, Economic Outlook, and Sales Expectations are qualitative indices on a 1–3 scale. Firm characteristics include Sales, Employment (headcount), Leverage (debt/assets), Exports (share), Assets, SME share, and High-leverage share (fractions in $[0,1]$).

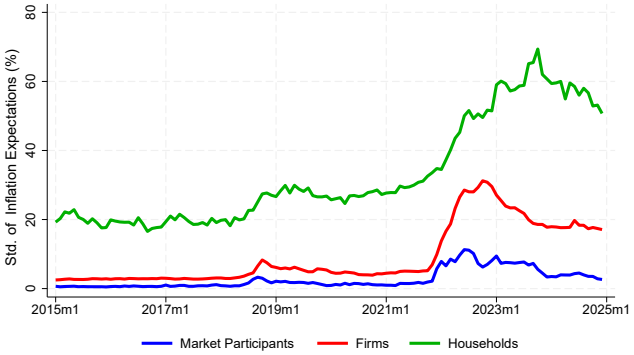
Table 1 shows that households report markedly higher one-year-ahead CPI expectations (mean 51.2%) than firms (mean 19.0%), with much greater dispersion among households. Qualitative indices cluster around the neutral value of 2: households' macro and income assessments hover near "no change," while firms' unit-cost index (≈ 2.37) points to cost pressures, and sales sentiment (≈ 2.17) is only mildly positive. In addition, Figure 1 shows that one-year-ahead CPI infla-

tion expectations differ systematically across respondent groups in Türkiye: households report the highest averages, firms sit in between, and market participants (professionals) are the lowest and most tightly clustered. This ranking aligns with models of limited information and rational inattention, where less-informed agents update more slowly and extrapolate salient price changes more strongly (Mankiw and Reis, 2002; Sims, 2003; Carroll, 2003). Empirically, household expectations track visible price movements and day-to-day shopping experience, whereas professionals anchor more on macro data, policy guidance, and model-based forecasts (Coibion and Gorodnichenko, 2015; D'Acunto et al., 2023). Firm expectations typically lie between these extremes, consistent with mixed exposure to retail salience and formal planning routines (Coibion et al., 2018; Akarsu et al., 2025).

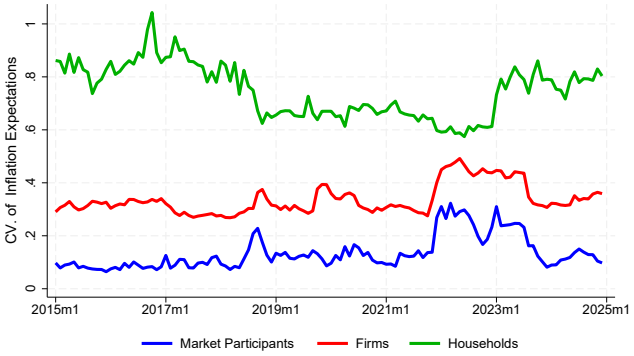
Figure 1b documents that cross-sectional *disagreement* (dispersion) in one-year-ahead expectations is largest for households, moderate for firms, and smallest for market participants—rising for all groups during macro volatility. The literature shows that disagreement co-moves with macro uncertainty, especially when inflation deviates from prior norms or when relative-price shocks intensify (Mankiw et al., 2004; Dovern et al., 2012; Bachmann et al., 2013). In noisy-information frameworks, common signals become less precise as inflation becomes more volatile, widening the distribution of beliefs; heterogeneous information sets and attention costs magnify dispersion among less-informed agents (Sims, 2003; Veldkamp and Wolfers, 2007). The ordering we observe—households > firms > professionals—maps closely to documented differences in information frictions and attention. In addition, Figure 1c scales dispersion by the group-specific mean (coefficient of variation). This normalization highlights two points. First, when the inflation level is high, raw standard deviations can rise mechanically; the coefficient of variation helps separate level effects from *relative* dispersion. Second, even after scaling, households display persistently greater relative heterogeneity than firms and professionals, consistent with costly and uneven information acquisition.



(a) Mean Expected Inflation



(b) Disagreement in Expected Inflation



(c) Coefficient of Variation of Expected Inflation

Figure 1: Inflation Expectations of Households, Firms, and Professionals

Notes: The figure shows monthly time series of one-year-ahead CPI inflation expectations for three respondent groups in Türkiye: market participants (blue, CBRT Survey of Market Participants), firms (red, CBRT Business Tendency Survey), and households (green, CBRT Consumer Tendency Survey). Panel (a) plots the cross-sectional mean expectation; Panel (b) plots "disagreement," measured as the cross-sectional standard deviation; Panel (c) reports the coefficient of variation, computed as the standard deviation divided by the mean. Units are percent; sample spans 2015–2024.

3.3 Weather Data and Anomaly Construction

We use province-level daily meteorological observations from the Turkish State Meteorological Service (TSMS)[6] and aggregate them to the province–month (p, t) level. For each province, daily series are averaged within the month to obtain monthly 2-meter air temperature $T_{p,t}$ (and, analogously, precipitation, humidity, and wind). Working with *anomalies*—month-by-month deviations of local weather from a long-run baseline—provides a high-frequency, comparable metric of climatic shocks across time and space. Early macro evidence shows that even modest temperature deviations can depress output, especially in developing or already-warm economies (Dell et al., 2012b); more recent contributions emphasize that higher moments—variance, skewness, and the probability of extremes—also shape macro outcomes and risk pricing (Donadelli et al., 2022; Winter and Kiehl, 2023; Volodin and Yurova, 2013).

To isolate unexpected weather conditions from geography and seasonality, let $m \in \{1, \ldots, 12\}$ denote the calendar month, and compute a province– and month-specific climatology over the World Meteorological Organization (WMO) 30-year normal $\mathscr{B}$ = 1991–2020.[7] Denote the baseline mean and standard deviation by $\overline{T}^{\mathscr{B}}_{p,m}$ and $\sigma^{\mathscr{B}}_{p,m}$. We then define the anomaly and its standardized version as

$$Z_{p,t} \equiv \frac{T_{p,t} - \overline{T}^{\mathscr{B}}_{p,m}}{\sigma^{\mathscr{B}}_{p,m}}.$$

By differencing relative to $\overline{T}^{\mathscr{B}}_{p,m}$, we remove fixed geographic differences (e.g., altitude, coast–inland) and regular seasonality (summer–winter), isolating within-province, month-specific surprises that are plausibly exogenous at monthly horizons. Magnitudes are straightforward to interpret: $Z_{p,t} > 0$ (< 0) indicates hotter (cooler) than usual "there and then," while $Z_{p,t} = 1$ corresponds to one local-standard-deviation above the usual temperature for that province and month. Our main specification anchors anomalies to the 1991–2020 WMO normal because the outcome sample

[6] TSMS is Türkiye's national meteorological authority responsible for the operation and quality control of surface and upper-air observations.

[7] A WMO *climate normal* is a 30-year average for each calendar month at a location, updated every decade (e.g., 1961–1990, 1981–2010, 1991–2020); it is the standard baseline for defining anomalies.

spans 2015–2024; to verify robustness to baseline choice, we replicate all estimates using a strictly pre-sample window (e.g., 1990–2014) that excludes the analysis period.

Table 2: Weather Anomalies and Temperature Benchmarks

	Mean	SD
Panel A: Province-Level Temperatures (°C)		
Mean Temperature (monthly average of daily mean)		
1991–2020	13.24	8.83
2015–2024	14.61	8.59
2020–2024	14.87	8.61
Minimum Temperature (monthly average of daily minima)		
1991–2020	-12.79	12.81
2015–2024	-11.59	12.15
2020–2024	-11.62	12.17
Maximum Temperature (monthly average of daily maxima)		
1991–2020	35.02	8.35
2015–2024	36.47	8.56
2020–2024	37.61	8.69
Panel B: Weather–Anomaly Exposure		
Weather–Anomaly Exposure	0.01	1.01

Notes: Temperatures are computed at the province level from monthly averages of daily observations: *Mean Temperature* uses daily mean; *Minimum Temperature* uses daily minima; *Maximum Temperature* uses daily maxima. Units are degrees Celsius (°C).

Table 2 documents the province–level temperature benchmarks and the distribution of our standardized weather–anomaly exposure. Panel A reports monthly averages of daily mean, minimum, and maximum temperatures across benchmark periods, showing that recent years (2015–2024 and especially 2020–2024) are warmer than the WMO 1991–2020 normal along all three margins. Panel B reports the standardized Weather–Anomaly Exposure (mean ≈ 0.01, SD ≈ 1.01), consistent with a z-score construction at the province–month level. Fırthermore, Figure 2 plots the national monthly temperature anomaly, constructed as the simple average of province–month deviations from the WMO 1991–2020 normal. By design, values oscillate around zero, but they are not mechanically mean–zero over time. The series exhibits sizable month-to-month volatility with episodic extremes (both warm and cold), and a visible drift toward more frequent positive

anomalies in the later years of the sample. Intuitively, the national curve is an aggregation of locally idiosyncratic shocks; persistence arises when many provinces experience the same sign deviation in the same calendar month. In addition, Figure E1 plots, for each calendar month (January–December), the national mean temperature anomaly relative to the 1991–2020 normal. Positive values indicate warmer-than-usual months and negative values cooler-than-usual months. Visually, late-summer/early-autumn panels tend to sit above zero more often, while January–February display the widest swings around zero.

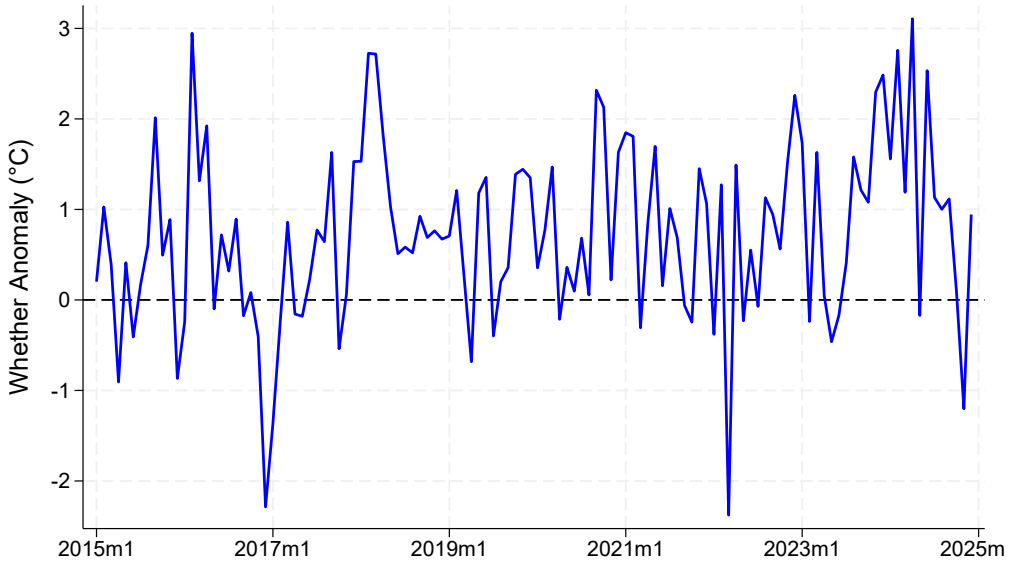


Figure 2: Time Series of Whether Anomaly Shock

Notes: The figure plots the national monthly weather anomaly series. For each province p and month t, we compute the temperature anomaly $A_{p,t} = T_{p,t} - \overline{T}^{(30\text{yr})}_{p,m(t)}$, where $T_{p,t}$ is the realized province–month mean temperature and $\overline{T}^{(30\text{yr})}_{p,m(t)}$ is the province-specific 30-year climatological mean for that calendar month (e.g., 1991–2020). The national series is the simple average $\bar{A}_t = \frac{1}{P}\sum_p A_{p,t}$. Positive values indicate warmer-than-normal months and negative values cooler-than-normal months; the dashed line marks the zero-anomaly baseline. Units are °C; sample 2015m1–2014m12.

Figure E2 relates the national anomaly to contemporaneous changes in a Google Search Index for climate-risk terms ("drought," "air frost," "climate change"). The binscatter slope is positive: months with higher temperature anomalies are associated with larger increases in climate-risk search intensity. Conceptually, this is an external validation that the anomaly measure captures salient, economy-wide weather realizations that enter public attention and information acquisi-

tion. While the relationship is modest in magnitude—as expected for a single climate dimension and a broad search basket—it is precisely the kind of co-movement one would anticipate if *unexpected* weather conditions heighten perceived climate risk.

4 Impact of Whether Anomalies on Expectations

4.1 Whether Anomalies and Food Inflation Pass-through

We quantify the dynamic effect of unexpected weather conditions on consumer food inflation using the local projection (LP) framework of Jorda (2005). Let Z_t denote the national monthly weather anomaly shock, measured as the simple average of province–month temperature anomalies standardized by the 1991–2020 normal (so one unit equals one local standard deviation for that calendar month). For horizon h, we estimate

$$\pi^{\text{food}}_{t+h} = \alpha_h + \beta_h Z_t + \sum_{p=1}^{12} \gamma^p_h \pi^{\text{food}}_{t-p} + X'_t \delta_h + \varepsilon_{t+h}, \qquad h = 0, 1, \ldots, 24, \tag{1}$$

where π^{food}_{t+h} is the (annualized) rate of food CPI inflation at horizon $t+h$ (headline food group in the official CPI), and X_t includes standard monthly controls: exchange-rate depreciation, international food commodity price inflation (e.g., FAO food price index), and month fixed effects.The coefficient of interest, β_h, traces the response of food inflation at horizon h to a one–standard-deviation positive weather anomaly at time t. We include twelve lags of the dependent variable to capture intrinsic persistence in food prices and slow-moving pricing factors. Inference relies on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987), computed separately by horizon.

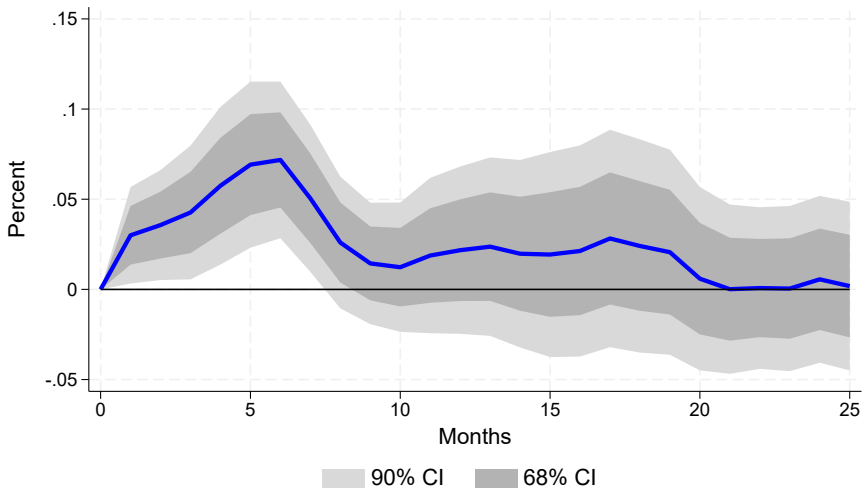


Figure 3: Dynamic Responses of Food Inflation to Whether Anomalies

Notes: This figure presents local projection estimates of the dynamic effects of one standard deviation of whether anomalies shock on food inflation. The blue line shows the point estimates of the response, while the shaded areas represent 90% (light gray) and 68% (dark gray) confidence intervals, computed using heteroskedasticity and autocorrelation-consistent (HAC) standard errors following Newey and West (1987).

Figure 3 reports local–projection impulse responses of food CPI inflation to a one–standard–deviation weather-anomaly shock. The response rises quickly and becomes statistically positive within the first few months, peaks around months 4–6, and then gradually declines; after roughly one year the effect attenuates and is generally statistically insignificant from zero, with mid-horizon wiggles that are not robust across intervals. Taken together, the pattern indicates a clear *dynamic* effect of weather anomalies on food prices: short-run supply disruptions (lower yields, harvest losses, spoilage, and logistics frictions), higher input and storage costs (cooling, transport, energy), and heightened consumer salience of food prices all raise measured inflation in the near term, with partial reversal as supply chains adjust and inventories, imports, and substitution mitigate pressures over subsequent months. We view this estimate as a "first-stage" relevance result: weather anomalies translate into tangible movements in food inflation, providing a salient price signal that we next use to study the response of inflation expectations across households and firms.

4.2 Household Expectations

Household inflation expectations are highly sensitive to salient, day-to-day signals in the economic environment. Unusually hot or cold months raise the visibility of energy and food expenditures, shift attention toward near-term price pressures, and can compress planning horizons—mechanisms consistent with limited-information updating and salience effects documented in the expectations literature. In high-inflation settings, these attention channels are amplified: households frequently revisit their mental models of prices, and locally unusual weather conditions serve as vivid cues about current and near-future living costs. Consequently, relating province-level weather anomalies to household beliefs offers a transparent way to isolate short-run, plausibly exogenous variation in perceived purchasing power and price dynamics. To assess the impact of locally unusual weather on household beliefs, our empirical model links household-level expectations to province–month weather anomalies as follows: To assess the impact of locally unusual weather on household beliefs, our empirical model links household-level expectations to province–month weather anomalies as follows:

$$y_{ipt} = \beta_0 + \beta_1 \,\text{WeatherAnomalies}_{pt} + X'_{ipt}\gamma + \delta_p + \lambda_t + \varepsilon_{ipt}, \tag{2}$$

where y_{ipt} denotes household i's expectation (e.g., next-12-month CPI inflation, perceived financial conditions, macro outlook, borrowing or unemployment likelihood) in province p and wave t; $\text{WeatherAnomalies}_{pt}$ is measured at the province–month level; δ_p and λ_t are province and wave fixed effects; and X_{ipt} includes standard household covariates (education, age, income group, gender).

Table 3 shows that unexpected monthly weather conditions systematically shift households' beliefs. A one–standard deviation increase in whether anomaly raises the log of 12-month-ahead CPI expectations by about 1.5%, with larger effects among lower-income households (0.022 vs. 0.016). This pattern matches a salience/cost-of-living channel in which extreme hot or cold months heighten attention to essentials and squeeze budgets: household inflation expectations co-move

strongly with prices of frequently purchased groceries (D'Acunto et al., 2021), and household inflation expectations track their own expectations for food and energy prices most closely (Dietrich et al., 2022; Dietrich, 2024).[8] Together with evidence that temperature shocks depress productivity and strain local supply in warmer economies (Dell et al., 2012b; Burke et al., 2015; Carleton and Hsiang, 2016), these findings provide a compact rationale for the Table 3's pattern: heat anomalies raise expected inflation while simultaneously worsening income and macro outlook, especially for more financially constrained households.

Panels B, C, D and E collectively reveal that exposure to weather anomalies consistently fosters pessimism across households' expectations about personal income, the broader economy, intentions to purchase durable goods and unemployment in the economy. These outcomes, each measured on a qualitative 1–3 scale, capture different facets of economic sentiment but share common patterns, reflecting how weather shocks ripple through household decision-making and perceptions of economic stability. Income expectations decline with exposure: a one–s.d. anomaly reduces the index by 0.005 pp in the full sample. This is consistent with weather anomalies acting as negative productivity shocks that erode confidence in wage growth and employment stability, especially in vulnerable economies (Burke et al., 2015; Dell et al., 2012b). Heterogeneity is pronounced: rural households see a larger decline (−0.009 pp) than urban (−0.005 pp), in line with agriculture's sensitivity to weather (Lobell et al., 2011). The muted response for males (+0.003 pp) alongside a negative and significant shift for females (−0.006 pp) is consistent with heterogeneous exposure and salience rather than pure noise. Women are more likely to (i) manage day-to-day household budgets and grocery purchases—precisely the categories that drive belief updates when prices move—amplifying attention to weather-sensitive essentials like food and electricity; (ii) work in lower-wage, less insured, and heat-exposed service activities where hours and tips respond quickly to adverse conditions; and (iii) absorb additional caregiving/time-use shocks (e.g., heat-related school disruptions), all of which tighten near-term income prospects.

[8] For instance, extreme weather can disrupt agricultural production, raising food prices and anchoring households' expectations to recent negative experiences (D'Acunto et al., 2021).

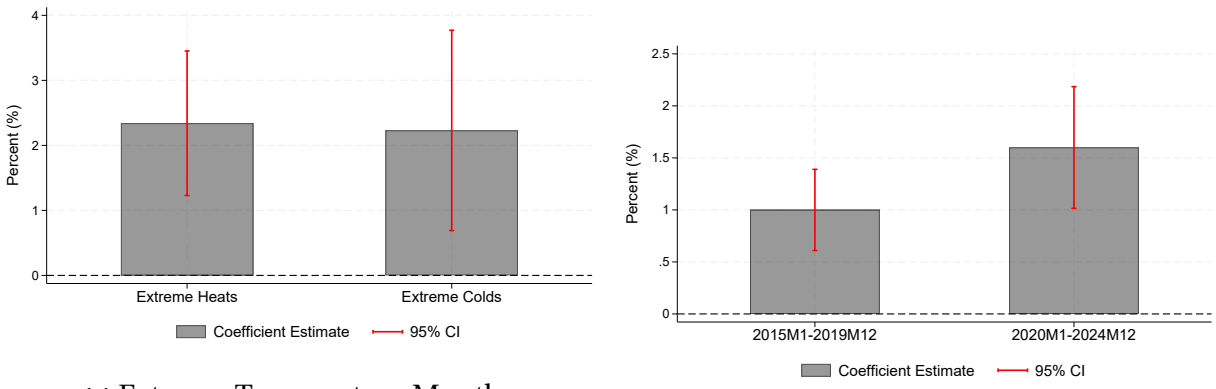
By income, the bottom group shows the largest drop (−0.010pp) versus a marginal effect at the top (−0.007 pp), consistent with greater vulnerability among financially constrained households (Hallegatte et al., 2016). In addition, durable goods purchase expectations in Panel C exhibit a parallel adjustment: a one–s.d. anomaly lowers the durable-intent index by −0.003 pp overall, with larger pullbacks in rural (−0.006 pp) and female (−0.006 pp) subsamples and a significant decline among bottom-income households (−0.005 pp), while the top-income effect is statistically indistinguishable from zero. This pattern aligns with precautionary saving and liquidity-constraint mechanisms whereby households facing tighter budgets and higher exposure defer big-ticket, postponable purchases when weather shocks raise uncertainty and essential expenditures (Carroll, 1997; Townsend, 1994).

Table 3: Effect of Whether Anomalies on Households' Expectations

	(1) All Sample	(2) Rural	(3) Urban	(4) Male	(5) Female	(6) Bottom Income Group	(7) Top Income Group
Panel A: Effect on CPI Expectations							
Weather Anomalies$_{pt}$	0.015***	0.019**	0.015***	0.015***	0.018***	0.022***	0.016***
	(0.002)	(0.007)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)
R-squared	0.299	0.335	0.297	0.300	0.351	0.306	0.420
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Panel B: Effect on Income Expectations							
Weather Anomalies$_{pt}$	-0.005**	-0.009***	-0.005**	0.003	-0.006**	-0.010***	-0.007*
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
R-squared	0.051	0.066	0.045	0.061	0.075	0.087	0.112
Observations	293,252	32,074	261,178	148,007	145,243	112,307	44,818
Panel C: Effect on Durable Purchases							
Weather Anomalies$_{pt}$	-0.003**	-0.006**	-0.002*	-0.003*	-0.006***	-0.005**	-0.005
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
R-squared	0.057	0.089	0.054	0.082	0.085	0.121	0.136
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Panel D: Effect on Macro Outlook							
Weather Anomalies$_{pt}$	-0.006**	-0.008**	-0.006**	-0.005*	-0.009**	-0.009***	-0.006**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
R-squared	0.076	0.088	0.064	0.078	0.109	0.109	0.119
Observations	293,252	32,074	261,178	148,007	145,243	112,307	44,818
Panel E: Effect on Unemployment							
Weather Anomalies$_{pt}$	0.003**	0.011**	0.002	0.004*	0.010***	0.007**	0.001
	(0.001)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
R-squared	0.057	0.094	0.054	0.085	0.081	0.101	0.142
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Wave FE	✓	✓	✓	✓	✓	✓	✓
Region x Year-Month FE	✓	✓	✓	✓	✓	✓	✓
Household Controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the estimation results for Equation 2, with each regression weighted by household sampling weights. Each panel corresponds to a different dependent variable as labeled. In Panel A, the dependent variable is the logarithm of households' 12-month-ahead inflation expectations. Panels B–E are qualitative indices measured on a 1–3 scale, where 1 indicates pessimism, 2 indicates no change, and 3 indicates optimism (lower values denote more pessimistic assessments). Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Panels D and E collectively reveal that exposure to weather anomalies fosters pessimism in households' expectations about the broader economy and heightens concerns about unemployment risks. Households appear to read unusual heat as a weakening signal for aggregate activity—consistent with evidence that temperature shocks depress productivity and output, especially where adaptation is limited. In parallel, concerns about unemployment rise, in line with the idea that weather-sensitive sectors (agriculture, construction, outdoor services) cut hours and hiring first, with spillovers through local demand and supply chains (Carleton and Hsiang, 2016). These belief shifts are strongest for groups with higher exposure and thinner buffers (rural, female, lower-income), matching the literature on unequal climate vulnerability (Hallegatte et al., 2016). Importantly, the macro and labor-market pessimism coexists with higher inflation expectations documented in Panel A: adverse weather raises attention to essentials like food and energy and tightens perceived budgets, so households simultaneously anticipate weaker growth and employment while expecting prices to rise. This combination—higher expected inflation alongside weaker activity—naturally fosters precaution and deferral of discretionary spending (Panel C) and helps explain the broad-based deterioration in economic sentiment.



(a) Extreme Temperature Months (Heat vs. Cold)

(b) Heterogeneity by Inflation Regime

Figure 4: Household Inflation Expectations and Local Temperature Anomalies

Notes: Figures presents the effect of local temperature anomalies on household inflation expectations. In Panel (a), we compare months with extreme heat to months with extreme cold. Bars plot coefficient estimates from Eq. (2), where the outcome is the log of 12-month-ahead CPI inflation expectations at the household level and the regressor is the province–month temperature anomaly. "Extreme heat" ("extreme cold") denotes months in which the standardized anomaly is positive (negative)—i.e., observations on the upper (lower) side of the distribution relative to 1991–2020 normals. Gray bars are point estimates and red whiskers denote 95% confidence intervals. All specifications include province and wave fixed effects and standard household covariates (education, age, income group, gender) and are weighted by survey sampling weights. In Panel (b), we estimate the same specification separately for the *low-inflation episode* (2015M1–2019M12) and the *high-inflation episode* (2020M1–2024M12); bars show the estimated effect of province–month anomalies on expected inflation with 95% confidence intervals. The larger response in the high-inflation period is consistent with limited-information updating and salience: unusual weather makes energy and food costs more salient, compresses planning horizons, and amplifies attention to near-term price pressures.

Panel (a) of Figure 4 contrasts months with *extreme heat* (positive standardized temperature anomalies) and *extreme cold* (negative anomalies) and shows *symmetric, positive* effects on households' 12-month-ahead inflation expectations. [9] The intuition is that *deviations from seasonal normals—regardless of sign*—make energy and food outlays unusually salient, compress planning horizons, and trigger faster belief updating under limited information. Real channels reinforce this—heat waves and cold snaps alike strain logistics and labor productivity, disrupt agriculture, and raise energy demand for cooling/heating, providing concrete price signals that households extrapolate to overall inflation. Consistent with salience-based models, household inflation expectations co-move with prices of frequently purchased groceries and track own food/energy price beliefs most closely (D'Acunto et al., 2021; Dietrich et al., 2022; Dietrich, 2024). In adition, Panel (b) of Figure 4 splits the sample into a low-inflation episode (2015M1–2019M12) and a high-inflation episode (2020M1–2024M12) and shows that the pass-through from province–month tem-

[9] A Wald test does not reject $H_0 : \beta^{\text{heat}} = \beta^{\text{cold}}$.

perature anomalies to 12-month-ahead inflation expectations is markedly larger in the high-inflation period. Taken together with Panel (a)'s near-symmetric responses to extreme heat and cold, the figures imply that *deviations from normal* systematically raise expected inflation, and that the salience of these deviations is amplified when overall inflation is already elevated. The intuition is standard: when inflation is high, households monitor prices more frequently, rely more on salient, high-frequency signals (energy and food outlays), and update beliefs more aggressively—mechanisms emphasized by limited-information and salience models and supported by evidence that household expectations co-move with frequently purchased grocery prices and with their own food/energy price beliefs (D'Acunto et al., 2021; Weber et al., 2025). Moreover, temperature shocks can tighten local supply conditions—through productivity losses, logistics frictions, and agricultural disruptions—providing a real basis for the stronger belief revisions observed in high-inflation settings.

Taken together, the estimates show a coherent pattern: monthly weather anomalies push up inflation expectations while simultaneously worsening views about personal income, macroeconomic conditions, durable purchase plans, and unemployment. The heterogeneity—stronger responses in rural areas, among females, and for lower-income households—points to differential exposure and thinner buffers as key amplifiers. These findings are consistent with a joint mechanism in which heat-related shocks raise the salience and cost of essentials, compress real disposable resources, and disrupt work in weather-exposed sectors, prompting precaution and broader macro pessimism.

4.3 Firm Expectations and Decisions

Firms in the food and beverage sector (NACE C10–C11) translate locally salient weather into procurement, processing, storage, and distribution choices. Unusually hot months raise refrigeration and cooling loads, shorten shelf life and yields for perishables, increase spoilage/shrinkage along the cold chain, and create logistics frictions in warehousing and transport; at the same time, tem-

perature shocks reallocate demand toward cold beverages and ready-to-eat items while dampening demand for heat-intensive products. Unusually cold months, in turn, increase heating and insulation needs in plants, retail, and transport; heighten risks of freezing and breakage in warehousing and last-mile delivery; slow handling and throughput; and disrupt logistics through snow/ice and road closures. Cold also shifts demand toward hot meals, soups, baked goods, and energy-dense staples while reducing sales of chilled drinks and fresh, cold-served items; for some categories it may extend shelf life, but upstream it can damage crops and delay harvests. In a high-inflation environment, these cost- and demand-side pressures make pass-through more salient and compress planning horizons, so locally unusual weather—hot or cold—is informative for managers' beliefs about selling prices, input costs, and overall business conditions. Measuring how food firms' expectations respond to weather anomalies therefore provides evidence on how transitory local shocks feed into price-setting and real activity. Accordingly, we quantify this impact by estimating the following regression:

$$y_{jpt} = \beta_0 + \beta_1 \text{WeatherAnomalies}_{pt} + X'_{jpt}\gamma + \alpha_j + \delta_{st} + \phi_{rt} + \varepsilon_{jpt}, \tag{3}$$

where y_{jpt} denotes firm j's outcome, which includes both *expectations* (12-month-ahead CPI inflation, unit cost, sales, and overall economic outlook) and *decisions* (domestic sales, purchases from other firms, exports, and employment), observed in province p at year–month t; $\text{WeatherAnomalies}_{pt}$ is the province–month exposure; α_j are firm fixed effects absorbing time-invariant heterogeneity (business model, managerial style, baseline pricing stance); δ_{st} are sector×year-month fixed effects that absorb sector-specific national shocks are region ×year-month fixed effects (with r denoting a NUTS-1 region) that net out time-varying shocks common to all provinces within the same region—e.g., regionally coordinated agricultural policies, energy supply constraints, transport disruptions, or broad weather systems spanning multiple provinces.are province fixed effects capturing time-invariant local characteristics. The control vector X_{jpt} includes leverage (total debt to total assets), exporter status, firm age, and firm size (employment).

Impact on Firms' Expectations

Weather anomalies, acting as supply shocks, disrupt agricultural production and supply chains, particularly in the food sector, where firms rely heavily on weather-sensitive inputs like crops and livestock. Extreme whether anomalies reduce supply availability, increase input costs, and create operational uncertainties, shaping firms' economic expectations (Kotz et al., 2024). Table 4 presents the estimated effects of exposure to these supply shocks on firms' expectations, based on Equation 3. The sample consists entirely of food sector firms, amplifying the relevance of supply shocks due to the sector's dependence on agricultural inputs vulnerable to climate variability.

Panel A shows that a one–s.d. weather anomaly raises firms' 12-month CPI expectations by 0.006 in the full sample, with larger effects for SMEs (0.009) and high-leverage firms (0.009) than for large (0.004) and low-leverage (0.005) firms. Panel B moves from prices to costs and reveals the supply-side origin of these beliefs: unit cost expectations increase by 0.011 overall, again with stronger sensitivity among SMEs and high-leverage firms (0.012 each) relative to large and low-leverage firms (0.009). For food producers and distributors, anomalous heat and related conditions depress upstream yields and quality, raise perishability and waste, and increase energy needs for refrigeration and transport—mechanisms that push input and logistics costs higher and naturally pass through to price expectations (Lobell et al., 2011; Dell et al., 2012b; Burke et al., 2015; Carleton and Hsiang, 2016). The sharper responses among SMEs and financially constrained (high-leverage) firms are consistent with thinner adaptation margins—fewer supplier options, limited cold-chain capacity, and tighter working-capital cycles—so the same weather shock translates into larger perceived cost pressure and stronger expected inflation.

Panel C shows that weather anomalies translate into broader macro pessimism for food-sector firms: the economic-outlook index falls by 0.022 pp in the full sample, with larger declines for SMEs (-0.032 pp) and high-leverage firms (-0.027 pp) than for large (-0.019 pp) and low-leverage (-0.016) firms. Panel D reveals the corresponding demand-side adjustment: sales expectations drop by 0.008 pp overall, again sharper for SMEs (-0.012 pp) and high-leverage firms (-0.015 pp) than for

large (-0.007 pp) and low-leverage (-0.007 pp; statistically weaker) peers. These patterns are consistent with adverse supply shocks from heat—lower labor productivity and handling efficiency, more frequent logistics frictions, and higher spoilage risk—propagating through the sector and curbing near-term activity (Zivin and Neidell, 2014; Burke et al., 2015; Carleton and Hsiang, 2016). Combined with Panels A–B, the results point to a classic squeeze: anomalies raise expected unit costs and CPI, compress margins, and, against tighter household budgets, lead firms—especially those with thinner buffers (SMEs, highly leveraged)—to mark down sales and macro prospects (Hallegatte et al., 2016).

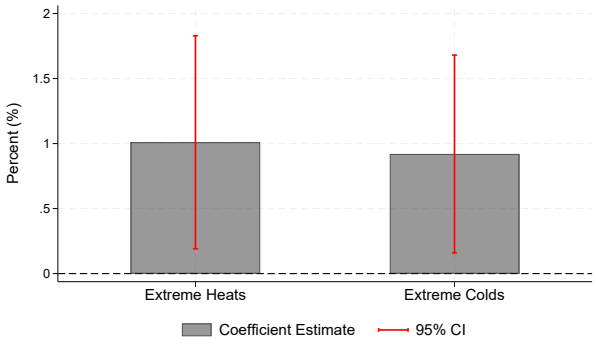
Table 4: Effect of Weather Anomalies on Firms' Expectations

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: CPI Expectations					
Weather Anomalies$_{pt}$	0.006***	0.009*	0.004**	0.009***	0.005***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
R-squared	0.872	0.883	0.872	0.876	0.880
Observations	20,394	10,844	9,486	14,967	5,341
Panel B: Unit Cost Expectations					
Weather Anomalies$_{pt}$	0.011***	0.012**	0.009*	0.012***	0.009*
	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)
R-squared	0.302	0.314	0.352	0.304	0.377
Observations	16,754	9,101	7,589	12,206	4,474
Panel C: Economic Outlook					
Weather Anomalies$_{pt}$	-0.022***	-0.032***	-0.019**	-0.027***	-0.016*
	(0.006)	(0.010)	(0.009)	(0.009)	(0.010)
R-squared	0.418	0.457	0.365	0.393	0.469
Observations	23,024	9,041	7,535	12,150	4,422
Panel D: Sales Expectations					
Weather Anomalies$_{pt}$	-0.008**	-0.012**	-0.007**	-0.015**	-0.007
	(0.004)	(0.005)	(0.003)	(0.008)	(0.009)
R-squared	0.296	0.341	0.336	0.332	0.370
Observations	23,026	9,041	7,535	12,150	4,422
Firm FE	✓	✓	✓	✓	✓
Industry x Year-Month FE	✓	✓	✓	✓	✓
Region x Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓

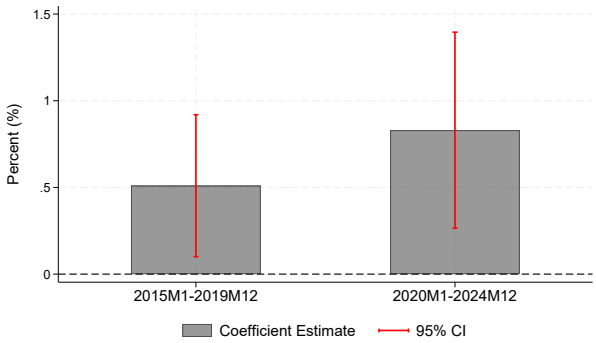
Notes: This table presents the estimation results for Equation 3. Each panel corresponds to a different dependent variable as labeled. In Panel A, the dependent variable is the logarithm of firms' 12-month-ahead CPI inflation expectations. Panels B–D are qualitative indices measured on a 1–3 scale, where 1 indicates pessimism, 2 indicates no change, and 3 indicates optimism (lower values denote more pessimistic assessments). An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Figure 5 presents the effect of local temperature anomalies on food-sector firms' inflation expectations. In Panel (a), months with extreme heat and extreme cold both raises 12-month-ahead CPI expectations by similar magnitudes, which is consistent with a salience mechanism in

which deviations from seasonal normals, regardless of sign, raise attention to energy/refrigeration or heating needs, shorten planning horizons, and transmit upstream agricultural and logistics disruptions into expected prices. In Panel (b), estimating the same specification separately by inflation regime shows a larger pass-through in the high-inflation episode (2020M1–2024M12) than in 2015M1–2019M12. This regime dependence matches the idea that, when inflation is already elevated, managers monitor prices more frequently and update beliefs more aggressively from salient cost signals (cooling/heating loads, spoilage risks, transport frictions), while thinner buffers in a high-inflation environment make near-term input-cost shocks more consequential for pricing plans (Akarsu et al., 2024; Akarsu and Aktuğ, 2025; Weber et al., 2025). The symmetry across hot and cold months and the amplification under high inflation together indicate that local, transitory weather shocks are informative for firms' beliefs about selling prices and near-term business conditions in this sector.



(a) Extreme Temperature Months (Heat vs. Cold)



(b) Heterogeneity by Inflation Regime

Figure 5: Firm Inflation Expectations and Local Temperature Anomalies

Notes: Figures presents the effect of local temperature anomalies on firm inflation expectations. In Panel (a), we compare months with extreme heat to months with extreme cold. Bars plot coefficient estimates from Eq. (3), where the outcome is the log of 12-month-ahead CPI inflation expectations at the firm level and the regressor is the province–month temperature anomaly. "Extreme heat" ("extreme cold") denotes months in which the standardized anomaly is positive (negative)—i.e., observations on the upper (lower) side of the distribution relative to 1991–2020 normals. Gray bars are point estimates and red whiskers denote 95% confidence intervals. All specifications include firm, industry-by-year-month and region-by-year-month fixed effects and standard firm covariates (leverage, export status, age and firm size). In Panel (b), we estimate the same specification separately for the *low-inflation episode* (2015M1–2019M12) and the *high-inflation episode* (2020M1–2024M12); bars show the estimated effect of province–month anomalies on expected inflation with 95% confidence intervals. The larger response in the high-inflation period is consistent with limited-information updating and salience: unusual weather makes energy and food costs more salient, compresses planning horizons, and amplifies attention to near-term price pressures.

Impact on Firms' Real Outcomes

In the full sample, a one-standard-deviation increase in Exposure lowers domestic sales by 0.8%. The effect is stronger for SMEs (a 1.1% decline) and for high-leverage firms (a 1.2% decline), and smaller for large and low-leverage firms (each 0.6% decline). At monthly frequency, these magnitudes indicate meaningful short-run contractions in cash-flow–relevant revenues. The pattern is consistent with two reinforcing mechanisms: (i) supply-side constraints—heat-related productivity losses, higher cooling and spoilage costs, equipment derating, and short disruptions in workflows and maintenance cycles—and (ii) demand-side headwinds—lower in-person customer traffic and a shift toward postponing discretionary purchases. Liquidity and scale buffer these shocks: SMEs and highly leveraged firms face tighter working-capital constraints and fewer adaptation margins (e.g., backup cooling, flexible overtime or inventory), amplifying the pass-through from anomalous heat to realized sales.

Export revenues are more sensitive than domestic sales. A one-standard-deviation increase in Exposure reduces exports by 1.2% in the full sample, with larger contractions among SMEs (1.4%) and smaller—but economically material—responses for large firms (0.8%). High-leverage firms register a 1.1% decline, compared with 0.6% for low-leverage firms. Exports compound the production frictions above with logistics and quality-assurance margins: minor delays in upstream processes, reduced line speeds, or heat-sensitive quality defects can trigger missed container cutoffs, partial shipments, or rejections in cold-chain segments. Because export orders are coordinated across multiple stages and jurisdictions, small heat shocks can propagate into outsized shipment-level disruptions, particularly for smaller or financially constrained firms that cannot readily reschedule capacity, pay surcharges for expedited transport, or draw down inventories to bridge shortfalls.

Total purchases of intermediate inputs decline by 0.6% in the full sample for a one-standard-deviation increase in Exposure, with sharper reductions for SMEs (0.7%) and high-leverage firms (0.9%) relative to large (0.3%) and low-leverage (0.4%) firms. This pattern is indicative of a working-

capital and inventory-management channel: faced with temporarily higher operating costs and softer sales, firms rationally scale back restocking and postpone non-essential purchases to preserve liquidity and manage inventory risks (including heat-sensitive spoilage and storage losses). Production planning also adjusts on the intensive margin—shorter runs, longer changeovers—lowering contemporaneous input demand even before employment margins move.

Employment is the slowest margin to adjust. A one-standard-deviation increase in Exposure reduces employment by 0.4% in the full sample, concentrated among SMEs (0.5%) and high-leverage firms (0.4%); the response for large firms is close to zero, while low-leverage firms show a modest 0.2% decline. This hierarchy is consistent with standard adjustment frictions—hiring and firing costs, internal labor markets, and implicit contracts—that favor short-run responses along hours, overtime, reassignments, and temporary closures rather than headcount changes. Only where financial constraints are tighter (SMEs, high leverage) do firms transmit monthly heat shocks more quickly to employment.

Table 5: Effect of Weather Anomalies on Firms' Real Outcomes

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: Domestic Sales					
Weather Anomalies$_{pt-1}$	-0.008***	-0.011***	-0.006***	-0.012***	-0.006**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
R-squared	0.907	0.888	0.902	0.891	0.925
Mean Dependent Var.	17.12	17.92	16.43	16.92	17.16
Panel B: Exports					
Weather Anomalies$_{pt-1}$	-0.012***	-0.014***	-0.008***	-0.011**	-0.006***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)
R-squared	0.885	0.862	0.894	0.872	0.865
Mean Dependent Var.	9.96	10.65	9.31	9.28	10.66
Panel C: Total Purchases					
Weather Anomalies$_{pt-1}$	-0.006**	-0.007**	-0.003*	-0.009**	-0.004**
	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)
R-squared	0.844	0.821	0.852	0.848	0.849
Mean Dependent Var.	16.54	17.33	15.86	16.44	16.56
Panel D: Employment					
Weather Anomalies$_{pt-1}$	-0.004**	-0.005**	0.001	-0.004**	-0.002*
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
R-squared	0.958	0.916	0.927	0.957	0.967
Mean Dependent Var.	5.78	6.61	5.08	5.69	5.81
Firm FE	✓	✓	✓	✓	✓
Industry × Year-Month FE	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Observations	20,864	10,919	9,979	10,284	10,614

Notes: This table presents the estimation results for Equation 3. Each panel corresponds to a distinct dependent variable: Panel A is log domestic sales, Panel B is log exports, Panel C is log purchases from other firms, and Panel D is log employment. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Impact on Firms' Credit Market Outcomes

Using the administrative credit registry, which tracks each bank–firm relationship at monthly frequency, we study how local weather shocks affect firms' credit outcomes at the bank–firm level.

Specifically, we estimate

$$y_{jbpt} = \beta_0 + \beta_1 \,\text{WeatherAnomalies}_{pt-1} + X'_{jpt}\gamma + \alpha_{jb} + \mu_{bt} + \delta_{st} + \phi_{rt} + \varepsilon_{jbpt}. \tag{4}$$

The dependent variable y_{jbpt} is one of three credit outcomes for the firm-bank relationship: natural logarithm of total outstanding credit, outstanding short-term credit, and outstanding long-term credit. Bank–firm fixed effects α_{jb} absorb all time-invariant features of the lending relationship, such as baseline credit limits, relationship capital, match-specific risk assessments, collateral that does not vary at monthly frequency, branch proximity, and any persistent sorting between a given firm and a given bank; identification therefore comes from within-pair changes in lending around local weather fluctuations rather than cross-sectional comparisons. Bank-by-year–month fixed effects μ_{bt} capture bank-specific credit supply conditions that vary over time and soak up shocks to funding costs, liquidity, capital constraints, portfolio rebalancing, internal risk limits, and exposure to macroprudential policy, so comparisons are made relative to other borrowers of the same bank in the same month. As in Equation (3), we include the same control vector X_{jpt} and the same sector-by-year–month and region-by-year–month fixed effects, δ_{st} and ϕ_{rt}.

Table 6 documents economically meaningful and precisely estimated effects of weather anomalies on firms' outstanding bank credit at the firm–bank–province–month level. A one–standard-deviation increase in the local anomaly is associated with a 1.7% increase in total outstanding credit (Panel A). This aggregate expansion is entirely accounted for by short maturities: short-term balances rise by 3.6% (Panel B), while long-term balances decline by 1.0% (Panel C). The implied gap between short- and long-term elasticities ($\approx$ 4.6 percentage points) indicates a pronounced maturity shortening of firms' credit stocks in anomalous months.[10]

[10]Identification leverages rich set of fixed effects: bank×firm effects purge time-invariant match quality and collateral; bank×month effects absorb time-varying bank-wide supply (funding costs, internal limits); and industry×month and region×month effects flexibly net out sectoral and geographic shocks. Given this design, the maturity shift is measured *within the same bank and month across its borrowers*, reducing concerns that the results are driven by common bank-supply movements rather than borrower-specific responses.

The maturity reallocation is strongest among borrowers with better access to bank finance, and is therefore unlikely to be purely supply-driven. Quantitatively, the total-credit response is larger for large than for SME borrowers (+2.0% vs. +1.4%), and the expansion on the short end is concentrated among large and low-leverage firms (+6.7% and +5.8%, respectively), whereas the decline in long-term balances is broad-based across leverage bins (−0.9% to −1.5%). These patterns are consistent with an *access-amplified working-capital channel*: locally unusual weather raises variable costs, disrupts logistics, and shortens effective product lifecycles in temperature- and perishability-sensitive supply chains, tightening near-horizon cash-flow needs and prompting firms to draw more heavily on short-maturity bank credit (Dell et al., 2012b; Burke and Emerick, 2016). In high-inflation environments, salient cost shocks transmit swiftly to prices and beliefs, compressing planning horizons and further increasing reliance on rollable finance to bridge operating cycles. On the lender side, our identification within bank×month cells implies that the observed maturity shortening reflects borrower-specific adjustments rather than common shifts in bank supply; it accords with theories in which debt maturity is used to provide liquidity while managing risk under heightened cash-flow uncertainty—favoring short-term, *option-like* exposure over expansions in long-term commitments (Diamond, 1991; Barclay and Smith, 1995; Rampini and Viswanathan, 2010). The fact that firms with stronger balance sheets scale up short-term borrowing more aggressively is in line with access-based amplification of working-capital finance—better-connected, less constrained borrowers tap bank lines at exactly the moment transitory financing needs spike—while more constrained firms still reallocate toward short maturities but to a smaller extent (Fazzari et al., 1988; Petersen and Rajan, 1997). Taken together, the combination of a pronounced short-term increase (+3.6%) and a concurrent decline in long-term balances (−1.0%) points to a state-dependent reshaping of liability structure in response to weather shocks, with attendant rollover-risk implications when uncertainty and inflation pressures are elevated.

Table 6: Effect of Weather Anomalies on Firms' Outstanding Credits

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: Total Outstanding Credits					
Weather Anomalies$_{pt-1}$	0.017**	0.014*	0.020**	0.013**	0.020***
	(0.008)	(0.008)	(0.011)	(0.007)	(0.007)
R-squared	0.497	0.486	0.471	0.501	0.525
Mean Dependent Var.	9.36	9.91	8.89	9.38	9.32
Panel B: Short-term Outstanding Credits					
Weather Anomalies$_{pt-1}$	0.036**	0.046**	0.067***	0.037**	0.058**
	(0.015)	(0.022)	(0.024)	(0.015)	(0.025)
R-squared	0.298	0.267	0.341	0.289	0.354
Mean Dependent Var.	6.91	7.21	6.64	6.94	6.83
Panel C: Long-term Outstanding Credits					
Weather Anomalies$_{pt-1}$	-0.010**	-0.009**	-0.015***	-0.012**	-0.014**
	(0.005)	(0.004)	(0.006)	(0.006)	(0.007)
R-squared	0.343	0.305	0.396	0.346	0.381
Mean Dependent Var.	4.27	4.58	4.02	4.45	3.96
Bank × Firm FE	✓	✓	✓	✓	✓
Bank × Year-Month FE	✓	✓	✓	✓	✓
Industry × Year-Month FE	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Observations	96,181	52,290	43,888	61,528	34,650

Notes: This table presents the estimation results for Equation 3. The unit of observation is firm–bank–province–year–month (j, b, p, t). In each panel, the dependent variable is defined as $y_{jbpt} = \log(X_{jbpt})$, where X_{jbpt} denotes the total outstanding credit amount in Panel A, the short-term outstanding credit amount in Panel B, and the long-term outstanding credit amount in Panel C. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Taken together, the estimates indicate that climate-related anomalies *reallocate* the liability structure of firms in real time: firms draw down more short-term bank credit while running down long-term balances. Because these responses are identified within bank×month cells, they reflect borrower-specific adjustments rather than common credit-supply shifts. In environments where weather shocks also raise salient food and energy prices, the maturity shortening we document is a natural manifestation of working-capital finance in the face of cost pressure and logistical

frictions, and is consistent with precautionary shortening of debt when uncertainty rises. From a policy perspective, such state dependence increases rollover exposure precisely when local supply shocks and inflation pressures are elevated, suggesting benefits from climate- and logistics-aware credit risk monitoring and from infrastructure that attenuates cold-chain and transport bottlenecks upstream.

5 Robustness Check

We assess the credibility and stability of the baseline results along four complementary dimensions: (i) placebo tests in settings where no effect should arise; (ii) re-estimation with alternative anomaly scaling based on strictly pre-sample moments; (iii) substitution of *weather uncertainty* for anomaly levels; and (iv) formal interaction tests that verify subgroup patterns rather than compositional drift. Across all exercises, the evidence points to a salient, contemporaneous supply channel that raises expected inflation, pessimistic real-side assessments, and shortens credit maturity, especially where buffers are thin.

Placebo test. We first verify that firm-expectations responses are specific to food-exposed production chains. Re-estimating Eq. (3) for manufacturing sectors excluding NACE C10–C12 yields economically trivial, statistically null coefficients across CPI and unit-cost expectations and broadly so for sales and outlook (Appendix B, Table D1). A few isolated 10% "stars" are neither systematic across outcomes nor consistent in sign, which is precisely the pattern expected from noise in a saturated panel. We further implement a *timing placebo* using Weather Anomalies$_{p,t-12}$. For households (Table D2) and for firms (Table D3), the one-year-lag coefficients are near zero and statistically null. If baseline results were driven by slow-moving province trends or seasonal confounds, such lagged anomalies would also matter; they do not. Together with rich fixed effects (province and wave for households; firm, industry×time, and region×time for firms), these tests support a *salient, contemporaneous* channel rather than spurious seasonality.

Alternative standardization with pre-sample moments. To rule out that normalizing expo-

sure with in-sample moments drives the findings, we reconstruct weather-anomaly exposure using only 1990–2014 means and standard deviations and re-estimate the main specifications. For households, Table C1 reproduces the baseline pattern: locally unusual weather raises 12-month CPI expectations and lowers income prospects, durable-purchase intentions, and macro outlook, while increasing unemployment concerns. For firms, Table C2 shows higher CPI and unit-cost expectations alongside more pessimistic sales and macro outlook, with larger effects among SMEs and high-leverage firms—the very groups with thinner cash buffers and fewer adaptation margins. Real activity moves in the same direction (domestic sales, exports, purchases, and employment all soften; Table C3). Credit-market responses are likewise intact (Table C4). In short, *rebasing exposure does not alter inference.*

Weather uncertainty in place of anomaly levels. We next replace Weather Anomalies$_{pt}$ with a province–month *weather-uncertainty* measure. For households (Table C5), greater local uncertainty raises expected inflation and depresses income, durable purchases, and macro outlook while lifting unemployment concerns—a mirror image of the level-shock results consistent with attention and precautionary channels. For firms (Table C6), uncertainty elevates expected CPI and unit costs and lowers sales expectations and macro outlook. Real outcomes respond in the same direction (Table C7). Credit responses—an increase in total balances driven by short-term credit alongside a decline in long-term balances—persist when we substitute uncertainty for levels (Table C8). Taken together, expectations and decisions respond not only to the level of anomalies but also to *second-moment risk*, reinforcing our interpretation that salience and cash-flow risk drive the transmission.

The credit-registry estimates are stable across all robustness exercises. With pre-sample normalization (Table C4) and with weather uncertainty (Table C8), total outstanding credit rises in anomalous/uncertain months because short-term balances expand while long-term balances contract. This maturity shortening is exactly what one expects if weather shocks tighten working-capital cycles (higher cooling/transport costs, spoilage risk, and logistics frictions) and raise near-term uncertainty: firms draw on revolving/short credit while postponing long-maturity commit-

ments.

Heterogeneity via formal interaction tests. Appendix D augments the baseline with interactions to test whether subgroup differences are statistically meaningful (Sec. C1). For households, Eq. (D1) and Table D1 show $\beta_3 > 0$ for CPI expectations when the indicator flags rural, female, or bottom-income households, and $\beta_3 < 0$ for income, durables, and macro outlook, with $\beta_3 > 0$ for unemployment expectations. This confirms *stronger belief updating and real-side pessimism* among more exposed or financially constrained groups. On the firm side, Eq. (D2) and Table D2 show $\beta_3 > 0$ for CPI and unit-cost expectations and $\beta_3 < 0$ for sales and outlook when the indicator flags SMEs and high leverage, while Table D4 documents larger real contractions for the same groups. These patterns reject a pure composition story: within-firm exposure effects are *larger* precisely where buffers are thinner.

6 Conclusion

This paper shows that locally unusual weather leaves a clear, measurable footprint on prices, beliefs, real activity, and credit in Türkiye. We first establish a dynamic first stage: a positive temperature anomaly pushes up food CPI for several months—peaking around months 4–6—before mean-reverting. We then trace this salient price signal into expectations and decisions. Households revise one-year-ahead CPI upward while reporting weaker income prospects, a darker macro outlook, lower willingness to buy durables, and heightened unemployment concerns. In the food sector, managers raise CPI and unit-cost expectations while marking down sales and overall conditions; realized outcomes soften at monthly horizons (domestic sales, exports, purchases, and—more slowly—employment). Credit adjusts along maturity rather than only quantity: firms draw more short-term bank credit and run down long-term balances, implying a temporary shortening of debt maturity consistent with working-capital needs when operating costs and logistics frictions rise.

Heterogeneity lines up with exposure and buffers: effects are stronger for rural, female, and

lower-income households, and for SMEs and highly leveraged firms; in credit, the maturity tilt is most pronounced among borrowers with better bank access (though constrained firms also reallocate toward short maturities). Crucially, the sign of the temperature deviation matters little for short-run beliefs: responses are *symmetric*—months with *extreme heat* and months with *extreme cold* raise inflation expectations by statistically similar magnitudes for both households and firms—because any sizeable departure from seasonal normals makes energy and food outlays unusually salient, compresses planning horizons, and, through mirrored cost and supply disruptions (cooling vs. heating loads, spoilage vs. freezing/breakage, logistics frictions, agricultural and productivity losses), generates comparable, sign-invariant near-term price pressure that agents extrapolate to overall inflation; moreover, state dependence is clear, as pass-through is *amplified in high-inflation episodes* relative to low-inflation episodes, when tighter liquidity and shorter planning horizons lead households and managers to monitor prices more frequently, rely more on salient food/energy signals, and update beliefs more aggressively.

Policy implications follow directly. In high-inflation environments, weather anomalies can temporarily widen the gap between headline inflation and underlying demand, complicating inference for monetary policy; clear communication that distinguishes transitory, climate-related supply impulses from persistent demand pressures can help stabilize expectations and limit second-round effects. Because transmission is heterogeneous and strongest for exposed or financially constrained agents, targeted adaptation and resilience—cold-chain and warehousing reliability, workplace heat mitigation, and logistics infrastructure—can dampen pass-through to costs, activity, and beliefs. Integrating high-frequency climate-risk metrics (province-level anomalies and probabilities of extremes) into policy and credit-risk dashboards can improve real-time assessment of near-term inflation risks and rollover vulnerabilities.

In sum, locally unusual weather is a salient, plausibly exogenous driver of short-run beliefs for both households and firms. By raising expected inflation while weakening perceived and realized conditions—and by shortening debt maturity—weather anomalies temporarily steepen the policy trade-off. Recognizing the symmetry of heat and cold shocks, the amplification under high

inflation, and the heterogeneity in transmission can help align monetary communication and climate-aware adaptation policies with an economy facing more frequent climate-related disturbances.

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Appendix - A - BTS and RCT Detailed Questionnaire

BTS Detailed Questionnaire

The BTS (Business Tendency Survey) collects data through monthly surveys of a representative sample of 1,800 to 2,200 manufacturing firms, since 2007. The questions from the BTS translated from Turkish are provided below:

Question 1: The production volume of your company over the last three month: Increased, Stayed the same, Decreased.

Question 2: The total amount of your currently registered orders: Above normal, Normal for the season, Below normal.

Question 3: The amount of your currently registered export orders: Above normal, Normal for the season, Below normal.

Question 4: The level of your current finished goods inventory: Above normal, Normal for the season, Below normal.

Question 5: Your production volume expectation for the next three months: It will increase, It will remain the same, It will decrease.

Question 6: Your sales price expectation for the next three months: It will increase, It will remain the same, It will decrease.

Question 7: Your total employment expectation for the next three months: It will increase, It will remain the same, It will decrease.

Question 8: The total amount of orders you received in the last three months: Increased, Stayed the same, Decreased.

Question 9: Your total order quantity expectation for the next three months: It will increase, It will remain the same, It will decrease.

Question 10: The amount of export orders you received in the last three months: Increased, Stayed the same, Decreased.

Question 11: Your export order quantity expectation for the next three months: It will increase,

It will remain the same, It will decrease.

Question 12: Your capacity utilization rate (Please indicate the actual capacity utilization as a percentage of physical capacity at present.)

Question 13: The amount of your currently registered domestic market orders: Above normal, Normal for the season, Below normal.

Question 14: The amount of domestic market orders you received in the last three months: Increased, Stayed the same, Decreased.

Question 15: Your domestic market order quantity expectation for the next three months: It will increase, It will remain the same, It will decrease.

Question 16: Your domestic market sales price expectation for the next three months: It will increase, It will remain the same, It will decrease.

Question 17: Compared to the past twelve months, your expectation for fixed capital investment expenditures in the next twelve months: It will increase, It will remain the same, It will decrease.

Question 18: Your average unit cost over the last three months: Increased, Stayed the same, Decreased.

Question 19: Your expectation for the average unit cost in the next three months: It will increase, It will remain the same, It will decrease.

Question 20: Your annual inflation expectation at the end of the next twelve-month period (Please specify as a percentage): (CPI:...) (PPI:...)

Question 21 :Your expectation for the short-term Turkish Lira interest rate in the upcoming three-month period: It will increase, It will remain the same, It will decrease.

Question 22: Your opinion on the general trend in your industry compared to a month ago: More optimistic, The same, More pessimistic.

Appendix - B - Placebo Test: Weather Anomaly Exposure and Firm Expectations in Non-Food Manufacturing

Table D1: Effect of Weather Anomalies on Other Manufacturing Firms' Expectations

	(1) All Sample	(2) Large	(3) SMEs	(4) High Leverage	(5) Low Leverage
Panel A: CPI Expectations					
Weather Anomalies$_{pt}$	-0.002	-0.002	0.003	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
R-squared	0.893	0.898	0.894	0.895	0.903
Observations	157,243	72,806	84,345	78,015	79,195
Panel B: Unit Cost Expectations					
Weather Anomalies$_{pt}$	0.002	0.002	0.003	0.003	0.001
	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
R-squared	0.324	0.315	0.353	0.331	0.348
Observations	182,102	83,226	98,816	89,919	92,162
Panel C: Economic Outlook					
Weather Anomalies$_{pt}$	-0.004	-0.003	-0.004	-0.003*	-0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.379	0.369	0.404	0.386	0.402
Observations	182,103	83,226	98,817	89,919	92,163
Panel D: Sales Expectations					
Weather Anomalies$_{pt}$	0.004	-0.002	0.002*	0.002*	-0.002
	(0.004)	(0.002)	(0.001)	(0.001)	(0.002)
R-squared	0.300	0.285	0.326	0.305	0.315
Observations	182,102	83,226	98,816	89,919	92,162
Firm FE	✓	✓	✓	✓	✓
Industry × Year-Month FE	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓

Notes: This table presents the estimation results for Equation 3 using manufacturing sectors excluding food-related manufacturing (NACE Rev. 2 C10–C12: food products, beverages, and tobacco). Each panel corresponds to a different dependent variable as labeled. In Panel A, the dependent variable is the logarithm of firms' 12-month-ahead CPI inflation expectations. Panels B–D are qualitative indices measured on a 1–3 scale, where 1 indicates pessimism, 2 indicates no change, and 3 indicates optimism (lower values denote more pessimistic assessments). An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table D2: Placebo: Effect of Lagged (t–12) Weather Anomalies on Households' Expectations

	(1) All Sample	(2) Rural	(3) Urban	(4) Male	(5) Female	(6) Bottom Income Group	(7) Top Income Group
Panel A: Effect on CPI Expectations							
Weather Anomalies$_{p,t-12}$	0.001	0.002	0.001	0.001	0.002	0.003	0.001
	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
R-squared	0.299	0.335	0.297	0.300	0.351	0.306	0.420
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Panel B: Effect on Income Expectations							
Weather Anomalies$_{p,t-12}$	-0.001	-0.002	-0.001	0.001	-0.001	-0.002	-0.001
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)
R-squared	0.051	0.066	0.045	0.061	0.075	0.087	0.112
Observations	293,252	32,074	261,178	148,007	145,243	112,307	44,818
Panel C: Effect on Durable Purchases							
Weather Anomalies$_{p,t-12}$	0.000	-0.001	0.000	0.001	-0.001	0.000	-0.001
	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
R-squared	0.057	0.089	0.054	0.082	0.085	0.121	0.136
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Panel D: Effect on Macro Outlook							
Weather Anomalies$_{p,t-12}$	-0.001	0.000	-0.001	-0.001	0.000	-0.001	0.000
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
R-squared	0.076	0.088	0.064	0.078	0.109	0.109	0.119
Observations	293,252	32,074	261,178	148,007	145,243	112,307	44,818
Panel E: Effect on Unemployment							
Weather Anomalies$_{p,t-12}$	0.000	0.001	0.000	0.000	0.001	0.000	0.000
	(0.002)	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
R-squared	0.057	0.094	0.054	0.085	0.081	0.101	0.142
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Wave FE	✓	✓	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓	✓	✓
Household Controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports *placebo* estimates of Eq. 2 where the regressor is the province–month temperature anomaly lagged by one year, Weather Anomalies$_{p,t-12}$. Each regression is weighted by household sampling weights and includes region-by-year-month and wave fixed effects and standard household covariates (education, age, income group, gender). Each panel corresponds to the labeled dependent variable. Standard errors, clustered by province, are in parentheses. None of the coefficients are statistically different from zero at conventional levels.

Table D3: Placebo: Effect of Lagged (t–12) Weather Anomalies on Firms' Expectations

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: CPI Expectations					
Weather Anomalies$_{p,t-12}$	0.001	0.002	0.001	0.001	0.002
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
R-squared	0.872	0.883	0.872	0.876	0.880
Observations	20,394	10,844	9,486	14,967	5,341
Panel B: Unit Cost Expectations					
Weather Anomalies$_{p,t-12}$	0.001	0.002	0.001	0.001	0.002
	(0.005)	(0.007)	(0.006)	(0.005)	(0.006)
R-squared	0.302	0.314	0.352	0.304	0.377
Observations	16,754	9,101	7,589	12,206	4,474
Panel C: Economic Outlook					
Weather Anomalies$_{p,t-12}$	-0.002	-0.003	-0.002	-0.003	-0.002
	(0.007)	(0.011)	(0.010)	(0.009)	(0.010)
R-squared	0.418	0.457	0.365	0.393	0.469
Observations	23,024	9,041	7,535	12,150	4,422
Panel D: Sales Expectations					
Weather Anomalies$_{p,t-12}$	-0.001	-0.002	-0.001	-0.002	-0.001
	(0.005)	(0.006)	(0.004)	(0.009)	(0.009)
R-squared	0.296	0.341	0.336	0.332	0.370
Observations	23,026	9,041	7,535	12,150	4,422
Firm FE	✓	✓	✓	✓	✓
Industry × Year-Month FE	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓

Notes: This table reports *placebo* estimates of Eq. 3 where the regressor is the province–month temperature anomaly lagged by one year, Weather Anomalies$_{p,t-12}$. Each panel corresponds to the labeled dependent variable. All regressions include firm fixed effects, industry×year-month and region×year-month fixed effects, and the standard firm covariates (leverage, exporter status, age, size). Standard errors, clustered by province, are in parentheses. None of the coefficients are statistically different from zero at conventional levels.

Appendix - C - Robustness Check

C1 Pre-Sample Moments

Table C1: Effect of Weather Anomalies on Households' Expectations (Pre-Sample Moments, 1990–2014)

	(1) All Sample	(2) Rural	(3) Urban	(4) Male	(5) Female	(6) Bottom Income Group	(7) Top Income Group
Panel A: Effect on CPI Expectations							
Weather Anomalies$_{pt}$	0.022***	0.027***	0.019**	0.020***	0.025***	0.030***	0.021***
	(0.005)	(0.010)	(0.007)	(0.005)	(0.006)	(0.011)	(0.006)
R-squared	0.328	0.364	0.326	0.329	0.380	0.335	0.449
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Panel B: Effect on Income Expectations							
Weather Anomalies$_{pt}$	-0.009**	-0.013**	-0.009**	0.008	-0.010**	-0.014**	-0.011*
	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)
R-squared	0.080	0.095	0.074	0.090	0.104	0.116	0.141
Observations	293,252	32,074	261,178	148,007	145,243	112,307	44,818
Panel C: Effect on Durable Purchases							
Weather Anomalies$_{pt}$	-0.006**	-0.010**	-0.005	-0.006*	-0.010***	-0.008**	-0.009
	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
R-squared	0.085	0.118	0.082	0.110	0.114	0.150	0.165
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Panel D: Effect on Macro Outlook							
Weather Anomalies$_{pt}$	-0.010**	-0.012**	-0.010**	-0.008	-0.013**	-0.014**	-0.010**
	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.006)	(0.004)
R-squared	0.105	0.117	0.093	0.107	0.138	0.140	0.148
Observations	293,252	32,074	261,178	148,007	145,243	112,307	44,818
Panel E: Effect on Unemployment							
Weather Anomalies$_{pt}$	0.008**	0.017**	0.007	0.009*	0.016***	0.012**	0.006
	(0.004)	(0.008)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
R-squared	0.085	0.122	0.082	0.110	0.106	0.126	0.166
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Wave FE	✓	✓	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓	✓	✓
Household Controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the estimation results for Equation 2, with each regression weighted by household sampling weights. Whether anomaly exposure standardized using the pre-sample mean and standard deviation (1990–2014). Each panel corresponds to a different dependent variable as labeled. In Panel A, the dependent variable is the logarithm of households' 12-month-ahead inflation expectations. Panels B–E are qualitative indices measured on a 1–3 scale, where 1 indicates pessimism, 2 indicates no change, and 3 indicates optimism (lower values denote more pessimistic assessments). Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table C2: Effect of Weather Anomalies on Firms' Expectations (Pre-Sample Moments, 1990–2014)

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: CPI Expectations					
Weather Anomalies$_{pt}$	0.009***	0.012**	0.006**	0.013**	0.007**
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)
Observations	20,394	10,844	9,486	14,967	5,341
R-squared	0.884	0.893	0.883	0.887	0.891
Panel B: Unit Cost Expectations					
Weather Anomalies$_{pt}$	0.015***	0.016**	0.012**	0.016***	0.013**
	(0.005)	(0.007)	(0.006)	(0.005)	(0.007)
Observations	16,754	9,101	7,589	12,206	4,474
R-squared	0.320	0.332	0.370	0.322	0.395
Panel C: Economic Outlook					
Weather Anomalies$_{pt}$	-0.029***	-0.041***	-0.026**	-0.036***	-0.022**
	(0.008)	(0.011)	(0.010)	(0.013)	(0.010)
Observations	23,024	9,041	7,535	12,150	4,422
R-squared	0.436	0.476	0.382	0.412	0.488
Panel D: Sales Expectation					
Weather Anomalies$_{pt}$	-0.012**	-0.017**	-0.010**	-0.022**	-0.011
	(0.005)	(0.007)	(0.004)	(0.010)	(0.012)
Observations	23,026	9,041	7,535	12,150	4,422
R-squared	0.315	0.359	0.354	0.350	0.386
Firm FE	✓	✓	✓	✓	✓
Industry x Year-Month FE	✓	✓	✓	✓	✓
Region x Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓

Notes: This table reports estimation results for Equation 3. Whether anomaly exposure standardized using the pre-sample mean and standard deviation (1990–2014). Each panel corresponds to a different dependent variable as labeled. In Panel A, the dependent variable is the logarithm of firms' 12-month-ahead CPI inflation expectations. Panels B–D are qualitative indices measured on a 1–3 scale, where 1 indicates pessimism, 2 indicates no change, and 3 indicates optimism (lower values denote more pessimistic assessments). An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table C3: Effect of Weather Anomalies on Firms' Real Outcomes (Pre-Sample Moments, 1990–2014)

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: Domestic Sales					
Weather Anomalies$_{pt-1}$	-0.012***	-0.015***	-0.009***	-0.016***	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R-squared	0.912	0.894	0.906	0.897	0.929
Mean Dependent Var.	17.12	17.92	16.43	16.92	17.16
Panel B: Exports					
Weather Anomalies$_{pt-1}$	-0.016***	-0.018***	-0.011***	-0.015**	-0.008***
	(0.005)	(0.006)	(0.004)	(0.006)	(0.003)
R-squared	0.892	0.869	0.900	0.879	0.872
Mean Dependent Var.	9.96	10.65	9.31	9.28	10.66
Panel C: Total Purchases					
Weather Anomalies$_{pt-1}$	-0.009**	-0.010**	-0.005**	-0.012**	-0.006**
	(0.004)	(0.004)	(0.002)	(0.005)	(0.003)
R-squared	0.851	0.827	0.859	0.855	0.856
Mean Dependent Var.	16.54	17.33	15.86	16.44	16.56
Panel D: Employment					
Weather Anomalies$_{pt-1}$	-0.006**	-0.007**	0.002	-0.006**	-0.003*
	(0.003)	(0.003)	(0.001)	(0.003)	(0.002)
R-squared	0.961	0.920	0.930	0.960	0.970
Mean Dependent Var.	5.78	6.61	5.08	5.69	5.81
Firm FE	✓	✓	✓	✓	✓
Industry × Year-Month FE	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Observations	20,864	10,919	9,979	10,284	10,614

Notes: Notes: This table presents the estimation results for Equation 3. Whether anomaly exposure standardized using the pre-sample mean and standard deviation (1990–2014). Each panel corresponds to a distinct dependent variable: Panel A is log domestic sales, Panel B is log exports, Panel C is log purchases from other firms, and Panel D is log employment. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table C4: Effect of Weather Anomalies on Firms' Outstanding Credits (Pre-Sample Standardization, 1990–2014)

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: Total Outstanding Credits					
Weather Anomalies$_{pt-1}$	0.021**	0.017*	0.024**	0.016**	0.024***
	(0.009)	(0.009)	(0.012)	(0.008)	(0.008)
R-squared	0.503	0.492	0.476	0.506	0.532
Mean Dependent Var.	9.36	9.91	8.89	9.38	9.32
Panel B: Short-term Outstanding Credits					
Weather Anomalies$_{pt-1}$	0.044**	0.055**	0.079***	0.046**	0.070**
	(0.017)	(0.024)	(0.026)	(0.016)	(0.027)
R-squared	0.305	0.275	0.349	0.296	0.360
Mean Dependent Var.	6.91	7.21	6.64	6.94	6.83
Panel C: Long-term Outstanding Credits					
Weather Anomalies$_{pt-1}$	-0.013**	-0.011**	-0.019***	-0.015**	-0.017**
	(0.006)	(0.005)	(0.007)	(0.007)	(0.008)
R-squared	0.349	0.312	0.402	0.352	0.388
Mean Dependent Var.	4.27	4.58	4.02	4.45	3.96
Bank × Firm FE	✓	✓	✓	✓	✓
Bank × Year-Month FE	✓	✓	✓	✓	✓
Industry × Year-Month FE	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Observations	96,181	52,290	43,888	61,528	34,650

Notes: This table presents the estimation results for Equation 3. Whether anomaly exposure standardized using the pre-sample mean and standard deviation (1990–2014). The unit of observation is firm–bank–province–year–month (j, b, p, t). In each panel, the dependent variable is defined as $y_{jbpt} = \log(X_{jbpt})$, where X_{jbpt} denotes the total outstanding credit amount in Panel A, the short-term outstanding credit amount in Panel B, and the long-term outstanding credit amount in Panel C. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C5: Effect of *Weather Uncertainty* on Households' Expectations

	(1) All Sample	(2) Rural	(3) Urban	(4) Male	(5) Female	(6) Bottom Income Group	(7) Top Income Group
Panel A: Effect on CPI Expectations							
Weather Uncertainty$_{pt}$	0.011***	0.014**	0.011***	0.011***	0.013***	0.016***	0.012***
	(0.003)	(0.008)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
R-squared	0.292	0.328	0.289	0.292	0.343	0.298	0.412
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Panel B: Effect on Income Expectations							
Weather Uncertainty$_{pt}$	-0.006**	-0.011***	-0.006**	0.002	-0.007**	-0.012***	-0.008**
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
R-squared	0.053	0.068	0.047	0.060	0.078	0.090	0.114
Observations	293,252	32,074	261,178	148,007	145,243	112,307	44,818
Panel C: Effect on Durable Purchases							
Weather Uncertainty$_{pt}$	-0.004**	-0.008**	-0.003**	-0.004**	-0.007***	-0.006**	-0.006
	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
R-squared	0.059	0.091	0.056	0.084	0.087	0.124	0.138
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Panel D: Effect on Macro Outlook							
Weather Uncertainty$_{pt}$	-0.008**	-0.010**	-0.007**	-0.006**	-0.011**	-0.011***	-0.008**
	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
R-squared	0.079	0.090	0.066	0.080	0.112	0.112	0.121
Observations	293,252	32,074	261,178	148,007	145,243	112,307	44,818
Panel E: Effect on Unemployment							
Weather Uncertainty$_{pt}$	0.002*	0.008**	0.001	0.003*	0.008**	0.005**	0.000
	(0.001)	(0.006)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
R-squared	0.058	0.095	0.054	0.084	0.083	0.103	0.142
Observations	184,363	14,788	169,574	96,530	87,774	58,718	33,449
Wave FE	✓	✓	✓	✓	✓	✓	✓
Region x Year-Month FE	✓	✓	✓	✓	✓	✓	✓
Household Controls	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the estimation results for Equation 3. The unit of observation is firm–bank–province–year–month (j, b, p, t). In each panel, the dependent variable is defined as $y_{jbpt} = \log(X_{jbpt})$, where X_{jbpt} denotes the total outstanding credit amount in Panel A, the short-term outstanding credit amount in Panel B, and the long-term outstanding credit amount in Panel C. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C6: Effect of *Weather Uncertainty* on Firms' Expectations

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: CPI Expectations					
Weather Uncertainty$_{pt}$	0.004***	0.007*	0.003**	0.007***	0.004**
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)
R-squared	0.870	0.881	0.871	0.874	0.878
Observations	20,394	10,844	9,486	14,967	5,341
Panel B: Unit Cost Expectations					
Weather Uncertainty$_{pt}$	0.008***	0.009**	0.007*	0.009***	0.007*
	(0.005)	(0.007)	(0.006)	(0.005)	(0.006)
R-squared	0.305	0.318	0.356	0.307	0.380
Observations	16,754	9,101	7,589	12,206	4,474
Panel C: Economic Outlook					
Weather Uncertainty$_{pt}$	-0.026***	-0.037***	-0.023**	-0.032***	-0.020**
	(0.007)	(0.011)	(0.010)	(0.010)	(0.011)
R-squared	0.423	0.463	0.371	0.399	0.474
Observations	23,024	9,041	7,535	12,150	4,422
Panel D: Sales Expectations					
Weather Uncertainty$_{pt}$	-0.010**	-0.015**	-0.009**	-0.018**	-0.008
	(0.004)	(0.006)	(0.004)	(0.009)	(0.010)
R-squared	0.300	0.346	0.340	0.336	0.374
Observations	23,026	9,041	7,535	12,150	4,422
Firm FE	✓	✓	✓	✓	✓
Industry x Year-Month FE	✓	✓	✓	✓	✓
Region x Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓

Notes: This table presents the estimation results for Equation 3. Each panel corresponds to a different dependent variable as labeled. In Panel A, the dependent variable is the logarithm of firms' 12-month-ahead CPI inflation expectations. Panels B–D are qualitative indices measured on a 1–3 scale, where 1 indicates pessimism, 2 indicates no change, and 3 indicates optimism (lower values denote more pessimistic assessments). An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table C7: Effect of *Weather Uncertainty* on Firms' Real Outcomes

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: Domestic Sales					
Weather Uncertainty$_{pt-1}$	-0.010***	-0.014***	-0.007***	-0.015***	-0.008**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
R-squared	0.909	0.891	0.904	0.894	0.927
Mean Dependent Var.	17.12	17.92	16.43	16.92	17.16
Panel B: Exports					
Weather Uncertainty$_{pt-1}$	-0.015***	-0.018***	-0.010***	-0.014**	-0.008***
	(0.005)	(0.006)	(0.003)	(0.004)	(0.003)
R-squared	0.888	0.866	0.897	0.876	0.868
Mean Dependent Var.	9.96	10.65	9.31	9.28	10.66
Panel C: Total Purchases					
Weather Uncertainty$_{pt-1}$	-0.008**	-0.009**	-0.004**	-0.012**	-0.006**
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)
R-squared	0.846	0.824	0.854	0.851	0.851
Mean Dependent Var.	16.54	17.33	15.86	16.44	16.56
Panel D: Employment					
Weather Uncertainty$_{pt-1}$	-0.005**	-0.006**	0.000	-0.006**	-0.003*
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
R-squared	0.959	0.918	0.928	0.958	0.968
Mean Dependent Var.	5.78	6.61	5.08	5.69	5.81
Firm FE	✓	✓	✓	✓	✓
Industry × Year-Month FE	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Observations	20,864	10,919	9,979	10,284	10,614

Notes: This table presents the estimation results for Equation 3. Each panel corresponds to a distinct dependent variable: Panel A is log domestic sales, Panel B is log exports, Panel C is log purchases from other firms, and Panel D is log employment. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table C8: Effect of *Weather Uncertainty* on Firms' Outstanding Credits

	(1) All Sample	(2) SMEs	(3) Large	(4) High Leverage	(5) Low Leverage
Panel A: Total Outstanding Credits					
Weather Uncertainty$_{pt-1}$	0.024***	0.021**	0.029**	0.018**	0.028***
	(0.008)	(0.009)	(0.012)	(0.008)	(0.008)
R-squared	0.503	0.494	0.479	0.508	0.533
Mean Dependent Var.	9.36	9.91	8.89	9.38	9.32
Panel B: Short-term Outstanding Credits					
Weather Uncertainty$_{pt-1}$	0.051***	0.063**	0.087***	0.052***	0.074**
	(0.017)	(0.025)	(0.027)	(0.017)	(0.028)
R-squared	0.305	0.276	0.350	0.296	0.362
Mean Dependent Var.	6.91	7.21	6.64	6.94	6.83
Panel C: Long-term Outstanding Credits					
Weather Uncertainty$_{pt-1}$	-0.015**	-0.013***	-0.022***	-0.018**	-0.020**
	(0.006)	(0.005)	(0.007)	(0.007)	(0.008)
R-squared	0.349	0.312	0.404	0.353	0.388
Mean Dependent Var.	4.27	4.58	4.02	4.45	3.96
Bank × Firm FE	✓	✓	✓	✓	✓
Bank × Year-Month FE	✓	✓	✓	✓	✓
Industry × Year-Month FE	✓	✓	✓	✓	✓
Region × Year-Month FE	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Observations	96,181	52,290	43,888	61,528	34,650

Notes: This table presents the estimation results for Equation 3. The unit of observation is firm–bank–province–year–month (j, b, p, t). In each panel, the dependent variable is defined as $y_{jbpt} = \log(X_{jbpt})$, where X_{jbpt} denotes the total outstanding credit amount in Panel A, the short-term outstanding credit amount in Panel B, and the long-term outstanding credit amount in Panel C. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix - D - Robustness: Group-Level Heterogeneity via Interaction Tests

To formally test whether subgroup responses differ from their counterparts, we augment the baseline specifications by including a group indicator D_{it} and its interaction with the shock of interest. For households, we estimate

$$y_{ipt} = \beta_0 + \beta_1 \text{WeatherAnomalies}_{pt} + \beta_2 D_{it} + \beta_3 \big(D_{it} \times \text{WeatherAnomalies}_{pt}\big) + X'_{ipt}\gamma + \delta_p + \lambda_t + \varepsilon_{ipt}. \tag{D1}$$

where y_{ipt} is household i's expectation outcome in province p and wave t (see Eq. 2). We define D_{it} at the household level for each comparison in turn:

- **Rural vs. Urban:** $D_{it} = 1$ for rural households; 0 for urban.
- **Male vs. Female:** $D_{it} = 1$ for female; 0 for male (so β_3 measures the female differential).
- **Income:** $D_{it} = 1$ for bottom income group; 0 for top income group.

In this parameterization, β_3 captures whether the sensitivity to local weather anomalies differs significantly for the $D_{it} = 1$ group relative to its counterpart. A positive (negative) β_3 implies a stronger (weaker) response for the subgroup coded as 1.

On the firm side, we estimate the analogous augmented model:

$$y_{jpt} = \beta_0 + \beta_1 \text{WeatherAnomalies}_{pt} + \beta_2 D_{jpt} + \beta_3 \big(D_{jpt} \times \text{WeatherAnomalies}_{pt}\big) + X'_{jpt}\gamma + \alpha_j + \delta_{st} + \phi_p + \varepsilon_{jpt}. \tag{D2}$$

where y_{jpt} denotes firm j's expectation (CPI inflation, unit cost, macro outlook, or sales) in province p and year–month t. We define D_{jpt} separately for each comparison:

- **Size:** $D_{jpt} = 1$ for SMEs; 0 for large firms.
- **Leverage:** $D_{jpt} = 1$ for high-leverage firms (debt-to-asset ratio above the NACE-2 industry

median); 0 for low leverage.

As above, β_3 measures whether weather-anomaly transmission differs for the $D_{jpt} = 1$ group relative to its counterpart.

The interaction estimates substantiate the subgroup patterns reported in the main tables. For households (Table D1), $\beta_3 > 0$ for CPI expectations when D identifies rural, female, or bottom-income households, indicating *stronger upward revisions* in salient inflation beliefs following locally unusual weather. Conversely, $\beta_3 < 0$ for income expectations, durable-purchase intentions, and macro outlook for the same groups, consistent with *more pessimistic real-side assessments* in response to adverse anomalies; $\beta_3 > 0$ for unemployment expectations reinforces this pattern of heightened near-term concern.

For firms (Table D2), $\beta_3 > 0$ for CPI and unit-cost expectations when D identifies SMEs and high-leverage firms, implying *larger perceived price/cost pressures* after heat anomalies, while $\beta_3 < 0$ for macro outlook and sales expectations, consistent with *tighter near-term conditions* (e.g., operating frictions, weaker demand). These interaction results confirm that the group-by-group estimates are statistically meaningful and not artifacts of sample composition.

Table D1: Heterogeneity in Household Expectations

	(1) CPI Expectations	(2) Income Expectations	(3) Macro Outlook	(4) Durable Purchases	(5) Unemployment Expectations
Panel A: Rural vs. Urban					
Weather Anomalies$_{pt}$ × Rural	0.003*	-0.005**	-0.002*	-0.005***	0.009***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)
R-squared	0.299	0.051	0.078	0.550	0.057
Panel B: Male vs. Female					
Weather Anomalies$_{pt}$ × Female	0.004**	-0.005***	-0.004**	-0.004***	0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
R-squared	0.306	0.054	0.076	0.058	0.061
Panel C: Bottom vs. Top Income					
Weather Anomalies$_{pt}$ × Bottom	0.005***	-0.002*	-0.004**	-0.007***	0.009***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
R-squared	0.301	0.051	0.072	0.057	0.059
Wave FE	✓	✓	✓	✓	✓
Region x Year-Month FE	✓	✓	✓	✓	✓
Household Controls	✓	✓	✓	✓	✓
Observations	184,363	293,252	293,252	184,363	184,363

Notes: This table presents the estimation results for Equation D1, with each regression weighted by household sampling weights. Each column corresponds to a different dependent variable as labeled: (1) CPI Expectations, (2) Income Expectations, (3) Macro Outlook, (4) Durable Purchases, and (5) Unemployment Expectations. Column (1) is the (log) 12-month-ahead inflation expectation; columns (2)–(5) are qualitative indices on a 1–3 scale, where 1 indicates pessimism, 2 no change, and 3 optimism (lower values denote more pessimistic assessments). Each panel reports the coefficient on an interaction between weather-anomaly exposure and a subgroup indicator from the augmented regression in Eq. (D1). Panel A estimates Exposure × Rural (rural vs. urban); Panel B estimates Exposure × Female (female vs. male); Panel C estimates Exposure × Bottom (bottom vs. top income group). A positive (negative) coefficient indicates a stronger (weaker) response for the indicated subgroup relative to its counterpart. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table D2: Heterogeneity in Firm Expectations

	(1) CPI Expectations	(2) Unit Cost Expectations	(3) Economic Outlook	(4) Sales Expectation
Panel A: SMEs vs. Large Firms				
Weather Anomalies$_{pt}$ × SMEs	0.004*	0.007**	-0.010**	-0.004*
	(0.002)	(0.003)	(0.004)	(0.002)
R-squared	0.869	0.309	0.405	0.295
Panel B: High- vs. Low-leverage Firms				
Weather Anomalies$_{pt}$ × Low Leverage	0.004**	0.006**	-0.009***	-0.012***
	(0.002)	(0.003)	(0.003)	(0.004)
R-squared	0.875	0.311	0.422	0.295
Firm FE	✓	✓	✓	✓
Industry x Year-Month FE	✓	✓	✓	✓
Region x Year-Month FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Observations	20,394	16,754	23,024	23,026

Notes: This table reports estimation results for Equation D2. Each column is a different dependent variable as labeled: (1) CPI Expectations, (2) Unit Cost Expectations, (3) Economic Outlook, (4) Sales Expectation. Column (1) is the (log) 12-month-ahead CPI inflation expectation; columns (2)–(4) are qualitative indices on a 1–3 scale, where 1 indicates pessimism, 2 no change, and 3 optimism (lower values denote more pessimistic assessments). Panel A reports Exposure × SME (SMEs vs. large firms); Panel B reports Exposure × High Leverage (firms above the industry-median debt-to-asset ratio vs. below). A positive (negative) coefficient indicates a stronger (weaker) response to weather anomalies for the indicated subgroup relative to its counterpart. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table D3: Heterogeneity in Firm Real Outcomes

	(1) Domestic Sales	(2) Exports	(3) Purchases	(4) Employment
Panel A: SMEs vs. Large Firms				
Weather Anomalies$_{pt}$ × SMEs	-0.005***	-0.005**	-0.006**	-0.006***
	(0.002)	(0.002)	(0.003)	(0.002)
R-squared	0.901	0.892	0.951	0.845
Panel B: High- vs. Low-leverage Firms				
Weather Anomalies$_{pt}$ × Low Leverage	-0.007**	-0.004**	-0.004**	-0.003*
	(0.003)	(0.002)	(0.002)	(0.002)
R-squared	0.899	0.895	0.948	0.842
Firm FE	✓	✓	✓	✓
Industry x Year-Month FE	✓	✓	✓	✓
Region x Year-Month FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Observations	20,864	20,864	20,864	20,864

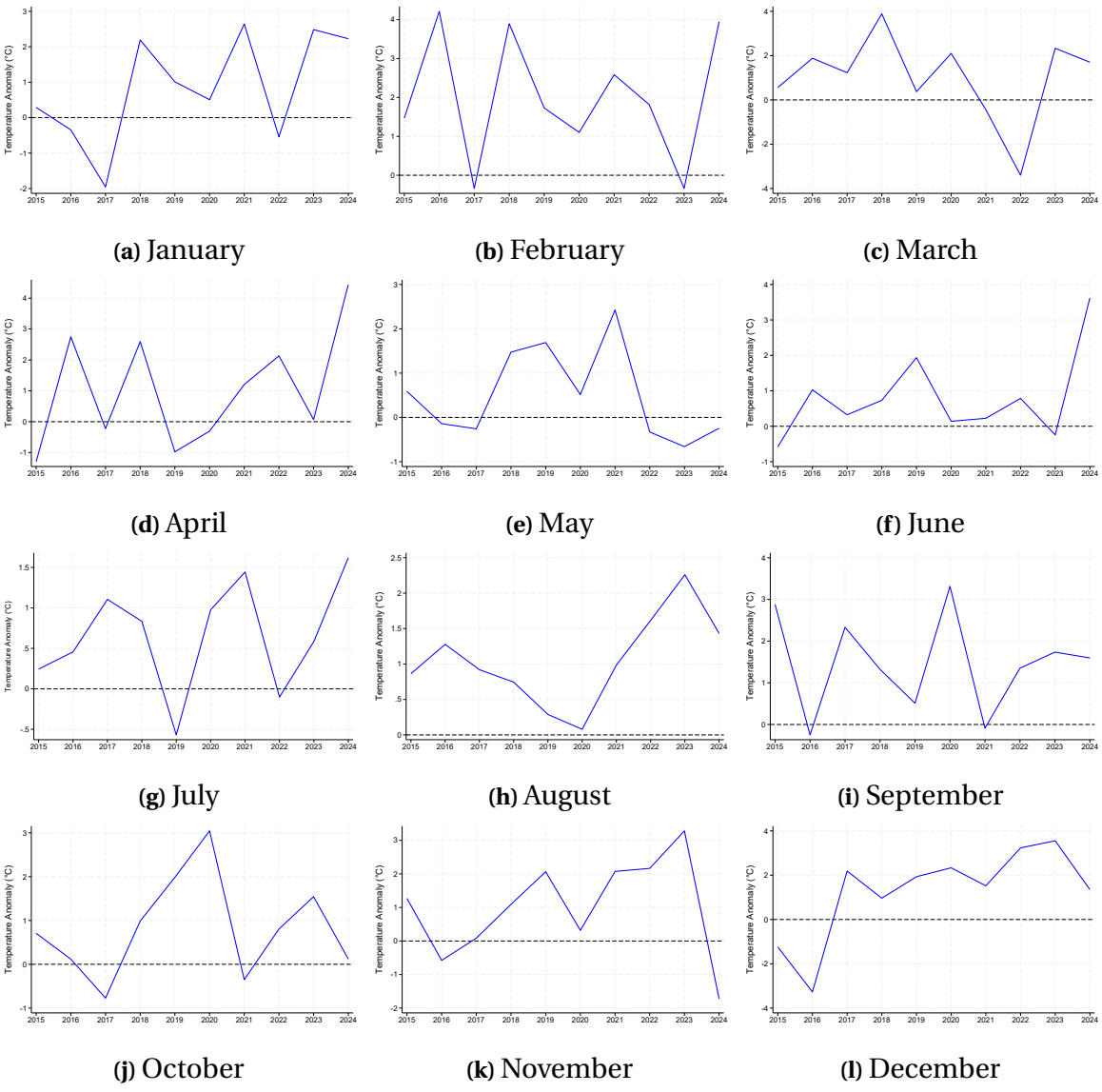
Notes: This table reports estimation results for Equation D2. Each column is a different dependent variable as labeled: (1) CPI Expectations, (2) Unit Cost Expectations, (3) Economic Outlook, (4) Sales Expectation. Column (1) is the (log) 12-month-ahead CPI inflation expectation; columns (2)–(4) are qualitative indices on a 1–3 scale, where 1 indicates pessimism, 2 no change, and 3 optimism (lower values denote more pessimistic assessments). Panel A reports Exposure × SME (SMEs vs. large firms); Panel B reports Exposure × High Leverage (firms above the industry-median debt-to-asset ratio vs. below). A positive (negative) coefficient indicates a stronger (weaker) response to weather anomalies for the indicated subgroup relative to its counterpart. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table D4: Heterogeneity in Firm Credit Market Outcomes

	(1) Domestic Sales	(2) Exports	(3) Purchases
Panel A: SMEs vs. Large Firms			
Weather Anomalies$_{pt}$ × SMEs	-0.005***	-0.005**	-0.006**
	(0.002)	(0.002)	(0.003)
R-squared	0.901	0.892	0.951
Panel B: High- vs. Low-leverage Firms			
Weather Anomalies$_{pt}$ × Low Leverage	-0.007**	-0.004**	-0.004**
	(0.003)	(0.002)	(0.002)
R-squared	0.899	0.895	0.948
Bank x Firm FE	✓	✓	✓
Bank x Year-Month FE	✓	✓	✓
Industry x Year-Month FE	✓	✓	✓
Region x Year-Month FE	✓	✓	✓
Firm Controls	✓	✓	✓
Observations	20,864	20,864	20,864

Notes: This table reports estimation results for Equation D2. Each column is a different dependent variable as labeled: (1) CPI Expectations, (2) Unit Cost Expectations, (3) Economic Outlook, (4) Sales Expectation. Column (1) is the (log) 12-month-ahead CPI inflation expectation; columns (2)–(4) are qualitative indices on a 1–3 scale, where 1 indicates pessimism, 2 no change, and 3 optimism (lower values denote more pessimistic assessments). Panel A reports Exposure × SME (SMEs vs. large firms); Panel B reports Exposure × High Leverage (firms above the industry-median debt-to-asset ratio vs. below). A positive (negative) coefficient indicates a stronger (weaker) response to weather anomalies for the indicated subgroup relative to its counterpart. An SME is a firm with fewer than 250 employees; firms with 250 or more employees are classified as large. High-leverage firms are those whose leverage ratio (total debt/total assets) lies in the top 20th percentile of the sector–year distribution; low-leverage firms are the remainder. Standard errors, clustered by province, are reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Appendix - E - Additional Figures



(a) January **(b)** February **(c)** March

(d) April **(e)** May **(f)** June

(g) July **(h)** August **(i)** September

(j) October **(k)** November **(l)** December

Figure E1: Monthly Temperature Anomalies by Calendar Month

Notes: Each panel (a)–(l) plots the time series of monthly temperature anomalies for a given calendar month (January … December). For each province p and month m, the anomaly is the deviation of that month's realized average temperature from its province-specific 30-year mean for the same calendar month. The figure shows the simple average of these province-level anomalies across all provinces, by month and year. Units are degrees Celsius. Baseline is a 30-year normal (e.g., 1991–2020).

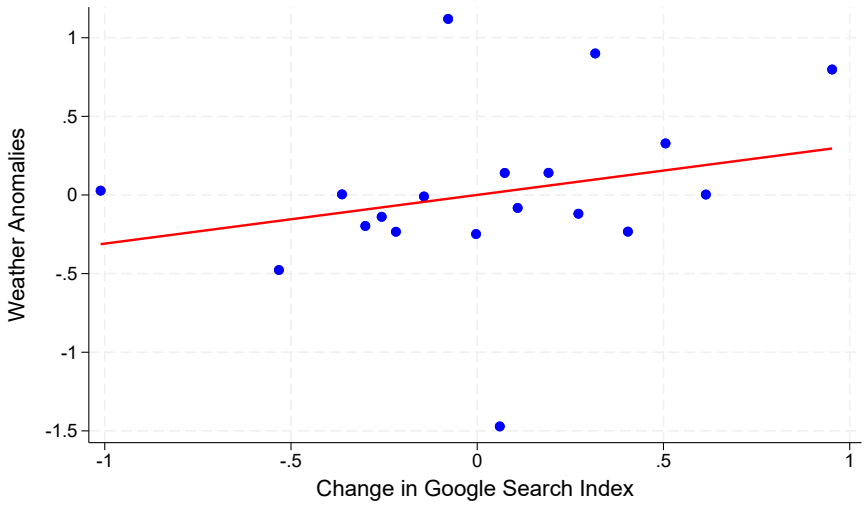


Figure E2: Whether Anomalies and Google Search Index for Climate Risks

Notes: *Notes*— The figure reports a binscatter of the national monthly weather anomaly (°C) against the change in the Google Search Index for "*drought, air frost and climate change*" (index points). Sample: 2015m1–2024m12.