

The impact of El Niño-Southern Oscillation on U.S. food and agricultural stock returns

Bebonchu Atems^{*}, Michael Maresca, Baomei Ma, Emily McGraw

Economics and Financial Studies, School of Business, Clarkson University, 8 Clarkson Avenue, Potsdam, NY, 13699, USA

ARTICLE INFO

JEL classification:

Q41
C32

Keywords:

Vector autoregression
El Niño-Southern Oscillation
Agriculture
Stock returns

ABSTRACT

The paper examines the response of twelve U.S. agricultural stock returns to El Niño-Southern Oscillation (ENSO) shocks using a recursive VAR model. Baseline results indicate that for seven of the stock returns, an ENSO shock has positive and significant effects. The effects, however, are shortlived, generally becoming statistically indistinguishable from zero three to six months after the shock. Variance decomposition analyses show that ENSO shocks have little explanatory power for fluctuations in U.S. agricultural stock returns. We also provide evidence that historically, movements in the stock returns of U.S. food and agricultural companies have been driven by other shocks, rather than ENSO shocks.

1. Introduction

El Niño Southern Oscillation (ENSO) is a naturally occurring weather phenomenon that involves fluctuations in winds and ocean surface temperatures in the central and east-central equatorial Pacific Ocean. The weather pattern, which usually occurs around December, can have varying intensities. El Niño refers to the warm phase of the ENSO cycle, while La Niña refers to the cool phase. The impacts of El Niño and La Niña are strongest in the winter, immediately following the onset of the event. Fig. 1 shows the typical wintertime effects of El Niño and La Niña for the U.S. The northern tier of the 48 contiguous U.S. states generally experiences above normal temperatures in the fall and winter seasons during El Niño episodes, while the Gulf Coast states exhibit below average temperatures. An unusually strong and more southerly subtropical jet stream during the El Niño phase brings above normal precipitation in Southern California, the Gulf Coast, and Southeastern U.S. states. In Hawaii, El Niño causes drier than normal conditions in the winter and early spring months, below average dry season precipitation in Guam, and above normal precipitation in American Samoa. In the eastern and central Pacific regions of the U.S., higher sea surface temperatures associated with El Niño increase the likelihood of hurricanes in these regions [1,2]. The effects of the La Niña phase of ENSO are generally the opposite of those of the El Niño phase, although the magnitudes, spatial dimension, and duration of its effects may differ.

These weather changes tend to have considerable impacts on the world's distribution of water resources and water supply. During the start of a typical ENSO cycle, trade winds blow westward, warming up surface waters in Oceania. Off the west coast of South America, these warmer ocean waters force nutrient-rich colder waters further down in the ocean to rise, disrupting fisheries. Anchovies, for example, which typically flourish in the cold waters off the coasts of Peru and Ecuador, are forced to flee south for colder waters. As already mentioned, ENSO can cause drought conditions or an increase in precipitation, depending on the ENSO phase. As

^{*} Corresponding author.

E-mail addresses: bateams@clarkson.edu (B. Atems), marescm@clarkson.edu (M. Maresca), mab@clarkson.edu (B. Ma), mcgrawer@clarkson.edu (E. McGraw).

many countries depend on rainfall and groundwater as sources of freshwater, ENSO can have significant impacts on freshwater resources, which in turn, may have considerable effects on human health, agricultural production, and even stock prices.

Extensive research has documented significant relationships between ENSO occurrences and U.S. agricultural output. While estimates of the impact of ENSO vary across studies and spatial areas, and the impacts differ depending on the ENSO phase (El Niño versus La Niña), there is no longer a debate on whether agricultural yields are affected following an ENSO occurrence. [3,4]; and [5] document evidence that deviations in corn yields from long term trend for several Midwestern states are associated with ENSO occurrences in the equatorial Pacific Ocean [6]. show that for several Southeastern U.S. states, ENSO phases significantly affect corn and tobacco yields, the volume of soybean and cotton harvested, and the values of corn, soybean, peanut, and tobacco [7]. Provide evidence of lower than expected corn yields during the La Niña phase of ENSO for states in the U.S. cornbelt, but higher than average yields during the El Niño phase. Other papers that report significant associations between ENSO and U.S. agricultural output include [8–11]; and [12].

The finding that ENSO affects agricultural output has motivated another line of research examining the impact of ENSO on agricultural commodity prices. Using a vector autoregressive (VAR) model [13], provides evidence that a one-standard deviation positive surprise in ENSO increases real commodity price inflation by 3.5–4% points. He also finds that ENSO accounts for almost 20% of the variation in commodity price inflation, and between 10% and 20% of the variability of world consumer price inflation and output growth [14] reports a close link between monthly soybean futures prices and the La Niña phase of the ENSO cycle, but no significant responses of corn and wheat futures price movements [15–17] also provide evidence of a link between ENSO cycles and commodity prices.

To the extent that ENSO affects agricultural output and agricultural commodity prices, it should affect the stock prices of major food and agricultural companies, as well. An ENSO cycle may affect food and agricultural stock prices in at least two possible ways. On the one hand, an ENSO cycle that decreases (increases) agricultural output should reduce (increase) current and expected cash flows to food and agricultural companies, which should in turn cause a decrease (increase) in their stock prices. On the other hand, if farmers respond to a fall (rise) in their output by raising (decreasing) current and future prices, firm cash flows may remain unchanged or even rise (fall). The overall effect of ENSO on the stock prices of food and agribusiness firms will depend on whether the fall (rise) in cash flows to these companies resulting from the decrease (increase) in output exceeds the increase (decrease) in cash flows caused by higher (lower) agricultural commodity prices. Therefore, while it is known that ENSO affects agricultural output and agricultural commodity prices, its impact on food and agricultural stock returns has received little or no attention, thereby motivating the need to study the impact of ENSO on agricultural stock returns.

The purpose of this paper is to estimate the effect of ENSO on the stock returns of major U.S. food and agricultural companies. In doing so, the paper makes several contributions to the literature on the economic and financial effects of ENSO. First, this paper represents the first attempt to estimate and evaluate the effects of ENSO on the stock returns of U.S. food and agricultural companies. Second, unlike previous studies that use dummy variable measures to identify periods of ENSO and non-ENSO events, our econometric specification employs a continuous measure of ENSO intensity based on sea surface temperature anomalies (SSTA). Third, the dynamic effects of ENSO on agricultural stock returns are estimated using a recursively identified vector autoregression (VAR) model. Our baseline results indicate that for seven of the twelve stock returns considered, an ENSO shock has a positive and significant effect, while the responses of the remaining stock returns are not significantly different from zero. Forecast error variance decompositions reveal that ENSO shocks explain only a relatively small proportion of the unpredictable movements in U.S. agricultural stock returns, with

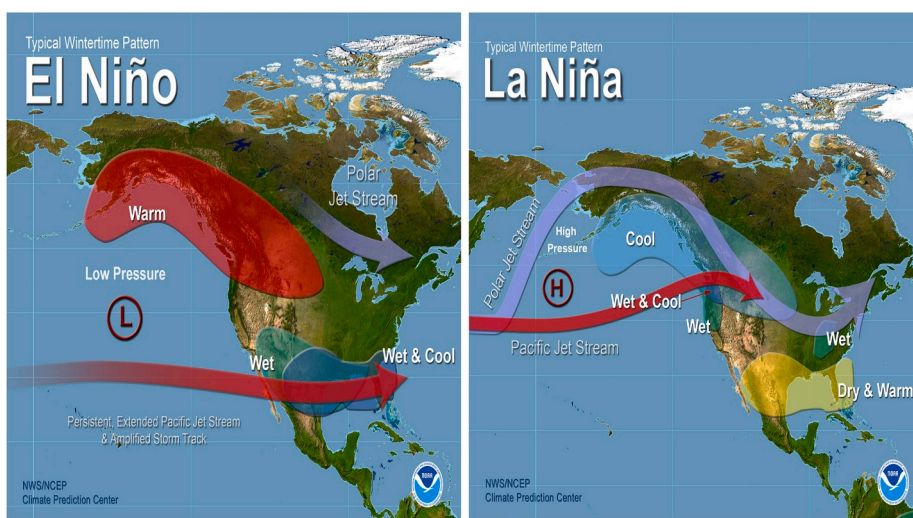


Fig. 1. Typical wintertime El Niño and La Niña Patterns.

Source: Pacific marine Environmental laboratory (PMEL) of the national oceanic and atmospheric administration (NOAA), U.S. Department of commerce <http://www.pmel.noaa.gov/elNiño/laNiña-faq>.

other factors responsible for much of the variability of these returns.

The remainder of the paper is as follows. The next section discusses the data and its time series properties. Section 3 presents the empirical methodology, while section 4 reports the baseline results. A concluding section is presented in section 5.

2. Data and time series properties

All the data used in this paper are monthly. Data on most of the stock prices for the food and agricultural companies considered begin in March 1980, although for other variables, the data start in January 1978. All series end in December 2018. Section 2.1 provides more details on the data on the stock prices of the food and agricultural companies considered. Section 2.2 describes the data on El Niño-Southern Oscillation (ENSO), while Section 2.3 discusses other variables used in the analysis. Section 2.4 examines the time series properties of the data as related to stationarity.

2.1. Data on stock prices of U.S. Food and agricultural companies

The dataset contains monthly data on the closing values of the stock prices of twelve U.S. food and agricultural companies, namely, The Archer Daniels Midland Company; The Campbell Soup Company; Conagra Brands, Inc; FMC Corporation; General Mills, Inc; The Hershey Company; Hormel Foods Corporation; McCormick & Company; The Mosaic Company; The J. M. Smucker Company; Sysco Corporation; and Tyson Foods, Inc. The data on the stock prices of these companies were collected from the Center for Research in Security Prices (CRSP). These firms were selected for several reasons. First, they represent some of the largest publicly-traded food and agribusiness firms trading in U.S. stock exchanges. In fact, all twelve firms are components of the S&P 500 index. Based on the Global Industry Classification Standard (GICS), we narrow down the number of companies to those in the Consumer Staples, and Materials sectors. From these sectors, we further narrow down the number of companies by selecting those in the Packaged Foods and Meats, and the Fertilizers and Agricultural Chemicals GICS Subsectors, leaving us with sixteen of the largest U.S. food and agricultural companies. We then consider only companies with long enough data on their stock prices, as our empirical methodology requires long time series. Hence, for all companies selected, we have monthly stock price data starting in March 1980, except for the Mosaic Company, and the J. M. Smucker Company, which begin in January 1988 and October 1994, respectively. The start dates were dictated by data availability. Second, the output, and therefore prices of these companies are most likely to be impacted by ENSO events than those of other agribusiness companies. This implies that their stock prices, as well, are more likely to be affected by ENSO events. We take a brief look at the companies below.

2.1.1. The Archer Daniels Midland Company

Archer Daniels Midland Company is a producer of ingredients that are made from agricultural commodities including oilseeds, wheat, corn, rice, and oats. The company operates within four segments: Agricultural Services, Corn Processing, Oilseeds Processing, and Wild Flavors and Specialty Ingredients. The Agricultural Services division focuses on buying, storing, cleaning, and transporting commodities. Corn processing involves wet and dry milling of corn, while oilseeds processing activities are concerned with origination, merchandising, crushing, and processing of oilseeds. The Wild Flavors and Specialty Ingredients segment engages in the manufacture, sale, and distribution of specialty products such as natural flavor ingredients, emulsifiers, proteins, and flavor systems. As found by Ref. [6]; corn, peanuts, and soybeans are all affected by ENSO events. Since Archer Daniels Midland utilizes these commodities in the production of their food and beverage ingredients, changes in the prices of these commodities are likely to affect the cash flows and eventual stock returns of the Archer Daniels Midland Company.

2.1.2. The Campbell Soup Company

The Campbell Soup Company (Campbell's) is a food and beverage manufacturer in the canned specialties industry. The company's business segments are Americas Simple Meals and Beverages, that produce soups, sauces, pasta, and juices; Global Biscuits and Snacks; and Campbell Fresh which includes dips, dressings, fresh carrots, and carrot ingredients. ENSO events affecting the production of the commodities within these products would affect their prices, eventually affecting cash flows and the returns on Campbell's stock.

2.1.3. Conagra Brands, Inc

Conagra Brands packages and distributes branded and unbranded food products to various retail outlets. Conagra operates within the frozen specialties industry but also within secondary industries such as potato chips and similar snacks, food preparation, prepared flour mixes and doughs, and flavoring extracts and syrups. Some of its products include peanut butter, frozen dinners, cooking oil, hot dogs, hot cocoa, and many more. The inputs used to make these products are susceptible to ENSO events, hence, it is worth investigating whether ENSO affects the stock returns of Conagra Brands, Inc.

2.1.4. FMC Corporation

FMC Corporation is a chemical company that serves the agricultural, consumer, and industrial global markets. FMC operates two business segments: FMC Agricultural Solutions and FMC Lithium. FMC Agricultural Solutions markets crop protection chemicals including: herbicides, insecticides, and fungicides. These chemicals are used to enhance crop yield and quality through the removal of crop damaging elements. FMC Lithium manufactures lithium for use in energy storage and chemical synthesis application. If the demand for, say, herbicides, insecticides, and fungicides changes due to an ENSO event that affects crop yields and prices, the stock returns of the FMC Corporation may be impacted, as well.

2.1.5. General Mills, Inc

General Mills manufactures consumer foods within the cereal breakfast foods industry. Some of the product categories within their North America Retail segment are ready-to-eat cereal, grain, fruit and savory snacks, yogurt, and dough products. General Mills also operates a Convenience Stores and Foodservice segment, and has locations in Europe, Australia, Asia, and Latin America, which produce products similar to those within the North America Retail segment. Precipitation and/or temperature anomalies affecting the output of wheat, soybeans, peanuts, or fruit would affect the supply and price of goods offered by General Mills, prompting us to investigate the impact on their stock returns.

2.1.6. The Hershey Company

The Hershey Company is primarily focused in the production of chocolate and non-chocolate confectionery products such as gum and mint refreshments, snacks, and pantry items. The main raw material used in the production of these goods are cocoa products processed from cocoa beans. Hershey also uses a substantial amount of sugar, peanuts, almonds, and dairy products throughout their production process. The strong emphasis on these few agricultural commodities poses a risk to Hershey's cash flows and stock performance through a decline in commodity output or increased prices.

2.1.7. Hormel Foods Corporation

Hormel Foods Corporation produces and markets a variety of meat products throughout the U.S. and internationally. The Refrigerated Foods division processes beef, pork, turkey, and chicken products for commercial customers. However, Hormel also produces non-meat products including salsas, tortillas, and peanut butter. Grains account for the largest cost share of animal feed. The grains used for the production of animal feed include corn, sorghum, barley, and oats, with corn accounting for over 95% of total feed grain.¹ While corn is grown in most U.S. states, the majority is grown in the Midwest [3–6] and [7] find that ENSO significantly affects corn yields for states in the U.S. Midwest. This implies a subsequent change in grain prices. If the ENSO event causes an increase in yields or increase in prices, cash flows to agribusiness firms directly engaged in grains rises, leading to an increase in stock returns for companies such as Hormel Foods Corporation.

2.1.8. McCormick & company

McCormick & Company is involved in the production, distribution, and sale of condiments, seasoning mixes, and spices to the food industry. Approximately half of the consumer sales is derived from McCormick's spices, herbs, and seasonings. The Company's segments are industrial and consumer, including retailers, food manufacturers, and foodservice businesses.² In addition to their North American locations, the Company has production, marketing, and distribution locations in Europe, China, South Africa, Thailand, Singapore, Mexico, Australia, and India. Most of the raw materials used to manufacture its products include rice and wheat, capsicums, pepper, garlic, vanilla, and dairy products.

2.1.9. The Mosaic Company

The Mosaic Company is a leading producer of concentrated phosphate and potash crop nutrients. Mosaic's three business segments are: Phosphates, Potash, and International Distribution. The Phosphate segment produces phosphate-based animal feed ingredients, while the Potash segment produces potash, a fertilizer for industrial application as well as animal feed ingredients. The International Distribution division is involved in the sales, blending, and warehousing of the phosphate and potash products. Demand for the Mosaic Company's products is dependent on agricultural production. Therefore, any change in agricultural output due to ENSO events could result in a change in the demand for Mosaic's products, impacting its cash flows and stock returns.

2.1.10. The J. M. Smucker Company

Smucker is a manufacturer of peanut butter, fruit spreads, coffee, baking mixes and ingredients, and pet food. The products sold within the U.S. retail market are sold through direct sales to retailers as well as online retailers. The raw goods used are primary commodities such as coffee, grains, fruit, oils and fats, sweeteners, and peanuts. Since Smucker's relies heavily on agricultural commodities, it is assumed that any change to these products would have a significant impact on the performance of the firm. Thus, precipitation and temperature anomalies resulting from ENSO may have adverse or beneficial effects on the commodities used by Smucker's as inputs, which may in turn cause changes in its stock returns, depending on price changes of these commodities.

2.1.11. Sysco Corporation

Sysco operates primarily in the Groceries, general line industry with four operating segments, namely U.S. Foodservice; International Foodservice; SYGMA, a U.S. distribution subsidiary; and Other, primarily focused on Sysco Labs and hotel supply operations. Food items distributed by Sysco include fresh meats and seafood, a full line of frozen, canned and dry foods, dairy products, produce, and beverages. The company's non-food items include paper products, cookware, restaurant equipment, and cleaning supplies. Pertaining to Sysco's food products, Sysco relies on agricultural commodities for their produce as well as feed for the animals. As mentioned with respect to similar companies above, relying on these commodities exposes Sysco Corporation, in general, and its stock returns, in particular, to ENSO events.

¹ <https://www.ers.usda.gov/topics/crops/corn/background/>.

² <https://www.reuters.com/finance/stocks/company-profile/MKC>.

2.1.12. Tyson Foods Inc

Tyson Foods focuses primarily on the production of chicken through breeding, feed production, processing, and further-processing. Cobb-Vantress, Inc., a wholly-owned subsidiary, serves as a poultry breeding stock supplier for Tyson. In addition to the chicken segment, Tyson reports three additional business segments: Beef, Pork, and Prepared Foods. Both the Beef and Pork divisions process live cattle and pigs and fabricate the carcasses into primal and sub-primal meat products. The Prepared Foods division include refrigerated meat products as well as snacks, side dishes, tortilla products, and appetizers. Similar to Hormel Foods, changes in grain prices that arise due to an ENSO effect affecting grain output will directly impact cash flows to Tyson Foods.

Table 1 provides a summary of the food and agricultural companies, GICS sectors and subsectors, and their Standard Industry Classification (SIC) and North American Industry Classification System (NAICS) codes.

2.2. Data on El Niño-Southern Oscillation (ENSO)

Monthly sea surface temperature anomalies (SSTA) for the “Niño 3.4” region (5°N to 5°S, 120°W to 170°W) are used as the measure of ENSO intensity in this paper. The data on SSTA come from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center. Fig. 2 shows the historical evolution of ENSO. The NOAA defines an El Niño (warm) event as average SSTA over three consecutive months of 0.5 °C (0.9 °F) or higher, while average SSTA of three consecutive months of −0.5 °C (−0.9 °F) or less represent the cool phase (La Niña) of ENSO. When SSTA over three consecutive months are between, −0.5 °C and 0.5 °C, they are referred to as neutral ENSO events. ENSO events are further categorized as very strong (SSTA over 2.0°); strong (SSTA between 1.5° and 1.9°); moderate (1.0°–1.4°); and weak (0.5°–0.9°). Based on these definitions, Fig. 2 shows most ENSO occurrences have been neutral, and that many El Niño and La Niña episodes have been weak or moderate, with only two episodes of very strong El Niño occurrences, four periods of strong El Niño, and only three relatively short periods of strong La Niña events.

While some papers have used the Southern Oscillation Index (SOI) anomalies to capture ENSO events, this paper exclusively uses SSTA for several reasons. First, the official measure of ENSO used by the NOAA - the Oceanic Niño Index (ONI) - is based on sea surface temperatures in the east-central tropical Pacific Ocean. It is perhaps for this reason that SSTA are the most widely used ENSO indicator in academic research (see e.g. Refs. [6,13]; and [18]). Second, the SOI is calculated as the difference between the atmospheric pressure at sea level over Tahiti and over Darwin, Australia. As pointed out by the NOAA, the fact that the SOI is derived from sea level pressure over just two stations implies that shorter term sea level pressure fluctuations not related to ENSO can affect the SOI.³ Third, the two stations over which sea level pressure data are collected to estimate the SOI - Tahiti and Darwin - are located south of the equator (Tahiti at 18°S, Darwin at 12°S). ENSO, however, is typically focused closer to the equator.

2.3. Other variables

Other variables used in the paper include monthly data on the S&P 500 index, and the U.S. industrial production index (output), all collected from the Federal Reserve Economic Database (FRED) of the Saint Louis Fed. Given the large literature on the role of inflation uncertainty for U.S. stock returns, we include the measure of inflation expectations from the Survey Research Center (SRC) at the University of Michigan. The VAR model also includes the broad currency real trade weighted U.S. Dollar index to control for the link between stock returns and the foreign exchange rate. The data on the real trade weighted index are from FRED.⁴ All estimated VAR models also include the monthly premium of the book-to-market factor (HML), the monthly premium of the size factor (SMB), and momentum of the stock market (UMD), all collected from the Wharton Research Data Services (WRDS). The starting date for most of the data is January 1978, and all series end in December 2018. Table 2 contains variable definitions, data sources, and the starting date for all the variables used in the paper. [ph] Variable Names, Definitions, and Sources.

2.4. Unit root and stationarity tests

As is standard in the time series literature, we pretest the variables for unit roots conducting four unit root tests, namely the augmented Dickey-Fuller [19] test (ADF), the Phillips-Perron [20] test (PP), the [21] modified Dickey Fuller (ERS) test, and the [22] test (KPSS). The first three tests, test the null hypothesis of an autoregressive unit root, while the KPSS tests the null of stationarity. While the ADF and PP tests are probably the most frequently used in time series modeling, they tend to have low power against the alternative hypothesis that the data are stationary with a large autoregressive root [23]. They also generally tend to over-reject the null when the data are characterized by a large negative moving average root [24]. The ERS test has been shown to outperform the ADF and PP tests in terms of both size and power, and seems to be the preferred alternative to the ADF and PP tests. Table 3 reports the unit root and stationarity tests for the series in levels and in (log) first differences. For the SSTA series, the ADF, ERS, and PP tests reject the null hypothesis that the series contains a unit root, while the KPSS finds significant evidence that the series is stationary at the 5% significance level. The premium of size factor, the book-to-market factor, and the momentum of the stock market are all stationary in levels, as well. All four tests also provide significant evidence that the S&P 500 index, output, the real trade-weighted U.S. dollar index,

³ <https://www.climate.gov/news-features/blogs/enso/why-are-there-so-many-enso-indexes-instead-just-one>.

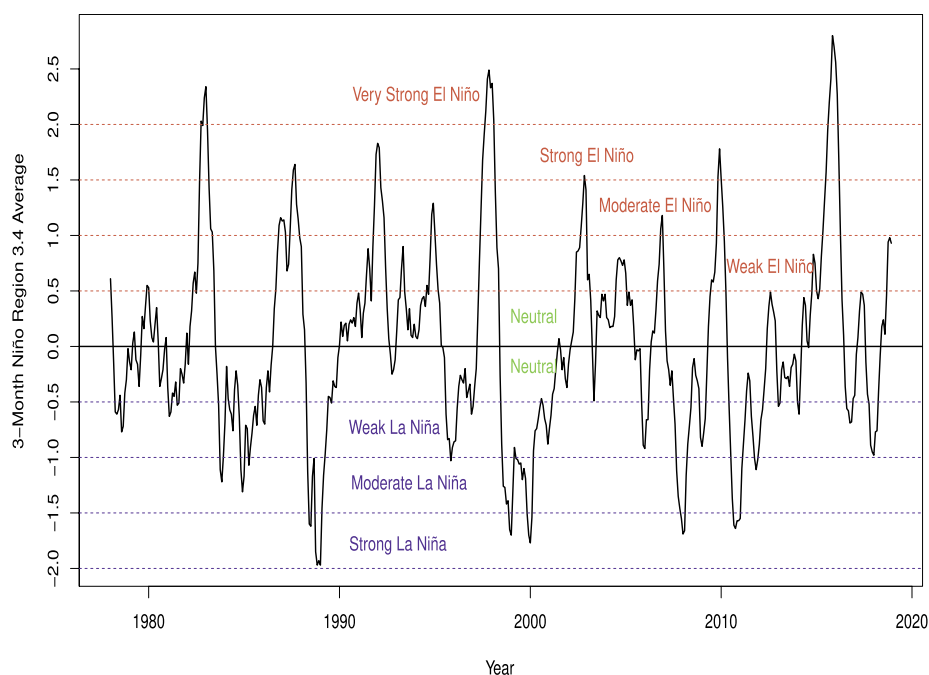
⁴ The broad currency index includes the Euro Area, Canada, Japan, Mexico, China, United Kingdom, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Switzerland, Thailand, Philippines, Australia, Indonesia, India, Israel, Saudi Arabia, Russia, Sweden, Argentina, Venezuela, Chile and Colombia. For more information about trade-weighted indexes see http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf.

Table 1

Description of U.S. Food and Agricultural Companies Used in this Paper.

Company	GICS Sector	GICS Sub Industry	SIC Code	NAICS Code
Archer Daniels Company	Consumer Staples	Agricultural Products	5191	493130
Campbell Soup Company	Consumer Staples	Packaged Foods & Meats	2099	311999
Conagra Brands, Inc.	Consumer Staples	Packaged Foods & Meats	2099	311999
FMC Corporation	Materials	Fertilizers & Agricultural Chemicals	2899	325998
General Mills, Inc	Consumer Staples	Packaged Foods & Meats	2099	311999
The Hershey Company	Consumer Staples	Packaged Foods & Meats	2066	311351
Hormel Foods Corporation	Consumer Staples	Packaged Foods & Meats	5147	424470
McCormick & Company	Consumer Staples	Packaged Foods & Meats	2099	311999
The Mosaic Company	Materials	Fertilizers & Agricultural Chemicals	5169	424690
J. M. Smucker Company	Consumer Staples	Packaged Foods & Meats	5099	423990
Sysco Corporation	Consumer Staples	Food Distributors	5149	424490
Tyson Foods, Inc	Consumer Staples	Packaged Foods & Meats	5149	424490

Notes: Data on SIC and NAICS codes come from <https://siccode.com/en/>. Note that we only report the primary SIC and NAICS codes.

**Fig. 2.** Historical evolution of El Niño Southern oscillation (ENSO): 1990:1 to 2018:12.

Source: National weather service climate prediction center of the national oceanic and atmospheric administration (NOAA): <http://www.cpc.ncep.noaa.gov/data/indices/sstoi.indices>.

and the agricultural stock prices are nonstationary in levels but stationary after first differencing. The finding that some variables are $I(0)$ in levels whereas others are $I(1)$ rules out the need to test for cointegration.

3. Empirical methodology

We begin the methodology section by first presenting a brief review of some key determinants of U.S. stock returns in Section 3.1. Section 3.2 presents the VAR model and discusses the identification restrictions underlying the model.

3.1. A brief review of the determinants of U.S. Stock returns

The literature on the determinants of U.S. stock returns is vast. We briefly review this literature to rationalize the choice of the variables we include in our VAR model. In conducting this review, we first briefly discuss the literature on the macroeconomic determinants of U.S. stock returns, and then proceed to discussing other determinants.

Table 2

Variable names, definitions, and sources.

Variable	Definition	Source	Start Date
SSTA	Sea surface temperature anomalies: Niño 3.4 region	NOAA	January 1978
S&P 500 index	Monthly values of the S&P 500 index	CRSP	January 1978
Output	Industrial Production Index	FRED	January 1978
Inflation uncertainty	University of Michigan: Inflation Expectation	FRED	January 1978
Real exchange rate	Real value of the trade-weighted dollar against a broad group of US trading partners	FRED	January 1978
Premium of the size factor	Average return on the three small portfolios minus the average return on the three big portfolios	WRDS	January 1978
Book-to-market factor	Average return on the two value portfolios minus the average return on the two growth portfolio	WRDS	January 1978
Momentum of the stock market	Average return on the two high prior return portfolios minus average return on the two low prior return portfolios	WRDS	January 1978
U.S. Food and Agricultural Companies			
The Archer Daniels Company	Stock prices of the Archer Daniels Midland Company	CRSP	March 1980
The Campbell Soup Company	Stock prices of the Campbell Soup Company	CRSP	March 1980
Conagra Brands, Inc.	Stock prices of Conagra Brands, Inc.	CRSP	March 1980
The FMC Corporation	Stock prices of the FMC Corporation	CRSP	March 1980
General Mills, Inc.	Stock prices of General Mills, Inc.	CRSP	March 1980
The Hershey Company	Stock prices of the Hershey Company	CRSP	March 1980
Hormel Foods Corporation	Stock prices of Hormel Foods Corporation	CRSP	March 1980
McCormick and Company	Stock prices of McCormick and Company	CRSP	March 1980
The Mosaic Company	Stock prices of the Mosaic Company	CRSP	January 1988
The J.M. Smucker Company	Stock prices of the J.M. Smucker Company	CRSP	October 1994
Sysco Corporation	Stock prices of Sysco Corporation	CRSP	January 1978
Tyson Foods, Inc.	Stock prices of Tyson Foods, Inc.	CRSP	March 1980

Notes: All data used are monthly. As shown in the table, the starting date for all the macroeconomic variables is January 1978. The stock price data for most companies begin in March 1980. All series end in December 2018.

Table 3

Augmented Dickey-Fuller (*ADF*), Elliott, Rothenberg and stock (*ERS*), Phillips-Perron (*PP*), and Kwiatkowski, Phillips, Schmidt and Shin (*KPSS*) unit root tests.

Variables SSTA*	Level				Log First Difference			
	<i>ADF</i>	<i>ERS</i>	<i>PP</i>	<i>KPSS</i>	<i>ADF</i>	<i>ERS</i>	<i>PP</i>	<i>KPSS</i>
SSTA*	-5.9505	-6.1968	-5.0419	0.0578	-11.9739	-5.9411	-12.6972	0.0113
S&P 500 index	-1.6325	-1.4834	-1.6837	0.5281	-15.9289	-6.0770	-21.0065	0.0480
Output	-1.3146	-2.4798	-1.5698	0.9607	-10.7598	-6.6072	-17.6652	0.0921
Real exchange rate	-2.1249	-1.7619	-1.9220	0.2905	-13.6885	-8.8738	-15.0693	0.0981
Inflation uncertainty*	-2.6823	-2.5796	-2.8467	0.8982	-18.5746	-3.0526	-29.0175	0.0340
Premium of size factor*	-15.3511	-8.0833	-22.8379	0.1215	-25.3961	-11.7443	-63.7761	0.0073
Book-to-market factor*	-14.2656	-7.0209	-18.6736	0.0475	-26.0917	-7.1354	-48.0597	0.0072
Momentum of the stock market*	-16.1686	-8.6905	-20.5587	0.0417	-27.4894	-9.6710	-52.8539	0.0067
Food & Agricultural Stock Prices								
The Archer Daniels Company	-3.5168	-3.1710	-3.6907	0.6730	-14.8434	-6.5174	-21.7183	0.0251
The Campbell Soup Company	-1.9765	-1.7600	-1.9240	0.5488	-16.4436	-7.7454	-23.4724	0.0542
Conagra Brands, Inc.	-2.7715	-2.5875	-2.6496	0.5114	-16.5080	-4.9470	-21.9045	0.0902
The FMC Corporation	-1.8438	-1.7802	-1.9019	1.1448	-14.2788	-9.4030	-20.8090	0.0759
General Mills, Inc.	-2.6150	-1.8349	-2.2628	1.0746	-16.8853	-9.0356	-23.5705	0.0472
The Hershey Company	-1.9137	-1.3831	-1.9040	1.0483	-15.9172	-11.0452	-24.2077	0.0595
Hormel Foods Corporation	0.1449	0.3206	0.4484	1.4014	-17.0843	-6.4003	-21.6571	0.0553
McCormick and Company	1.7751	0.8559	2.0258	1.4406	-16.3027	-2.2467	-23.8326	0.0396
The Mosaic Company	-2.9883	-3.3459	-3.2133	0.3134	-12.7920	-3.8339	-18.5210	0.0559
The J.M. Smucker Company	-2.5327	-1.6010	-2.3895	0.7320	-12.6860	-6.8351	-17.8444	0.0743
Sysco Corporation	-1.8422	-0.5547	-1.5422	0.6391	-17.5107	-8.9887	-22.2766	0.0607
Tyson Foods, Inc.	-1.7397	-1.6303	-1.7911	0.8584	-15.8882	-10.2827	-19.6345	0.0457

Notes: * These variables can be negative or positive, so we only take the first difference, not the log first difference. All tests include an intercept and a linear trend. 5% critical values for the respective tests are: 3.42, -2.89, -3.42, 0.146.

3.1.1. Macroeconomic determinants of U.S. Stock returns

Asset pricing theory postulates that factors that influence individuals' consumption decisions and investment opportunities should also impact asset prices [25,26]. Variables that influence the macroeconomy, are certainly examples of such factors. Hence, changes in some macroeconomic variables are likely to have impacts on stock returns. The first, and perhaps most obvious measure of economic activity is an economy's total output (measured by the gross domestic product (GDP) or industrial production). A rise in aggregate output should increase current and expected cash flows to firms, which should in turn cause a rise in stock prices and returns. Hence, the VAR model shown hereinafter contains a measure of U.S. aggregate output to control for its effect on U.S. agricultural stock returns.

Another recognized macroeconomic determinant of stock returns is inflation uncertainty [27]. Points out that uncertainty about the inflation rate raises the required risk premium, leading to an increase in the discount rate, lowering the present discounted value of expected future firm cash flows, which in turn causes a decline in stock prices. In addition, inflation uncertainty creates uncertainty about future economic activity. This uncertainty, which has a negative impact on aggregate economic activity, also has an adverse impact on stock returns. Thus, in all the VAR models, we control for the impact of inflation uncertainty.

Exchange rate fluctuations have also been discussed as another important determinant of stock returns. Assuming that exchange rates and prices cannot be costlessly hedged, and are volatile, an appreciation of the value of the domestic currency relative to the foreign currency negatively affects domestic exporting firms. As pointed out by Ref. [28]; the share prices of these firms may then reflect an ex ante premium for exchange risk. Conversely, cash flows, and hence stock returns of importing firms rise following an appreciation of the real value of the domestic currency [28] also argue that the cash flows and stock prices of domestic firms that are not engaged in international trade may also be impacted because of the impact of exchange rate movements on their "foreign competitors, input costs, aggregate demand, or other factors that affect cash flows and required returns". (page 542).

Certainly, a multitude of other macroeconomic variables are known to impact stock returns. We limit our discussion to these three because they are perhaps the three most recognized determinants of stock market returns in the literature [27]. Secondly, they are the macro variables most likely to impact food and agricultural companies and their profitability. In addition, VAR models with many variables often suffer from technical and computational difficulties related to a loss of degrees of freedom, while rendering identification restrictions imposed on the VAR model questionable.

3.1.2. Other determinants of U.S. Stock returns

We also consider the relationship between agricultural stock returns and the Fama-French-Carhart model variables (see e.g. Refs. [29–31]; and [32]), namely the monthly premium of the size factor (SMB), the monthly premium of the book-to-market factor (HML), and momentum of the stock market (UMD) [29] find weak support for the hypothesis that the beta coefficient fully captures the risk-return relationship. They developed the three-factor model and showed, consistent with the capital asset pricing model (CAPM), that the risk premium depends on the factor market, but also on the size of the firm, as well as the ratio of the book value of a firm's common stock to its market value [32] extended the Fama-French three factor model by including a momentum factor for asset pricing of stocks, which measures the stock market's ability to sustain a positive or negative change in prices.

The premium of the size factor (SMB) is defined as the difference between the average return on the three small portfolios and the average return on the three large portfolios:

$$\frac{1}{3}(\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) - \frac{1}{3}(\text{Big Value} + \text{Big Neutral} + \text{Big Growth})$$

The book-to-market factor (HML) is defined as the difference between the average return on the two value portfolios and the average return on the two growth portfolios:

$$\frac{1}{2}(\text{Small Value} + \text{Big Value}) - \frac{1}{2}(\text{Small Growth} + \text{Big Growth})$$

The momentum factor measures the difference between the average return on the two high prior return portfolios and the average return on the two low prior return portfolios:

$$\frac{1}{2}(\text{Small High} + \text{Big High}) - \frac{1}{2}(\text{Small Low} + \text{Big Low})$$

To save space, and because these variables are not the main variables of interest in the current paper, but are only included to control for their impacts on U.S. agricultural stock returns, we refer the reader to, among others [29–31], and [32] for details of the construction of and rationale for these factors. These authors find empirical evidence that these factors have reliable explanatory power for U.S. stock returns.

3.2. The VAR model

The baseline VAR model relating ENSO and agricultural stock returns is:

$$A_0 X_t = \alpha + \sum_{i=1}^k A_i X_{t-i} + \varepsilon_t \quad (1)$$

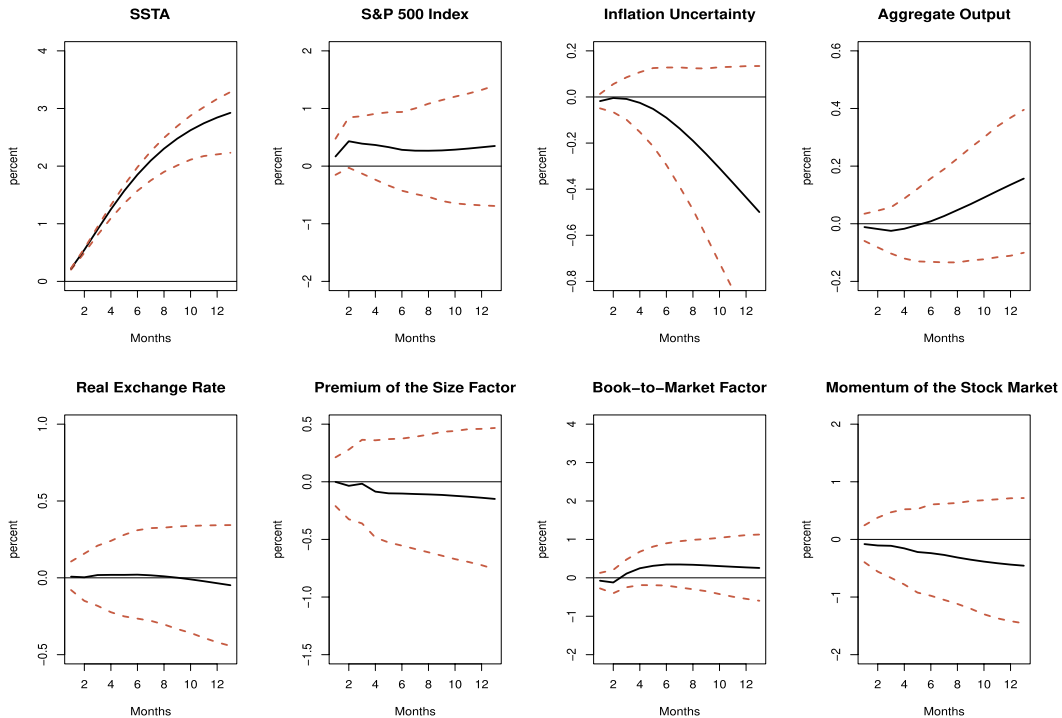
where ε_t denotes serially and mutually uncorrelated innovations, and k denotes the maximum lag length. X is a vector of endogenous

variables containing, in the order listed, our SSTA measure of ENSO intensity, GDP growth, the measure of inflation uncertainty, the real trade-weighted dollar index, the monthly premium of the book-to-market factor, the monthly premium of the size factor, momentum of the stock market, and a measure of the percentage change in agricultural stock prices. We select the optimal lag length using the Akaike Information Criterion (AIC), with $1 \leq k \leq 12$ in equation (1).

The delay restrictions imposed are such that the reduced-form residuals, e_t are related to the structural shocks, ε_t according to $e_t = A_0^{-1} \varepsilon_t$. We assume that ENSO events do not respond contemporaneously to shocks to the other variables. It is reasonable to treat the ENSO variable as exogenous since shocks to the U.S. economy are not large enough to impact global weather events such as ENSO. The ordering of the remaining variables is consistent with the related economics literature (see e.g. Refs. [33,34] that U.S. output can be treated as largely exogenous in relation to the contemporaneous values of the other economic variables and stock returns. The final identifying assumption is such that U.S. food and agricultural stock returns are assumed to react to the preceding variables within a given month.

4. Impulse responses and variance decompositions

In order to shed light on the need for studying the impacts of ENSO on the stock returns of food and agricultural companies, we first examine the effects of ENSO on aggregate stock returns and the macroeconomy in Section 4.1. In Section 4.2, we present the dynamic effects of ENSO on U.S. agricultural stock returns. Throughout the paper, we trace out these dynamic impacts with the help of impulse response functions. An impulse response function shows the dynamic response of a variable over a specified time horizon following a shock (or impulse) to the same or another variable at a given instant. It is predominantly used in modern empirical macroeconomics for causal inference and to analyze policy effectiveness. To take potential heteroscedasticity of the residuals into account, the dashed lines in the figures shown hereinafter are the 90% confidence bands constructed using the wild bootstrap as described by Ref. [35]; with 1000 repetitions. The solid lines in all the figures represent the cumulative response coefficients. The procedure for the wild bootstrap is as follows. First, an artificial vector of shocks for each draw is constructed by multiplying an independent and identically distributed (iid) shock from a standard normal distribution with each element of the vector of residuals, e_t . These artificial shocks, together with the coefficients of the estimated VAR model are then used to construct artificial datasets. We then re-estimate the VAR models and compute impulse response functions with these artificial data invoking the same recursive assumptions (Cholesky decomposition) described in Section 3.2. We repeat this process 1000 times. The 5th and the 95th percentiles of the 1000 bootstrapped impulse



Notes: Solid lines denote the cumulative response estimates. Dashed lines represent the 90% confidence intervals constructed using a recursive design wild bootstrap.

Fig. 3. Responses of U.S. Macroeconomic and Stock Market Variables to ENSO shocks.

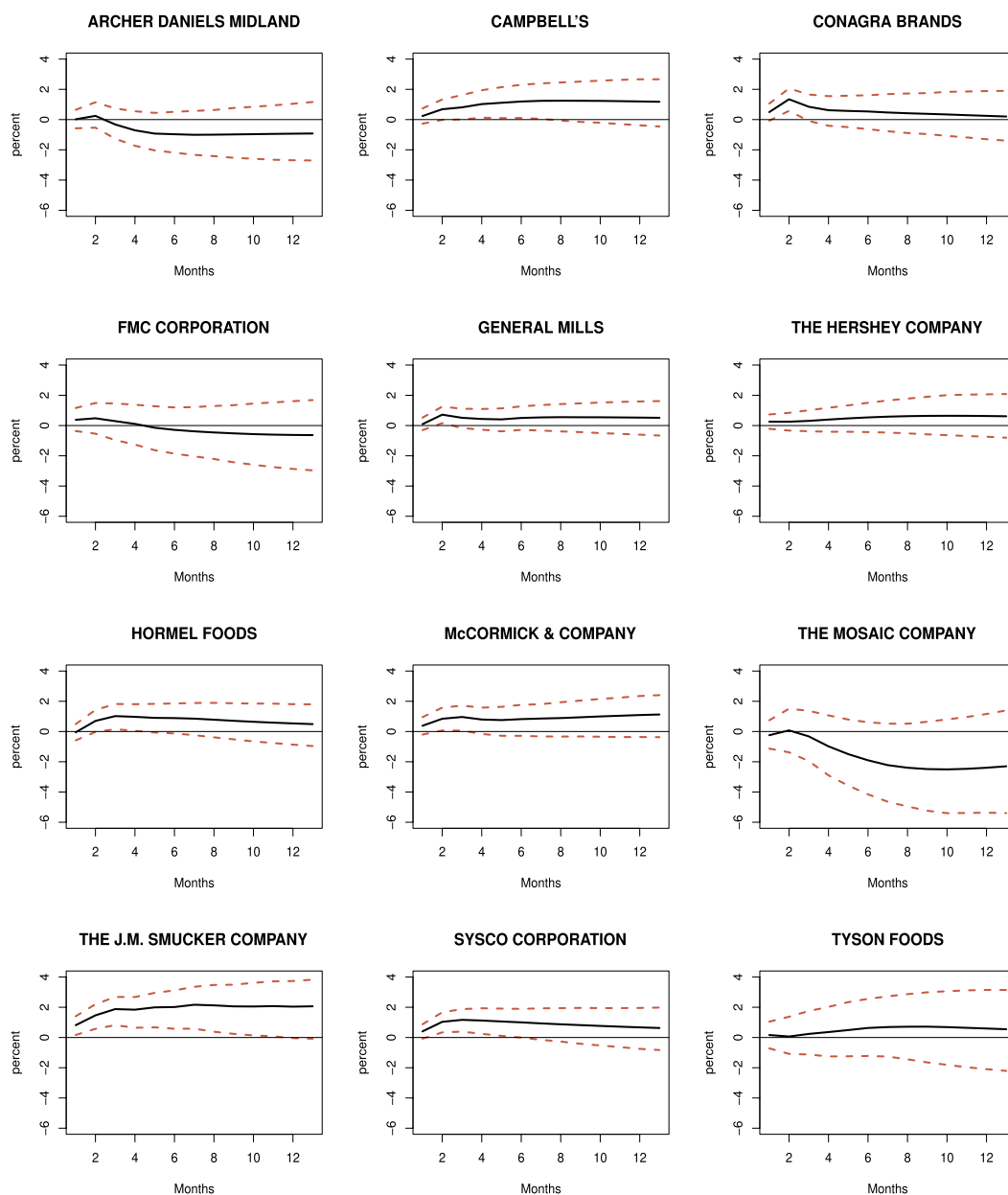
Notes: Solid lines denote the cumulative response estimates. Dashed lines represent the 90% confidence intervals constructed using a recursive design wild bootstrap.

response functions are then used as the 90% confidence bands.

4.1. The effects of ENSO on the macroeconomy and aggregate stock returns

It is useful to first examine the responses of U.S. macroeconomic variables and aggregate stock returns to ENSO shocks, before proceeding to the responses of the stock returns of the food and agricultural companies. As a measure of aggregate stock returns, we use the monthly percentage change in the S&P 500 index. Fig. 3 presents the impulse responses estimated for a horizon of up to 12 months and their corresponding 90% confidence intervals.

As expected, Fig. 3 shows that a positive ENSO shock causes a significant and persistent increase in SSTA. The key result in Fig. 3,



Notes: Solid lines denote the cumulative response estimates. Dashed lines represent the 90% confidence intervals constructed using a recursive design wild bootstrap.

Fig. 4. Responses of U.S. Food and Agricultural Stock Returns to ENSO Shocks.

Notes: Solid lines denote the cumulative response estimates. Dashed lines represent the 90% confidence intervals constructed using a recursive design wild bootstrap.

however, is that ENSO shocks have no statistically significant impact on aggregate stock returns and the macroeconomy. [13]; using data for the G-7 countries also finds that ENSO has no significant effects on average G-7 output growth and aggregate prices, arguing that this insignificant effect is expected as primary commodities that are likely to be affected by ENSO account for only a small percentage of aggregate output of the G-7 countries [18] document similar insignificant macroeconomic effects of ENSO for the U.S. economy. While no studies, to the best of our knowledge have estimated the impact of ENSO on the S&P 500 index, similar arguments can be made for the insignificance of the response of the S&P 500 index. These findings, however, do not necessarily imply that ENSO has no effect on agricultural stock prices as broad measures such as the S&P 500 index (and aggregate economic variables) might conceal the impacts of ENSO on U.S. agricultural stock returns.

4.2. The effects of ENSO on U.S. Agricultural stock returns

4.2.1. Impulse response functions

Fig. 4 shows the cumulative impulse response functions of the stock returns of the twelve food and agricultural companies to an ENSO shock. Of the twelve returns considered, seven experience statistically significant increases in response to an ENSO shock, albeit of different magnitudes and horizons. Following an unanticipated surprise in ENSO, stock returns of the Campbell Soup Company, Conagra Brands, Inc., General Mills, Inc., Hormel Foods Corporation, McCormick and Company, the J. M. Smucker Company, and Sysco Corporation, rise. Except for the returns of the J.M. Smucker Company, which rise on impact following an ENSO shock, the contemporaneous responses of the returns of the other companies are statistically indistinguishable from zero. The response of the returns of Campbell's turns significantly positive three months after the ENSO shock, and remains significant for the next five months. A similar pattern is found with respect to the response of Sysco Corporation. The responses of the returns of Conagra Brands, Inc., General Mills, Inc., Hormel Foods Corporation, McCormick & Company display similar patterns both qualitatively and quantitatively. That is, after an initial delay, the returns of the companies increase following an ENSO surprise, but the increase is shortlived, generally becoming statistically indistinguishable from zero three to four months after the ENSO shock.

These responses are in fact consistent with expectation. Consider the response of the returns of Hormel Foods Corporation, for example. The company is one of the world's largest meat and poultry producers and distributors. Grains account for the largest cost share of animal feed. The grains used for the production of animal feed include corn, sorghum, barley, and oats, with corn accounting for over 95% of total feed grain.⁵ While corn is grown in most U.S. states, the majority is grown in the Midwest. [3]; and [4–7] find that ENSO significantly affects corn yields for states in the U.S. Midwest. This implies a subsequent change in grain prices. If the ENSO event causes an increase in yields or increase in prices, cash flows to agribusiness firms directly engaged in grains rises, leading to an increase in stock returns for companies such as Hormel Foods Corporation. A similar argument can, in fact, be made with respect to the returns of the other six companies whose returns exhibit a statistically significant positive response following a shock to ENSO.

Fig. 4 also shows that the impulse responses of five stock returns, however, are not statistically different from zero at any forecast horizon. For some of these companies, this is expected, as their products are not directly associated with weather events. The FMC Corporation and the Mosaic Company are leading providers of crop nutrients, specifically concentrated phosphate, potash, and nitrogen nutrients to maintain healthy and productive soils. ENSO shocks should have no direct impacts of these nutrients as they are produced from mineral deposits (potash and phosphate) and from the atmosphere (nitrogen). While ENSO might affect these companies indirectly through changes in the demand for their products by companies who use their products as inputs, these companies generally enter contractual price agreements (hedging) long before ENSO occurrences, so that unanticipated ENSO shocks should have only small effects, if any, on the stock returns of the Mosaic Company and FMC Corporation. On the other hand, the finding of statistically insignificant responses of some returns was surprising as some of these firms are directly engaged in crop production, whose yields and prices are impacted by ENSO events. For example, Tyson Foods focuses on the production of chicken through breeding, feed production, and processing. In addition to the chicken segment, their Beef and Pork segments process live cattle and pigs into primal and sub-primal meat products. Their Prepared Foods division includes refrigerated meat products as well as snacks, side dishes, tortilla products, and appetizers. Similar to Hormel Foods, changes in grain prices due to ENSO should impact cash flows to Tyson Foods. Given the similarity with Hormel Foods, Inc., it is rather puzzling that its stock returns are insignificant. The Archer Daniels Midland Company specializes in global foods processing as well as commodity trading. The company is primarily engaged in the processing of oil seeds such as soybeans, cottonseed, sunflower seeds, canola, peanuts, flaxseed, and palm kernel (National Oilseed Processors Association). The Archer Daniel Midland's Corn Processing segment specializes in corn wet milling and dry milling activities.⁶ With previous research reporting evidence that the output of these firms are quite vulnerable to ENSO events, the insignificant responses shown in Fig. 4 are rather surprising.

4.2.2. Variance decomposition

The finding that an ENSO shock has a positive impact on the stock returns of some U.S. food and agricultural stock returns, does not necessarily mean that ENSO events are important determinants of these stock returns, because the ENSO shocks might be small. To take an extreme example, suppose meteorological advances made it possible to perfectly predict all future extreme ENSO events. In this case, there will be no shocks at all to ENSO, because it could be predicted perfectly in every time period. Therefore, no matter how severe an ENSO occurrence is, the shock would have no importance for agricultural stock returns. Therefore, it is both the impact and

⁵ <https://www.ers.usda.gov/topics/crops/corn/background/>.

⁶ <http://www.adm.com/en-US/products/feed/corn-co/Pages/default.aspx>.

the variance of an ENSO shock that determine its importance.

To gauge the relative importance of ENSO events for U.S. agricultural stock returns, Table 4 presents the percent contribution of ENSO shocks to the overall variability of the stock returns resulting from the variance decomposition of the SVAR model (1). At all forecast horizons, ENSO shocks have negligible explanatory power for fluctuations in the stock returns of U.S. food and agricultural companies. On impact, the effect of the shock is 0. As the time horizon lengthens, the quantitative importance of the ENSO shocks gradually increases. Nonetheless, at no point does a shock to ENSO explain more than 3% of the movements in any of the stock returns. The main conclusion from the variance decompositions in Table 4 is that ENSO shocks explain only a relatively small portion of the unpredictable fluctuations of the stock returns of U.S. food and agricultural firms, with other factors responsible for much of the variability of these returns.

The finding in Table 4 that other shocks, rather than ENSO have negligible explanatory power for fluctuations in the stock returns of U.S. food and agricultural companies, coupled with the insignificant responses of some returns and the shortlived significant responses of other returns in Fig. 4, is potentially explained by the efficient market hypothesis. Assuming that U.S. agricultural markets are efficient, then the impacts of ENSO shocks will be incorporated in the stock returns of food and agricultural companies, especially at longer horizons, so that if ENSO shocks have any impacts, these impacts occur in the short run, and are relatively shortlived. For instance, suppose ENSO shocks raise spot prices of food and agricultural commodities. Over time, the market anticipates these higher spot prices, and moves the forward curve steeply into forwardation, as sea surface temperatures change. Given that of ENSO cycles have been occurring more frequently, as shown in Fig. 2 and as documented by, among others, Trenberth and Hoar (1996) and Qian et al. (2011), it is plausible that ENSO shocks are incorporated in agricultural stock returns, explaining the insignificant responses of the stock returns of The Archer Daniels Midland Company, Hershey's, and Tyson Foods, Inc., and the short term, shortlived significant responses of the other stock returns in Fig. 4.

4.2.3. Historical decomposition

While impulse response functions and variance decompositions are usually the main focus in the VAR literature, they mostly show the timing and magnitude of the responses to a *one-time* shock. Historical decompositions of the effects of a sequence of shocks can provide additional information to help assess the cumulative effect of this sequence of shocks [36,37]. This is particularly important in our case because historical ENSO shocks have not been limited to one-time occurrences, but rather a vector sequence of shocks, often of different magnitudes, and frequently alternating between El Niño and La Niña. Accordingly, Fig. 5 presents the historical decomposition of the sequence of ENSO shocks on fluctuations in U.S. agricultural stock returns (solid lines) to evaluate the cumulative effect of such shocks. Dashed lines depict the actual values of the U.S. agricultural stock return series. It is apparent from the Figure that historically, movements in the stock returns of U.S. food and agricultural companies have been driven by other shocks, rather than ENSO shocks.

4.2.4. How sensitive are the responses to changes in the lag length?

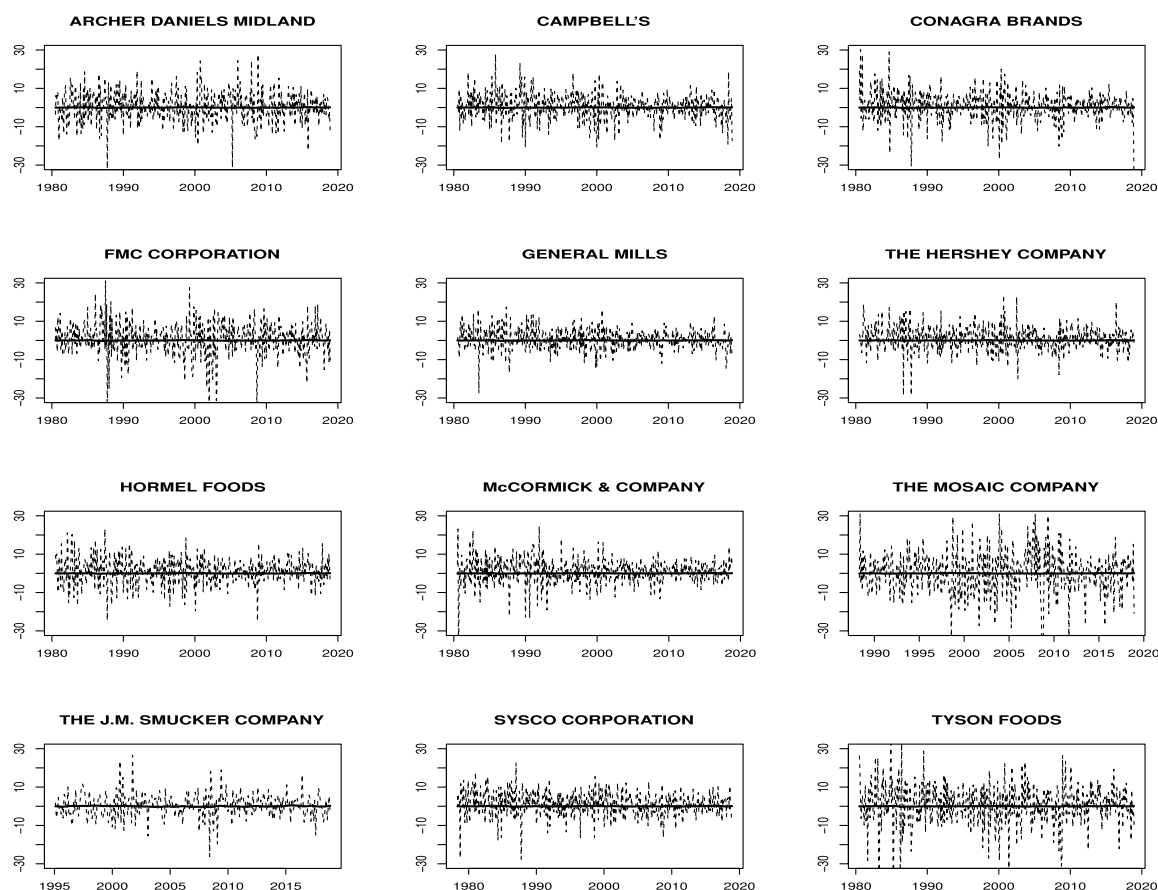
The impulse responses in Fig. 4 are based on VAR models in which the lag lengths were chosen using the AIC. At least three problems arise when using information criteria to select the lag order for VAR models. First, information criteria are known for selecting extremely short lag lengths. In fact, in no instance does the AIC select a lag length greater than three for any of the VAR models used to construct the impulse response functions shown in 4. Second, for long enough monthly time series, it is generally recommended to use long lags in order to cover seasonality. Third, VAR models are known to be quite sensitive to the lag order specification. Hence, if the results from VAR analyses are to be credible, their sensitivity to alternative lag lengths must be studied.

Fig. 6 shows the impulse response functions of the stock returns to an ENSO shock in VAR models including 12 lags of the endogenous variables. Looking at the Figure, it is apparent that the underlying findings continue to hold. Six of the twelve returns

Table 4
Percent contribution of ENSO to overall variability of agricultural stock returns.

Horizon	Archer Daniels	Campbell's	Conagra	FMC Corp	General Mills	Hershey's
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
3	0.6314	0.2374	0.0287	0.0125	0.0521	0.0339
6	1.9352	0.1717	0.1104	0.0614	0.1744	0.0172
12	2.6509	0.1361	0.1240	0.0672	0.2088	0.0152
18	2.6753	0.1330	0.1212	0.0700	0.2170	0.0161
24	2.6697	0.1333	0.1218	0.0758	0.2193	0.0163
36	2.6667	0.1339	0.1225	0.0806	0.2206	0.0163
Horizon	Hormel	McCormick	Mosaic	Smucker's	Sysco	Tyson
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
3	0.9324	0.0111	0.0142	0.0297	0.1687	0.1443
6	1.0439	0.0283	0.5783	0.3756	0.4829	0.1798
12	0.9281	0.0237	0.7227	0.6982	0.6280	0.2648
18	0.9070	0.0279	0.7121	0.7046	0.6491	0.2621
24	0.9040	0.0297	0.7131	0.7024	0.6517	0.2619
36	0.9028	0.0300	0.7129	0.7025	0.6520	0.2631

Notes: Based on variance decomposition of the recursive VAR models (1).



Notes: Historical decompositions based on the VAR model (1) described in section 3.

Fig. 5. Historical decompositions: contribution of ENSO to U.S. Agricultural Stock Returns.

Notes: Historical decompositions based on the VAR model (1) described in section 3.

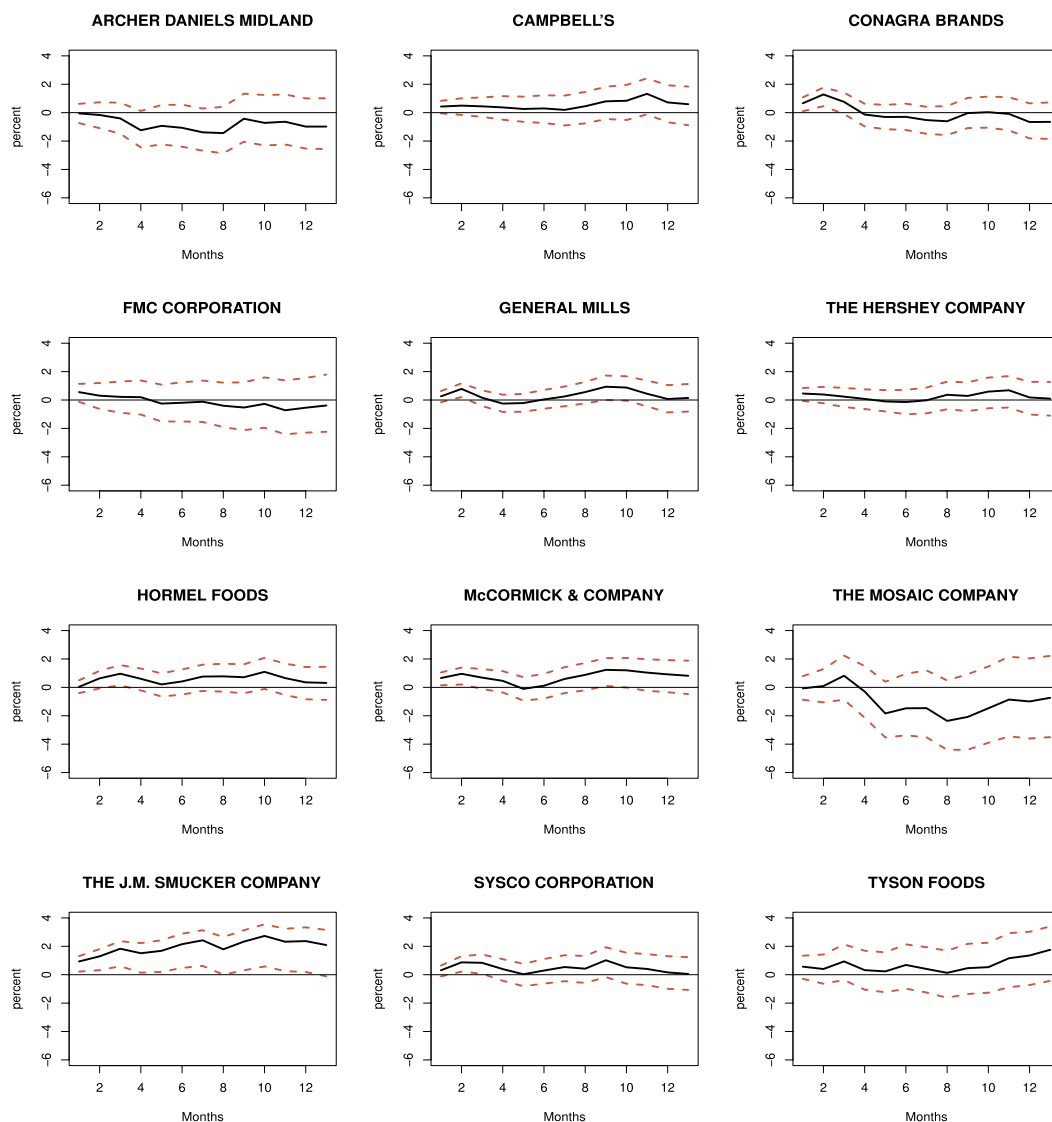
exhibit significant increases in response to an ENSO shock. These are the same returns shown to rise following an ENSO surprise in Fig. 4. While the response of Campbell's is still positive, it is now not different from zero in a statistical sense. Taken together, we conclude that the general findings of the paper are robust to lag order specification.⁷

4.2.5. How sensitive are the responses to the ordering of the variables?

Another limitation of VAR analyses is that impulse response functions can be sensitive to the ordering of the variables in the VAR model. While we follow the convention in the VAR literature to order the more exogenous variables ahead of the less exogenous ones, it is necessary to check the robustness of the results to alternative ordering of the variables. This section does that. Of course, with an 8-variable VAR model, it is not possible to verify the robustness of the results to all possible ordering schemes, as there are multiple possible ways of ordering the variables. Consequently, we only present results of the reverse ordering. That is, the impulse response functions are estimated from VAR models containing, in the order listed, the agricultural stock return of interest, momentum of the stock market, the premium of the size factor, the premium of the book-to-market factor, the real trade-weighted dollar index, the measure of inflation uncertainty, output growth, and the SSTA measure of ENSO intensity. We only perform this analysis to examine the stability of the results to alternative ordering of the variables. Admittedly, this ordering is not plausible, as it is unlikely for agricultural stock returns to have contemporaneous effects of ENSO, aggregate output, and the other aggregate economic and financial variables.

Fig. 7 presents the impulse response functions of this specification. Recall that the ordering of the variables now reflects the assumption that the stock returns of U.S. food and agricultural companies impact ENSO immediately, but that ENSO affects stock returns with a delay of a month. Hence, by construction, the impulse responses in Fig. 7 are at zero on impact. Subsequent responses mirror those shown in Fig. 4. That is, stock returns of the Campbell Soup Company, Conagra Brands, Inc., General Mills, Inc., Hormel

⁷ We also experimented with lag lengths of 4, 6, 8, and 10, generally finding that the results are invariant to the lag order specification.



Notes: Solid lines denote the cumulative response estimates. Dashed lines represent the 90% confidence intervals constructed using a recursive design wild bootstrap.

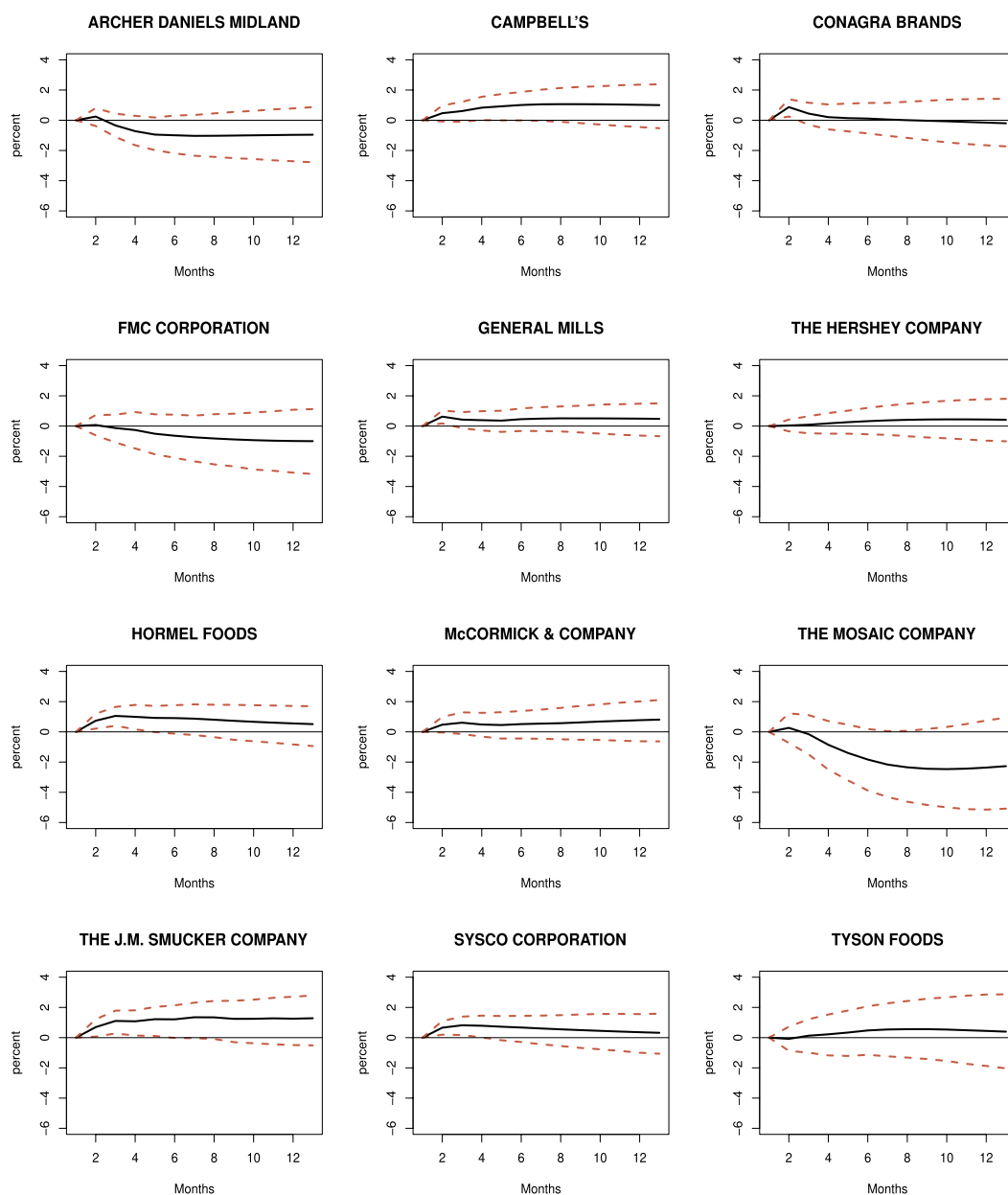
Fig. 6. Responses of U.S. Food and Agricultural Stock Returns to ENSO Shocks: 12-Lag VAR model.

Notes: Solid lines denote the cumulative response estimates. Dashed lines represent the 90% confidence intervals constructed using a recursive design wild bootstrap.

Foods Corporation, McCormick and Company, the J. M. Smucker Company, and Sysco Corporation, increase, but the positive responses tend to be shortlived. The responses of the returns of the five other companies, as in Fig. 4, are not different from zero. This analysis gives us some degree of confidence that the results of this paper are not sensitive to the ordering of the variables in the VAR models.

5. Conclusion

The paper estimates the response of twelve U.S. agricultural stock returns to ENSO shocks using a recursively identified VAR model. The delay restrictions imposed for identification of the structural shocks are achieved by applying a Cholesky decomposition of the reduced-form residual covariance matrix. Our results indicate that the responses of five of the twelve stock returns are not significantly different from zero, while seven of the stock returns rise significantly following an ENSO shock. The rise in the stock returns, however, are relatively shortlived, typically turning indistinguishable from zero three to six months after the ENSO shock. Results of variance decompositions show that ENSO shocks explain only a relatively small portion of the unpredictable fluctuations of U.S. agricultural



Notes: Solid lines denote the cumulative response estimates. Dashed lines represent the 90% confidence intervals constructed using a recursive design wild bootstrap.

Fig. 7. Responses of U.S. Food and Agricultural Stock Returns to ENSO Shocks: Reverse ordering.

Notes: Solid lines denote the cumulative response estimates. Dashed lines represent the 90% confidence intervals constructed using a recursive design wild bootstrap.

stock returns. We also find that historically, movements in U.S. agricultural stock returns have been driven by other shocks, rather than ENSO shocks.

The empirical reliance on a linear VAR model has some limitations. Recent empirical papers have found that ENSO may have asymmetric economic effects (see e.g. Ubilava D. and Holt M., 2013; and [38]). It is therefore plausible that ENSO shocks may have nonlinear and/or asymmetric effects on agricultural stock returns, as well. If this is indeed the case, then the simple VAR analysis of this paper may not be sufficient to capture these asymmetries/nonlinearities. It is possible that it is not just an ENSO shock that matters for U.S. agricultural stock returns, but the type and magnitude of the ENSO shock. The responses of these returns may depend on whether the ENSO shock is an El Niño, La Niña, or neutral shock. Thus future research may examine asymmetries and nonlinearities in the impact of ENSO on agricultural stock returns.

Author statement

Bebonchu Atems: Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Supervision, Project administration. Michael Maresca: Conceptualization, Writing - original draft, Investigation, Data curation. Baomei Ma: Conceptualization, Data curation, Writing - original draft. Emily McGraw: Data curation, Writing - review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.wre.2020.100157>.

References

- [1] M. Bove, J.J. O'Brien, J.B. Eisner, C.W. Land sea, X. Ni, Effect of El Niño on U.S. Land falling hurricanes, revisited, *Bull. Am. Meteorol. Soc.* 79 (11) (1998) 2476–2482.
- [2] M.A. Saunders, R.E. Chandler, C.J. Merchant, F.P. Roberts, Atlantic hurricanes and NW Pacific typhoons: ENSO spatial impacts on occurrence and landfall, *Geophys. Res. Lett.* 27 (2000) 1147–1150.
- [3] P. Handler, E. Handler, Climatic anomalies in the tropical Pacific Ocean and corn yields in the United States, *Science* 220 (4602) (1983) 1155–1156.
- [4] P. Handler, Corn yields in the United States and sea surface temperature anomalies in the equatorial Pacific Ocean during the period 1868–1982, *Agric. For. Meteorol.* 31 (1) (1984) 25–32.
- [5] P. Handler, USA corn yields, the El Niño and agricultural drought: 1867–1988, *Int. J. Climatol.* 10 (8) (1990) 819–828.
- [6] J. Hansen, A. Hodges, J. Jones, ENSO influences on agriculture in the Southeastern United States, *J. Clim.* 11 (3) (1998) 404–411.
- [7] R. Cadson, D. Toyed, S. Taylor, Midwestern corn yield and weather in relation to extremes of the southern oscillation, *J. Prod. Agric.* 9 (3) (1996) 347–352.
- [8] R. Adams, C. Chen, B. McCall, R. Wei her, The economic consequences of ENSO events for agriculture, *Clim. Res.* 13 (3) (1999) 165–172.
- [9] J. Jones, Atlantic and Pacific sea surface temperatures and corn yields in the Southeastern USA: lagged relationships and forecast model development, *Int. J. Climatol.* 31 (4) (1999) 592–604.
- [10] D. Legler, K. Bryant, J. O'Brain, Impact of ENS-related climate anomalies on crop yields in the U.S., *Climatic Change* 42 (2) (1999) 351–375.
- [11] M. Dalton, El Niño, expectations, and fishing effort in Monterrey Bay, California, *J. Environ. Econ. Manag.* 42 (3) (2001) 336–359.
- [12] W. Schlenker, M. Roberts, Nonlinear effects of weather on corn yields, *Appl. Econ. Perspect. Pol.* 28 (3) (2006) 391.
- [13] A. Brunner, El Niño and world primary commodity prices: warm water or hot air? *Rev. Econ. Stat.* 84 (1) (2002) 176–183.
- [14] C.L. Keppenne, An ENSO signal in soybean futures prices, *J. Clim.* 8 (1995) 1685–1689.
- [15] D. Letson, B. McCullough, ENSO and soybean prices: correlation without causality, *J. Agric. Appl. Econ.* 33 (3) (2001) 513–521.
- [16] M. Holt, A. Inoue, Climate Anomalies and World Primary Commodity Prices: The Effects of El Niño and His Promos Segundo as Viewed through a Rolling Window, CENSUS Working Paper, 2006. April 10, 2006.
- [17] D. Ubilava, M. Holt, El Niño southern oscillation and its effects on world vegetable oil prices: assessing asymmetries using smooth transition models, *Aust. J. Agric. Resour. Econ.* 57 (2013) 2273–2297.
- [18] B. Berry, A. Okulicz-Kozaryn, Are there ENSO signals in the macroeconomy? *Ecol. Econ.* 64 (2008) 3625–3633.
- [19] D. Dickey, W. Fuller, Distribution of the estimators for auto regressive time series with a unit root, *J. Am. Stat. Assoc.* 74 (366) (1979) 427–431.
- [20] P. Phillips, P. Perron, Testing for unit root in time series regression, *Biometrika* 75 (2) (1988) 335–346.
- [21] G. Elliott, T. Nuremberg, J. Stock, Efficient tests for an auto regressive unit root, *Econometrica* 64 (4) (1996) 813–836.
- [22] D. Kwiatkowski, P. Phillips, P. Schmidt, Y. Shin, Testing the null hypothesis of stationary against the alternative of a unit root: how sure are we that economic time series have a unit root? *J. Econom.* 54 (1–3) (1992) 159–178.
- [23] D.N. DeJong, J.C. Bernanke, N.E. Sivan, C.H. Whitman, The power problems of unit root test in time series with auto regressive errors, *J. Econom.* 53 (1–3) (1992) 323–343.
- [24] W. Schwert, Test for unit roots: a Monte Carlo investigation, *J. Bus. Econ. Stat.* 7 (1989) 147–159.
- [25] R. Merton, An intertemporal capital asset pricing model, *Econometrica* 41 (5) (1973) 867–887.
- [26] D. Breeden, An intertemporal asset pricing model with stochastic consumption and investment opportunities, *J. Financ. Econ.* 7 (3) (1979) 265–296.
- [27] S. Azar, The determinants of US stock market returns, *Open Econ. Manag. J.* 1 (2014) 1–13.
- [28] W. Bailey, P. Chung, Exchange rate fluctuations, political risk, and stock returns: some evidence from an emerging market, *J. Financ. Quant. Anal.* 30 (4) (1995) 541–561.
- [29] E. Fama, K. French, The cross-section of expected stock returns, *J. Finance* 47 (2) (1992) 427–465.
- [30] E. Fama, K. French, Common risk factors in the returns on stocks and bonds, *J. Financ. Econ.* 33 (1993) 3–56.
- [31] E. Fama, K. French, Size and book-to-market factors in earnings and returns, *J. Finance* 50 (1) (1995) 131–155.
- [32] M. Carhart, On persistence in mutual fund performance, *J. Finance* 52 (1) (1997) 57–82.
- [33] R. Jimenez-Rodríguez, M. Sanchez, Oil price shocks and real GDP growth: empirical evidence for some COED countries, *Appl. Econ.* 37 (2) (2005) 201–228.
- [34] K. Lee, S. Ni, On the dynamic effects of oil price shocks: a study using industry level data, *J. Monetary Econ.* 49 (2002) 823–852.
- [35] L. Kilian, S. Goncalves, Bootstrapping auto regressions with conditional heteroskedasticity of unknown form, *J. Econom.* 123 (1) (2004) 89–120.
- [36] L. Kilian, Exogenous oil supply shocks: how big are they and how much do they matter for the U.S. Economy? *Rev. Econ. Stat.* 90 (2) (2008) 216–240.
- [37] A. Herrera, E. Pesavento, Oil price shocks, systematic Monetary policy, and the “great moderation”, *Macroecon. Dyn.* 13 (1) (2009) 107–137.
- [38] D. Ubilava, The ENSO effect and asymmetries in wheat price dynamics, *World Dev.* 96 (2017) 490–502.