Climate Change and Efficiency of Sales Forecasts*

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Abstract

We test the efficiency of food-industry sales forecasts with respect to drought trends driven by rising global temperatures. Using consensus analyst forecasts from thirty-one countries with publicly-traded food companies between 1996 and 2015, panel regressions with country and time fixed-effects find that sales forecasts significantly decline with the Palmer Drought Severity Index. However, these forecasts are inefficient predictors of sales as they over-estimate sales in countries with negative drought trends. Similar results hold using management forecasts. These predictable forecast errors are significantly correlated with food-industry stock returns across countries.

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1 Introduction

Quantifying the effects of global warming on the economy depend in large part on understanding the expectations of households and firms. A large literature on integrated assessment models aims to measure the potential damages from climate change and help policy makers trade off the costs and benefits of emissions interventions (Nordhaus (2017), Pindyck (2013), Stern (2007)). The most recent studies in this climate-economy literature argue for using year-to-year fluctuations in temperature to identify the effects of climate change on a variety of outcomes such as crop yields or mortality, just to name a few of the dependent variables of interest (Dell, Jones, and Olken (2014), Deschenes and Greenstone (2007), Schlenker and Roberts (2009)). The expectations channel, how agents might learn from weather and update their beliefs regarding a warming climate, is widely acknowledged to be important for understanding long-run effects as agents adapt and shift investments (Lemoine (2017), Hsiang (2016)). But it has not been studied, in part due to a lack of survey data on such forecasts.

At the same time, financial market regulators are increasingly worried about the efficiency of such forecasts, particularly in regards to the beliefs of households and firms about their financial and real investments, respectively (Carney (2015)). Risks include a potential price for carbon that adversely affects fossil fuel companies and natural disasters such as hurricanes and droughts that negatively impact the insurance or agricultural sectors. Regulators are already proposing various costly disclosure requirements to address climate risks. At the same time, the potential benefits depend on the biases of these forecasts, which at this point are unknown. A recent climate finance literature has begun to examine whether stock markets are efficiently pricing in these risks (Hong, Li, and Xu (2017), Bansal, Kiku, and Ochoa (2014), Andersson, Bolton, and Samama (2016)). But stock prices are noisy measures of expectations, particularly the ones held by managers, which over the long run influence real investment decisions (Gennaioli, Ma, and Shleifer (2016)).

With these motivations in mind, we analyze the efficiency of sales forecasts, made by security analysts and managers, for food companies in a warming climate. Climate science finds that the trend increase in global temperatures generates dispersion in drought trends across countries with many countries potentially adversely affected while some might actually benefit (Trenberth, Dai, van der Schrier, Jones, Barichivich, Briffa, and Sheffield (2014)). Since food output falls severely with droughts and most food companies are small to medium sized firms, the food industries are significantly exposed to the climate conditions of their country of origin and hence climate change risk.[1] As such, sales forecasts are highly correlated with beliefs about climate change. By examining these sales forecasts, we can better understand how firms form such expectations about the underlying climate parameters driving drought frequency and intensity.

Specifically, we test the efficiency of food-industry sales forecasts with respect to drought trends driven by higher global temperatures. We implement a rational forecasts test, where we regress various measures of realized sales or long-term sales growth at the firm level on the corresponding consensus sales forecasts (Nordhaus (1987)). Our empirical design expands on Hong, Li, and Xu (2017) who study whether food stock prices efficiently price in drought risks. Using data from thirty-one countries with publicly-traded food companies, they rank these countries each year based on their long-term trends toward droughts using the Palmer Drought Severity Index (Palmer (1965), Alley (1984)), a widely used measure of droughts in the climate sciences. A poor trend ranking for a country forecasts relatively poor profit growth and importantly stock returns for food companies in that country, consistent with food stock prices underreacting to climate change risks. In contrast, we examine the extent to which forecast errors are predictable based on publicly available information regarding drought trends.

For these same thirty-one countries with publicly traded food stocks from 1996 to 2016, we gather the consensus analyst sales forecasts, which are available for the next year (FY1) and the year after (FY2), and long-term sales growth (LTG) forecasts for years three through

[1]A recent study (Lesk, Rowhani, and Ramankutty (2016)) found that droughts have the most severe effects on output compared to other natural disasters. They found that droughts cut a country's crop production by ten percent, heat waves by nine percent, but floods and cold spells had no effects on agricultural production levels.

five out. For seven countries in our sample, we can also get management forecasts of 1-year ahead sales. Not surprisingly, management forecasts are highly correlated with the consensus analyst forecasts due to management guidance. In addition, we back out managers' long-term sales growth forecasts using the tractable investment model of Bolton, Chen, and Wang (2011). These implied forecasts are also highly correlated with actual sales projections.

We focus on sales rather than earnings as our baseline since earnings are subject to the differential treatment of capital expenses across the world. Sales is more uniformly treated by accounting standards. Given that demand for agricultural goods are price elastic, droughts should directly translate to a decline in sales volume.[2] As such, sales forecasts by analysts and management should take into account the persistence and intensity of droughts and are hence proxies for their beliefs about climate change.

We begin our empirical analysis by verifying the premise of our study that accounting for droughts and the persistence of droughts is a first-order concern of sales forecasts. We find using panel regressions with country and time fixed effects that sales forecasts significantly decline with droughts as measured by the Palmer Drought Severity Index (Karl (1986), Dai, Trenberth, and Qian (2004))). We obtain the strongest results when we consider a 36-month moving average of PDSI (PDSI36). Our empirical approach borrows from the climate-economy literature by using country fixed-effects and time fixed-effects to deal with omitted variables in a panel data setting. Essentially we are using only the time series variations in droughts in a country to see how it affects sales forecasts. Since droughts are mean-reverting, we can use country-specific variations in PDSI to measure this effect. As such, we do not have to worry about differences in forecast biases across countries per se.

PDSI is among the strongest explanatory variables for sales forecasts. It affects both FY1 and FY2 but has no effect on the long-term growth rates. There is some mixed evidence that

[2]Indeed, there are an increasing number of reports of dramatic short-falls in earnings and compressed profitability ratios or margins due to drought. See "Feeding Ourselves Thirsty: How the Food Sector is Managing Global Water Risks", *A Ceres Report*, May 2015.

analysts in negative trending countries drop their LTG forecasts when PDSI is low. Overall, this evidence is consistent with analysts and managers believing that droughts significantly affect sales for the next couple of years but that the effects of droughts do not persist over the long term. We conduct a similar set of analyses for other industries, which we can think of as a placebo check that the response of sales forecasts to droughts is not due to omitted variables, and indeed find that only the sales forecasts for the food industry responds to droughts. When we replace PDSI with temperature, which is widely used in the new climate-economy literature, we find that analyst forecasts do not respond to temperature. That is, analysts and management in our sample are likely learning about climate change through outcomes in droughts as opposed to temperature per se.

We then test the extent to which these sales forecasts are optimal. We regress realized FY1 and FY2 sales and LTG sales growth outcomes at the firm level on the corresponding consensus sales forecasts. The null hypothesis that these sales forecasts efficiently utilize all available information corresponds to the coefficient in front of the sales forecasts being be one. Moreover, under this null hypothesis, no other variables should come in besides sales forecasts when predicting actual sales. That is, the sales forecasts are sufficient statistics or best predictor for future sales.

We implement these regressions using both country and time fixed effects. For FY1, the coefficient is close to 1, around 0.7. Consistent with the literature, this coefficient declines as we go further out to FY2 and LTG outcomes. That is, longer-term forecasts are less efficient than near-term ones. As a result, high sales forecasts in these countries on average predict negative errors, where error is defined as sales minus the consensus forecasts. We also find that the coefficient is much smaller for negative trending PDSI countries. To a lesser degree, the coefficient is also smaller for positive trending PDSI countries. That is, we can predict the forecast error using the past drought trends of the country. Sales forecasts underreact to these climate trends. This is true even in the recent sub-sample after 2007, when climate change concerns are publicly known. We find similar results when we use earnings rather than sales for all of our analyses.

We then relate these predictable forecast errors to food industry returns across the 31 countries. We regress annual returns to food industry portfolios on these predictable forecast errors and unforecastable forecast errors. We find a strong positive relationship between the predictable forecast errors and returns. Our findings suggest that the underreaction in food industry stock returns documented in Hong, Li, and Xu (2017) is due to predictable forecasts errors from consensus analyst and management forecasts underreacting to drought trends. While our analysis points to underreaction, it stops short of specifying the causal mechanisms, of which there can be many. One might be agency issues where managers are short-termist (Stein (1989)) or analysts have career concerns (Scharfstein and Stein (1990), Hong, Kubik, and Solomon (2000)). Alternatively, this underreaction might be driven by rational inattention mechanisms (Sims (2003)), or behavioral biases (De Bondt and Thaler (1990), Barberis, Shleifer, and Vishny (1998)).

Our paper proceeds as follows. We present the data and construction of the key variables of interest in Section II. In Section III, we present our findings on how sales forecasts respond to droughts as measured by PDSI36. In Section IV, we present our findings on whether sales forecasts are efficient predictors of future sales with respect to drought trends. In Section V, we relate these predictable forecast errors to stock returns. We conclude in Section VI.

2 Data, Variables and Summary Statistics

2.1 Analyst Forecasts

Accounting variables for international countries are obtained from the Compustat North America database for U.S. and Canadian stocks, and Compustat Global for the remaining countries in our analysis. Our sample is limited to common stocks, those that are the primary securities of their respective companies, and those traded on major stock exchanges.[3] The sample includes live as well as dead stocks, ensuring that the data are free of survivorship bias.

We obtain the analyst consensus forecast data from I/B/E/S, which is calculated as the median of individual forecasts. We analyst forecasts of 1-year ahead (FY1) and 2-year ahead (FY2) sales and net income, as well as long-term growth rates (LTG). We average the monthly consensus forecast data within the same fiscal year (an obtain an average annual number) to match the frequency of accounting variables. Based on the 4-digit SIC code, we classify all firms into 17 industries based on Fama-French 17 industry classification. Finally, country-level macroeconomic variables including GDP growth, GDP per capital, inflation rate, risk-free rate and unemployment rate are from World Bank database. The sample period is from year 1996 to year 2015.

Table 1 provides the summary statistics of these variables. For sales forecasts, the mean of FY1/Asset (FY1 sales forecast scaled by total asset) is 1.18 with a standard deviation of 0.76, and the mean of FY2/Asset (FY2 sales forecast scaled by total asset) is 1.28 with a standard deviation of 0.84. The mean of long-term sales growth forecast LTG is 0.14 with a standard deviation of 0.13. These figures are often referred to as asset turnover ratios, which depending on the industry ranges from 0.5 for utilities companied on the low end to 3 for retail companies on the high end. Food companies are somewhere in the middle of this range.

For earnings forecasts, the mean of Earnings FY1/Asset (or forecast of return on assets ROA) is 0.05 with a standard deviation of 0.048, and the mean of Earnings FY2/Asset is 0.06 with a standard deviation of 0.049. The mean of the annual sales growth of food companies (Sales Growth) is 0.16 with a standard deviation of 0.58. The median GDP growth rate is

[3]For most countries, there is only one major exchange on which the majority of stocks in that country are listed, except for the following countries: Canada (Toronto Stock Exchange and TSX Ventures Exchange), China (Shanghai Stock Exchange and Shenzhen Stock Exchange), India (Bombay Stock Exchange and National Stock Exchange), Japan (Osaka Securities Exchange, Tokyo Stock Exchange, and JASDAQ), Russia (Moscow Interbank Currency Exchange (MICEX) and Russian Trading System (RTS), which were later merged to form Moscow Exchange), South Korea (Korea Stock Exchange and KOSDAQ, which were later merged to form Korea Exchange but remained as separate divisions), and U.S.(NYSE, AMEX and NASDAQ).

3.20%, inflation rate is 2.66%, GDP per capita is about 30000 (constant 2010 US dollar), and Unemployment rate is about 7%.

2.2 Management Forecasts and Implied Management Forecasts

The managerial guidance data is available from the I/B/E/S guidance database. The coverage of I/B/E/S guidance data for international countries is sparse. We can get managers' sales forecast data from 7 countries, including US, Belgium, Denmark, France, United Kingdom, Ireland and Italy. Table 2 reports the summary statistics of managerial forecast of sales. As we can see, except US, we have very few observations with limited sample period coverage for other countries. Panel B shows that managers' forecast of 1-year ahead sales is highly correlated with analysts' consensus forecast. For US, the time series correlation between managers' and analysts' forecast at industry and firm level is 1.00 and 0.93, respectively. For other countries with available data, we calculate a panel correlation between managers' and analysts' forecast, which is 0.99. The high correlation is partially driven by the practice that managers frequently communicate their forecast with analysts to make sure they do not surprise the market when announcing their performance. This suggests that analysts' consensus forecast could be used as a reasonable proxy for managers' own forecast.

Due to the small sample of managerial forecasts, we also back out managers' expectation of sales growth using a neoclassical model of optimal investment without financing frictions, as in Bolton, Chen, and Wang (2011). In the model, firm employs physical capital for production. We denote by K and I the level of capital stock and gross investment, respectively. Firm's capital stock K evolves according to:

$$dK_t = (I_t - \delta K_t)dt \tag{1}$$

where $\delta >= 0$ is the rate of depreciation.

The firm's revenue at time t is proportional to its capital stock K_t, and is given by $K_t dA_t$, where dA_t is the firm's revenue shock over time increment dt. The firm's cumulative productivity evolves according to:

$$dA_t = \mu dt + \delta dZ_t \tag{2}$$

where Z is a standard brownian motion under risk-neural measure. The parameters $\mu > 0$ and $\delta > 0$ are the mean and volatility of the productivity shock dA_t.

The firm's incremental operating profit dY_t over time increment dt is given by:

$$dY_t = K_t dA_t - I_t dt - G(I_t, K_t)dt \tag{3}$$

where $G(I, K)$ is the additional adjustment cost that the firm incurs in the investment process. As is standard in the literature, the adjustment cost takes the form of $G(I, K) = g(i)K$, where i is the firm's investment capital ratio ($i = I/K$) and $g(i)$ is the standard quadratic function

$$g(i) = \theta i^2/2 \tag{4}$$

where the parameter θ measures the degree of adjustment cost.

Bolton, Chen, and Wang (2011) show that without financing frictions, the first-best investment rate i_{FB} in this continuous time AK model of investments with quadratic adjustment cost is given by the following equation:

$$i_{FB} = r + \delta - \sqrt{(r + \delta)^2 - 2(\mu - (r + \delta))/\theta} \tag{5}$$

Assuming observed investment rate i equals to first-best investment rate i_{FB}, we can back out the manager's expected productivity growth from the observed investment level:

$$\mu = \theta/2 \times ((r+\delta)^2 - (r+\delta-i)^2) + r + \delta \tag{6}$$

The interest rate for each country-year is from World Bank database. The depreciation rate is the mean annual depreciation rate of food industry in each country, calculated as depreciation expenses scaled by lagged total assets. For the adjustment cost parameter θ, we follow the literature (Whited (1992)) and set the parameter value to 1.5. i is the actual investment rate for each food company in each year, calculated as capital expenditures divided by lagged total assets. After plugging in all the parameters, we can estimate the managers' expected productivity growth μ for each food company in each year, which should be correlated with the LTG sales forecasts from the analysts.

We measure the actual long-term growth of sales following Dechow and Sloan (1997) and I/B/E/S methodology. Dechow and Sloan (1997) argue that discrete annualized geometric growth rates can be extremely volatile when the base year is close to zero and when the base year or final year in the series contains significant nonrecurring items. Following their method, we compute five-year annualized sales growth rates by fitting a least squares growth line to the logarithms of the annual sales observations to avoid the extreme outliers due to discrete compounding and placing excessive weight on the first and last observations in the growth series, particularly when there could be substantial nonrecurring items. We require a minimum of three years of sales observations to estimate the regression.

Table 3 provides the summary statistics of these variables. The investment variable Inv (capital expenditure scaled by lagged total asset) has a mean of 0.06 and a standard deviation of 0.08. The depreciation variable Depr (depreciation expense scaled by lagged total asset) has a mean of 0.04 and a standard deviation of 0.01. The mean risk-free rate (Rf) is 0.04. The model-implied sales growth forecast (Mu), estimated from our model equation (6) above, has a mean of 0.08 and a standard deviation of 0.13. Finally, the mean of the actual long-term sales growth rate (RSG) is 0.02 with a standard deviation of 0.30.

2.3 Drought Measures and Trends in Droughts

Our data for the global (excluding the US) Palmer Drought Severity Index comes from Dai, Trenberth, and Qian (2004).[4] The index is a measurement of drought intensity based on a supply-and-demand model of soil moisture developed by Palmer (1965). The index takes into account not only temperature and the amount of moisture in the soil, but also hard-to-calibrate factors such as evapotranspiration and recharge rates. It is a widely used metric in climate studies. The index grades drought and moisture conditions in the following scale: -4 and below is extreme drought, -3.9 to -3 is severe drought, -2.9 to -2 is moderate drought, -1.9 to 1.9 is mid-range (normal), 2 to 2.9 is moderately moist, 3 to 3.9 is very moist, 4 and above is extremely moist. The extreme values for PDSI are -10 and 10.

The data consists of the monthly PDSI over global land areas computed using observed or model monthly surface air temperature and precipitation. The global PDSI dataset is structured in terms of longitude and latitude coordinates and we extract each country's PDSI based on that country's geographic coordinates. The sample period of global PDSI is from January 1900 to December 2014.

Our PDSI data for the US comes from the National Centers for Environmental Information (NCEI) of the US National Oceanic and Atmospheric Administration (NOAA). The PDSI is updated monthly on the NOAA's website, and the index value extends back to the early 1900s.

In addition, the temperature anomaly data for each country is obtained from NASA.[5] It comes from The GISS Surface Temperature Analysis (GISTEMP), which is an estimate of global surface temperature change.[6] The data extends back to 1880 and is updated monthly.

[4]The data is available for download at http://www.cgd.ucar.edu/cas/catalog/climind/pdsi.html.

[5]The data can be downloaded from `https://data.giss.nasa.gov/gistemp/`.

[6]For more information on the GISS temperature analysis, please see Hansen, Reudy, Sato, and Lo (2010).

Following Hong, Li, and Xu (2017), we measure the trends in droughts across different countries using the following simple empirical specification, which is an AR(1) model for drought (PDSI) that is augmented with a deterministic time trend t:

$$PDSI_{i,t} = a_i + b_i t + c_i PDSI_{i,t-1} + \epsilon_{i,t}. \tag{7}$$

Here we allow the coefficients for the intercept term (a_i), the trend term (b_i) and the autoregressive term (c_i) to potentially differ across countries. The trend term (b_i) is our parameter of interest that captures the differential time trends in droughts for countries and the long-run effect of climate change on a country's drought vulnerability. We will denote this (estimated) time trend for a country i, estimated using data from 1900 (or earliest date available) up to time m as $Trend_{i,m}$.

We estimate the above trend model for our sample of countries on a rolling basis. That is, in each month t, we estimate the time trend $Trend_{i,t}$ for each country using its PDSI data from January 1900 (or the earliest starting date) up to month t. Then we use these time trends to rank which countries are most vulnerable to droughts (i.e. the negative time trends in PDSI) and least vulnerable to droughts (i.e. the positive time trends in PDSI).

The summary statistics of our drought measure and drought trend are given in Table 1. Across all countries, the 36-month moving average of PDSI (PDSI36) has a mean of -0.24 with a standard deviation of 1.51, and the drought trend (Trend) has a mean of -0.42 bps with a standard deviation of 1.48 bps. Furthermore, Table 4 reports the results of the complete drought trend estimates for each individual country. For each country, the constants and trend estimates and t-statistics shown are the averages of the estimates and t-statistics (Newey-West adjusted) over all months from the rolling estimation. As we can see, there is significant heterogeneity in time trends of droughts across countries, consistent with climate studies that there are potential winners and losers when it comes to the effect of global temperature increases on droughts across the world.

3 Sensitivity of Sales Forecasts to Droughts

In this section, we study whether our drought measure PDSI36 are important for sales forecasts. We first carry out the analysis using various analyst sales forecast measures, then we redo the analysis using our model-implied sales growth forecasts.

3.1 Analyst Sales Forecasts

To examine the sensitivity of analyst sales forecasts to droughts, we estimate the following panel regression model:

$$F_{i,j,t,t+k} = \mu PDSI36_{j,t} + \phi z_{i,j,t} + \gamma X_{j,t} + u_j + v_t + \epsilon_{i,j,t} \tag{8}$$

where the dependent variable $F_{i,j,t,t+k}$ denotes the analyst sales forecast measure of food company i headquartered in country j made at year t for the future year $t+k$. This can be FY1/Asset (1-year ahead sales forecast over total asset), FY2/Asset (2-year ahead sales forecast over total asset), or LTG (long-term sales growth forecast). The main explanatory variable is our drought measure $PDSI36_{j,t}$, which is the 36-month moving average of PDSI for country j. $z_{i,j,t}$ denotes the annual sales growth of food company i (Sales Growth) headquartered in country j. $X_{j,t}$ denotes the vector of country-level control variables for country j, including the GDP growth rate (GDP Growth), the inflation rate (Inflation), the log of the GDP per capita (Log(GDP per capita)), and the unemployment rate (Unemployment). Finally, u_j denotes the country fixed effect, v_t denotes the year fixed effect, and $\epsilon_{i,j,t}$ is the error term.

We first estimate the model (8) in a simple specification without any control variables z or X but with both country and year fixed effect, then we add in the controls together with the fixed effects in our full specification. More importantly, to tease out whether sales forecasts are more sensitive to our drought measures for countries where the trends in droughts have been very low (negative) or very high (positive), we include in our full specification two additional explanatory variables, Low Trend and High Trend, and interact them with our drought measure PDSI36. Low Trend is a dummy equal to 1 for countries in the bottom quintile of its PDSI time trend at the end of each year, and High Trend is a dummy equal to 1 for countries in the top quintile of its PDSI time trend at the end of each year. The estimation results are reported in Table 5.

In column (1) and (2), we show the results for the case where the dependent variable is FY1/Asset. We see that 1-year ahead analyst sales forecasts of food companies significantly decline with droughts (PDSI36), as indicated by the positive coefficient 0.028 with a t-statistic of 2.78 in column (1). A one standard deviation fall in PDSI36 would lead to a fall of about 0.042 in FY1/Asset, which is about 6% of its standard deviation. Moreover, this effect is more pronounced in countries with negative drought trends. The interaction term Low Trend$\times$PDSI36 in column (2) has a coefficient 0.09 with a large t-statistics of 3.37, suggesting that sales forecasts are more sensitive to droughts in countries that have been experiencing a worsening in droughts over time.

In column (3) and (4), we find similar results where the dependent variable is FY2/Asset. The 2-year ahead sales forecasts of food companies also respond significantly to droughts (a coefficient estimate of 0.034 with a t-statistic of 3.42), and this sensitivity is greater in countries that have been suffering from negative drought trends (as measured by the significant coefficient estimate of the interaction term Low Trend$\times$PDSI36). Finally, In column (5) and (6), we find that the long-term sales growth forecast (LTG) is not as sensitive to droughts as FY1/Asset or FY2/Asset.

In Table 6, we re-run these panel regressions by splitting our sample in half with approximately an equal number of observations to illustrate the robustness of our findings across sub-periods. The three columns with "Pre-2007" show the results for the pre-2007 sub-sample while the other three columns with "Post-2007" show the results for the post-2007 sub-sample. The results are similar to our full-sample estimation.

3.2 Model-Implied Sales Growth Forecasts

In the same spirit, we can also examine whether our model-implied sales growth forecasts are sensitive to our drought measure PDSI36. As a result, we estimate the same panel regression model (8) using our model-implied growth forecast Mu based on Bolton, Chen, and Wang (2011) as the dependent variable. The estimation results are summarized in Table 7. In Columns (1) and (2), the sample is restricted to big and old firms only, as these firms are less subject to financial constraints and the implied sales growth is estimated more accurately from observed investment. Big (old) firms are defined as those firms whose asset (age) is larger than the sample median for each country. In Columns (3) and (4), we show the results using the full sample.

Overall, we find that our model-implied growth forecasts are not very sensitive to our drought measure PDSI36.

3.3 Sensitivity of Sales Forecasts to Droughts for Companies in Other Industries

To further address omitted variables concerns, we do a placebo analysis by examining whether sales forecasts are sensitive to drought measure PDSI36 for other industries. To examine the sensitivity of sales forecasts to droughts for companies in other industries in the Fama-French 17-industry categorization besides food companies, we re-run the sensitivity panel regression model (8) for companies in each of other industries. The results of this placebo analysis are summarized in Table 8. It is clear that, apart from food companies, sales forecasts are not sensitive to our drought measure PDSI36, for almost all other industries. The only noticeable exception (with a positive significant coefficient) is Oil and Petroleum Products in the case of FY1/Asset.

3.4 Sensitivity of Sales Forecasts to Temperature Anomalies

We next consider whether sales forecasts are sensitive to temperature anomalies, which is the main independent variable of interest in the climate-economy literature. We run the sensitivity panel regression model (8) for analyst sales forecasts of companies in each of the Fama-French 17 industries (including Food), but using temperature anomaly as our explanatory variable instead of our drought measure PDSI36. The estimation results are shown in Table 9. It is clear that analyst sales forecasts of firms in different industries do not respond to temperature anomalies, That is, analysts and management in our sample period are likely learning about climate change through outcomes in droughts as opposed to temperature per se.

4 Efficiency of Sales Forecasts to Drought Trends

In this section, we examine the more important issue, which is whether sales forecasts are efficient predictors of future sales with respect to drought trends. As in the previous section, we first carry out the analysis using various analyst sales forecast measures, then we re-do the analysis using our model-implied sales growth forecasts.

4.1 Analyst Sales Forecasts

To study the efficiency of analyst sales forecasts with respect to drought trend information, we estimate the following panel regression model:

$$Sales_{i,j,t+k} = \beta_0 + \beta_1 F_{i,j,t,t+k} + \beta_2 Low\ Trend_{j,t} + \beta_3 F_{i,j,t,t+k} \times Low\ Trend_{j,t} + \zeta_j + \omega_t + \psi_{i,j,t} \quad (9)$$

where the dependent variable $Sales_{i,j,t+k}$ denotes the k-year ahead actual sales or sales growth of food company i headquartered in country j measured w.r.t. year t. The explanatory variable $F_{i,j,t,t+k}$ denotes the analyst sales forecast of food company i in country j made at year t for the future year $t+k$. This can be FY1 (1-year ahead sales forecast), FY2 (2-year ahead sales forecast), or LTG (long-term sales growth forecast). *Low Trend* is a dummy equal to 1 for countries in the bottom quintile of its PDSI time trend at the end of each year, and $F_{i,j,t,t+k} \times Low\ Trend_{i,t}$ is the interaction term of $F_{i,j,t,t+k}$ with $Low\ Trend_{i,t}$. Finally, ζ_j denotes the country fixed effect, ω_t denotes the year fixed effect, and $\psi_{i,j,t}$ is the error term.

From model (9), the efficient null hypothesis (efficiency of sales forecasts) is that $\beta_1 = 1$ and $\beta_0 = \beta_2 = \beta_3 = 0$. Against this null, the alternative underreaction hypothesis is that $\beta_1 < 1$ and $\beta_3 < 0$. In particular, $\beta_3 < 0$ of the underreaction alternative says that analyst sales forecasts would over-estimate future sales in countries with negative drought trends. This is the key test that we are interested in.

To test the efficiency of analyst sales forecasts against the underreaction alternative, we first estimate model (9) using $F_{j,t,t+k}$ as the only explanatory variable, besides country and year fixed effects. We then estimate the full specification, together with country and year fixed effects. The estimation results are reported in Table 10.

In column (1) and (2), we report the results for the case where the dependent variable $Sales_{j,t+k}$ is the 1-year ahead actual sales and the explanatory variable $F_{j,t,t+k}$ is the 1-year ahead analyst sales forecasts FY1. In column (1), we see that the coefficient estimate of the forecast FY1 is 0.65, which is less than one. But more importantly, in column (2), we see that the interaction term $F_{j,t,t+k} \times Low\ Trend_{i,t}$ (Forecast×Low Trend) has a significantly negative coefficient estimate of -0.745 with a t-statistic of -14.8. This indicates there is a large underreaction of analyst sales forecasts to drought trends information in countries that have been experiencing negative drought trends. In other words, the sales forecasts made in countries with negative drought trends over-estimate the actual sales in the future, and these forecasts are inefficient with respect to the information in drought trends.

In column (3) and (4), we report the results for the case where the dependent variable $Sales_{j,t+k}$ is the 2-year ahead actual sales and the explanatory variable $F_{j,t,t+k}$ is the 2-year ahead analyst sales forecasts FY2. In column (3), we see that the coefficient estimate of the forecast FY2 is 0.04, which is almost 0. More importantly, in column (4), we see that the interaction term $F_{j,t,t+k} \times Low\ Trend_{i,t}$ (Forecast×Low Trend) also has a significantly negative coefficient estimate of -0.531 with a t-statistic of -2.72. Thus the 2-year ahead sales forecasts made in countries with negative drought trends also over-estimate the actual 2-year ahead sales in the future and are inefficient with respect to the information in drought trends.

In column (5) and (6), we report the results for the case where the dependent variable $Sales_{j,t+k}$ is the actual sales growth over the next five years and the explanatory variable $F_{j,t,t+k}$ is the long-term growth forecasts LTG. The results are very similar to those using FY1 and FY2 forecasts in the previous columns, i.e. the long-term growth forecast underreact to drought trends information in countries with negative drought trends.

In Table 11, we re-do these tests for the efficiency of sales forecasts with respect to drought trends information by splitting our sample in half with approximately an equal number of observations, in order to illustrate the robustness of our findings across sub-periods. The three columns with "Pre-2007" show the results for the pre-2007 sub-sample while the other three columns with "Post-2007" show the results for the post-2007 sub-sample. The results are consistent with our full-sample results.

4.2 Model-Implied Sales Growth Forecasts

In the same spirit, we can also carry out this same efficiency test with respect to drought trends information using our model-implied sales growth forecasts instead. To this end, we estimate the panel regression model (9) using our model-implied growth forecast Mu based on Bolton, Chen, and Wang (2011) as the explanatory variable, and interact it with the Low Trend dummy.

The estimation results are summarized in Table 12.

The results are similar to those using analyst sales forecasts. That is, the model-implied growth forecasts are also not efficient predictors of future sales growths. They underreact to drought trend information and over-estimate the actual long-term sales growth in countries that have been experiencing negative drought trends.

4.3 Robustness Analysis using Earnings and Earnings Forecasts

To illustrate the robustness of our findings, we use earnings forecasts instead of sales forecasts, and re-do both the sensitivity analysis (model (8)) and the efficiency test (model (9)). The results of these are shown in Table 13 (sensitivity analysis) and Table 14 (efficiency test).

We reach two main conclusions that are consistent with our earlier findings using sales forecasts. First, analyst earnings forecasts are sensitive to our drought measure PDSI36, thus droughts are important for earnings forecasts too. Second, earnings forecasts underreact to drought trends information in the same way as sales forecasts, in that those forecasts significantly over-estimate actual earnings in the future for food companies in countries with negative drought trends.

5 Predictable Forecast Errors and Food Industry Stock Returns Across Countries

We now relate our findings to the underreaction in food-industry stock returns across the 31 countries documented in Hong, Li, and Xu (2017) by regressing annual returns to food industry portfolios on these predictable forecast errors and the unforecastable forecast errors. To obtain forecast errors for food industries, we first compute the forecast error for each individual food company. This forecast error at the firm level, $Ferror_{i,j,t,t+1}$, is defined as the realized 5-year future sales growth of food company i in country j minus the LTG sales forecast of that company made at time t. We then aggregate the firm-level forecast errors to the industry-level forecast error, $Ferror_{j,t,t+1}$, by taking the weighted average of the firm-level errors across all food companies in a country, using the lagged market capitalization of each company as weight. Table 15 reports the summary statistics for these forecast errors by drought trend groups. It is interesting to observe that the forecast errors are more negative for low or negative trend group countries and that this error is monotonically increasing toward high trend countries.

We run the following 2-stage panel regression. In the first stage, we perform

$$Ferror_{j,t,t+1} = \alpha_0 + \alpha_1 Trend_{j,t} + \theta_t + \epsilon_{j,t} \tag{10}$$

where $Ferror_{j,t,t+1}$ is our industry-level forecast error for the food industry in country j as defined above, $Trend_{j,t}$ is our drought trend for country j at time t when the forecast is made, θ_t is the year fixed effect, and $\epsilon_{j,t}$ is the error term. From here we obtain the predicted value of the forecast error from the regression, $FerrorPredict_{j,t,t+1}$, as well as the residual value of the forecast error, $FerrorResidual_{j,t,t+1} = Ferror_{j,t,t+1} - FerrorPredict_{j,t,t+1}$. In the second stage, we run

$$FOODRET_{j,t+1} = \beta_0 + \beta_1 FerrorPredict_{j,t,t+1} + \eta_t + \varepsilon_{j,t+1} \tag{11}$$

Where $FOODRET_{j,t+1}$ is country j's 1-year ahead food industry return, $FerrorPredict_{j,t,t+1}$ is the predicted value of the forecast error as defined in the first stage, η_t is the year fixed effect, and $\varepsilon_{j,t+1}$ is the error term.

The result of the 2-stage panel regression is shown in column (1) and (2) of Table 16. We can see that in the first stage, our drought trend has significant predictive power for the forecast error. Furthermore, in the second stage, the predicted forecast error has significant explanatory power for FOOD return over the next year too.

For comparison, we also run a panel regression of food industry return over the next year on our drought trend only:

$$FOODRET_{j,t+1} = \gamma_0 + \gamma_1 Trend_{j,t} + \psi_t + \nu_{j,t+1} \tag{12}$$

where we just control for year fixed effect ψ_t. The result is shown in column (3) of Table 16. Consistent with the findings of our earlier paper, the drought trend has significant forecasting power for future food industry return.

Next, we run the panel regression of food industry return over the next year on both the predictable forecast error (predicted value $FerrorPredict_{j,t,t+1}$ as defined above) and the unpredictable forecast error (residual value $FerrorResidual_{j,t,t+1}$ as defined above):

$$FOODRET_{j,t+1} = \alpha + \beta FerrorPredict_{j,t,t+1} + \gamma FerrorResidual_{j,t,t+1} + \phi_t + u_{j,t+1} \tag{13}$$

where we control for year fixed effect ϕ_t. This is try to see whether the predictable and the unpredictable forecast error can explain food industry returns. As a benchmark, we also run this regression with year fixed effect only. The results are shown in Table 17. We can see that the unpredictable forecast error does not have explanatory power for food industry returns — the adjusted R^2 is actually lowered when the unpredictable forecast error $FerrorResidual_{j,t,t+1}$ is included in the regression.

6 Conclusion

A question of broad interest is the effects of climate change on the economy. Answering this question depends in large part on the efficiency of climate change forecasts on the part of households and firms. But study of this issue is limited to a lack of survey data. To address this issue, we focus on food-industry sales forecasts. Since food output falls severely with droughts and most food companies are small to medium sized firms, the food industries are significantly exposed to the climate conditions of their country of origin and hence climate change risk. As such, sales forecasts by analysts and management in the food industry are also implicitly climate change forecasts.

Using consensus analyst and management forecasts from thirty-one countries with publicly-traded food companies, panel regressions with country and time fixed effects find that sales forecasts significantly indeed decline with droughts as measured by the Palmer Drought Severity Index. However, these forecasts are inefficient predictors of future sales as they nonetheless over-estimate sales in countries with negative drought trends. Our findings suggest that sales forecasts underreact to climate trends. But our work stops short of pinpoint the exact mechanisms for this underreaction, which would be informative for policy makers. We leave this for future research.

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Table 1: Summary Statistics

This table reports summary statistics of our variables for the full sample. FY1/Asset is 1-year ahead consensus sales forecast over assets. FY2/Asset is 2-year ahead consensus sales forecast over assets. LTG is the long-term growth sales growth forecast. Earnings FY1/Asset is 1-year ahead consensus earnings forecast over assets. Earnings FY2/Asset is 2-year ahead consensus earnings forecast over assets. Sales is the actual sales in trillions. Earnings is the actual earnings in trillions. Sales growth is the annual sales growth of food companies. PDSI36 is the 36-months moving average of PDSI. Trend is the time trend of PDSI estimated using equation (1). We also report the summary statistics of country-level variables including annual GDP growth rate, inflation rate, GDP per capita and unemployment.

	Mean	S.D.	Median	P25	P75
FY1/Asset	1.18	0.76	1.07	0.64	1.57
FY2/Asset	1.28	0.84	1.15	0.69	1.68
LTG	0.14	0.13	0.11	0.06	0.19
Earnings FY1/Asset	0.051	0.048	0.040	0.021	0.067
Earnings FY2/Asset	0.060	0.049	0.048	0.027	0.078
Sales (trillions)	0.322	2.090	0.004	0.001	0.059
Earnings (trillions)	0.0070	0.0251	0.0002	0.00002	0.0017
Sales Growth	0.16	0.58	0.06	-0.01	0.18
PDSI36	-0.24	1.51	-0.30	-1.14	0.56
Trend (bps)	-0.42	1.48	-0.37	-1.40	0.59
GDP growth (%)	3.23	3.38	3.20	1.61	5.08
Inflation (%)	3.90	5.81	2.66	1.57	4.48
GDP per capita (constant 2010 US$)	27279.75	21043.57	29578.63	8215.87	41741.12
Unemployment (%)	7.63	4.84	6.95	4.20	9.26

Table 2: Summary Statistics of Managerial Forecasts

This table reports the summary statistics of managerial forecast of FY1 sales scaled by assets. Panel A reports summary statistics of managerial forecast for each country where the data is available. Panel B reports the correlation between managerial and analyst forecast of FY1 sales where they overlap.

Panel A: Summary Statistics of Managerial Forecast of FY1 Sales/Assets

Country	sample period	# of obs	Mean	S.D.
United States	2002-2015	563	1.76	2.18
Belgium	2012-2013	2	0.36	
Denmark	2009-2012	12	1.09	
France	2013-2014	5	1.14	
United Kingdom	2012-2013	5	0.84	
Ireland	2008-2009	3	0.84	
Italy	2013	1	1.22	

Panel B: Correlation between managerial and analyst forecast of FY1 sales

TS correlation for US at industry level	1.00
TS correlation for US at firm level	0.93
Panel correlation for other countries	0.99

Table 3: Summary Statistics of Model-implied Sales Growth Forecasts

This table reports the summary statistics of model-implied sales growth and the parameters used in the model. Inv is the capital expenditures scaled by lagged assets. Depr is the depreciation expenses scaled by lagged assets. RSG is the actual 5-year long-term growth rate starting from the forecast year. Following Dechow and Sloan (1997) and I/B/E/S methodology, actual long-term growth is measured as the slope from a regression of log(Sales) on a time trend over a five-year period beginning in the forecast year. We require a minimum of three years of sales observations to estimate the regression. Mu is the model-implied sales growth forecast. Rf is the annual risk free rate.

	Mean	S.D.	Median	p25	p75
Inv	0.063	0.080	0.040	0.018	0.076
Depr	0.035	0.010	0.033	0.028	0.044
RSG	0.024	0.297	0.042	-0.012	0.117
Mu	0.080	0.128	0.057	0.034	0.099
Rf	0.041	0.043	0.035	0.023	0.053

Table 4: Summary Statistics of PDSI Trend Estimates over Time, Country by Country

This table reports the summary statistics of the coefficients from estimating the time trends in PDSI for each country on a rolling basis, using the following model: $PDSI_{i,t} = a_i + b_i t + c_i PDSI_{i,t-1} + \epsilon_{i,t}$. In each month (sample period) t, we use the PDSI data for a country from January 1900 (or the earliest possible starting date) up to month t to estimate the model. We report the intercepts (a_i), and coefficients on time trend (b_i) along with their t-statistics. The coefficient estimates and their t-statistics are the averages of the estimates and t-statistics (Newey-West adjusted) across all months. The sample period is from December 1984 to December 2014.

Country	Intercept	t-stat	Trend (bps)	t-stat
Peru	0.28	2.84	-3.69	-3.03
Israel	0.32	2.90	-3.31	-2.77
Japan	0.17	2.01	-2.61	-2.16
Poland	0.08	1.87	-1.29	-2.09
Philippines	0.16	2.31	-2.10	-1.92
Greece	0.09	1.43	-1.76	-1.86
Thailand	0.09	1.63	-1.27	-1.78
Chile	0.11	2.69	-1.08	-1.77
Switzerland	0.06	1.24	-1.24	-1.52
Brazil	0.14	1.31	-1.68	-1.33
France	0.01	0.22	-0.61	-0.89
Germany	0.01	0.38	-0.46	-0.84
Belgium	0.06	1.43	-0.49	-0.68
Netherlands	0.06	1.43	-0.49	-0.68
Malaysia	0.09	1.09	-0.74	-0.56
South Africa	0.01	0.17	-0.37	-0.42
Finland	0.04	0.89	-0.22	-0.33
Turkey	0.08	1.03	-0.23	-0.26
Indonesia	-0.02	-0.47	0.20	0.19
Portugal	-0.05	-1.12	0.16	0.21
United Kingdom	-0.03	-0.46	0.40	0.44
United States	0.00	-0.18	0.29	0.54
China	-0.20	-1.58	1.18	0.59
India	-0.10	-1.20	1.15	0.99
Russian Federation	-0.05	-0.82	0.84	1.03
Denmark	-0.04	-0.87	0.92	1.09
South Korea	-0.09	-1.56	1.01	1.11
Canada	-0.12	-2.39	1.13	1.55
Australia	-0.21	-3.47	1.55	1.75
Mexico	-0.18	-2.29	2.07	1.98
New Zealand	-0.27	-3.21	2.51	2.16

Table 5: Sensitivity of Sales Forecasts to Droughts

This table reports panel regression results of the sensitivity of analysts' consensus sales forecasts to our drought measure PDSI36 for FOOD companies. In column (1) and (2), the dependent variable is 1-year ahead forecast (FY1) over actual asset. In column (3) and (4), the dependent variable is 2-year ahead forecast (FY2) over actual asset. In column (5) and (6), the dependent variable is long-term growth forecast (LTG). The explanatory variable PDSI36 is our drought measure. Low Trend is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. High Trend is a dummy equal to 1 for countries in the top quintile of its estimated PDSI time trend at the end of each year. The control variables are lagged sales growth rate of the food company (Sales Growth), and country-level controls including GDP growth rate, inflation rate, log of GDP per capita and unemployment rate. Both country and year fixed effects are included. Standard errors are clustered at both the country and the year level. *t*-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	Dep Var: FY1/Asset		Dep Var: FY2/Asset		Dep Var: LTG	
	(1)	(2)	(3)	(4)	(5)	(6)
PDSI36	0.0277**	0.0117	0.0335***	0.0117	-0.0035	-0.0029
	(2.78)	(0.98)	(3.42)	(0.91)	(-1.14)	(-0.69)
Low Trend		0.0207		0.0756		-0.0143
		(0.85)		(1.29)		(-0.97)
Low Trend×PDSI36		0.0912***		0.1059***		0.0014
		(3.37)		(3.63)		(0.35)
High Trend		0.0274		0.0423		0.0134
		(0.68)		(0.89)		(0.69)
High Trend×PDSI36		0.0145		0.0180		0.0023
		(0.81)		(0.74)		(0.42)
Sales Growth		0.0202		0.0174		0.0190***
		(0.71)		(0.63)		(3.42)
GDP Growth		0.0009		0.0060		0.0007
		(0.12)		(0.83)		(0.53)
Inflation		0.0011		-0.0031		-0.0013*
		(0.29)		(-0.39)		(-1.75)
Log(GDP per capita)		0.1194		0.2677**		-0.0619
		(1.41)		(2.39)		(-0.90)
Unemployment		-0.0034		0.0003		-0.0009
		(-0.29)		(0.03)		(-0.45)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Sensitivity of Sales Forecasts to Droughts, Subsample Analysis

This table reports panel regression results of the sensitivity of analysts' consensus sales forecasts to our drought measure PDSI36 for FOOD companies in two subsamples. The first subsample is pre-2007 and the second subsample is post-2007. The whole sample is split this way to have roughly an equal number of observations in each subsample. In column (1) and (2), the dependent variable is 1-year ahead forecast (FY1) over actual asset. In column (3) and (4), the dependent variable is 2-year ahead forecast (FY2) over actual asset. In column (5) and (6), the dependent variable is long-term growth forecast (LTG). The explanatory variable PDSI36 is our drought measure. Low Trend is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. High Trend is a dummy equal to 1 for countries in the top quintile of its estimated PDSI time trend at the end of each year. The control variables are lagged sales growth rate of the food company (Sales Growth), and country-level controls including GDP growth rate, inflation rate, log of GDP per capita and unemployment rate. Both country and year fixed effects are included. Standard errors are clustered at both the country and the year level. *t*-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	Dep Var: FY1/Asset		Dep Var: FY2/Asset		Dep Var: LTG	
	Pre-2007	Post-2007	Pre-2007	Post-2007	Pre-2007	Post-2007
PDSI36	-0.0138	0.0094	-0.0068	0.0120	-0.0084	-0.0032
	(-0.74)	(0.68)	(-0.35)	(0.98)	(-1.75)	(-0.39)
Low Trend	-0.0420	-0.0090	0.1290	0.0191	-0.0076	-0.0090
	(-0.92)	(-0.09)	(0.76)	(1.00)	(-0.31)	(-0.34)
Low Trend×PDSI36	0.1504***	0.0134	0.1662***	0.0108	0.0122	0.0042
	(3.80)	(1.12)	(3.59)	(1.04)	(1.49)	(0.42)
High Trend	0.2884**	-0.0905	0.1121	-0.0829	0.0208	0.0161
	(3.11)	(-0.87)	(1.15)	(-0.85)	(0.57)	(0.47)
High Trend×PDSI36	0.0376	0.0306	0.0532	0.0292	0.0019	-0.0045
	(0.62)	(0.89)	(1.02)	(0.98)	(0.12)	(-0.30)
Sales Growth	0.0265	0.0173	0.0165	0.0300	0.0046	0.0289***
	(1.01)	(0.36)	(0.59)	(0.55)	(1.04)	(4.72)
GDP Growth	-0.0056	0.0070	-0.0025	0.0143	0.0012	0.0003
	(-0.53)	(0.99)	(-0.24)	(1.69)	(0.53)	(0.11)
Inflation	-0.0006	-0.0068	0.0027	-0.0147**	-0.0009	-0.0024
	(-0.17)	(-0.92)	(0.44)	(-2.40)	(-1.52)	(-0.31)
Log(GDP per capita)	-0.6815	0.3493*	-0.0884	0.5121***	0.2888	-0.0555
	(-1.26)	(2.12)	(-0.34)	(5.44)	(1.45)	(-0.70)
Unemployment	-0.0278	0.0144**	-0.0210	0.0235**	0.0007	0.0033*
	(-1.74)	(2.37)	(-1.07)	(2.84)	(0.26)	(2.13)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Sensitivity of Model-implied Sales Growth to Droughts

This table reports panel regression results of the sensitivity of model-implied sales growth (Mu) to our drought measure PDSI36 for FOOD companies. The dependent variable is the model-implied sales growth based on Bolton, Chen, and Wang (2011). The explanatory variable PDSI36 is our drought measure. Low Trend is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. High Trend is a dummy equal to 1 for countries in the top quintile of its estimated PDSI time trend at the end of each year. The control variables are lagged sales growth rate of the food company (Sales Growth), and country-level controls including GDP growth rate, inflation rate, log of GDP per capita and unemployment rate. Both country and year fixed effects are included. In Column (1) and (2), the sample is restricted to big and old firms only. In Column (3) and (4), we use the full sample. Big (old) firms are defined as firms whose asset (age) is larger than the sample median for each country. Standard errors are clustered at both the country and the year level. *t*-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	Big&Old Firm Sample		Full Sample	
PDSI36	0.0011	0.0008	0.0019	0.0019
	(0.28)	(0.20)	(0.52)	(0.48)
PDSI36*Low Trend		0.0031		0.0025
		(0.42)		(0.37)
PDSI36*High Trend		0.0064		0.0068
		(1.30)		(1.69)
High Trend		-0.0194		-0.0119
		(-1.38)		(-0.73)
Low Trend		0.0060		0.0042
		(0.93)		(0.75)
Sales Growth		0.0338***		0.0197***
		(3.33)		(4.63)
GDP Growth		-0.0014		-0.0023
		(-0.77)		(-1.39)
Inflation		0.0012		0.0006
		(0.71)		(0.47)
Log(GDP per capita)		0.0014		0.0217
		(0.05)		(0.80)
Unemployment		-0.0022		-0.0019
		(-0.89)		(-0.62)
Country FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes

Table 8: Sensitivity of Sales Forecasts to Droughts for Other Industries

This table reports panel regression results of the sensitivity of analysts' sales forecasts to our drought measure PDSI36 for companies in other industries. The coefficient estimates of PDSI36 (Coef Estimate) are shown along with their associated t-statistics (t-stat) in parentheses. In column (1) and (2), the dependent variable is 1-year ahead forecast (F1) over actual asset. In column (3) and (4), the dependent variable is 2-year ahead forecast (F2) over actual asset. In column (5) and (6), the dependent variable is long-term growth forecast (LTG). Both country and year fixed effects are included. Standard errors are clustered at both the country and the year level. Industry classification is the Fama-French 17 industries.

	Dep Var: F1/Asset		Dep Var: F2/Asset		Dep Var: LTG	
	Coef Estimate	t-stat	Coef Estimate	t-stat	Coef Estimate	t-stat
Food	0.0277	(2.78)	0.0335	(3.42)	-0.0035	(-1.14)
Mining and Minerals	-0.0511	(-2.44)	-0.0513	(-1.97)	-0.0055	(-0.82)
Oil and Petroleum Products	0.0516	(2.02)	0.0426	(1.65)	-0.0036	(-0.41)
Textiles, Apparel, Footware	-0.0291	(-1.46)	-0.0383	(-1.70)	0.0010	(0.16)
Consumer Durables	-0.0063	(-0.40)	-0.0196	(-1.11)	-0.0206	(-2.31)
Chemicals	0.0039	(0.40)	-0.0025	(-0.20)	-0.0053	(-0.74)
Drugs, Soap, Perfumes, Tobacco	-0.0082	(-0.55)	-0.0152	(-1.10)	-0.0012	(-0.29)
Constructions	0.0053	(0.49)	0.0012	(0.09)	0.0008	(0.14)
Steel	-0.0262	(-1.47)	-0.0358	(-1.87)	-0.0192	(-1.65)
Fabricated Products	0.0064	(0.42)	0.0042	(0.24)	0.0175	(1.66)
Machinery and Business Equipment	-0.0156	(-1.97)	-0.0244	(-2.37)	0.0005	(0.08)
Cars	-0.0037	(-0.22)	-0.0022	(-0.10)	0.0042	(0.72)
Transportation	0.0207	(1.52)	0.0227	(1.18)	-0.0068	(-1.41)
Utilities	-0.0062	(-0.60)	-0.0040	(-0.32)	-0.0005	(-0.11)
Retail	-0.0170	(-0.67)	-0.0241	(-0.79)	0.0030	(0.47)
Financial	0.0034	(0.46)	0.0017	(0.17)	-0.0025	(-0.50)
Other	-0.0045	(-0.42)	-0.0095	(-0.79)	-0.0039	(-1.34)

Table 9: Sensitivity of Sales Forecasts to Temperature Anomaly

This table reports panel regression results of the sensitivity of analysts' sales forecasts to country-level temperature anomalies for companies in different industries. The country-level temperature anomaly series are from NASA and can be obtained at `https://data.giss.nasa.gov/gistemp/`. The coefficient estimates (Coef Estimate) of Temperature Anomaly are shown along with their associated t-statistics (t-stat) in parentheses. In column (1) and (2), the dependent variable is 1-year ahead forecast (F1) over actual asset. In column (3) and (4), the dependent variable is 2-year ahead forecast (F2) over actual asset. In column (5) and (6), the dependent variable is long-term growth forecast (LTG). Both country and year fixed effects are included. Standard errors are clustered at both the country and the year level. Industry classification is the Fama-French 17 industries.

	Dep Var: F1/Asset		Dep Var: F2/Asset		Dep Var: LTG	
	Coef Estimate	t-stat	Coef Estimate	t-stat	Coef Estimate	t-stat
Food	-0.0127	(-1.37)	-0.0045	(-0.35)	0.0039	(1.37)
Mining and Minerals	-0.0114	(-1.35)	-0.0138	(-1.39)	-0.0058	(-0.72)
Oil and Petroleum Products	0.0217	(1.09)	-0.0137	(-0.59)	-0.0009	(-0.17)
Textiles, Apparel, Footware	-0.0178	(-1.08)	-0.0013	(-0.11)	-0.0000	(-0.01)
Consumer Durables	0.0028	(0.38)	0.0005	(0.06)	0.0020	(0.34)
Chemicals	0.0048	(0.98)	-0.0021	(-0.23)	0.0063	(1.08)
Drugs, Soap, Perfumes, Tobacco	-0.0126	(-1.10)	-0.0074	(-1.20)	0.0013	(0.52)
Constructions	-0.0081	(-0.61)	0.0099	(1.03)	0.0057	(1.45)
Steel	-0.0046	(-0.45)	-0.0013	(-0.14)	0.0057	(1.34)
Fabricated Products	0.0039	(0.25)	-0.0187	(-1.05)	0.0072	(0.81)
Machinery and Business Equipment	-0.0034	(-0.46)	0.0068	(0.75)	0.0037	(0.94)
Cars	0.0085	(0.55)	0.0099	(1.17)	-0.0015	(-0.41)
Transportation	-0.0080	(-0.83)	0.0132	(1.27)	0.0048	(1.02)
Utilities	-0.0056	(-0.94)	-0.0050	(-0.76)	-0.0017	(-0.67)
Retail	-0.0121**	(-2.18)	0.0106	(0.79)	0.0085***	(3.27)
Financial	0.0019	(0.50)	0.0023	(0.77)	0.0032	(1.48)
Other	-0.0118	(-1.45)	-0.0014	(-0.22)	0.0040*	(1.77)

Table 10: Efficiency of Sales Forecasts with respect to Drought Trends

This table reports panel regression results of the efficiency of analysts' consensus sales forecasts with respect to drought trends for FOOD companies. In column (1) and (2), the dependent variable is 1-year ahead actual sales and the explanatory variable Forecast is FY1. In column (3) and (4), the dependent variable is 2-year ahead actual sales and the explanatory variable Forecast is FY2. In column (5) and (6), the dependent variable is actual sales growth over the next 5 years and the explanatory variable Forecast is LTG. Low Trend is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. High Trend is a dummy equal to 1 for countries in the top quintile of its estimated PDSI time trend at the end of each year. Both country and year fixed effects are included. Standard errors are clustered at both the country and the year level. t-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	Dep Var: Actual Sales		Dep Var: Actual Sales		Dep Var: Actual 5-yr Sales Growth	
	Forecast is FY1		Forecast is FY2		Forecast is LTG	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast	0.6457***	1.1187***	0.0394	0.3794*	0.2007***	0.2864***
	(3.19)	(28.20)	(0.23)	(1.83)	(3.52)	(4.94)
Low Trend		-0.0664		-0.7773		-0.0477
		(-0.15)		(-1.26)		(-0.92)
Forecast×Low Trend		-0.7446***		-0.5305**		-0.3091**
		(-14.79)		(-2.72)		(-2.17)
High Trend		0.3947***		0.3794		0.0822
		(4.59)		(1.48)		(1.49)
Forecast×High Trend		-0.3065*		-0.2941		-0.2214
		(-1.83)		(-1.06)		(-1.49)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Efficiency of Sales Forecasts with respect to Drought Trends, Subsample Analysis

This table reports panel regression results of the efficiency of analysts' consensus sales forecasts with respect to drought trends for FOOD companies in two subsamples. The first subsample is pre-2007 and the second subsample is post-2007. The whole sample is split this way to have roughly an equal number of observations in each subsample. In column (1) and (2), the dependent variable is 1-year ahead actual sales and the explanatory variable Forecast is FY1. In column (3) and (4), the dependent variable is 2-year ahead actual sales and the explanatory variable Forecast is FY2. In column (5) and (6), the dependent variable is actual sales growth over the next 5 years and the explanatory variable Forecast is LTG. Low Trend is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. High Trend is a dummy equal to 1 for countries in the top quintile of its estimated PDSI time trend at the end of each year. Both country and year fixed effects are included. Standard errors are clustered at both the country and the year level. t-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	Dep Var: Actual Sales		Dep Var: Actual Sales		Dep Var: Actual 5-yr Sales Growth	
	Forecast is FY1		Forecast is FY2		Forecast is LTG	
	Pre-2007	Post-2007	Pre-2007	Post-2007	Pre-2007	Post-2007
Forecast	0.7667***	0.8530***	0.6826**	0.1468	0.1779	0.3120***
	(3.45)	(5.69)	(3.01)	(0.72)	(1.28)	(6.22)
Low Trend	0.1390	-0.1667	-0.9132	-0.8185*	0.0617	0.0556***
	(0.20)	(-0.63)	(-1.23)	(-2.16)	(0.75)	(8.42)
Forecast×Low Trend	-0.3812	-0.4268**	-0.7845**	-0.3595***	-0.3001	-0.2510***
	(-1.19)	(-2.37)	(-2.63)	(-9.59)	(-0.85)	(-12.75)
High Trend	0.3283	0.3594*	1.2118***	-0.2836	0.0198	-0.0100
	(1.13)	(2.26)	(8.79)	(-0.74)	(0.29)	(-0.21)
Forecast×High Trend	0.1116	-2.2008	-1.0701***	1.5418***	-0.0962	-0.1547
	(0.34)	(-1.43)	(-5.78)	(4.74)	(-0.49)	(-0.69)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Efficiency of Implied Sales Growth Forecasts with respect to Drought Trends

This table reports panel regression results of the efficiency of model-implied sales forecasts with respect to drought trends for FOOD companies. The dependent variable is actual sales growth over the next 5 years and the explanatory variable Mu is the model-implied sales growth forecast based on Bolton, Chen, and Wang (2011). Low Trend is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. High Trend is a dummy equal to 1 for countries in the top quintile of its estimated PDSI time trend at the end of each year. Both country and year fixed effects are included. Standard errors are clustered at both the country and the year level. t-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	Big&Old Firm Sample		Full Sample	
mu	0.1757***	0.1565*	0.1538***	0.1686***
	(3.60)	(2.07)	(3.28)	(3.95)
Low Trend		-0.0777		-0.0634
		(-0.88)		(-1.07)
mu*Lowtrend		-0.2055*		-0.1014**
		(-2.00)		(-2.08)
High Trend		-0.0152		-0.0112
		(-0.93)		(-1.02)
mu*Hightrend		0.1169		0.0697
		(1.06)		(0.82)
Country FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes

Table 13: Sensitivity of Earnings Forecasts to Droughts

This table reports panel regression results of the sensitivity of analysts' consensus forecasts of earnings (net income) to our drought measure PDSI36 for FOOD companies. In column (1) and (2), the dependent variable is 1-year ahead forecast (FY1) over actual asset. In column (3) and (4), the dependent variable is 2-year ahead forecast (FY2) over actual asset. The explanatory variable PDSI36 is our drought measure. Low Trend is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. High Trend is a dummy equal to 1 for countries in the top quintile of its estimated PDSI time trend at the end of each year. The control variables are lagged sales growth rate of the food company (Sales Growth), and country-level controls including GDP growth rate, inflation rate, log of GDP per capita and unemployment rate. Both country and year fixed effects are included. In Column (1) and (2), the sample is restricted to big and old firms only. In Column (3) and (4), we use the full sample. Big (old) firms are defined as firms whose asset (age) is larger than the sample median for each country. Standard errors are clustered at both the country and the year level. t-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	FY1/Total Asset		FY2/Total Asset	
PDSI36	0.0015**	0.0011*	0.0008*	0.0011*
	(2.24)	(1.72)	(1.72)	(1.94)
PDSI36×Low Trend		0.0021		0.0028
		(0.84)		(1.26)
PDSI36×High Trend		-0.0007		-0.0010
		(-0.34)		(-1.01)
High Trend		0.0062***		0.0069
		(3.42)		(1.59)
Low Trend		0.0121*		0.0083*
		(1.79)		(2.01)
Sales Growth		0.0001		-0.0003
		(0.41)		(-0.28)
GDP Growth		-0.0007		-0.0005
		(-1.56)		(-1.48)
Inflation		-0.0002		-0.0001
		(-0.80)		(-0.35)
Log(GDP per capita)		0.0283***		0.0302***
		(3.76)		(3.63)
Unemployment		0.0013		0.0013*
		(1.72)		(1.99)
Country Fixed Effect		Yes		Yes
Year Fixed Effect		Yes		Yes

Table 14: Efficiency of Earnings Forecasts with respect to Drought Trends

This table reports panel regression results of the efficiency of analysts' consensus forecasts of earnings (net income) with respect to drought trends for FOOD companies. In column (1) and (2), the dependent variable is 1-year ahead actual earnings and the explanatory variable Forecast is FY1. In column (3) and (4), the dependent variable is 2-year ahead actual earnings and the explanatory variable Forecast is FY2. Low Trend is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. High Trend is a dummy equal to 1 for countries in the top quintile of its estimated PDSI time trend at the end of each year. Both country and year fixed effects are included. Standard errors are clustered at both the country and the year level. *t*-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	Forecast is FY1		Forecast is FY2	
	(1)	(2)	(3)	(4)
Forecast	1.2448***	1.4965***	0.9863***	1.1520***
	(5.64)	(36.33)	(6.19)	(25.12)
Low Trend		0.0014		0.0010
		(1.61)		(1.49)
Forecast×Low Trend		-0.6741***		-0.4725***
		(-13.44)		(-7.26)
High Trend		-0.0002		-0.0003
		(-0.21)		(-0.26)
Forecast×High Trend		-0.0196		0.0225
		(-0.37)		(0.29)
Country Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes

Table 15: Summary Statistics of Forecast Errors

This table reports the summary statistics of forecast errors for the food industry. $Ferror$ is the forecast error of the food industry as defined in the main paper. $Ferror$ (Low Trend), $Ferror$ (Medium Trend) and $Ferror$ (High Trend) denote the forecast error for countries in the bottom quintile of the drought trend, in the middle quintiles and in the top quintile respectively. $FerrorPredict$ is the predicted forecast error obtained from regressing forecast error on our drought trend as explained in the main paper. $FOODRET$ is the food industry return at the annual level.

	Mean	SD	Median	p25	p75
$Ferror$ (%)	-9.43	22.91	-5.47	-11.53	-0.36
$Ferror$ (Low Trend)	-11.99	27.03	-6.65	-11.18	-2.50
$Ferror$ (Medium Trend)	-9.86	24.52	-5.25	-12.23	0.10
$Ferror$ (High Trend)	-5.70	8.57	-5.03	-10.66	0.32
$FerrorPredict$ (%)	-0.94	2.83	-0.87	-2.66	1.08
$FOODRET$ (%)	11.12	56.48	10.75	-4.44	26.45

Table 16: Panel Regression of Food Industry Return on Drought Trend and Forecast Error

This table shows the panel regression results of food industry return on our drought trend and forecast error. In the first two columns, we run the 2-stage regression, where in the first stage we regress the forecast error $Ferror$ on the drought trend $Trend$ to obtain the predicted forecast error $FerrorPredict$ and in the second stage we regress the 1-year ahead food industry return on this predicted error. In column (3), we show as a comparison the result of regressing the 1-year ahead food industry return directly on the drought trend. We control for year fixed effects in all regressions. Standard errors are clustered at the year level. t-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	2-Stage		OLS
	1st stage	2nd stage	
	Dep Var: ferror	Dep Var: 1-yr ahead $FOODRET$	Dep Var: 1-yr ahead $FOODRET$
$Trend$	1.8462**		1.9815*
	(2.14)		(1.91)
$FerrorPredict$		1.0733*	
		(1.91)	
Year FE	Yes	Yes	Yes
Adj.R-sq	0.071	0.335	0.335
No. of Obs.	309	309	309

Table 17: Panel Regression of Food Industry Return with Decomposition of Forecast Errors

This table shows the panel regression results of food industry return on both the predictable forecast error and the unpredictable forecast error of the food industry. In column (1), we perform a benchmark regression where the 1-year ahead food industry return is regressed on year fixed effects only. In column (2), we regress the 1-year ahead food industry return on the predictable forecast error ($FerrorPredict$) and year fixed effects. In column (3), we regress the 1-year ahead food industry return on both the predictable forecast error ($FerrorPredict$) and the unpredictable forecast error ($FerrorResidual$), plus year fixed effects. Standard errors are clustered at the year level. t-statistics are shown in parentheses, with *, **, *** denoting statistical significance at 10%, 5%, 1% respectively.

	Dep Var: 1-year ahead $FOODRET$		
	(1)	(2)	(3)
$FerrorPredict$		1.0733*	1.0733*
		(1.91)	(1.90)
$FerrorResidual$			-0.0035
			(-0.03)
Year FE	Yes	Yes	Yes
Adj.R-sq	0.330	0.335	0.332
No. of Obs.	309	309	309