Climate Risks of Sales Forecasts: Evidence from Satellite Readings of Soil Moisture*

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Abstract

We show that recently-available satellite readings of soil moisture, used to study the impact of climate change on hydrological cycles, predict the output of the water-intensive food industry. Using sales and forecasts data from thirty-one countries with publicly-traded food companies from 1994-2014, we obtain causal estimates for soil moisture by using as instruments climatic measures of droughts based on temperature and precipitation. Soil moisture is particularly important for food industry sales in the last decade of historically high temperatures. Consensus sales forecasts by security analysts, widely used to guide corporate investments and adaptations, have not recognized this structural change. Yet, we find that mitigating innovations measured using patents have become more important in explaining output.

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1 Introduction

The last decade has witnessed the development of satellite readings of soil moisture to advance our understanding of the impact of global warming (Dorigo *et al.* (2017), Dorigo & de Jeu (2016)). These readings, which cover many more countries than on site measurements, are being used to study how global warming impacts a range of outcomes, from climate processes such as evaporation and the hydrological cycle to crop yields.[1] Of course, water is crucial for not only crops but sustaining all aspects of the food industry including meat production, fisheries, and other fundamental aspects of the global food supply. Among all industries, the food industry is the most reliant on water (Blackhurst *et al.* (2010)).

Using data from thirty-one countries with publicly-traded food companies over the period 1994-2014, we use these satellite readings of soil moisture to investigate how climate change is impacting the food industry. We focus on annual food industry sales growth, the log of sales in year t divided by assets in year $t-1$, as our dependent variable of interest and examine the extent to which it can be predicted by soil moisture.[2] Food industry sales growth is an economically meaningful way to aggregate different crops and food products into a single metric. Since food output depends on soil moisture and most food companies are small to medium sized firms, these companies are significantly exposed to the climate conditions of their country of origin and hence climate change risk. We use satellite-based readings of soil moisture from the Global Land Evaporation Amsterdam Model (GLEAM) (Martens *et al.* (2017), Miralles *et al.* (2011)) as our independent variables of interest. These measures, which are given in volumetric water content (cubic meter/cubic meter or m^3/m^3) and shown in Figure 1, capture water availability near the surface and also in the root zone where plants derive their nutrients.

Our empirical approach, as in the new climate-economy literature (Dell *et al.* (2014), Deschenes & Greenstone (2007), Schlenker & Roberts (2009)), uses country fixed-effects and time fixed-effects to deal with omitted variables in a panel data setting. We collapse firms in each country into two groups, small versus large companies, and identify the effect of lagged soil moisture on sales growth using year to year fluctuations within a country. But in contrast to the new climate-economy literature which typically uses temperatures as the independent variables of interest, even year to year changes in soil moisture might not be exogenous since soil moisture can be influenced by production and adaptation.

As such, we propose as an instrument for annual changes in soil moisture the annual changes in an older climatic-based measure of water in the ground — the Palmer Drought Severity Index or PDSI (Palmer (1965), Alley (1984)). Simply put, climatologists can estimate the water in the ground based on cumulative rainfall

[1] See *ESA Climate Change Initiative Phase II Soil Moisture Climate Assessment Report*, November 29, 2017.

[2] We also focus on sales rather than earnings since earnings are subject to the differential treatment of capital expenses across the world. Sales is more uniformly treated by accounting standards.

over some period and temperature which would lead to evaporation. PDSI is given on a scale between -10 (extreme dry) to 10 (extreme wet). This PDSI measure has been around since the 1960s and its formula has not changed markedly over time. Annual changes in PDSI reflect year to year fluctuations in temperature and precipitation numbers, which can be viewed as exogenous weather shocks. The exclusion restriction is that annual changes in PDSI affects agricultural sales only through annual changes in soil moisture (or shocks to supply or productivity) and not through a demand channel. We think this is a plausible instrument since it is not clear how essentially transient weather shocks to temperature and precipitation in a given year would affect the demand side per se.

In short, these satellite-based soil moisture measures are likely to be more powerful predictors of food industry sales in contrast to climatic-based soil moisture measures. But the downside is potential endogeneity. This instrumental-variables approach allows us to naturally get causal estimates for soil moisture on food industry sales. Moreover, the instrument also helps us address other measurement error worries with satellite readings. If satellite technology has improved over time, then we might be picking up better measurements of soil moisture as opposed to the changing impact of climate on food-industry sales per se.

First, we show that our dependent variable of interest $log(Sales/Assets)$ increases with lagged soil moisture. The instrumental variable estimates imply that a one standard deviation increase in surface moisture leads to an increase in $log(Sales/Assets)$, which is about 80% of its standard deviation. The economic impact of root zone soil moisture is similarly large. The first-stage regression estimates of soil moisture on PDSI are all positive and statistically significant at the 1% level. The F-statistic is 66, allaying any concerns about weak instruments.

We then take 2005, the mid-point of our sample, and implement a structural break test across the two-halves of our sample period. As we show in Figure 2, there is a fairly large jump in land temperatures before and after 2005. As such, this structural break test informs us about the impact of soil moisture on food industry in the last decade of historically high temperatures compared to the previous decade. Higher global temperatures due to climate change put greater stress on food production.[3] As the number of extreme temperature days have increased in the recent decade, many studies (see Daryanto *et al.* (2016) for a meta-analysis) find that global warming trends are significant enough as to reverse productivity increases from improved technology for some crops in a number of countries. One auxiliary implication of the greater stress from higher temperatures is that soil moisture becomes a more important determinant of food industry output. Studies point to the particularly beneficial effects of water and soil moisture under greenhouse

[3]For instance, research on modeling the impact of climate change on crop yields points to increasingly adverse effects of higher temperatures for some types of crops such wheat (see, e.g., Lobell *et al.* (2011), Lesk *et al.* (2016)). The effect on crop yields is non-linear in the number of extreme temperature days (Schlenker & Roberts (2009)) for reasons rooted in plant biology (see Fahad *et al.* (2017) for a review).

conditions for different parts of food industry output (see, e.g., Al-Kayssi *et al.* (1990)). In other words, when the food industry are exposed to many more days of higher temperatures, soil moisture becomes a buffer against higher temperatures and all the more important for food output.

Consistent with this auxiliary prediction, we find that the economic and statistical significance of soil moisture for industry sales are also much larger in recent years. A test for the equality of coefficients across the two sub-periods can reject equality for soil moisture measures at the 5% level. That is, food industry sales have become more predictable using these soil moisture variables during the last decade of historically high temperatures compared to the decade previous to that.

We then examine the extent to which security analysts, whose forecasts are widely used to guide corporate investments and adaptations globally, have recognized this structural change. 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 intervention (Nordhaus (2017), Pindyck (2013), Stern (2007)). However, quantifying the costs of climate change on the economy depends in large part on understanding how efficiently financial markets account for these risks and the innovations that help mitigate them (Lemoine (2017), Hsiang (2016)). Inefficient market forecasts would lead to misallocation of capital expenditures, increase the cost of adjusting to climate change, and even potentially affect financial stability to the extent risky assets are not appropriately pricing in climate risks (Carney (2015), Hong *et al.* (2017), Bansal *et al.* (2014), Andersson *et al.* (2016)). But this issue has not been systematically studied until now. By examining these consensus sales forecasts, we can better understand how analysts and firms form such sales expectations in a changing climate.

We implement a rational forecasts test (Nordhaus (1987)) of consensus sales forecasts to see if these forecasts are efficiently accounting for this structural break. We regress realized industry sales on the consensus sales forecasts along with lagged soil moisture. We implement this test also using country and time fixed effects in a panel setting.[4] The null (rational-expectations) hypothesis that these sales forecasts efficiently utilize all available information which corresponds to the coefficient in front of the sales forecasts being 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 predictors for future sales.

We find that the coefficient on the consensus forecast is significantly less than one. This is consistent with other findings that consensus forecasts deviate from the rational expectations benchmark. There are potentially different explanations for this finding, which is not the focus of our paper per se. More interestingly, we find that lagged soil moisture also strongly forecast future sales. This means that these lagged

[4] Country and time fixed effects should address any cross-section variation in agency problems, i.e. omitted variables, that have been documented to influence consensus forecasts (Chan *et al.* (2007), Chiang *et al.* (2018)).

climate variables can predict consensus forecast errors. The economic and statistical significance can be large. Importantly, we find that the inefficiency with regard to soil moisture measures is mostly coming from the second half of the sample period. We implement another standard structural break test: a test for the equality of coefficients across the two sub-periods can reject equality for soil moisture measures at the 5% level. Overall, our rational expectations tests find that consensus sales forecasts by security analysts, widely used to price stocks, have not fully recognized this structural or climate change in how soil moisture impact food industry sales.

These inefficient forecasts are likely to have allocative consequences since they guide adaptations and innovations to address climate change. While innovations in other industries typically only impact long-term growth in sales, innovations in the food industry are associated in one form or another with improving soil moisture be it water management technology or drought-resistant seeds that take less moisture from the soil. These mitigating innovations can have a near-term effect on sales.[5]

To account for the effect of mitigating adaptations on sales, we gather patent application data from the US Patent and Trademark Office for the thirty-one countries in our sample. While patents can often be applied across countries, the number of applications in a country, particularly year to year fluctuations, likely pick up adaptations and innovations in that country first and foremost. We use $IHS(Patents_{i,t})$ (an inverse hyperbolic sine transformation of patents) for country i at time t to adjust for zeros and fat tails in the patent data.

We begin by showing that patents and soil moisture are highly correlated. We then show the impact of mitigation on sales is also large: a one standard deviation increase in patent applications leads to an increase in $log(Sales/Assets)$ that is about 25% of the standard deviation of the dependent variable of interest. This effect is significantly larger in recent periods. In other words, even as consensus sales forecasts by security analysts, widely used to guide corporate investments and adaptations, have not recognized this structural change, the role of mitigating innovations measured using patents have also become more important in explaining output. We do not have a strategy to identify causation of patents for sales per se. Our analysis here is simply to point out that inefficient forecasts are likely to have even larger costs in the future of global warming.

Finally, we consider a robustness exercise in the form of a placebo test using the machinery and manufacturing industry. The idea is that soil moisture should not be explaining outcomes in this placebo industry unless it is picking up some missing economy-wide variables. We do not find any effects of soil moisture and patents on sales in machinery and manufacturing. This does not however mean that soil moisture might

[5] Moreover, theories of innovation (Klette & Kortum (2004)) also predict that industry sales should rise with innovations as captured by aggregate patents. Firms always have to keep adapting and innovating to improve the quality of their goods or be forced to exit by a more innovative competitor.

not impact a few other water-intensive industries such as construction.

Our paper is closely related to Hong *et al.* (2017). In contrast to their focus on developing trading strategies based on past trends in droughts in different countries due to climate change, our focus is on measuring the increasingly important effects of soil moisture on food industry output and to investigate the efficiency of consensus sales forecasts with regard to structural changes in the food industry induced by global warming. They use cross-country differences in drought trends as their independent variable of interest to predict cross-country stock returns. Since their interest is in stock returns, omitted variables is naturally risk and can be dealt with using standard multi-factor models. But we share a similar conclusion that financial markets are not efficiently recognizing the implications of climate change for the food industry.

Our paper proceeds as follows. We present the data and construction of the key variables of interest in Section 2. In Section 3, we briefly discuss our methodology. In Section 4, we present our empirical findings on sales and forecasts. We conclude in Section 5.

2 Data, Variables and Summary Statistics

2.1 Financial and Forecasting Variables

Accounting variables for international countries including firm-level sales and assets 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.[6] The sample includes live as well as dead stocks, ensuring that the data are free of survivorship bias. Following the literature (Fazzari *et al.* (1987); Baker *et al.* (2003)), we construct several firm-level controls including market-to-book ratio, Cash Flow (Operating cash flows over assets), and Cash (cash holding over assets).

We obtain the consensus analyst forecast data of 1-year ahead sales (FY1) from Institutional Brokers' Estimate System (I/B/E/S), which is calculated as the median of individual analyst forecasts. We average the monthly consensus forecast data within the same fiscal year (and obtain an average annual number) to match the frequency of annual accounting variables.

Accounting variables and analyst forecasts of firms from different countries or time periods are not directly comparable as they are expressed in local currencies in nominal values. To deal with this issue, we

[6]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).

first convert all accounting variables and forecasts into US dollar using the annual exchange rates between local currencies and US dollar. We then convert these variables into real values using the US GDP deflators. After conversion, all accounting variables and forecasts are expressed in USD in real values, so they are comparable across countries and years.

Based on the 4-digit SIC code, we classify all firms into 17 industries based on the Fama-French 17 industry classification. We use the Fama-French classification "Food" in our analysis. Country-level macroeconomic variables including GDP growth, inflation rate, risk-free rate, exchange rate, and unemployment rate are obtained from World Bank database. The sample period is from year 1994 to year 2014. The countries in our sample are shown in Table 1.

2.2 Soil Moisture Measures

We rely on surface or soil moisture data from GLEAM (Martens *et al.* (2017), Miralles *et al.* (2011)). The moisture data relies on satellite images of the surface and algorithms to then infer the amount of surface moisture. The structure of the data is given in latitude and longitude by country. GLEAM also provides a root-zone soil moisture. As the definitions of these variables suggest, the surface moisture variable measures moisture near the surface while the root-zone measure, which is more complicated involving models of evaporation, tries to infer the moisture beneath the surface at the roots of plants.

Our data for the global (excluding the US) Palmer Drought Severity Index comes from Dai *et al.* (2004).[7] The index is a measurement of drought intensity based on a supply-and-demand model of soil moisture developed by Palmer (1965). This is a climatic measure of drought that only takes into account precipitation and temperature. Many days of rain with cool temperature would lead to a high PDSI as there is less evaporation. Few days of rain and hot temperatures mean more evaporation and less cumulative water in the ground. The index grades 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 GLEAM soil moisture and global PDSI datasets are 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

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

NOAA's website.

2.3 Patent Applications

Our dataset is prepared by the United States Patent and Trademark Office (USPTO) and Patent Technology Monitoring Team (PTMT). The dataset profiles patents in 30 product fields that are based on the 2002 North American Industry Classification System (NAICS). Patenting activity in the NAICS industry categories has been determined by the primary U.S. Patent Classification System (USPC) classification assigned to each patent and a USPC to NAICS concordance. The upside of using this patent data as opposed to the OECD data, which we describe below, is that the patent office aggregate patents into the most relevant industry affected. Food and beverage, which is our industry of interest, is one of the industries. This allows us to naturally merge the relevant patents in that industry as judged by the US patent office. Geographic Origin is grouped into country origin categories and is determined by the residence of the first-named inventor at the time of grant, as displayed on the patent. As such, we can measure the number of patent applications for our sample of 31 countries each year.

We collect patent counts based on their year of application as opposed to grant date. Since the average time period between the filing for a patent and issuing of the patent is around 32 months, the date that an application was filed more accurately reflects when the technology was developed. Moreover, fluctuations in patent data distributed by application date are much more likely to reflect changes in technological activity since such fluctuations, for the most part, would be less affected by changes in patent office processing, such as occurred in years such as 1986 when the USPTO issued fewer patents than would normally have been expected due to a lack of funds. One downside of the data is that the patent applications data is noisy since the application is recorded with a delay based on the issuance of the grant. As a result, there is a mechanical fall off across all countries in number of patent applications at the end of the sample.

2.4 Summary Statistics

Table 2 reports the summary statistics of these variables. We begin with our climate variables, which are Surface Moisture and PDSI. Recall that Surface Moisture is given in volumetric water content (cubic meter/cubic meter). The mean of Surface Moisture is 0.305 with a standard deviation of 0.096. The mean of Root-Zone moisture is 0.293 with a standard deviation of 0.096. Across all countries, the annual average of PDSI has a mean of -0.176 with a standard deviation of 1.99. IHS(Patents), which is defined as the inverse hyperbolic sine of patents, has a mean of 1.47 and a standard deviation of 1.73. We use inverse hyperbolic sine rather than log to transform patents because a number of patents have zeros. IHS is similar to log but can accomodate zeros.[8]

The mean of Log(Sales$_t$/Assets$_{t-1}$), our main dependent variable of interest, is -0.064 with a standard deviation of 0.416. Sales over assets is often referred to as asset turnover ratios, which varies considerable across industries, with utilities on the low end and retail companies on the high end. Food companies are somewhere in the middle of this range. The mean of Log(Forecasts$_t$/Assets$_{t-1}$) is -0.123 with a standard deviation of 0.870. The median sales growth is -0.056 while the median growth forecast is 0.023. Notice that there is significantly higher dispersion in forecasts than actual sales growth which is to be expected.

In addition to these main variables of interest, we also gather control variables, both at the country level and firm level, to help soak out some variance in our regressions. At the country level, the mean unemployment rate across all countries is around 7%, the average GDP growth rate is 3.45% and the average inflation rate is around 3.6%. At the firm level, the mean Market-to-book is 1.992, the mean Cash holding/assets is 0.097 and the mean operating cashflow to assets (OCF/assets) is 0.088.

3 Methodology

3.1 Structural-Break Test for the Impact of Soil Moisture on Sales

As we mentioned at the outset, a large body of research on modeling the impact of climate change points to increasingly adverse effects of higher temperatures on crop yields in recent years (see, e.g., Lobell *et al.* (2011), Lesk *et al.* (2016), Schlenker & Roberts (2009)), Fahad *et al.* (2017), Daryanto *et al.* (2016)). An auxiliary implication is a greater sensitivity of food-industry output to soil moisture. To get at this trend, we first propose a parsimonious model for annual food company sales growth $r_{i,j,t}$, which we define as the log of sales of company i in country j in year t divided by assets in year $t-1$ (i.e. $r_{i,j,t} = log(Sales_{i,i,t}/Assets_{i,j,t-1})$). We model the expected growth rate each year as $E[r_{i,j,t}] = bS_{i,j,t-1}$, where S include our measures of soil moistures for country j. We focus on a lag of these variables because there are natural lags in agricultural sales production on the order of a year or so. We can think of soil moisture as productivity in the tradition of standard investment models (see, e.g., Bolton *et al.* (2011)). We expect the impact of soil moisture to be positive.

Every year, we group firms within each country j into small and big firms based on whether its total assets is below or above the median value in that country. We then take the average of the log of sales/assets for each size group i and denote this value as $log(Sales/Assets)_{i,j,t}$. We use the same approach to average firm-level control variables to country level, including market-to-book ratio, cash holdings over assets (cash)

[8] Otherwise we could use a log(1+Patents) as the transformation. Most of our results are similar regardless of the transformation used.

and operating cash flow over assets (CF).

We then estimate the following panel regression model

$$log(Sales/Assets)_{i,j,t} = bS_{i,j,t-1} + \phi Z_{i,j,t-1} + \gamma X_{j,t-1} + u_j + v_t + \epsilon_{i,j,t}, \tag{1}$$

where i indicates small or big firms. For reasons of precision, we collapse individual firms into two groups: a large versus a small firm group. The main explanatory variable is our lagged soil moisture measure $S_{i,j,t-1}$, which is the average of the soil moisture for country j over period t of stock i. $Z_{i,j,t-1}$ denotes firm-level controls of food companies headquartered in country j in period t and averaged across small and big firms separately. $X_{i,j,t-1}$ denotes the vector of country-level control variables, including the annual GDP growth rate (GDP Growth), the annual inflation rate (Inflation), and the unemployment rate (Unemployment). Finally, u_j denotes the country fixed effects, v_t denotes the time fixed effects, and $\epsilon_{i,j,t}$ is the error term. Standard errors are clustered at country level. We can in principle estimate the above regressions at various horizons, ranging from 1 year to 10 years. We focus on the 1 year horizon given we only have a 20-year sample.

The regression model captured in Equation (1) follows from the one used in Dell *et al.* (2014). The panel regression method with country and time fixed effect has several advantages in identifying the causal effect of soil moisture on the outcome variables we are interested in. The country fixed effects, u_j, absorb fixed country characteristics, whether observed or unobserved, disentangling the soil moisture shock from many possible sources of omitted variable bias. The time-fixed effects, v_t, further neutralize any common trends and thus help ensure that the relationships of interest are identified from idiosyncratic local shocks.

We can estimate Equation (1) before and after 2004 and implement a structural break test for equality of the coefficient of interest b in front of lagged soil moisture $S_{i,j,t-1}$. As such, we expect that the estimates for Equation ((1)) to be stronger after 2004. Ideally, if we had a longer time series, we can consider a more elaborate time trend approach rather than this coarse sub-sample split, which is essentially a structural break test. But the basic motivation is the same, which is to see if we can capture indirectly using soil moisture the effects of a changing climate on food company sales.

3.2 Instrumenting Soil Moisture Using PDSI

But in contrast to the new climate-economy literature which uses temperature as the independent variable of interest, even year to year changes in soil moisture might not be exogenous since soil moisture can be influenced by production and adaptation. As such, we need an instrument for satellite readings of soil moisture. We use as an instrument the Palmer Drought Severity Index—-an older measure of soil moisture based on purely climatic inputs of temperature and precipitation. Sales or adaptation should have no influence on these climatic inputs. This instrumental-variables approach allows us to naturally address endogeneity concerns of soil moisture. It also helps us address other measurement error worries with satellite readings. If satellite technology has improved over time, then we might be picking up better measurements of soil moisture as opposed to the changing impact of climate on food-industry sales per se. This PDSI measure has been around since the 1960s and its formula has not changed markedly over time.

The 2SLS is then given by the following. The first-stage regression is given by:

$$S_{i,j,t} = cPDSI_{i,j,t} + \psi Z_{i,j,t} + \rho X_{i,j,t-1} + u_j + v_t + \epsilon_{i,j,t}, \tag{2}$$

where i indicates small or big firms. The dependent variable of interest is soil moisture $S_{i,j,t}$. The main explanatory variable is $PDSI_{i,j,t}$ for country j over period t of stock i. The rest of controls are similar to Equation ((1)). Standard errors are clustered at country level. The second-stage regression is Equation ((1)) where we exclude $PDSI$. The reduced-form regression is given by the following panel regression model:

$$log(Sales/Assets)_{i,j,t} = dPDSI_{i,j,t-1} + \phi Z_{i,j,t-1} + \gamma X_{j,t-1} + u_j + v_t + \epsilon_{i,j,t}. \tag{3}$$

The exclusion restriction is that PDSI affects agricultural sales only through soil moisture (or the supply or productivity side) and not through a demand channel. One particular worry is that a negative PDSI, which is correlated with droughts, leads to more demand for food products. But this demand channel would lead to a negative sign in the reduced form of PDSI and food industry sales and hence our reduced-form estimate would be downward biased.

3.3 Rational Expectations Test Regarding Structural Break

To study the efficiency of analyst sales forecasts with respect to drought information, we estimate the following panel regression model motivated by the rational expectations test (Nordhaus (1987)):

$$\begin{aligned} \log(Sales/Assets)_{i,j,t} = {} & bS_{i,j,t-1} + \theta \log(Forecasts/Assets)_{i,j,t} \\ & + \rho Z_{i,j,t-1} + \delta X_{i,j,t-1} + u_j + v_t + \epsilon_{i,j,t}, \end{aligned} \tag{4}$$

where i indicates small or big firms. The dependent variable in Equation (4) is the log of sales over lagged assets, the same as in Equation (1). The main explanatory variable is our soil moisture $S_{i,j,t-1}$, which is the average of climate variables for country j over period $t-1$ that is not overlapped with the dependent variable. The independent variable $\log(Forecasts/Assets)$ is the log of sales forecasts over lagged assets. All other control variables are the same as in Equation (1). Finally, u_j denotes the country fixed effects, v_t denotes the time fixed effects, and $\epsilon_{i,j,t}$ is the error term.

If analysts efficiently use the past climate information when making forecast on future sales, **b** in Equation (4) should be equal to zero, and θ would be equal to 1. The alternative hypothesis is inefficiency — this would imply that $\theta < 1$, and more importantly, $\mathbf{b} > 0$. This is the key test that we are interested in. An equivalent way to interpret the efficiency regression is to subtract $log(Forecasts/Assets)_{i,j,t}$ from both sides of (4) to yield

$$\begin{aligned}\log(Sales/Forecasts)_{i,j,t} = bS_{i,j,t-1} + (\theta - 1)\log(Forecasts/Assets)_{i,j,t} \\ + \rho Z_{i,j,t-1} + \delta X_{j,t-1} + \omega_j + \zeta_t + \varepsilon_{i,j,t},\end{aligned} \tag{5}$$

where ω_j denotes the country fixed effects, ζ_t denotes the time fixed effects, and $\varepsilon_{i,j,t}$ is the error term. The dependent variable in Equation (5) is the log forecast error — the log of sales in year t over analysts' consensus 1-year ahead sales forecast (for year-t sales). We can interpret the coefficients of interest **b** as predicting analyst forecast errors.

The second portion of our tests then focuses on estimating Equation (4) before 2004 and after 2004. To the extent we find that estimates of Equation (1) are stronger after 2004 and analysts do not efficiently account for this structural change, we then expect soil moisture and patents in Equation (4) to have more predictive power. If forecasters are accounting for climate change, we should not see any differences in the estimates of the efficiency regression specification across the two time periods.

4 Empirical Results

In this section, we first examine whether soil moisture in a country significantly affect sales revenue of food companies located in that country. We then look at whether analysts efficiently utilize the soil moisture information when forecasting future sales. Finally, we focus on the role of mitigating adaptations and conduct robustness analysis.

4.1 Structural Break in Relationship between Soil Moisture and Food Industry Sales

The estimation results for the food industry sales specification given in Equation (1) are reported in Table 3. We always estimate this specification using country by firm-size group fixed effects, year fixed effects as well as country level and firm level controls. Columns (1)-(2) show the results for the full sample period. We estimate each of the climate variables separately since they are correlated. Surface moisture and root-zone moisture are meant to capture the same dryness conditions.

In column (1), we report the results for surface moisture. We see that lagged surface moisture positively impact food company sales. The coefficient is around 0.749 but is not statistically significant. However, the coefficient is economically sizeable. A one standard deviation increase in surface moisture (which is 0.096) increases sales growth by 0.07, or 17% of the standard deviation of the dependent variable of interest (0.416). Additional lags beyond the past year are generally much weaker.

In column (2), we find similarly that root-zone moisture also explains sales growth, though by a lesser degree than surface moisture. As we can see, sales revenue of food companies significantly increase with root-zone moisture, as indicated by the positive coefficient of 0.636 for the lagged value. A one standard deviation (.096) increase in root-zone moisture would lead to an increase of about 0.061 in sales growth, which is about 15% of its standard deviation.

Figure 3 plots the relationship between sales growth and these two independent variables of interest for the country of Australia as an illustrative example. Panel A shows the time series relationship between surface moisture in the black line and sales in the red line. Panel B reports the time series for root-zone moisture and sales. The time series are illustrative of our estimation strategies relying on country fixed effects. So we are essentially capturing in Table 2 the time series comovements of these series. In this figure, we are showing the sales of large capitalization stocks. We can see consistent with our estimates in Table 2 that surface moisture, root-zone moisture and patents all move together with sales growth. We do not report the time series for other countries but this comovement is robust, i.e. our results in Table 2 are not coming from just one country.

Returning to Table 3, we then show these results by the early sub-period of 1994-2004 (columns (3) and (4)) and the later sub-period of 2005-2014 (columns (4) and (6)). In column (3), the coefficient on lagged surface moisture is -1.984 and statistically insignificant. In column (5), we see that the coefficient is 1.674 and highly statistically significant at the 1% level. A one standard deviation increase of surface moisture implies an increase in sales that over 50% using the full sample standard deviation. In column (5), we also report the test of equality comparing the coefficient in column(1) with the coefficient in column (5). The t-statistic for the test of equality is 2.14. We can reject that the coefficients are similar. Another way of putting it is that in the latter period, soil moisture are having an increasingly large effect on food industry sales, consistent with climate change and its worsening impact on crop yields found in climate change studies.

In columns (4) and (6), we compare the coefficients on lagged root-zone moisture across the two sub-periods. In column (4), the coefficient is -1.943 and not statistically significant. In column (6), the coefficient is 1.273 and statistically significant at the 5% level. The test of equality does not reject that the point estimates across the two periods are different, though the t-statistic is close at 1.6. The reason is that the standard errors in the first sub-period are quite large.

We can visualize this stark difference across the two sub-periods in Figure 4. In Panel A, we show the scatterplot of sales growth residualized of controls against lagged surface moisture residualized of controls. The red dots are the 1994-2004 observations and the blue dots are the 2005-2014 observations. The red line is the fitted line through the red observations, while the blue line is the fitted line through the blue observations. We can visually see the stark difference in predictability of sales growth across the two periods. The same is true, though to lesser degrees, for root-zone moisture in Panel B. Overall, we conclude that soil moisture are having increasingly predictable and important effects on food industry sales.

Admittedly, we are taking a leap in two dimensions. The first is that food industry sales are more than just crop yields and the second is that we are using coarse measures. But both leaps would likely bias us against finding any predictability. The fact that the predictability findings are so striking and consistent leads us to conclude that climate change is leading to increasingly important effects of soil moisture on food industry sales.

4.2 Instrumental Variables Results

We next present the results when we instrument soil moisture with PDSI. In Table 4, we present the results of the first-stage regression given by Equation (2). In columns (1) and (2), we present the full sample results. In column (1), the dependent variable of interest is surface moisture. The coefficient in front of PDSI is 0.004 and significant at the 1% level. A one standard deviation increase in PDSI (1.99) increases surface moisture by 0.008, which is around 8% of a standard deviation of the dependent variable of interest. The F-statistic is 66, pointing to the power of PDSI as an instrument for surface moisture. In column (2), where root-zone moisture is the dependent variable of interest, the results are similar. The F-statistic is 63.1, so again PDSI is a powerful instrument for both surface and root-zone moisture.

In columns (3) and (4), we present the results for the 1994-2004 sub-period. The coefficient is slightly smaller at 0.003 for both surface and root-zone moisture but nonetheless statistically significant at the 1% level. The F-statistic is 11.9 for surface moisture and 13.7 for root-zone. As such, PDSI would be a powerful instrument even in the sub-period of 1994-2004. In columns (5) and (6), we present the results for the 2005-2014 sub-period. The coefficient is slightly larger at 0.005 for both surface and root-zone moisture and both are statistically significant at the 1% level. The F-statistic is 31.5 for surface moisture and 31.7 for root-zone. As such, PDSI would also be a powerful instrument in the sub-period of 2005-2014.

In Table 5, we then present the IV results for a first-stage regression given by Equation (2) and a second-stage given by Equation (1). For the full sample results given in column (1), we see that the coefficient is 3.616 for surface moisture and significant at the 5% level. The economic effect is large, whereby a one-standard deviation increase in surface moisture leads to an increase in sales growth that is around 80% of the standard deviation of the dependent variable of interest. In column (2), the coefficient in front root-zone moisture is 3.587 and comparable to that in column (1). The economic effect is similarly large.

It is worthwhile to compare these 2SLS estimates to the OLS ones in Table 3. Recall the coefficients there were around 0.749 and 0.636 for surface and root-zone moistures, respectively. The 2SLS coefficients are around 5 times as large. One important reason why the coefficients are much larger is of course measurement error. It might be that satellite readings are of course also noisy measures. So instrumenting with PDSI cleans up this measurement error.

In columns (3) and (4), we present the results for 1994–204 sub-period. The coefficients are negative in this sub-period, which is similar to the OLS findings in Table 3, though the negative coefficients are smaller in absolute value. In columns (5) and (6), we see that the 2SLS estimates are 2.5 and 2.4 for surface and root-zone moisture, respectively. Both are statistically significant at the 10% level. As such, we can conclude that soil moisture is having a larger causal effect in the recent decade of historically high temperatures.

Moreover, this IV estimate rules out an alternative explanation for our structural break (pre- versus post- 2004) findings. Namely, time trends in measurement error of GLEAM soil moisture can potentially be consistent with our findings. If satellite technology has improved over time, then we might simply be picking up better measurements of soil moisture as opposed to the changing impact of climate on food-industry sales per se. But our IV estimates suggest that this is not the case since this PDSI measure has been around since the 1960s and its formula has not changed markedly over time.

Table 6 presents the reduced-form estimates for lagged PDSI as the independent variable of interest. We see that in the full sample, the first column, lagged PDSI does explain sales. In column (1), the coefficient is 0.017 and significant at the 5% level. The economic significance is around 7% of the standard deviation of the dependent variable of interest. The economic effect is much smaller as we expect compared to our 2SLS soil moisture measure estimates since PDSI is a crude climatic measure of soil moisture. In the next two columns, we repeat this estimation but for the before and after 2004 sub-samples. Here we find in the earlier sub-sample that coefficient on lagged PDSI is not significant. Indeed, in column (2), the coefficient on lagged PDSI are nearly zero. Moreover, the coefficient is much more significant in the latter sample period. In column (3), the coefficient on lagged PDSI is 0.013 and statistically significant at the 10% level. Again, the economic effects are not nearly as large as what we found for soil moisture as we would expect since PDSI is a crude measure of soil moisture. Nonetheless, the findings in Table 5 suggest point to a causal relationship between soil moisture and food-industry sales.

4.3 Efficiency of Sales Forecasts with respect to Structural Break

Up to this point, our paper contributes to the climate change and agricultural yields literature in two ways. First, we show that even recent satellite readings of soil moisture data predict food-industry sales especially well in the last decade. Second, we propose an instrumental variables method to identify the effect of soil moisture on food-industry sales, which is new to the literature.

We now implement rational expectation tests to see whether consensus sales forecasts by security analysts, widely used to price stocks, have recognized this structural change. We return to Figure 3 of Australia, where we also plot in blue the mean sales growth forecasts. We can see that the time series of the sales growth forecasts broadly co-move with the sales series. The question however is the extent to which these forecasts efficiently incorporate implications of the climate variables across Panel A-B for sales.

To do this, we estimate Equation (4) and report the results in Table 7. The specification is similar to Table 3 except we add in consensus or aggregate forecast as an independent variable. In column (1), we show the results with aggregate forecast and lagged surface moisture. Notice that aggregate forecasts are naturally lagged and hence it incorporates time $t-1$ information. The coefficient on aggregate forecast is 0.178 and statistically significant at the 5% level. The coefficient is less than 1, which is inconsistent with rational expectations. This finding is already well known in the literature, which has examined a variety of reasons for why the coefficient is less than 1 including issues with aggregating individual forecasts. The literature typically concludes that the forecasts are not efficient as opposed to being due to some measurement error issues. Of more interest to us is that the coefficient on lagged moisture is significant. Notice that the coefficient is 0.803, but it is not statistically significant. In column (2), we report the results for lagged root-zone moisture. The coefficient is 0.656 but is also not statistically significant. The coefficient on aggregate forecast is largely unchanged.

In columns (3)-(6), we then re-estimate these specifications but for the two sub-periods, 1994-2004 and 2005-2014. In other words, in this table, we are interested in whether analysts efficiently discount the findings in Tables 3 and 5, which point to increasingly important effects of soil moisture and mitigating innovations on sales. We first compare the coefficients in columns (3) and (5) for soil moisture. The coefficient in front of aggregate forecast is similar across the two columns, 0.132 compared to 0.151. They are both statistically significant. However, the coefficient in front of lagged surface moisture differs markedly. It is -1.653 in column (3) and not statistically significant and 1.526 in column (5) and statistically significant at the 1% level. Indeed, the test of equality yields a t-statistic of 2.15 and hence we are able to reject that the two coefficients are similar. That is, we can conclude that the consensus forecasts is not fully recognizing the structural change in the impact of surface moisture on food industry sales due to climate change.

Turning to columns (4) and (6) for lagged root-zone moisture, we obtain a similar conclusion. The coefficient in front of lagged root-zone moisture is -1.836 in column (4) and 1.222 in column (6). The coefficient is not statistically significant in column (4) but statistically significant in Panel column (6) at the 5% level. Indeed, the estimates are very similar to those in Table 3. However, unlike in Table 4, the test of the equality of coefficients across the two sub-samples yields a t-statistic of 1.70, rejecting the equality of the coefficients. Note that the coefficient on aggregate forecast is very similar across the two sub-periods. So forecasts just are not factoring in root-zone moisture either. As such, we conclude that consensus forecasts are not fully incorporating information in lagged soil moisture for food industry sales.

In Panels A and B of Figure 5, we plot sales growth residualized of all controls and aggregate forecast against residualized surface and root-zone moisture. We can see the line through the scatterplot as representing the predictability of sales by these variables even controlling for aggregate forecasts. To connect back to Figure 1, we also put a red dot to represent the Australian drought in the middle of the 2000s. It can be seen that the blue line for forecast are above the red line for sales when the black lines are low.

Overall, we can definitively conclude that analysts are not recognizing the implications of a structural change in surface or root-zone moisture for food industry sales due to climate change. One worry is that the results for soil moisture might be driven by a small subset of countries. In Figure 6, we report the forecast inefficiency with regard to surface moisture country by country. We put the x-axis the label for the country and on the y-axis the coefficient on surface moisture in the efficiency test. Panel A shows the coefficients for 1994-2004 while Panel B shows the coefficients for 2005-2014. We can see that there is increasingly more positive coefficients in the latter period across a large number of countries. In Panel A, many countries actually have a negative coefficient in the early period. But in the Panel B, many more countries have a positive coefficient and far fewer countries have a negative coefficient.

4.4 Role of Mitigating Innovations

We now address the potential role of mitigation and expectations regarding mitigation. As we mentioned at the outset, innovations in the food-industry are associated in one form or another with improving soil moisture be it water management technology or drought-resistant seeds that take less moisture from the soil. These mitigating innovations can have a near-term effect on sales. As such, to the extent our findings regarding soil moisture are correct, we also expect that mitigation innovations to impact sales and have a larger impact in recent periods. In this analysis, we do not have a strategy to identify causation of patents for sales per se. Our analysis here is simply to see whether there is consistency with our soil moisture findings.

We begin by showing that patents and soil moisture are highly correlated—consistent with the mitigating role of innovations. First, in Panel C of Figure 3, we show in the time series for Australia that patents are also correlated with sales. Figure 7 illustrates the correlation between soil moisture and raw number of patents. On the x-axis, we group countries into soil moisture buckets. We report on the y-axis the average number of patents in the different buckets. We can see that the number of patents is increasing in soil moisture. We do not try to disentangle causal relationships between adaptation and soil moisture in this paper. One might have thought that adaptation could also reflect a negative correlation whereby worst soil moisture outcomes lead to more adaptation and innovation (see, e.g., Miao & Popp (2014)). The fact that there is a positive correlation suggests that it is likely that patents will also positively predict sales growth.

A theoretical model to motivate this positive correlation is to think of patents are proxying for Schumpeterian innovations as modeled in Klette & Kortum (2004). Their model is for general industries and encompasses the food industry. The reason why sales increases with patents is that firms always have to keep adapting and innovating to improve the quality of their goods or be forced to exit by a more innovative competitor. Think of goods as being different types of crops. Then in the model the most efficient firm produces one crop. But adaptations or innovations are continuously made by all firms, including incumbents and potential entrants, who can displace incumbents. In Klette & Kortum (2004), industry sales rise with industry innovations as captured by patents.

In Table 8, we repeat the analysis of Table 6 except that we focus on lagged IHS (Patents) as the independent variable of interest. We see that in the full sample, the first two columns, lagged IHS(Patents) does predict sales growth. In column (1), the coefficient is 0.051 and significant at the 1% level. A one-standard deviation increase in IHS(Patents) leads to an increase in sales growth that is 20% of the dependent variable of interest. In column (2), we add in the consensus forecast and find the coefficient on lagged patents still comes in significantly, consistent with the inefficiency of sales forecasts with regard to soil moisture that we documented earlier using GLEAM soil moisture data.

In the next four columns, we repeat these estimations but for the before and after 2004 sub-samples. Here we find in the earlier sub-sample that coefficient on lagged IHS(Patents) is not significant. Indeed, in column (3), the coefficient on lagged IHS (Patents) is nearly zero. Moreover, the coefficient is much more significant in the latter sample period. In column (5), the coefficient on lagged IHS (Patents) is 0.026 and statistically significant at the 5% level. We can conclude, consistent with the prediction on soil moisture, that mitigating innovations influence sales much more in the recent decade of historically high temperatures.

In Panel C of Figure 2, we visualize this stark difference across the two sub-periods. We show the scatterplot of sales growth residualized of controls against lagged IHS (Patents) residualized of controls. The red dots are the 1994-2004 observations and the blue dots are the 2005-2014 observations. The red line is the fitted line through the red observations, while the blue line is the fitted line through the blue observations. We can visually see the stark difference in predictability of sales growth across the two periods by lagged patents. Overall, we conclude that mitigating innovations are having increasingly predictable and important effects on food industry sales.

Returning to Table 7, we can compare the coefficients of columns (4) and (6), where we add in the consensus forecast. The coefficient in the 1994-2004 period is not statistically significant, while the one for 2005-2014 is. So this is also qualitatively consistent with the soil moisture results regarding inefficient forecasts though the results here are much weaker. That is, the consensus forecasts is not fully accounting for the impact of climate change on food industry sales as far as measures such as soil moisture. Panel C of Figure 3 helps us visualize how residualized patents predicts forecast errors.

4.5 Placebo Tests

In Table 9, we consider a placebo exercise where we repeat our main analysis but for the Fama-French industry classification of machinery and equipment. Table 9 is similar in structure to Table 3. The idea is that soil moisture should not be explaining outcomes in this placebo industry unless it is picking up some missing economy-wide variables. We do not see any statistically significant coefficients for any of our soil moisture measures or for patents. When we contrast the point estimates between the sub-period of 1994-2004 and 2005-2014, we again do not discern any systematic patterns as far as differences. If anything, the coefficients are of the opposite sign compared to our baseline results. This reassures us that our analysis is not picking up any type of spurious factors.

5 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 due to a lack of survey data. To address this issue, we focus on sales and consensus analyst forecasts from thirty-one countries with publicly-traded food companies. Since 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 in the food industry are also implicitly climate change forecasts.

Our analysis of this issue is motivated from recent research on crop yields that points to increasingly predictable and deleterious effects of higher temperatures. We point out that an important auxiliary implication of this research is a greater sensitivity of food industry output to soil moisture. Consistent with this large body of research, panel regressions with country and time fixed effects find that satellite readings of soil moisture predict food-industry sales especially well in the last decade. Mitigating innovations, which focus on conserving on soil moisture and measured by industry patents, have also become more important in explaining agricultural sales.

We then implement rational expectation tests to see if consensus sales forecasts by security analysts, widely used to price stocks, have recognized this structural change. Our analysis indicates that sales forecasts have not recognized this structural change in terms of the impact of soil moisture on food industry sales, even as we find that mitigating innovations have become more important in explaining sales. That is, the costs of inefficient forecasts are likely to be higher with global warming.

For future research, we ask what might be generating this inefficiency. Recall that we are using consensus sales forecasts in these rational expectations tests. Analysts are paid to generate individual security forecasts. Aggregating to an industry consensus is a good proxy for industry-wide expectations only under certain settings. For instance, in a rational inattention setting where analysts need to pay for gathering different types of information, i.e. stock specific versus common or industry wide factors, then consensus industry forecasts might not capture such climatic risks if they are not incentivized properly. We leave these questions for future research.

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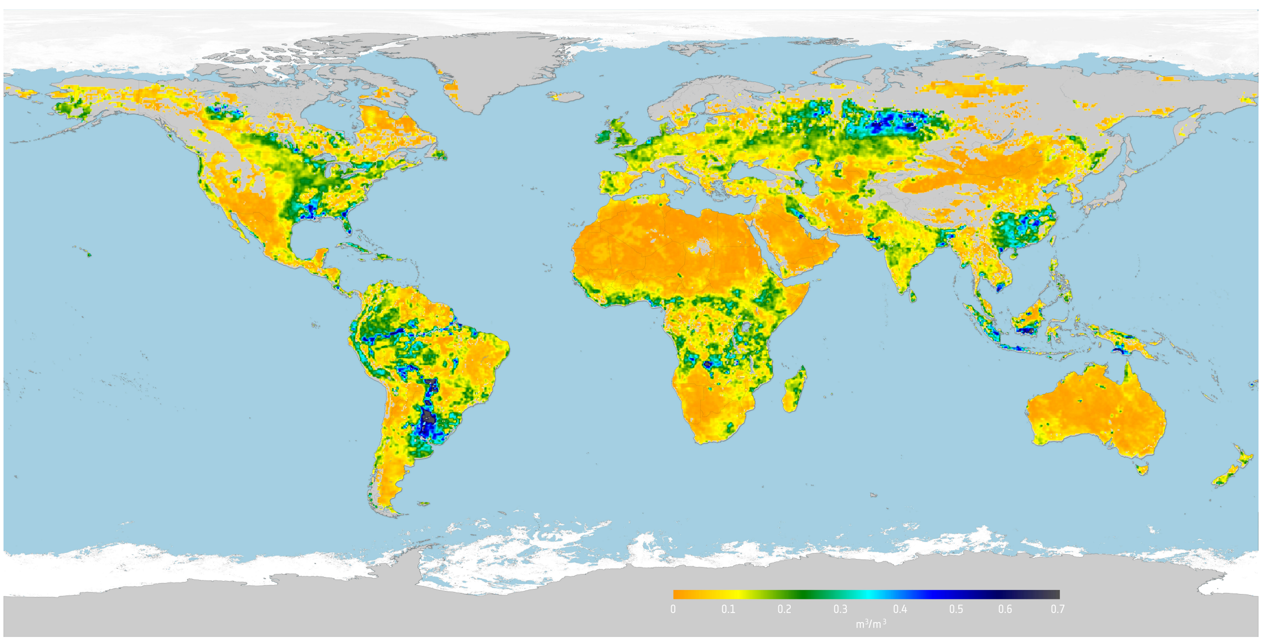
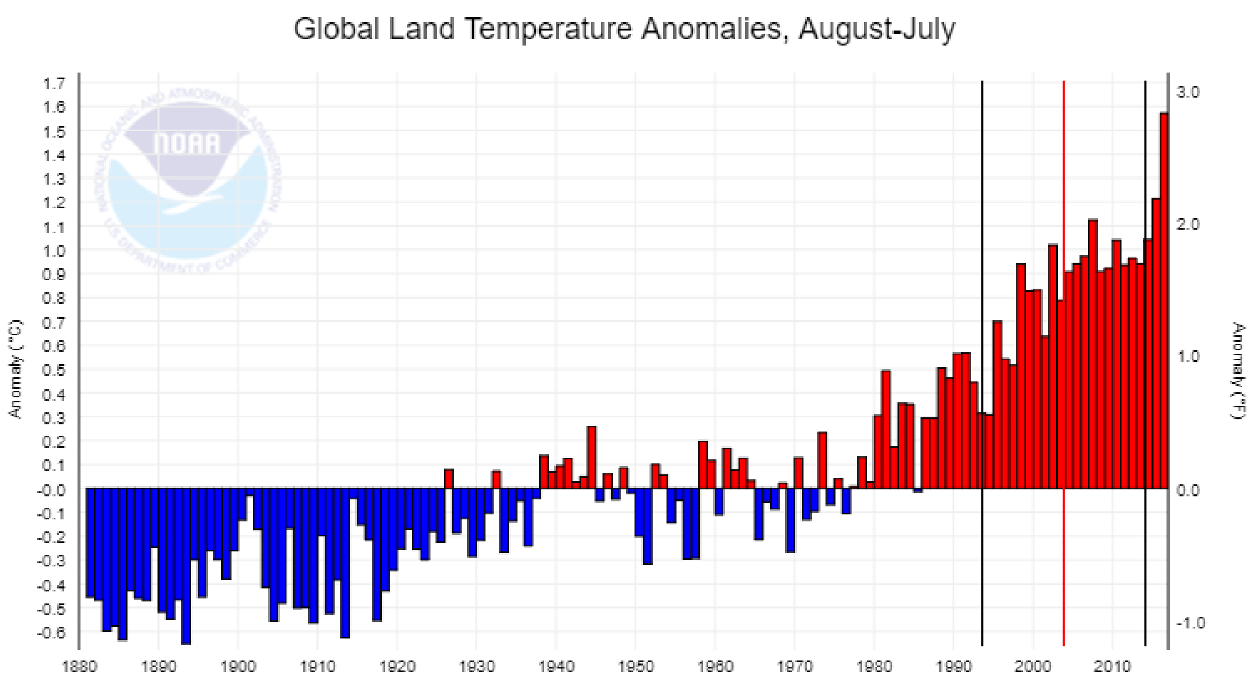
FIGURE 1: SATELLITE-READINGS OF ROOT-ZONE SOIL MOISTURE

ROOT-ZONE MOISTURE



Notes: May 2016 GLEAM root-zone soil readings.

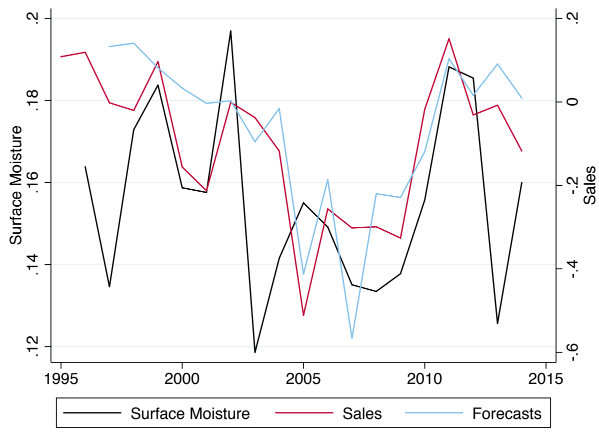
FIGURE 2: LAND TEMPERATURE ANOMALIES



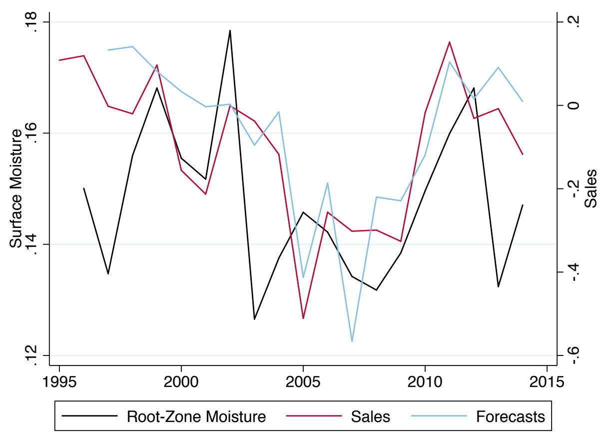
Notes: NOAA land temperature anomalies. Three lines represent start (1994), mid-point (2005) and end of our sample (2014).

Figure 3: Droughts, Sales and Forecasts: Australia

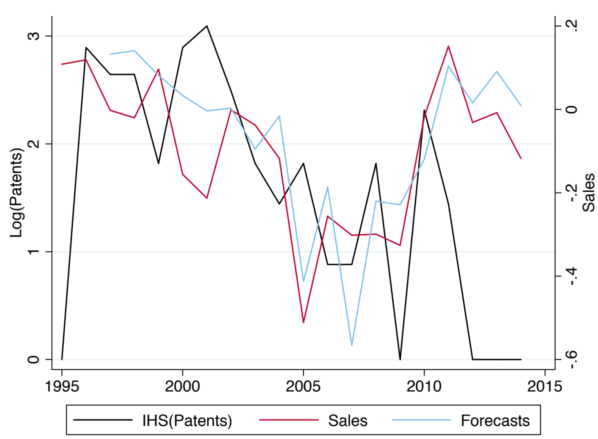
Panel A: Surface Moisture



Panel B: Root-Zone Moisture



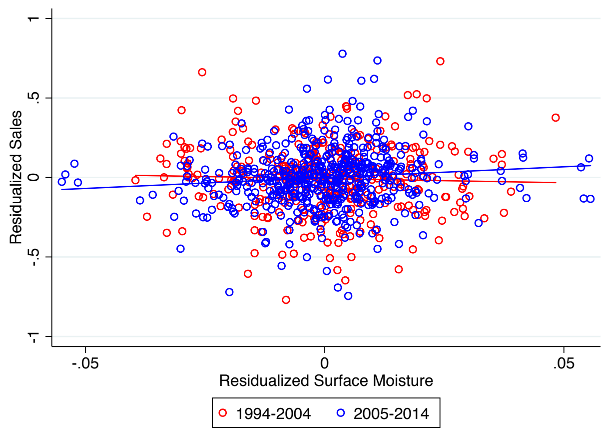
Panel C: Patents



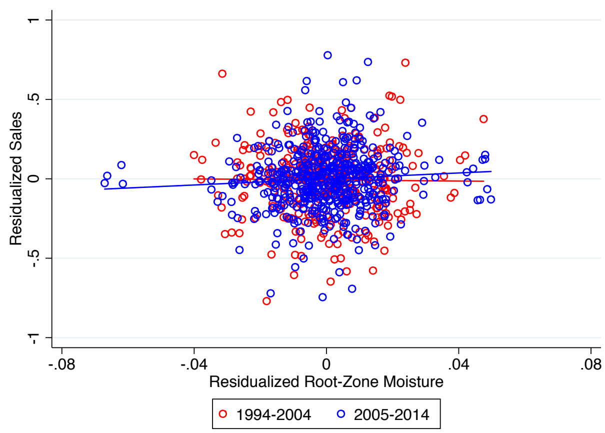
Notes: For an example country (Australia), we plot Log($\text{Sales}_t/\text{Assets}_{t-1}$), Log($\text{Forecasts}_t/\text{Assets}_{t-1}$), and each of surface soil moisture according to GLEAM, root-zone soil moisture according to GLEAM, and the inverse hyperbolic sine of patents (IHS(patents)) in Panels A, B, and C, respectively. All variables are shown over our full sample period: 1994-2014, and averaged at the country-year level. Only sales for large cap stocks are shown.

FIGURE 4: SURFACE MOISTURE AND PATENTS PREDICT SALES AFTER 2004

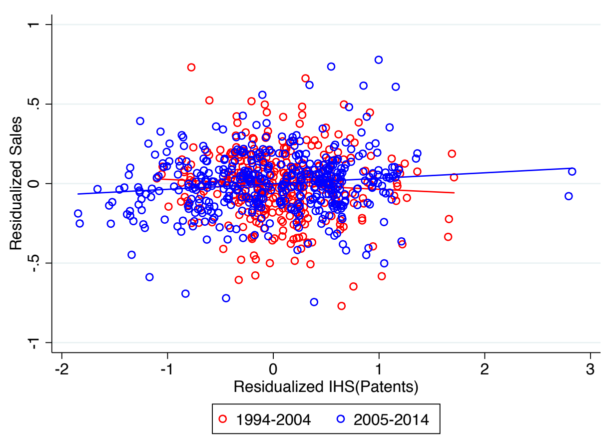
PANEL A: SURFACE MOISTURE



PANEL B: ROOT-ZONE MOISTURE



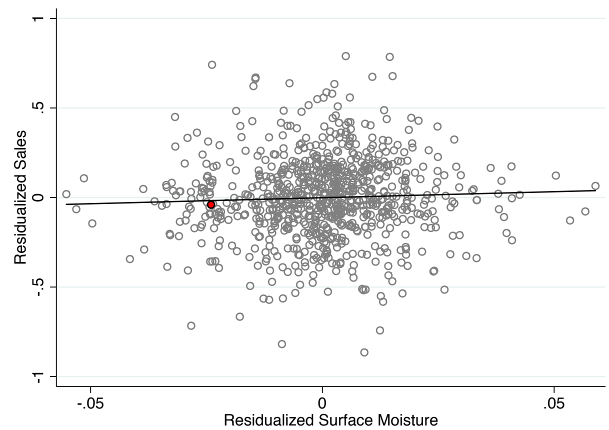
PANEL C: PATENTS



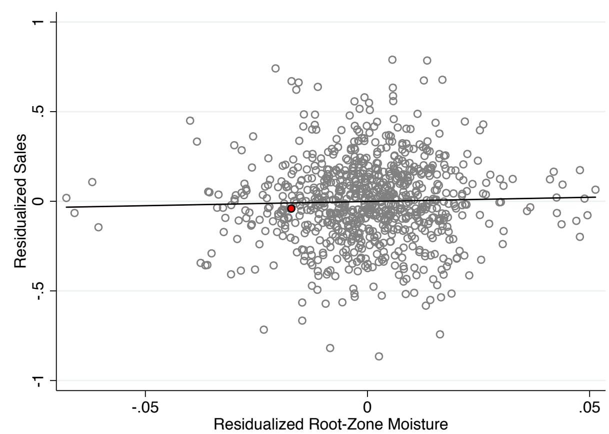
Notes: Scatter plots and linear fits of residualized sales against residualized surface soil moisture according to GLEAM, root-zone soil moisture according to GLEAM, and the inverse hyperbolic sine of patents (IHS(patents)) in Panels A, B, and C, respectively. Each is measured at the country-year-cap size level (large vs. small cap). All variables are residualized with respect to all controls, country $\times$ large cap fixed effects, and year fixed effects separately for 1994-2004 (in red) and 2005-2014 (in blue).

FIGURE 5: FORECAST INEFFICIENCY FOR SOIL MOISTURE AND PATENTS

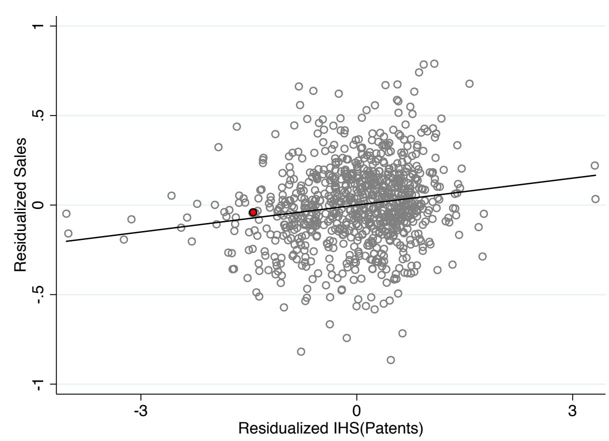
PANEL A: SURFACE MOISTURE



PANEL B: ROOT-ZONE MOISTURE



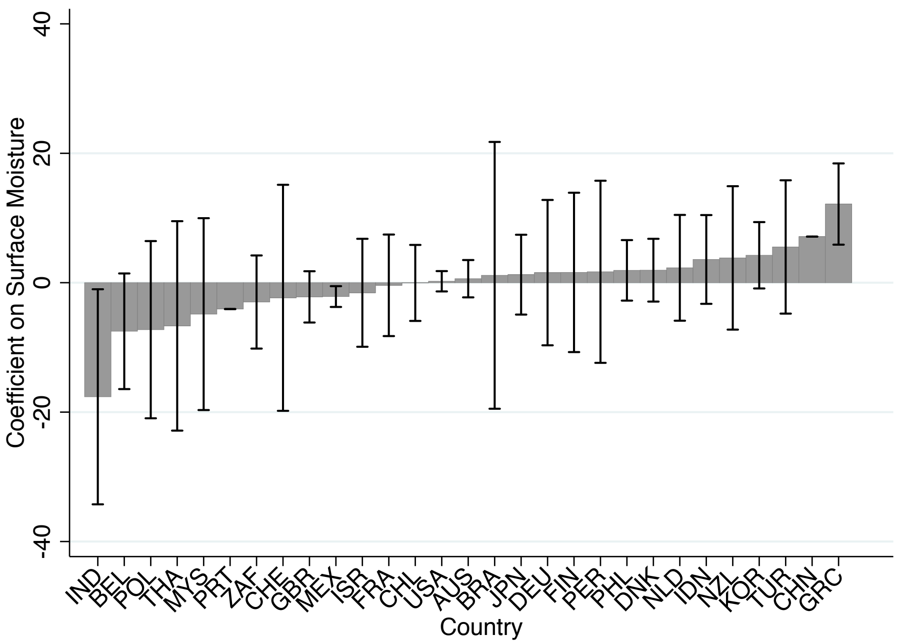
PANEL C: PATENTS



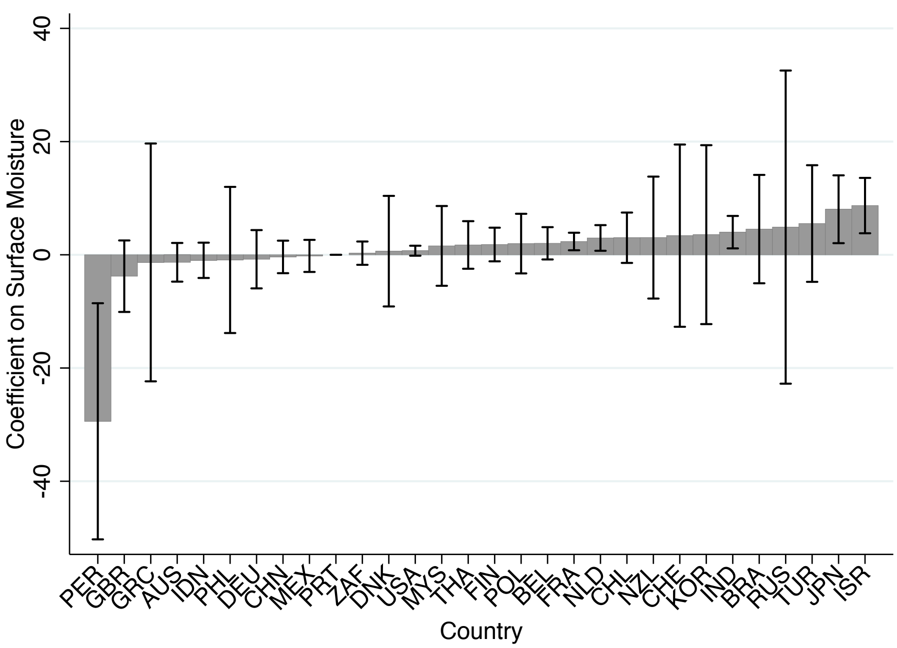
Notes: Scatter plots and linear fits of residualized sales against residualized surface soil moisture according to GLEAM, root-zone soil moisture according to GLEAM, the inverse hyperbolic sine of patents (IHS(patents)) in Panels A, B, and C, respectively. All variables are residualized with respect to all controls, country $\times$ large cap fixed effects, and year fixed effects. Each is measured at the country-year-cap size level (large vs. small cap). Additionally, all variables are residualized with respect to one year ahead forecasts from time $t-1$. The red point in each plot denotes large cap Australian stocks in 2009, for comparison to Figure 3.

FIGURE 6: FORECAST INEFFICIENCY BY COUNTRY: SURFACE MOISTURE

PANEL A: 1994-2004

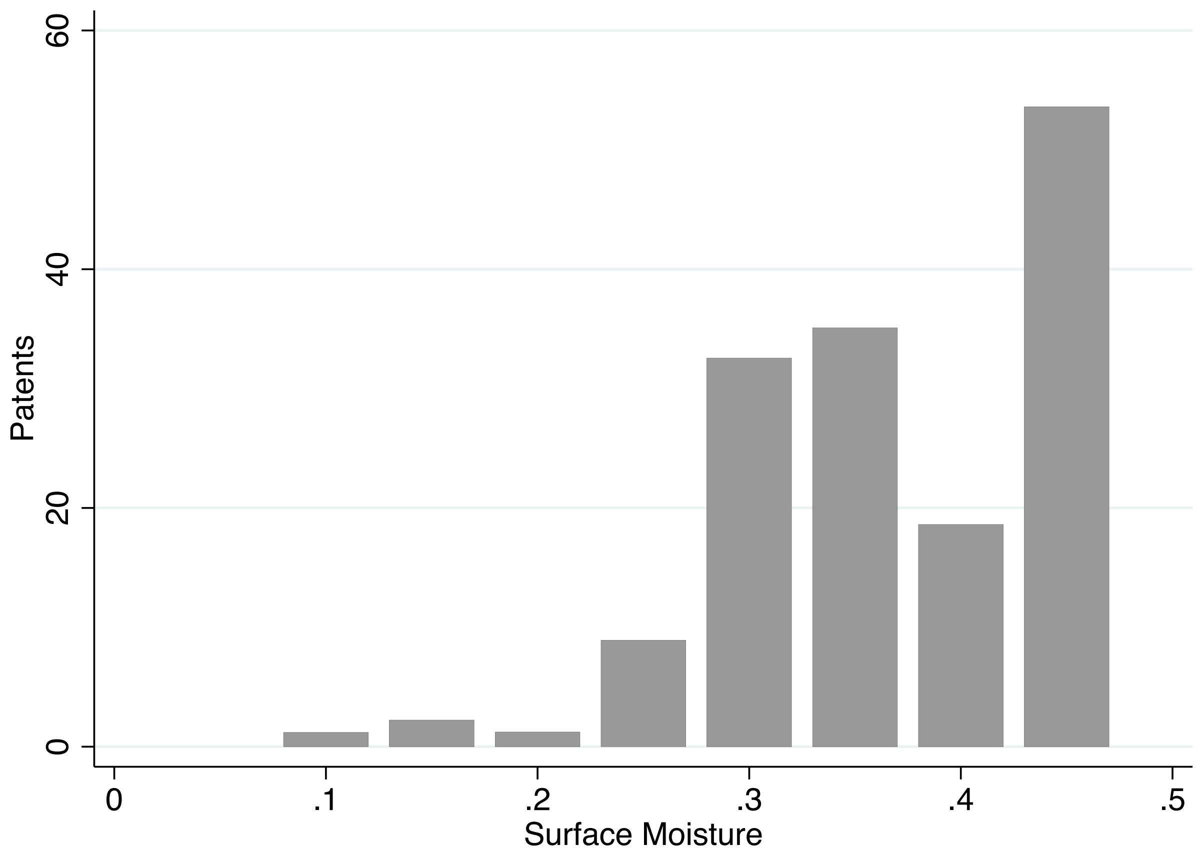


PANEL B: 2005-2014



Notes: Coefficients from country by country regressions of Log(Sales$_t$/Assets$_{t-1}$) on surface moisture, controlling for Log(Forecasts$_t$/Assets$_{t-1}$). Each regression includes yearly observations for large and small camp stocks within each country, and includes a dummy for large cap as a control. Panel A includes the years 1994-2004. Panel B includes the years 2005-2014.

FIGURE 7: RAW CORRELATION BETWEEN SURFACE MOISTURE AND PATENTS



Notes: Average number of patents with country× years by surface soil moisture.

TABLE 1: COUNTRIES IN OUR SAMPLE

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 2: SUMMARY STATISTICS

	Mean	S.D.	Median	P25	P75
Surface Moisture	0.305	0.096	0.326	0.234	0.378
Root-Zone Moisture	0.293	0.096	0.309	0.214	0.372
PDSI	-0.176	1.990	-0.300	-1.465	0.878
IHS(Patents)	1.47	1.73	0.88	0	2.64
Log(Sales$_t$/Assets$_{t-1}$)	-0.064	0.416	-0.056	-0.334	0.230
Log(Forecasts$_t$/Assets$_{t-1}$)	-0.123	0.870	0.023	-0.288	0.303
Unemployment	7.074	4.286	6.300	4.130	8.675
GDP growth (%)	3.453	2.992	3.444	1.780	5.114
Inflation (%)	3.570	3.172	2.716	1.577	4.637
Market-to-book	1.992	1.979	1.544	0.985	2.418
Cash holding/assets	0.097	0.069	0.084	0.050	0.126
OCF/assets	0.088	0.052	0.084	0.057	0.116

This table reports summary statistics of all variables. Surface and root-zone moisture is gathered from GLEAM, and averaged at the country $\times$ year level. PDSI refers to the Palmer Drought Severity Indexed, again averaged to the country $\times$ year level). Accounting variables are collected from Compustat. IHS($\cdot$) refers to the inverse hyperbolic sine. Forecasts are 1-year ahead sales forecasts, collected from I/B/E/S. The sample period is from 1994 to 2014.

TABLE 3: SOIL MOISTURE PREDICTS SALES (OLS)

	Log(Sales$_t$/Assets$_{t-1}$)					
	Full Sample		1994-2004		2005-2014	
Surface Moisture	0.749		-1.984		1.674***	
	(0.641)		(1.499)		(0.550)	
Root-Zone Moisture		0.636		-1.943		1.273**
		(0.657)		(1.728)		(0.588)
Test of Equality (t-stat)					2.14	1.60
Mean of Dep. Var.	-0.065	-0.065	0.041	0.041	-0.12	-0.12
N	738	738	252	252	481	481
Country $\times$ Large Cap FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from regressions of Log(Sales$_t$/Assets$_{t-1}$) on surface and root-zone soil measures. Surface moisture and root-zone moisture are derived from GLEAM and averaged within country at the yearly level. The first two columns include country by year by large vs small cap observations for 31 countries between 1994-2014, the third and fourth columns include 1994-2004, and the fifth and sixth columns include 2005-2014. Controls include two lags of unemployment, GDP growth, inflation, market-to-book, Cash holdings/assets, and OCF/assets. All specifications include year and country $\times$ large cap fixed effects. Tests of equality show t-statistics on the difference in the coefficients on surface and root-zone moisture across the two time periods. These t-statistics are calculated by estimating a pooled model on the full period, and fully interacting all regressors with an indicator for the 2005-2014 period. Standard errors, clustered at the country level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4: PDSI IS POSITIVELY CORRELATED WITH SOIL MOISTURE (FIRST STAGE)

	Full Sample		1994-2004		2005-2014	
	Surface	Root-Zone	Surface	Root-Zone	Surface	Root-Zone
PDSI	0.004***	0.004***	0.003***	0.003***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Kleibergen-Paap F-stat	66.0	63.1	11.9	13.7	31.5	31.7
Mean of Dep. Var.	0.31	0.29	0.30	0.29	0.31	0.29
N	846	846	252	252	481	481
Country $\times$ Large Cap FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from regressions of surface and root-zone soil measures on PDSI, the Palmer Drought Severity Index. Surface moisture and root-zone moisture are derived from GLEAM and averaged within country at the yearly level. PDSI is also averaged within country at the yearly level. The first two columns include country by year by large vs small cap observations for 31 countries between 1994-2014, the third and fourth columns include 1994-2004, and the fifth and sixth columns include 2005-2014. Controls include two lags of unemployment, GDP growth, inflation, market-to-book, Cash holdings/assets, and OCF/assets. All specifications include year and country $\times$ large cap fixed effects. Standard errors, clustered at the country level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5: IMPACT OF SOIL MOISTURE ON SALES (IV)

	Log(Sales$_t$/Assets$_{t-1}$)					
	Full Sample		1994-2004		2005-2014	
Surface Moisture	3.616^{**}		-0.582		2.514^{*}	
	(1.681)		(2.785)		(1.325)	
Root-Zone Moisture		3.587^{**}		-0.609		2.416^{*}
		(1.679)		(2.906)		(1.305)
Mean of Dep. Var.	-0.071	-0.071	0.041	0.041	-0.12	-0.12
N	846	846	252	252	481	481
Country × Large Cap FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from IV regressions of Log(Sales$_t$/Assets$_{t-1}$) on surface and root-zone soil measures instrumented by PDSI. Surface moisture and root-zone moisture are derived from GLEAM and averaged within country at the yearly level. PDSI is also averaged within country at the yearly level. The first two columns include country by year by large vs small cap observations for 31 countries between 1994-2014, the third and fourth columns include 1994-2004, and the fifth and sixth columns include 2005-2014. The first two columns include country by year by large vs small cap observations for 31 countries between 1994-2014, the third and fourth columns include 1994-2004, and the fifth and sixth columns include 2005-2014. Controls include two lags of unemployment, GDP growth, inflation, market-to-book, Cash holdings/assets, and OCF/assets. All specifications include year and country × large cap fixed effects. Standard errors, clustered at the country level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 6: PDSI CORRELATES WITH SALES (REDUCED FORM)

	$\text{Log}(\text{Sales}_t/\text{Assets}_{t-1})$		
	Full Sample	1994-2004	2005-2014
PDSI	0.017^{**}	-0.002	0.013^{*}
	(0.007)	(0.010)	(0.006)
Mean of Dep. Var.	-0.065	0.041	-0.12
N	738	252	481
Country $\times$ Large Cap FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Coefficients from egressions of $\text{Log}(\text{Sales}_t/\text{Assets}_{t-1})$ on PDSI. PDSI is also averaged within country at the yearly level. The first two columns include country by year by large vs small cap observations for 31 countries between 1994-2014, the third and fourth columns include 1994-2004, and the fifth and sixth columns include 2005-2014. The first two columns include country by year by large vs small cap observations for 31 countries between 1994-2014, the third and fourth columns include 1994-2004, and the fifth and sixth columns include 2005-2014. Controls include two lags of unemployment, GDP growth, inflation, market-to-book, Cash holdings/assets, and OCF/assets. All specifications include year and country $\times$ large cap fixed effects. Standard errors, clustered at the country level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7: FORECAST EFFICIENCY WITH RESPECT TO SOIL MOISTURE

	Log(Sales$_t$/Assets$_{t-1}$)					
	Full Sample		1994-2004		2005-2014	
Aggregate Forecast	0.178^{**}	0.178^{**}	0.132^{*}	0.133^{*}	0.151^{**}	0.152^{**}
	(0.085)	(0.085)	(0.066)	(0.066)	(0.068)	(0.069)
Surface Moisture	0.803		-1.653		1.526^{***}	
	(0.518)		(1.321)		(0.484)	
Root-Zone Moisture		0.656		-1.836		1.222^{**}
		(0.533)		(1.587)		(0.528)
Test of Equality (t-stat)					2.15	1.70
Mean of Dep. Var.	-0.071	-0.071	0.025	0.025	-0.12	-0.12
N	729	729	243	243	481	481
Country $\times$ Large Cap FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from regressions of Log(Sales$_t$/Assets$_{t-1}$) on surface and root-zone soil measures and one year ahead forecasts at time $t-1$. Surface moisture and root-zone moisture are derived from GLEAM and averaged within country at the yearly level. The first two columns include country by year by large vs small cap observations for 31 countries between 1994-2014, the third and fourth columns include 1994-2004, and the fifth and sixth columns include 2005-2014. Controls include two lags of unemployment, GDP growth, inflation, market-to-book, Cash holdings/assets, and OCF/assets. All specifications include year and country $\times$ large cap fixed effects. Tests of equality show t-statistics on the difference in the coefficients on surface and root-zone moisture across the two time periods. These t-statistics are calculated by estimating a pooled model on the full period, and fully interacting all regressors with an indicator for the 2005-2014 period. Standard errors, clustered at the country level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 8: FORECAST EFFICIENCY WITH RESPECT TO PATENTS

	Log(Sales$_t$/Assets$_{t-1}$)					
	Full Sample		1994-2004		2005-2014	
IHS(Patents)	0.051^{***}	0.053^{***}	-0.001	0.031	0.026^{**}	0.028^{**}
	(0.015)	(0.015)	(0.047)	(0.026)	(0.012)	(0.011)
Aggregate Forecast		0.174^{*}		0.133		0.138^{*}
		(0.086)		(0.079)		(0.070)
Mean of Dep. Var.	-0.067	-0.076	0.019	-0.00099	-0.12	-0.12
N	820	804	312	296	506	506
Country $\times$ Large Cap FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from regressions of Log(Sales$_t$/Assets$_{t-1}$) on the inverse hyperbolic sine of patents in the food and beverage industry at time t-1, as well as one year ahead sales forecasts. Controls include unemployment, GDP growth, inflation, market-to-book, Cash holdings/assets, and OCF/assets. The first two columns include country by year by large vs small cap observations for 31 countries between 1994-2014, the third and fourth columns include 1994-2004, and the fifth and sixth columns include 2005-2014. Standard errors, clustered at the country level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 9: PLACEBO ANALYSIS USING MACHINERY AND EQUIPMENT

	Log(Sales$_t$/Assets$_{t-1}$)								
	Full Sample			1994-2004			2005-2014		
Surface Moisture	1.250			5.498			-1.859		
	(2.288)			(4.650)			(2.078)		
Root-Zone Moisture		1.524			4.882			-0.465	
		(2.030)			(4.663)			(1.408)	
IHS(Patents)			0.021			0.181			-0.033
			(0.093)			(0.219)			(0.050)
Mean of Dep. Var.	0.019	0.019	-0.096	-0.037	-0.037	-0.21	0.064	0.064	0.017
N	531	531	764	241	241	359	287	287	397
Country $\times$ Large Cap FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from regressions of Log(Sales$_t$/Assets$_{t-1}$) on contemporaneous and lagged surface moisture, root-zone moisture, and the inverse hyperbolic sine of patents (IHS(patents)) for a placebo industry: machinery and equipment. Surface moisture and root-zone moisture are derived from GLEAM and averaged within country at the yearly level. Controls include unemployment, GDP growth, inflation, market-to-book, Cash holdings/assets, and OCF/assets. The first three columns include country by year observations for 31 countries between 1994-2014, split into small and large cap within each country. The second three columns show only the years of 1994-2004. The final three columns show 2005-2014. Standard errors, clustered at the country level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.