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Climate Risks and Market Efficiency*

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Abstract

Climate science finds that the trend towards higher global temperatures exacerbates the risks of droughts. We investigate whether the prices of food stocks efficiently discount these risks. Using data from thirty-one countries with publicly-traded food companies, we rank these countries each year based on their long-term trends toward droughts using the Palmer Drought Severity Index. A poor trend ranking for a country forecasts relatively poor profit growth for food companies in that country. It also forecasts relatively poor food stock returns in that country. This return predictability is consistent with food stock prices underreacting to climate change risks.

Keywords: Climate Risks, Climate Change, Stock Market, Efficiency, Return Predictability

JEL Classification: G1, G12, G14

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1 Introduction

Regulators are increasingly worried about the extent to which stock markets efficiently price climate change risks. Most notably, Mark Carney, the head of the Bank of England, recently linked these risks to financial stability (Carney (2015)). Such risks include energy corporations' exposure to carbon assets, which might be affected by future carbon prices or taxes. This so-called "stranded asset issue" has attracted the most discussion in regulatory and market circles at this point.[1] But climate change risks need not be so narrowly confined to carbon exposures. Vulnerability of corporations' production processes to natural disasters amplified by climate change can impose significant damage to corporate profits, as we detail below. In particular, regulators are concerned that markets have had little experience in dealing with such risks and might not pay enough attention, and thereby underreacting to them as a result. Various regulatory bodies are promoting both voluntary and mandatory disclosures of corporations' climate risk exposures to address this issue.[2] However, there is little systematic research on the topic of climate risks and market efficiency up to this point.

We tackle this important question by focusing on the efficiency with which the stock prices of food companies respond to trends in droughts across the world. The motivation for our study is that climate scientists have found that the trend increase in global temperatures exacerbates the risks of droughts, generating dispersion across countries with many potentially adversely affected while some might actually benefit (Trenberth, Dai, van der Schrier, Jones, Barichivich, Briffa, and Sheffield (2014)). Among the natural disasters that might be amplified by climate change, including drought, heat waves, floods, and cold spells, drought is considered one of the most devastating for food production.[3] The food industry in countries suffering adverse trends

[1]See, e.g., "The elephant in the atmosphere," *Economist* July 19th, 2014.

[2]Examples of the more prominent voluntary disclosure initiatives include the Carbon Standards Disclosure Board, Integrated Reporting, the Carbon Disclosure Project, and the UN Principles for Responsible Investment.

[3]A recent study (Lesk, Rowhani, and Ramankutty (2016)) looks at 2,800 weather disasters along with data on 16 different cereals grown in over 100 countries. 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.

in droughts are likely to experience lower profits since this industry is the most reliant on water and hence the most sensitive to drought risk (Blackhurst, Hendrickson, and Vidal (2010)). As we document below, most countries' food industries are comprised of small to medium sized firms that are significantly exposed to the climate conditions of their country of origin.[4] As a result, the food companies of a country with an adverse (favorable) drought trend are likely to experience relatively poor (good) subsequent profit growth.

We test the hypothesis of whether food stocks are efficiently pricing in such risks associated with these trends for future food industry cashflows. Using data from thirty-one countries with publicly traded equities in the food industry, we develop and test our hypothesis in three steps. First, we measure time trends in droughts across countries with publicly-traded equities in the food industry and categorize countries into those with negative (or adverse trends) versus those with non-negative (or in some instances even positive trends) by using publicly available data up to a given year t. Second, we then document that these trend rankings, measured using data only up to year t, can forecast the relative performance of food industry cashflows (in years $t+1$, $t+2$, ...), i.e. the food industries in countries with negative trends experience subsequently poor profit growth relative to the food industries in countries with positive trends.

Third, we test the null hypothesis of market efficiency. These trends, which are publicly available information in a given year t, should not then forecast future food industry stock returns to the extent that markets have efficiently priced in the implications of these trends for future cashflows. On the other hand, to the extent negative (positive) trend rankings forecast poor (good) relative stock price performance for food industries in those countries points to markets not sufficiently pricing in the information contained in these trends for future cashflow growth, i.e. that stock markets are under-reacting to climate change risks.

We begin by estimating drought time trends by using the Palmer Drought Severity Index

[4]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.

(PDSI), a widely used monthly metric in climate studies (Palmer (1965)). PDSI combines information such as temperature and the amount of moisture in the soil to create an index that does an accurate job of measuring drought intensity. Less positive values of PDSI are associated with more drought-like conditions. While not perfect, it is by far the most widely used in climate studies and the most readily available (Alley (1984)). Globally, it is available at the country level and goes back to the early 1900s.

For each of the 31 countries in our international sample, we construct a new measure of a country's vulnerability to droughts as a result of climate change. Recall that the premise of our measure is that climate studies point out that there is a time trend in global temperatures (see Figure 1) leading to potentially differential trends in droughts across countries over time. Using long time series of PDSI for each country going back to the early 1900s, we can calculate $Trend_{i,t}$, the time trend of drought for each country i using data up to a given year t. We estimate this time trend using a trend-stationary model: an AR(1) model for drought (PDSI) that is augmented with a linear deterministic time trend.[5] Consistent with earlier climate studies, we find that there is significant dispersion in trends towards droughts, with a more significant left-tail, i.e. more countries with statistically significant negative trends in drought than countries with positive or improving trends.

We sort countries based on their estimated trends in any given time t into quintile groups, with the bottom or Quintile 1 group comprised of the negative trending countries and the top or Quintile 5 group comprised of the positive trending countries. That is, we use these time trends to rank which countries are most vulnerable to droughts (i.e. the negative time trends and rising risk) and least vulnerable to droughts (i.e. the positive time trends and falling risk). These drought trend rankings are stable over time and capture the long-run effect of climate change on a country's drought vulnerability.

[5]Adding additional lags to the autoregressive structure yields similar cross-country rankings based on the linear deterministic time trend. Appendix Table 2 shows that the return predictability of PDSI time trends remains using these alternative specifications.

Our focus is on the spread in future performance of the food industries in the Quintile 1 or rising drought-risk group of countries relative to the Quintile 5 or falling drought-risk group of countries as opposed to the mean performance of the overall food sector (or the middle Quintiles 2-4 group of non-trending countries). The rationale is that the overall effect of climate change on global food production or crop yields is ambiguous (Mendelsohn, Nordhaus, and Shaw (1994)), while the spread in performance as driven by sensitivity to drought risk is clear cut. In other words, we are implementing a difference-in-difference estimate of the differential impact of drought trends on the stock market.

To this end, we then examine the extent to which these simple cross-sectional country rankings at year t can forecast changes in food industry profitability (net income divided by total assets) and food industry stock returns across countries over the sample period of 1985 to 2014. Our dependent variable of interests are the change in profitability ratios and the returns of the FOOD industry of each country.[6] FOOD combines food processing, beverage and agricultural companies. We focus on this aggregated industry portfolio as opposed to the finer industry classifications, which separate FOOD into smaller components. The reason is that drought is likely to have a direct impact on the profits of both food processing and agricultural companies.[7] We confirm below that adverse trends in droughts have significant impact on all three sub-sectors of the Food industry.

We show that there is strong forecastability of changes in food industry profitability out a number of years. Countries with the negative time trends experience subsequently lower growth in profits than countries with positive time trends. For countries in the negative trend group, the mean cumulative change in profits from year t to year $t + 3$ is -0.46%. For those in the positive trend group, the corresponding mean is 0.61%. The difference has a t-statistic of 2.2.

[6] We use Datastream industry classifications for the international sample to identify food industry. For the US, we use the Fama and French (1997) 17-industry classification.

[7] Drought also creates water shortages which impact agricultural companies. While some of these cost increases can be temporarily passed onto consumers, prolonged drought ultimately also severely impacts agriculture as well.

This spread of 1% is ten times larger than the unconditional sample mean and one-third of the unconditional standard deviation of annual changes in profitability ratios. We show that this spread persists even after accounting for different industry and country characteristics.

We can re-run our analysis by using only trend rankings calculated at the end of 1984. That is, for the remaining years of our sample from 1985-2014, we fix the rankings and just track this set of countries over time. Given how persistent the trend rankings are, we get similar results, which accentuates the point that our findings reflect long-run drought trends for long-run food industry profitability.

In an efficient market, such publicly available rankings, even though they forecast profits, should not then be able to forecast stock returns years out if the stock market is efficient. We show that these same rankings, however, do forecast stock returns. The food stocks in the negative trend group have an excess return of .33% per month. The stocks in the positive trend group have an excess return of .89% per month. The difference is 0.56% per month (or around 7% annualized) with a t-statistic of 2.03. This 7% annual difference is reasonable given the substantial spread in changes in profits across the two groups, as we explain below.

The results are similar whether we adjust the return spread using the global Sharpe (1964) CAPM, Carhart (1997) four factor model, or the currency factor model of Lustig, Roussanov, and Verdelhan (2011). These adjustments make clear that while the mean returns of the middle group of non-trending countries is sensitive to the model of risk, the spread between the Quintile 1 group and Quintile 5 group is robust. Food stocks in the Quintile 1 group under-perform the stocks in the middle group, while stocks in the Quintile 5 group out-perform stocks in the middle group.

Using cross-country Fama and MacBeth (1973) regressions, we show that this excess return predictability remains even after we control for additional country and industry characteristics. This predictability is also significant even if we re-run our analysis by using only trend rankings calculated at the end of 1984. This predictability is present across sub-samples of 1985-1999 and 2000-2014. Nonetheless, we want to be modest about our excess predictability results since our international sample only has 31 countries. Given the food stocks in our sample are mostly small to medium sized firms, however, arbitrage would be very costly so that the large alpha of our long/short strategy does not mean there is easy money to be made.

We next conduct a placebo analysis where we repeat these exercises for all other industries and find that drought is uniquely tied to the FOOD industry. The next largest industry, which is however not statistically significant, is UTILITIES. It is known to be next to FOOD a highly water-reliant industry. This placebo test serves as a way to show that we are identifying climate change risks related to drought and our main results are not driven by unobserved differences in country characteristics (i.e. to address omitted-variables concerns in cross-country regressions).

In our robustness analyses (available in our Supplementary Internet Appendix), we consider a downside-risk CAPM and construct an alternative drought ranking measure as a country's 36-month moving average of the PDSI (denoted as PDSI36m) net of the long-run mean of that country divided by the standard deviation of PDSI, with the mean and standard deviation estimated using data from 1900 to 1939. The cross-sectional rankings of this standardized PDSI36m measure are correlated with the drought trend rankings but are less persistent as they also capture prolonged droughts. We obtain similar results in both instances.

Our findings are related to the recent literature on attention and return predictability (see, e.g., Hong, Torous, and Valkanov (2007), DellaVigna and Pollet (2007), and Cohen and Frazzini (2008)), whereby the market underreacts to many types of value relevant information such as industry news, demographic shifts, and upstream-downstream relationships. Even for these types of obviously relevant news, the market can be inattentive.

Our first set of results on cashflows differs from prior work using weather shocks to estimate the damage to crops from climate change (Deschenes and Greenstone (2007), Schlenker and Roberts (2009), Dell, Jones, and Olken (2014)). This weather-economy literature argues that short-run temperature shocks estimated in a panel regression with location fixed effects are useful from an identification perspective to measure potential damages to food production from temperature increases. But the extrapolation to climate-change damages is uncertain given adaptation in the long run and potential intensification effects not captured in local weather shocks. Our drought-trends approach, along with a placebo analysis using other non-agricultural industries to address omitted variables in cross-country regressions, complements this literature in better measuring the long-run effects of climate change on agricultural industry profits.

Our second set of results on excess return predictability distinguish our work from earlier work on the pricing of weather derivatives, which focuses again on only short-term fluctuations in weather (see, e.g., Roll (1984), Campbell and Diebold (2005)). Our study of climate change risks and market efficiency helps characterize the nature of the potential inefficiencies, which might inform regulatory responses and be useful for practitioners interested in the construction of quantitative risk-management models (Shiller (1994)).

There is a large literature on the economic analysis of how to design government policies to deal with climate change (see, e.g., Stern (2007), Nordhaus (1994)), be it through emissions trading (Montgomery (1972)) or taxes (Golosov, Hassler, Krusell, and Tsyvinski (2014)). In contrast, our analysis highlights the role of markets in potentially mitigating the risks brought on or exacerbated by climate change. Understanding the role of financial markets in pricing climate risks is a natural one, though work is limited at this point with some notable exceptions. Bansal, Kiku, and Ochoa (2014) argue that long-run climate risks as captured by temperature are priced into the market. Daniel, Litterman, and Wagner (2016) and Giglio, Maggiori, Stroebel, and Weber (2015) show how stock and real estate markets might help guide government policies assuming markets efficiently incorporate such climate risks. Our analysis suggests, however, that such climate risk information, at least when it comes to natural disasters, are incorporated into stock prices with a significant delay.

Our paper proceeds as follows. We present our data and discuss the PDSI metric in Section 2. In Section 3, we present the results of time trends in droughts. In Section 4, we present the results of drought trend rankings and predictability of changes in food industry profitability. In Section 5, we present the results of drought trend rankings and food stock excess return predictability. We conclude in Section 6.

2 Data, Variables and Summary Statistics

2.1 Global Food Stocks

We obtain firm-level stock returns and accounting variables for a broad cross section of countries (except for the U.S.) from Datastream and Worldscope, respectively. The sample includes live as well as dead stocks, ensuring that the data are free of survivorship bias. We compute the stock returns in local currency using the return index (which includes dividends) supplied by Datastream and convert them to U.S. dollar returns using the conversion function built into Datastream. In some of our tests, we also use price-to-book ratio and dividend-to-price ratio which are directly available from Worldscope database. Inflation rate for international countries is from the World Bank database.

Datastream classifies industries according to Industrial Classification Benchmark (ICB). The food portfolio includes stocks in the food & beverage supersector.[8] We further apply the following sequence of filters that are derived from the extensive data investigations by Ince and Porter (2006), Griffin, Kelly, and Nardari (2010) and Hou, Karolyi, and Kho (2011). First, we require that firms selected for each country are domestically incorporated based on their home country information (GEOGC). A single exchange with the largest number of listed stocks is chosen for most countries, whereas multiple exchanges are used for China (Shanghai and Shenzhen) and Japan (Tokyo and Osaka). We eliminate non-common stocks such as preferred stocks, warrants,

[8]ICB Supersector Level classifies industries as follows: Oil & Gas, Chemicals, Basic Resources, Construction & Materials, Industrial Goods & Services, Automobiles & Parts, Food & Beverage, Personal & Household Goods, Health Care, Retail, Media, Travel & Leisure, Telecommunications, Utilities, Banks, Insurance, Real Estate, Financial Services, Equity/Non-Equity Investment Instruments, and Technology.

REITs, and ADRs. A cross-listed stock is included only in its home country sample. If a stock has multiple share classes, only the primary class is included. For example, we include only A-shares in the Chinese stock market and only bearer-shares in the Swiss stock market. To filter out suspicious stock returns, we set returns to missing for stocks that rises by 300% or more within a month and drops by 50% or more in the following month (or falls and subsequently rises). We also treat returns as missing for stocks that rise by more than 1,000% within a month. Finally, in each month for each country, we winsorize returns at the 1st and the 99th percentiles, to reduce the impact of outliers on our results (McLean, Pontiff, and Watanabe (2009)).

Our US food industry return data comes from Kenneth French's website.[9] It contains the monthly value-weighted returns for the Fama-French 17 industry portfolios from January 1927 to December 2014. We obtain accounting data for the US from Compustat. We get monthly data of inflation rate and the dividend-price ratio of the S&P 500 index from Amit Goyal's website.[10]

In addition, to meaningfully identify the drought impact in our international sample, in any given time t, we only include the food stocks of a country in our portfolio or regressions if the number of food stocks in that country is equal to or greater than 10. The final sample includes 31 countries, among which 16 are developed countries and 15 are developing countries. Panel A of Table 1 reports the summary statistics of our international sample. The sample starts at year 1985, or the earliest year when a country has at least 10 food stocks and ends at 2014. The time-series average number of stocks in the food industry varies considerably across countries, from 134 in US to 10 in Finland. We also report the mean market capitalization of food stocks within each country as of the end of 2014 millions of U.S. dollars. Notice that most of the food companies have market capitalizations that would be considered small to medium size companies by the standard of the NYSE firm size distribution. As a result, it is likely that food

[9] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`
[10] `http://www.hec.unil.ch/agoyal/docs/PredictorData2014.xlsx`

industries in most countries are significantly exposed to the climate condition of their country of origin since only very large multinationals are able to diversify across countries.

For each country, each month, we calculate its food industry return as the value-weighted average return of individual firms within food industry, using lagged firm market capitalization as weight. We also construct annual food portfolio return by continuously compounding monthly food returns and denote it as FOODRET12. Panel B of Table 1 shows the summary statistics for our variables. Our baseline dependent variable of interest, FOODRET12, has a mean of 12.02% and a standard deviation of 33.03%.[11] The change in the food industry profitability ratio in year t is defined as $CP_t = NI_t/A_t - NI_{t-1}/A_{t-1}$, where NI is the food industry-level net income and A is the food industry-level total book assets. The food industry-level net income and total asset are obtained respectively by aggregating the net income and the book assets of individual firms within the food industry. The cashflow variable CP has a mean of 0.11% and a standard deviation of 3.62%.

Panel B of Table 1 also reports the summary statistics for the control variables. The market predictor variables we have for the international sample include the lagged 12-month returns of the country market index (MRET12), the lagged inflation rate of the country (INF12), and the dividend-to-price ratio of the country market index (DP). Food industry-specific controls include the price-to-book ratio of the food industry stocks (FOODPB) and the lagged 12-month returns of the food industry (FOODRET12). The mean annual market return is 8.83% with a standard deviation of 33.37%. The median annual inflation rate is 3.27%, annual dividend-to-price ratio is 2.36%. The median price-to-book ratio for the food stocks is 2.09. In Panel C, we report the contemporaneous correlations among these variables along with their correlations to our two drought trend measures, which we now describe in detail.

[11] The large annualized standard deviation compared to the mean is in line with panel studies of international stock markets. This large standard deviation will be reflected in our t-statistics and affect our interpretation of the economic significance of our excess-return predictability regressions. As such, we will calculate what a one standard deviation increase in the PDSI trend implies for expected food industry returns as a fraction of this unconditional standard deviation of food stock returns.

2.2 Drought Trend Measures

Our data for the global (excluding the US) Palmer Drought Severity Index comes from Dai, Trenberth, and Qian (2004).[12] 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.[13]

Figure 2 plots the time series of monthly PDSI values for Peru and New Zealand along with the fitted trend lines. The figure shows that Peru experienced worsening droughts over time while New Zealand experienced improving climate conditions. Anecdotal evidence confirms

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

[13] Appendix Figure 1 illustrates the historical evolution of this drought measure from January 1900 to December 2014, with its value shown on the vertical axis. The PDSI for USA measure identifies some of the most recognizable droughts in the US history. For example, we can see the infamous "Dust Bowl" period of prolonged droughts in the 1930s, and an extended period of severe droughts in the 1950s, with the PDSI value falling frequently below -2 and even breaking -8. From the 1960s to the 1980s, the US experienced several spells of relatively shorter yet significant droughts. Since the turn of the 21st century, the US has experienced various droughts that include the current ongoing drought in California.

that the countries shown here did exhibit drought experiences which resonate with these PDSI trends. For example, in Peru, deforestation and forest degradation in the Peruvian Amazon and receding glaciers in the Andes exemplify the occurrences of drought. Glacial areas of the Peruvian Andes retreated by 20 percent to 35 percent between the 1960s and the 2000s, with most of that retreat occurring since 1985.[14] On the other hand, for New Zealand, and similarly Australia, studies have shown that climate change could actually make these countries wetter (despite it becoming hotter) and bring more rain to its desert regions.[15]

3 Ranking Countries Based on their Trends in Droughts

As pointed out by climate studies, the steady increase in global temperatures has led to both more droughts on average over time and dispersion across countries, i.e. differential trends in droughts. We measure these 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:

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

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 will also denote the expanding window from 1990 to the month m below as month t.)

[14] http://www.un.org/climatechange/blog/2014/11/peru-evidence-climate-change-abundant-hope-solution/
[15] http://www.smh.com.au/national/climate-alert-aust-becoming-warmer-wetter-20120313-1uyuz.html

We have tried different specifications of estimating PDSI time trends including: (1) PDSI time trend estimated without the lagged PDSI and (2) PDSI time trend estimated with lagged PDSI and month dummies. The correlation between our baseline PDSI trend with these alternative measures of PDSI trends are very high, and our subsequent results are robust to these alternative measures of PDSI trends. (These results are available from the authors upon request.) Hence we opt for parsimony and stay with our AR(1) specification with a time trend. We would like to point out that we can estimate our time trend model by including no lags of PDSI or more lags of PDSI. Our results below about the relationship between these estimated trends and stock market performance are the same regardless of the model we use.

We estimate the above trend model for our sample of 31 countries on a rolling basis. That is, in each month t from December 1984 to December 2014, 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).

Table 2 reports the results of these trend estimates. (We do not report the coefficient on lagged PDSI for brevity and our cross-country rankings are not sensitive to the particular trend model. The coefficient is between .85 and .9 for all countries and statistically significant.)[16] 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. For instance, Israel and Peru have very negative time trends in droughts (-3.69 bps and -3.31 bps respectively) that are statistically significant at the 1% level (t-statistics of -3.03 and -2.77 respectively), while New

[16]There are no issues with unit roots in our monthly PDSI series using Dickey-Fuller tests.

Zealand and Australia have significant positive trends (2.51 bps and 1.55 bps respectively, with t-statistics of 2.16 and 1.75). As argued by Dai, Trenberth, and Qian (2004), the global land areas in either very dry or very wet conditions have increased from 20% to 38% since 1972, with surface warming as the primary cause after the mid-1980s. These results provide observational evidence for the increasing risk of droughts as anthropogenic global warming progresses and produces both increased temperatures and increased drying.

Furthermore, we can test whether the negative time trends in droughts experienced by some countries are significantly different from the positive time trends in other countries. To do this, we sort countries into quintile groups (portfolios) based on its estimated PDSI time trend at the end of each year (from 1984 to 2014).[17] Then we obtain the time trend for each quintile group at the end of each year by taking the median value of the corresponding time trend estimates of the countries in the group. Let us denote the trend of the Quintile 1 group as $trend\_Q1$ and the trend of the Quintile 5 group as $trend\_Q5$, and let $trend\_diff = trend\_Q1 - trend\_Q5$. We want to test the null hypothesis $trend\_diff = 0$ (i.e. no difference between the trends from the two groups) against the alternative that $trend\_diff < 0$ (i.e. the trend of the Quintile 1 group is less than that of the Quintile 5 group). Using the trends of the two groups from 1984 to 2014, this is a one-sided t test of testing $trend\_diff = 0$ against $trend\_diff < 0$. The resulting t-statistic has a value of -18.87 (using Newey-West adjusted standard errors), so the null hypothesis of the trends of the two groups being equal is rejected at any reasonable statistical significance level, in favor of the trend of the Quintile 1 group being less than that of the Quintile 5 group. Therefore, this indicates that there is a statistically significant difference in the time trend of drought among different countries.

[17] We could alternatively carry out the sorts on a monthly basis from December 1984 to December 2014 and then do the test for the trends over all months. The result does not change and is available from the authors upon request.

4 Drought Trend Rankings and Predictability of Changes in Food Industry Profitability

In this section, we show that these trend measures (whether using information only up to end of 1984 or on a rolling basis) are highly predictive of changes in profitability of the food industry across countries over the sample period of 1985 to 2014, when we have data from international stock markets. Specifically, we expect that countries that are trending down experience worsening profits over time than countries that are trending up.

4.1 Portfolio Sorts

Following Fama and French (2000), we measure change in food industry profitability from year t to $t+1$ as $CP_{t+1} = NI_{t+1}/A_{t+1} - NI_t/A_t$, where NI is the food industry net income and A is the food industry total book assets. The food industry-level net income and total asset are obtained respectively by aggregating the net income and the book assets of individual firms within the food industry.

In Table 3, we report the future change in food industry profitability for countries across the quintile portfolios sorted by PDSI time trend measured up to the end of year t. Change in profitability for a portfolio is the equal-weighted average change in profitability of countries within each portfolio. We then track the change in food industry profitability over subsequent years, out to three years. We group together the middle three quintiles and call it the Quintiles 2-4 group. We can compare the difference in the change in profitability between the Quintile 1 and Quintile 5 groups. Note that Quintile 1 are those negative trending countries with rising drought risk, and Quintile 5 are those positive trending countries with falling drought risk. This difference is 0.49% in year $t+1$ and grows to 0.63% in year $t+2$ and 1.06% in year $t+3$. The differences are statistically significant. Notice that out to three years, the difference of 1.06% is quite economically large since we are deflating by total assets. The mean change in profitability in our sample is only 0.11% with a standard deviation of 3.62%. So this spread in change in profitability is 10 times the sample mean and over one-fourth of the sample standard deviation.

4.2 Cross-Country Regressions

In Panel A of Table 4, we re-do this cross-country sorting analysis by running Fama and MacBeth (1973) regressions, where we can then control for country and industry characteristics to see how robust these univariate sorts are. Each year t, we run a cross-sectional regression with the future 1-year change in food industry profitability CP (in percentage points) as our dependent variable:

$$\text{CP}_{i,t+1} = \mu + \lambda \, \text{Trend Quintile } 1_{i,t} + \gamma' X_{i,t} + e_{i,t+1} \tag{2}$$

Our key independent variable "Trend Quintile 1" is a dummy variable equal to 1 if the country is in the quintile 1 group of its estimated PDSI time trend at end of each year and zero otherwise. X is a set of additional controls and e is the error term. We repeat this regression for each year of the sample period from 1985-2014. We report the time-series average of this coefficient following Fama and MacBeth (1973). The t-statistics are calculated using Newey and West (1987) adjusted standard errors. In Column (1), the coefficient of "Trend Quintile 1" is -0.41 with a t-statistic of -3.41. Notice that this -.41 coefficient can be interpreted as the difference in change in future profitability between the Quintile 1 and the other groups is -.41%.[18] This figure is similar to that from the univariate sorts by construction. As we add in controls, the coefficient remains negative. In column (3) with the most stringent set of controls, the coefficient is -.27 and statistically significant with a t-statistic of -2.04. This says that controlling for cross-country differences do not affect the general conclusion that these trends are highly predictive of deteriorations in profitability of countries with negative PDSI time

[18] Our dependent variable of interest, the change in profitability CP, is expressed in percentage points. Trend Quintile 1 is a dummy variable equal to 1 if the country is in the bottom quintile of estimated PDSI trend and 0 otherwise. Hence, a regression coefficient of -0.41 in front of the dummy variable implies then that the difference in CP between the Quintile 1 group of countries and other countries is -.41%.

trends. Among the control variables, lagged inflation rate has a significant negative coefficient. This could be due to squeezed profit margin for food producers when price of inputs rises quickly. Coefficients on the food sector price-to-book ratio and lagged 12-month returns are positive, consistent with the idea that market valuation and past stock returns contain information about growth in profitability.

In Panel B of Table 4, we re-do the Fama and MacBeth (1973) regressions but rather than using year-t trend rankings, we use the same trend rankings measured using data up to the end of 1984. The reason for this analysis is to show that the trend rankings are highly persistent, i.e. the 1984 ranking is highly correlated with the rankings in subsequent years given that we use data going back to the early 1900s to create these trend measures. This analysis also makes very clear that our trend rankings are not picking up temporary or even prolonged weather fluctuations. The results are virtually identical to the previous table.

In short, we have significantly linked these trends in drought to long-term cashflows of food industries across the countries in our sample. The fact that there is a significant link is not surprising given that these drought trends are highly persistent and long-term trends in droughts in different countries would according to industry estimates, and our own estimates, impact overall food industry profitability.

5 Drought Trend Rankings and Cross-Country Excess Stock Return Predictability

5.1 Portfolio Sorts

In this section, we conduct a portfolio strategy test of market efficiency. We want to see if global markets are efficiently responding to information on long-run trends in drought. In contrast to our analysis of food sector net income, which are only available annually, we have access to monthly stock returns. To this end, in any given month, we construct a trading strategy that is longing the food portfolio in countries with positive PDSI trends and shorting the food portfolio in countries with negative PDSI trends. We expect this strategy to generate abnormal returns if markets indeed underreact to climate risks as proxied by our PDSI time trends measure.

Our use of portfolio sorting approach could help mitigate the errors-in-variables problem that may lead to underestimated standard errors in the regression approach (Shanken (1992)). When variables are measured with noise, the portfolio sorts will be less accurate as some countries will be assigned to the wrong portfolio. Under the assumption of cross-sectional predictability, this leads to smaller return differences across portfolios. Since inference is based on portfolio returns, the measurement error usually leads to a decrease in statistical significance (Boguth and Kuehn (2013)).

Our trading strategy is constructed as follows. At the end of each month t, we sort the food-industry portfolios across all countries into quintiles based on its PDSI trends measured up to month t. Returns for each quintile portfolio is the equal-weighted average returns of the countries within each portfolio.[19] We then hold each portfolio for K months (where K can range anywhere from 12 month to 36 months). We follow Jegadeesh and Titman (1993) to construct the overlapping portfolios. For each quintile portfolio at month t, we have K portfolios formed from month $t-1$ to $t-K$. Returns on the K portfolios are then equally-weighted to get the average return for each quintile portfolio at month t. The quintile portfolios are rebalanced monthly as we replace $1/K$ fraction of the portfolio that have reached the end of its holding horizons. In addition to the mean excess returns net of US risk-free rate, we also report portfolio alphas adjusted using global CAPM and Carhart (1997) 4-factor model.[20] Our sample starts from January 1985 when we have at least 10 countries to do the portfolio sorting exercise. The result is reported in Table 5. There are a range of results but they all point toward the same

[19]Equal-weighting could mitigate the concern that the quintile portfolios are dominated by a single country with a large total market capitalization of the food sector.

[20]The global market, size, book-to-market and momentum factors are the weighted average of the respective country-specific factors, where the weight is the lagged total market capitalization in that country.

conclusion.

In Panel A, we report the monthly mean excess returns and factor-adjusted alphas for quintile portfolios with a holding horizon of $K = 1$ year. Excess return is raw portfolio return net of US risk-free rate. The middle three portfolios are grouped together by equal weighting their respective returns. In column (1), the mean excess returns increase from Quintile 1 to Quintile 5 countries. The mean excess return for countries in the bottom quintile of PDSI time trend is 0.33% per month, and for countries in the top quintile, the number is 0.89%. The difference between the Quintile 5 (positive trending and falling risk) and Quintile 1 (negative trending and rising risk) group is 0.56% per month (t=2.03) in excess returns or 6.72% annualized. In column (2) and (3), we also report the portfolio alphas adjusted using a global CAPM and Carhart (1997) four factor model. Our results are not affected as the long/short strategy generates a monthly alpha of 0.55% (t=1.98) and 0.58% (t=2.03).[21] Given the food stocks in our sample are mostly small to medium sized firms, however, arbitrage would be very costly so the large alpha of our long/short strategy does not mean there is easy money to be made. In addition, we are modest about our excess predictability results since our international sample only has 31 countries.

To the extent that commodities dominate the food industry, the significant return spread of our long/short portfolio could reflect compensation for exposure to exchange rate risk. This is a plausible alternative as countries with negative trends in drought would suffer reduced revenues from exporting food and agricultural products, resulting in currency depreciation. To explicitly control for currency risks, we examine whether the currency factor model of Lustig, Roussanov, and Verdelhan (2011) could explain our long/short portfolio. Lustig, Roussanov, and Verdelhan (2011) propose two currency factors that could price the cross-sectional variation of currency

[21] We have calculated the alpha of "Middle Quintiles - Quintile 1" and "Quintile 5- Middle Quintiles" portfolio. For excess returns, CAPM and 4-factor alpha, the majority of the long/short portfolio spread comes from the "Middle Quintiles - Quintile 1" group. For currency factor model, both contribute equally to the spread. However, the difference between "Middle Quintiles - Quintile 1" and "Quintile 5 - Middle Quintiles" are not statistically significant.

returns. Specifically, the first factor, RX, is the average currency excess return. The second factor, HML, is the return in dollars on a zero-cost strategy that goes long in the highest interest rate currencies and short in the lowest interest rate currencies. We download the time series of these two currency factors from Hanno Lustig's website.[22] The right most column of Table 5 reports the portfolio alpha adjusted by the currency factor model. The spread is now .44% per month or 5.28% annualized. The latter estimate is borderline in terms of statistical significance at 1.56.

Notice that the Quintiles 2-4 group of countries have positive alphas. As we noted in the Introduction, our focus is on the spread in future performance of the food industries in the Quintile 1 (or negative trending) group of countries versus the Quintile 5 (or positive trending) group of countries as opposed to the performance of the overall food sector (or the Quintiles 2-4 of non-trending countries). The rationale being that the overall effect of climate change on global food production or crop yields is ambiguous (Mendelsohn, Nordhaus, and Shaw (1994)), while the spread in performance as driven by sensitivity to drought risk is clear cut.[23]

In Panels B and C, we consider portfolio returns with a holding horizon of 2 and 3 years. The estimates get larger across all specifications and are statistically significant throughout. Moreover, regardless of the benchmark adjustments we use, we get a strong under-performance of the Quintile 1 group relative to the middle group of countries in all instances. There is also some outperformance by the Quintile 5 group but the spread between the Quintile 1 and Quintile 5 groups is coming strongly from the Quintile 1 group under-performing.

In our baseline case, we estimate the time trends in PDSI using AR(1) model with a de-

[22]https://sites.google.com/site/lustighanno/data

[23]Our portfolio sorts for a single industry is different from the typical portfolio sorts such as sorting based on book-to-market or momentum, where usually all stocks in the market are sorted into quintile portfolios so the value-weighted alpha across all portfolio must be zero. In untabulated results, we construct a global food portfolio that average the returns of food sector in each country in our sample. This global food portfolio generates a significantly positive 4-factor alpha of 0.68% (t=3.56) when each country return is weighted equally. To the extent that the global food industry could subject to some unobserved common shock, taking the difference between low and high PDSI trend countries could remove this common shock and better isolate the effect of differential trends in drought on food stocks.

terministic time trend. Our results are robust to alternative models of estimating time trends with more lags of PDSI. Appendix Table 2 shows the Fama-MacBeth regression results when the time trend is estimated with 2 and 3 lags of PDSI. As we can see, food returns in countries with most negative PDSI trends still underperform those in other countries significantly.

Are the magnitude of the under-performance of these negative PDSI trend countries aligned with the short-fall in net income of the countries? During a 3-year period, the net income of countries with negative PDSI trend relative to countries with positive PDSI trend decreases by 1.06% as a fraction of total assets. Given the average ratio of Total Assets/Net Income of the food sector is 20.3, this means the growth rate of net income is -21.5% for negative PDSI trend countries over 3 years. This matches well with the return spread of 23% (0.64%*36) of our long/short portfolio with a 3-year holding horizon.

5.2 Cross-Country Regressions

In Panel A of Table 6, we run Fama-MacBeth regressions of future 12-month food return (in percentage) on a dummy "Trend Quintile 1":

$$\text{FOODRET12}_{i,t+1} = \kappa + \nu \, \text{Trend Quintile } 1_{i,t} + \psi' X_{i,t} + \eta_{i,t+1} \tag{3}$$

"Trend Quintile 1" is a dummy equal to 1 for countries in the bottom quintile of its PDSI time trend at the end of each year. The dependent variable is the non-overlapping food return over the future 12 months. The control variables in X are the same as in the cashflow regression, including lagged 12-month food industry return (FOODRET12), lagged 12-month market return (MRET12), log of food industry price-to-book ratio (FOODPB), lagged inflation rate (INF12) and the market dividend-to-price ratio (DP). In column (1), without any controls, the coefficient in front of Trend Quintile 1 is -7.03 with a t-statistic of 3.56. This means that compared to countries in other groups, food stocks in the Quintile 1 countries have a 7% lower annual return compared to other groups. As we add in more controls, our coefficient estimate fluctuates and in all specifications, there is a meaningful underperformance in future returns for countries with decreasing PDSI trends. For the control variables, we find that high market Dividend/Price ratio predicts positive returns and high Price/Book ratio of food industry predict negative returns, consistent with the value effect in international stock market (Fama and French (2012)).

In Panel B of Table 6, we re-do the Fama-MacBeth cross-sectional return regressions using only the PDSI trends measured up to the end of 1984. We see that the coefficient estimates are nonetheless fairly similar to our earlier tables. The reason of course is that these rankings are highly persistent since they are estimated using long samples going back to early 1900s. The rolling estimates of PDSI time trends differ some as trends might change over our sample period for some countries, but for the most part, these trends are fairly persistent and our assessments of which countries are likely to benefit or suffer from droughts are not changed.

In Table 7, we re-run these Fama-MacBeth regressions by splitting our sample in half to illustrate the robustness of our findings across sub-periods. Column (1) shows the results for the 1985-1999 sub-sample while column (2) shows the results for the 2000-2015 sub-sample. The point estimates are virtually identical but of course the precision varies since we have cut the sample in half to calculate the standard errors.

5.3 Placebo Analysis Using Non-Agricultural Industries

A priori, time trends in droughts should not have strong predictive power for future returns in other industries that are not as vulnerable to droughts as the Food industry. The other major industry perhaps comparable to food companies in terms of water use is the power industry, but utilities are regulated. The only other industry that also consumes a significant amount of water in its production process is the automotive industry but its reliance on water is much less than that of the food industry. In short, this placebo analysis will demonstrate that we are identifying climate change risks related to drought and our main results are not driven by unobserved differences in country characteristics.

We carry out this placebo analysis by re-conducting the long-short portfolio strategy for other industries. The first column of Table 8 shows the names of other industries besides Food in our international sample. The industry classification is based on Industrial Classification Benchmark (ICB) supersectors. As before, for each industry at the end of each month, we sort countries into quintile portfolios based on their PDSI time trends, and then construct a long/short portfolio that short countries whose PDSI time trends are in the bottom quintile and long those countries in the top quintile. We construct the overlapping portfolio following Jegadeesh and Titman (1993) in the same way as our previous return analyses and the portfolios are held for future 12 months.

In columns 2 and 3 of Table 8, we show the Carhart (1997) 4-factor alpha of these portfolios for other industries and their associated t-statistics, benchmarked against those of the Food industry. It is very clear that, apart from the Food industry, time trends in drought has no statistically significant forecasting power for the return of any other industry. In addition, the Food industry also has the second largest alpha among all industries. The only other industry that has a larger alpha is Utilities that is also quite drought sensitive, but its t-statistic is not significant. This placebo analysis helps allay omitted-variables concerns associated with cross-country regressions.

5.4 Return Predictability for Sub-Sectors of Food Industry

We repeat the same return predictability analysis for the three sub-sectors of the Food industry separately to ensure that our results are not driven by any particular sub-sector. In our sample, the three Food sub-sectors are Beverage, Farm, and Food Products. Panel A of Table 9 shows the number of firms for three sub-sectors within each country. For each sub-sector in the food industry, we construct a long/short portfolio that short countries whose PDSI time trends are in the bottom quintile and long the top quintile. The portfolios are overlapping as before and are held for future 12 months.

As can be seen from Panel B of Table 9, our trends in droughts have significant forecasting power for returns in all three Food sub-sectors, whether it is pure excess return or Carhart (1997) 4-factor alpha. The similarity across three different sub-sectors shows that our earlier results are not driven by any particular type of firms within the Food industry.

5.5 Robustness

We carry out two robustness analyses. The first one is to implement a downside-risk CAPM model (DR-CAPM) as an alternative risk benchmark. The second one is to construct an alternative drought ranking measure using a country's 36-month moving average of the PDSI net of the long-run PDSI mean of that country divided by the standard deviation of PDSI. We then repeat the portfolio return analysis using this alternative measure. The details of these analyses are shown in our Supplementary Internet Appendix. In short, our results remain robust to this alternative risk benchmark. And using the alternative drought ranking measure also generates similar results as before, with the long/short portfolio yielding both significant excess returns and factor-adjusted alphas over time.

6 Conclusion

We show that stock markets are inefficient with respect to information about drought trends, one of the most important climate risks that are brought on or exacerbated by climate change according to climate scientists. Using a global dataset of the widely-used Palmer Drought Severity Index (PDSI) from climate studies, which goes back to 1900, we can calculate the time trend of drought for each country using data up to a given year t. Poor trend rankings for a country forecast poor subsequent growth in profitability of the food industry in that country. Poor rankings, even adjusting for a variety of risk benchmarks, also forecast subsequent poor returns for food stocks in that country. This excess return predictability is consistent with food stock prices underreacting to climate-change risks.

Our findings have a number of implications for academics, policymakers and practitioners. First, it would be useful to pinpoint the sources of underreaction. Simple inattention might be one mechanism. But given that we are considering international portfolios, home country equity bias and other institutional investor frictions might also be relevant for the efficient reallocation of capital flows. Second, our findings confirm regulatory worries about markets underreacting to climate risks and suggest further exploration of the value of corporate disclosure of exposure risk. Third, our findings show that PDSI might be a very useful metric of drought to form portfolios and manage risks. We leave these topics for future research.

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Table 1: Summary Statistics

This table reports the summary statistics of our sample. Panel A reports the average number of stocks and the mean market capitalization of food stocks in each country. Panel B reports the summary statistics of our variables for the full sample. Panel C reports the pairwise correlation among our variables where they overlap. FOODRET12 is the annual food industry return. Change in food industry profitability (CP) from year t to $t+1$ is defined as $CP_{t+1} = NI_{t+1}/A_{t+1} - NI_t/A_t$, where NI is the food industry-level net income and A is the food industry-level total book assets. MRET12 is the annual return of country market index. INF12 is the annual inflation rate. DP is the dividend/price ratio of country market index. FOODPB is the food industry price-to-book ratio. Trend is the time trend of PDSI estimated using equation (1). PDSI36m* is a country's 36-month moving average of the PDSI net of the long-run mean of that country divided by its standard deviation, with the mean and standard deviation of PDSI36m are estimated using data from 1900 to 1939. A country is in our sample only when the number of food stocks in that country is at least 10. All returns are expressed in US dollars. The sample period is from January 1985 to December 2014.

Panel A: Summary Statistics by Country

Number	Country	Average # of Stocks	Mean Firm Size (Millions USD)
1	United States	134	3789
2	India	107	18
3	Japan	77	363
4	China	58	458
5	Malaysia	49	141
6	United Kingdom	40	182
7	South Korea	39	162
8	Thailand	32	69
9	France	28	217
10	Australia	28	124
11	Greece	25	60
12	Indonesia	22	122
13	Poland	21	81
14	Israel	20	103
15	Peru	19	76
16	Chile	19	120
17	Turkey	18	79
18	Canada	15	208
19	Germany	15	438
20	South Africa	15	346
21	Brazil	14	907
22	Switzerland	13	714
23	New Zealand	13	141
24	Netherlands	13	2888
25	Mexico	11	293
26	Belgium	11	126
27	Philippines	11	243
28	Denmark	11	417
29	Russian Federation	11	295
30	Portugal	11	25
31	Finland	10	209

Table 1 Continued

Panel B: Summary Statistics of Variables

	Mean	S.D.	Median	P10	P90
CP (%)	0.11	3.62	-0.02	-2.89	2.88
FOODRET12 (%)	12.02	33.03	11.31	-25.17	48.78
Trend (bps)	-0.50	1.52	-0.47	-2.71	1.51
PDSI36m*	-0.29	1.41	-0.34	-2.05	1.42
MRET12 (%)	8.83	33.37	10.47	-30.97	44.71
FOODPB	2.54	1.83	2.09	0.83	4.85
DP (%)	3.49	6.81	2.36	0.94	4.82
INF12 (%)	9.34	33.32	3.27	1.00	11.28

Panel C: Correlations

	CP	FOODRET12	Trend	PDSI36m*	MRET12	FOODPB	DP	INF12
CP	1.000							
FOODRET12	0.048	1.000						
Trend	0.016	0.060	1.000					
PDSI36m*	0.070	0.117	0.536	1.000				
MRET12	0.044	0.162	-0.025	0.051	1.000			
FOODPB	-0.005	-0.139	0.059	0.142	-0.126	1.000		
DP	-0.002	0.076	-0.063	-0.066	0.067	-0.188	1.000	
INF12	-0.043	0.178	0.137	0.162	0.256	0.045	-0.047	1.000

Table 2: 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 3: Change of Profitability to Portfolios Sorted on PDSI Time Trend

This table reports the change of food industry profitability for quintile portfolios sorted on PDSI time trends. Change in food industry profitability (CP) from year t to $t+1$ is defined as $CP_{t+1} = NI_{t+1}/A_{t+1} - NI_t/A_t$, where NI is the food industry-level net income and A is the food industry-level total book assets. At the end of each year t, we sort countries into quintile portfolios based on its PDSI trends estimated using data up to year t and hold the portfolios for future 1 to 3 years. Column (1), (2) and (3) report the change of profitability in the 1-year, 2-year and 3-year period following portfolio formation date, respectively. Change in profitability for a portfolio is the equal-weighted average change in profitability of countries within each portfolio. Quintile 1 are those countries with negative trending PDSI and rising drought risk, and Quintile 5 are those countries with positive trending PDSI and falling risk. We group the middle three portfolios together by equal-weighting their respective profitability changes and denote it as "Quintiles 2-4". "5 - 1" reports the difference in profitability change between the top and bottom quintile portfolios. The sample period is from 1985 to 2014.

Portfolio	(t, t+1)	(t, t+2)	(t, t+3)
Quintile 1	-0.09%	-0.32%	-0.46%
Quintiles 2-4	0.21%	0.10%	-0.03%
Quintile 5	0.40%	0.32%	0.61%
5 - 1	0.49%	0.63%	1.06%
t-stat	3.15	1.65	2.22

Table 4: Fama-MacBeth Regression of Change in Food Industry Profitability on PDSI Time Trend

This table presents the Fama-MacBeth regression of future 1-year change in food industry profitability on a dummy "Trend Quintile 1". Change in food industry profitability (CP) from year t to $t+1$ is defined as $CP_{t+1} = NI_{t+1}/A_{t+1} - NI_t/A_t$, where NI is the food industry-level net income and A is the food industry-level total book assets. In Panel A, "Trend Quintile 1" is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. In Panel B, "Trend Quintile 1" is a dummy equal to 1 for countries in the bottom quintile based on its estimated time trend in PDSI at the end of 1984. The dependent variable is the future 1-year change in food industry profitability (in percentage). The control variables are lagged food industry return (FOODRET12), lagged market return (MRET12), log of food industry price-to-book ratio (FOODPB), lagged inflation rate (INF12) and the market dividend price ratio (DP). Standard errors are Newey-West adjusted. *, **, *** denote statistical significance at 10%, 5%, 1% respectively. The sample period is from 1985 to 2014.

Panel A: Ranking based on estimated PDSI trend at end of each year

	(1)	(2)	(3)
Trend Quintile 1	-0.4131***	-0.2427***	-0.2692*
	(-3.41)	(-3.47)	(-2.04)
FOODPB		-0.2250	0.1041
		(-1.40)	(0.53)
FOODRET12		0.0017	0.0081
		(0.23)	(1.54)
DP			0.0202
			(0.22)
MRET12			-0.0112*
			(-1.81)
INF12			-0.0410*
			(-1.89)
Constant	0.2980**	0.0746	0.2183
	(2.55)	(0.34)	(0.67)
Ave.R-sq	0.035	0.281	0.557

Panel B: Ranking based on estimated PDSI trend at end of 1984

	(1)	(2)	(3)
Trend Quintile 1	-0.2078**	-0.2265**	-0.3989***
	(-2.19)	(-2.58)	(-3.60)
FOODPB		-0.2117	0.1244
		(-1.35)	(0.62)
FOODRET12		0.0004	0.0047
		(0.05)	(0.72)
DP			0.0194
			(0.24)
MRET12			-0.0125**
			(-2.48)
INF12			-0.0466**
			(-2.26)
Constant	0.2556**	0.0453	0.2689
	(2.47)	(0.19)	(0.78)
Ave.R-sq	0.030	0.276	0.556

Table 5: Returns to Portfolios Sorted on PDSI Time Trend

This table reports the monthly excess returns (raw returns net of US risk-free rate) and alphas (in percentage) to quintile portfolios sorted on PDSI time trend. At the end of each month t, we sort countries into quintile portfolios based on its PDSI trends estimated using data up to month t. Returns for each quintile portfolio is the equal-weighted average returns of the countries within each portfolio. Portfolios are then held for future 12 months in Panel A, 24 months in Panel B and 36 months in Panel C. We follow Jegadeesh and Titman (1993) to construct the overlapping portfolio returns. Quintile 1 are those countries with negative trending PDSI and rising drought risk, and Quintile 5 are those countries with positive trending PDSI and falling risk. We group the middle three quintile portfolios together by equal-weighting their respective returns and denote it as "Quintiles 2-4". We report the mean excess returns, alphas based on CAPM, Carhart (1997) 4-factors and the currency factor model of Lustig, Roussanov, and Verdelhan (2011). "5 - 1" reports the return spread between the top and bottom quintiles. The sample period is from 1985 to 2014.

Panel A: 1-year holding horizon

	Excess Return	CAPM	Carhart 4-factor	Currency Factors
Quintile 1	0.33	0.23	0.19	-0.19
Quintiles 2-4	0.75	0.63	0.68	0.03
Quintile 5	0.89	0.78	0.78	0.25
5 - 1	0.56	0.55	0.58	0.44
t-stat	2.03	1.98	2.03	1.56

Panel B: 2-year holding horizon

	Excess Return	CAPM	Carhart 4-factor	Currency Factors
Quintile 1	0.30	0.19	0.17	-0.23
Quintiles 2-4	0.71	0.59	0.64	-0.01
Quintile 5	0.91	0.80	0.80	0.27
5 - 1	0.62	0.60	0.63	0.49
t-stat	2.21	2.16	2.19	1.72

Panel C: 3-year holding horizon

	Excess Return	CAPM	Carhart 4-factor	Currency Factors
Quintile 1	0.28	0.18	0.15	-0.24
Quintiles 2-4	0.68	0.56	0.60	-0.05
Quintile 5	0.93	0.81	0.81	0.28
5 - 1	0.64	0.63	0.66	0.52
t-stat	2.30	2.25	2.28	1.81

Table 6: Fama-MacBeth Regression of future 12-month Non-overlapping Food Return on PDSI Time Trend

This table presents the Fama-MacBeth regression of future 12-month food return (in percentage) on a dummy "Trend Quintile 1". In Panel A, "Trend Quintile 1" is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. In Panel B, "Trend Quintile 1" is a dummy equal to 1 for countries in the bottom quintile based on its estimated time trend in PDSI at the end of 1984. The dependent variable is the non-overlapping food return over the future 12 months. The control variables are lagged food industry return (FOODRET12), lagged market return (MRET12), log of food industry price-to-book ratio (FOODPB), lagged inflation rate (INF12) and the market dividend-to-price ratio (DP). Standard errors are Newey-West adjusted. *, **, *** denote statistical significance at 10%, 5%, 1% respectively. The sample period is from 1985 to 2014.

Panel A: Ranking based on estimated PDSI trend at end of each year			
	(1)	(2)	(3)
Trend Quintile 1	-7.0251***	-2.0315*	-5.3988***
	(-3.56)	(-1.84)	(-2.76)
FOODPB		-3.9076***	-1.4628
		(-3.44)	(-1.50)
FOODRET12		0.0010	-0.1394
		(0.01)	(-0.85)
DP			1.2994**
			(2.18)
MRET12			-0.0217
			(-0.61)
INF12			2.5806
			(1.43)
Constant	15.5358***	14.6431***	3.9722
	(9.29)	(4.18)	(1.42)
Ave.R-sq	0.075	0.343	0.601

Panel B: Ranking based on estimated PDSI trend at end of 1984			
	(1)	(2)	(3)
Trend Quintile 1	-3.9186	-2.7447**	-3.3472
	(-1.42)	(-2.30)	(-1.54)
FOODPB		-4.2718***	-1.8746*
		(-3.44)	(-1.74)
FOODRET12		-0.0063	-0.1454
		(-0.07)	(-0.89)
DP			1.3949**
			(2.45)
MRET12			0.0024
			(0.07)
INF12			2.6246
			(1.48)
Constant	14.9471***	14.9011***	3.5646
	(8.17)	(4.12)	(1.19)
Ave.R-sq	0.060	0.331	0.593

Table 7: Fama-MacBeth Regression of future 12-month Non-overlapping Food Return on PDSI Time Trend, Sub-sample Analysis

This table presents the Fama-MacBeth regression of future 12-month food return (in percentage) on a dummy "Trend Quintile 1" separately for two sub-samples. "Trend Quintile 1" is a dummy equal to 1 for countries in the bottom quintile of its estimated PDSI time trend at the end of each year. The dependent variable is the non-overlapping food return over the future 12 months. Column (1) shows the result for the sub-sample 1985 to 1999, while Column (2) shows the result for the sub-sample 2000-2014. The control variables are lagged food industry return (FOODRET12), lagged market return (MRET12), log of food industry price-to-book ratio (FOODPB), lagged inflation rate (INF12) and the market dividend-to-price ratio (DP). Standard errors are Newey-West adjusted. *, **, *** denote statistical significance at 10%, 5%, 1% respectively. The overall sample period is 1985 to 2014.

	1985-1999	2000-2014
Trend Quintile 1	-5.2835	-5.5305**
	(-1.05)	(-2.95)
FOODPB	-1.1401	-1.8316
	(-0.48)	(-0.89)
FOODRET12	-0.2331	-0.0324
	(-0.62)	(-0.29)
DP	0.2377	2.5128***
	(0.75)	(3.79)
MRET12	-0.0721	0.0359
	(-1.11)	(0.62)
INF12	4.5318	0.3506
	(1.45)	(0.54)
Constant	5.8554	1.8200
	(1.39)	(0.44)
Ave.R-sq	0.722	0.463

Table 8: Returns to Portfolios Sorted on PDSI Time Trend For Other Industries

This table reports the Carhart (1997) 4-factor alpha of the long/short portfolio based on PDSI time trends. For each industry at the end of each month t, we sort countries into quintile portfolios based on its PDSI trends estimated using data up to month t and hold the portfolios for future 1 year. Reported is the return spread between the top and bottom quintile. Industry classification is based on Industrial Classification Benchmark (ICB) supersectors. We construct the overlapping portfolio following Jegadeesh and Titman (1993). The sample period is from 1985 to 2014.

Industry	4-factor alpha	t-stat
Food & Beverage	**0.58**	**2.03**
Utilities	0.69	1.47
Construction & Materials	0.35	1.25
Basic Resources	0.22	0.80
Automobiles & Parts	0.36	0.80
Health Care	0.27	0.80
Chemicals	0.25	0.76
Technology	0.22	0.66
Personal & Household Goods	0.10	0.44
Oil & Gas	0.17	0.37
Insurance	0.03	0.06
Industrial Goods & Services	-0.01	-0.07
Retail	-0.06	-0.17
Financial Services	-0.08	-0.24
Media	-0.14	-0.34
Travel & Leisure	-0.12	-0.37
Telecommunications	-0.47	-0.49
Real Estate	-0.20	-0.70
Banks	-0.29	-1.02

Table 9: Returns to Portfolios Sorted on PDSI Time Trend for Three Food Sub-sectors

Panel A of this table presents the average number of firms in the three sub-sectors of food industry: Beverage, Farm and Food Products. This sample includes countries for which the number of food stocks is larger than ten. Panel B reports the excess returns (raw returns net of US risk-free rate) and Carhart (1997) 4-factor alpha of the long/short portfolios based on PDSI time trend. For each food sub-sector at each month t, we sort countries into quintile portfolios based on its PDSI trends estimated using data up to month t and hold the portfolios for future 1 year. Overlapping portfolio returns are calculated following Jegadeesh and Titman (1993). We only include a country in our sample when the number of stocks in a sub-sector is at least five. The overall sample is from 1985 to 2014. Portfolios for Farm sub-sector starts from January 1991.

Panel A: Number of Firms for Three Subsectors of Food Industry

Number	Country	Beverage	Farm	Food Products
1	Australia	7	7	17
2	Belgium	5	3	8
3	Brazil	6	4	9
4	Canada	10	1	12
5	Chile	7	7	12
6	China	25	28	29
7	Denmark	5	4	4
8	Finland	1	0	5
9	France	14	6	21
10	Germany	17	3	12
11	Greece	2	7	18
12	India	15	19	88
13	Indonesia	2	11	9
14	Israel	4	4	17
15	Japan	11	5	60
16	Malaysia	2	34	16
17	Mexico	6	1	8
18	Netherlands	0	0	8
19	New Zealand	4	4	6
20	Peru	9	11	10
21	Philippines	4	1	10
22	Poland	5	2	19
23	Portugal	2	4	4
24	Russian Federation	1	4	6
25	South Africa	3	6	8
26	South Korea	6	8	30
27	Switzerland	7	0	7
28	Thailand	3	6	26
29	Turkey	4	1	17
30	United Kingdom	13	10	34
31	United States	22	15	79

Panel B: Returns to L/S Portfolio Sorted on PDSI Time Trend

Subsectors	Starting Date	Excess Return	t-stat	4-factor alpha	t-stat
Food Products	198501	0.67	2.27	0.71	2.33
Beverage	198501	0.53	1.75	0.54	1.72
Farm	199101	0.86	2.24	0.71	1.75

Figure 1: Global Temperature Anomaly

This figure plots the global temperature anomaly data from 1880 to 2015. Global temperature anomaly data come from the Global Historical Climatology Network-Monthly (GHCN-M) data set and International Comprehensive Ocean-Atmosphere Data Set (ICOADS), which have data from 1880 to the present. These two datasets are blended into a single product to produce the combined global land and ocean temperature anomalies. The term temperature anomaly means a departure from a reference value or long-term average. A positive anomaly indicates that the observed temperature was warmer than the reference value, while a negative anomaly indicates that the observed temperature was cooler than the reference value. The time series of global-scale temperature anomalies are calculated with respect to the 20th century average.

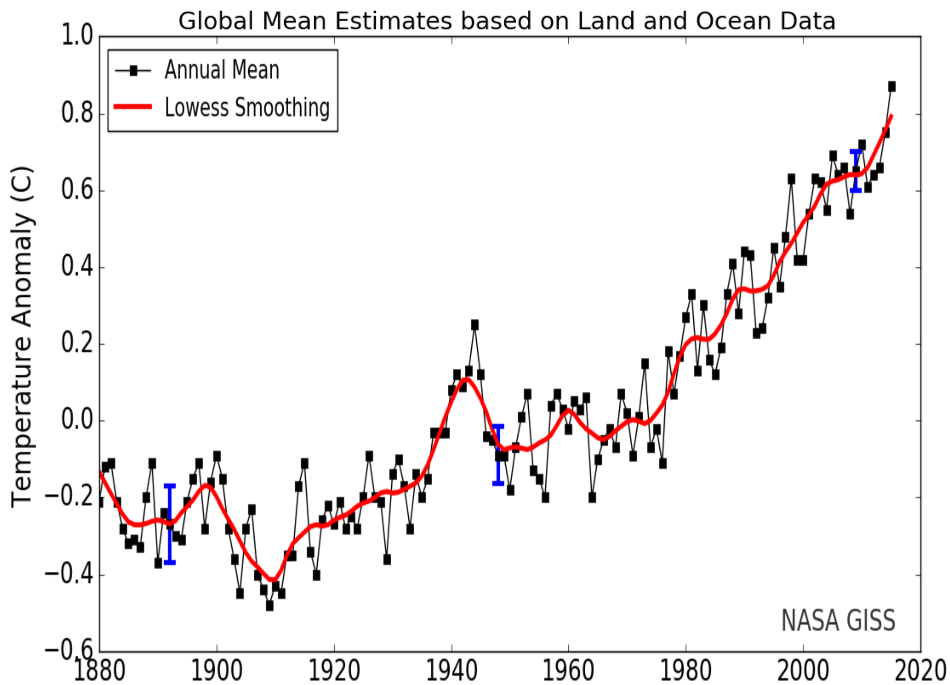

Figure 2: Historical PDSI for Selective Countries

This figure plots the time series of monthly PDSI value for Peru and New Zealand. The sample period runs from January of 1900 (or the earliest possible starting date) to December of 2014. The PDSI value is shown on the vertical axis. The horizontal axis is time. The black dashed line is the linear trend line through the time series.