Exploring Asymmetries in the Effects of El Niño-Southern Oscillation on U.S. Food and Agricultural Stock Returns

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Abstract

State-dependent local projection (Jorda, 2005) methods have become the state-of-the-art technique for investigating asymmetric or nonlinear responses to economic (and other) shocks. We apply this methodology to examine whether El Niño-Southern Oscillation (ENSO) has asymmetric impacts on U.S. food and agricultural stock returns. Using weekly data from 1990:01 to 2019:04, we find support for the hypothesis that food and agricultural stock returns respond asymmetrically to ENSO shocks. In particular, we provide evidence that El Niño shocks typically decrease or have no effects on U.S. food and agricultural stock returns, whereas La Niña shocks generally increase returns. The analysis, thus, emphasizes the need to consider asymmetries in the impacts of ENSO, as failure to do so might result in misleading conclusions about the effect of ENSO on U.S. food and agricultural stock returns.

JEL Classification: Q41, C32

Keywords: Local projections; El Niño-Southern Oscillation; agriculture; stock returns

1 Introduction

The El Niño-Southern Oscillation (ENSO) is an important source of interannual variability in weather and climate patterns in many parts of the world (Shabbar and Khandekar, 1996). It involves fluctuations in trade winds, precipitation, sea level pressure, and sea surface temperatures in the central and east-central equatorial Pacific basin (L'Heureux, 2014). The warm phase of ENSO, known as El Niño, is characterized by a weakening of easterly trade winds due to higher surface pressure in the eastern Pacific and lower pressure in the west, a rise in sea surface temperatures, increased rainstorms in the central and east-central equatorial Pacific ocean, wetter conditions in the Pacific coast of South America, and dry conditions in Southeast Asia and the northern tier of Australia.[1] In the United States, El Niño typically causes higher wintertime temperatures in the northern states, cooler temperatures in the Gulf Coast, higher precipitation in the southern regions, drier wintertime conditions in Hawaii and Guam, and increased rainfall in American Samoa.[2] The cold phase of ENSO, known as La Niña, generally has opposite effects. That is, easterly winds strengthen, sea surface temperatures and rainstorms decrease in the central and east-central equatorial Pacific Ocean, the Pacific coast of South America experiences drier conditions, while Southeast Asia and the northern tier of Australia encounter much wetter than normal conditions. In La Niña episodes, northwestern U.S. states experience cooler than average temperatures, Southeastern and Gulf Coast areas witness warmer weather, Hawaii and Guam encounter much wetter conditions, and American Samoa experiences reduced precipitation.

A large empirical literature has documented evidence that the effect of ENSO on agricultural output and prices varies between the El Niño and La Niña phases of the ENSO cycle. Hansen et al. (1998) present evidence of lower than expected corn and tobacco yields in the years immediately following La Niña events for several Southeastern U.S. states. They also find that the areas of soybean, cotton, and peanut harvested respectively decreased by

[1] https://www.americangeosciences.org/critical-issues/faq/what-are-el-niño-and-la-Niña

[2] https://oceanservice.noaa.gov/facts/niñoNiña.html

about 8.3%, 5.3%, and 8.7% in La Niña years compared to non-La Niña years. Adams et al. (1999) estimate that the consequences of ENSO vary from approximately \$1.5 to \$6.5 billion in losses, with La Niña events associated with greater losses than El Niño. Cadson et al. (1996) report lower than expected corn yields during the La Niña phase of ENSO for states in the U.S. cornbelt. Iizumi et al. (2014) find that El Niño increases global average soybean yield by 2.1% to 5.4%, but changes yields of corn, rice and wheat by between -4.3% to 0.8%. On the other hand, they find lower yields of between 0% and -4.5% for all four crops in La Niña years. Using smooth transition models, Ubilava and Holt (2013) show that El Niño events cause an increase in global vegetable oil prices, while La Niña events cause a decrease in prices. Applying a vector smooth transition autoregressive (VSTAR) methodology, Ubilava (2017) reports an increase in wheat prices following La Niña, and a decrease in prices after El Niño occurrences. Further evidence of asymmetries in the impacts of El Niño and La Niña on agricultural output and prices has been documented by Hall et al. (2001), Schlenker and Roberts (2006), Ubilava (2012a, 2012b, 2014), and Smith and Ubilava (2017).

While considerable evidence exists on the (asymmetric) impacts of ENSO on agricultural yields and prices, much less research has examined the impact of ENSO on food and agricultural stock returns. Suppose, as highlighted by previous studies, that an ENSO shock decreases agricultural yields. This fall in output is expected to decrease current and future cash flows to food and agricultural companies, resulting in a decline in their stock returns. It is also possible, however, that if food and other agricultural prices rise in response to this decrease in supply, cash flows, profitability, and hence, the stock returns of food and agricultural companies may rise. The literature has largely ignored the possibility that the stock returns of food and agribusiness companies may respond to ENSO shocks.

This paper contributes to the literature on the economic and financial effects of ENSO along several dimensions. First, the paper considers the impact of ENSO on U.S. food and agricultural stock returns. Second, we employ weekly data spanning the period January 1990 to April 2019, as opposed to much of the related literature that typically employs monthly or quarterly data to examine the economic effects of ENSO. While the use of monthly or quarterly data in studies that examine the impact of ENSO on agricultural output and prices is perhaps appropriate, as the full impact of ENSO on agricultural yields and prices may take a long time to become apparent, our use of higher frequency (weekly) data provides a much richer and more appropriate data set for estimating the impacts of ENSO on stock returns. As pointed out by Geweke (1978), using lower frequency data for such a study may lead to considerable bias. Hence, in our case, the use of weekly rather than monthly or quarterly data results in more reliable estimates, especially if, as expected, U.S. food and agricultural stock returns respond much faster to ENSO anomalies. As further pointed out by Geweke (1978), the use of low frequency data can result in a form of omitted variable bias because of misspecification of the intertemporal lag distribution. Third, we explore asymmetries in the effects of ENSO shocks by investigating the extent to which the responses of U.S. food and agricultural stock returns differ depending on whether the ENSO events are El Niño or La Niña. Given the significant evidence that the output and price responses to ENSO anomalies may be asymmetric depending on the ENSO cycle (El Niño or La Niña), there is need to estimate a model that allows for such asymmetries. Fourth, we use state-of-the-art state-dependent local projection methods (Jorda, 2005), which provide a flexible, parsimonious empirical modeling framework that is ideal for capturing asymmetries without the need to impose the type of dynamic restrictions generally required in standard VAR, and other nonlinear and regime-dependent modeling techniques.

The empirical results of the paper provide evidence of asymmetries in the responses of U.S. food and agricultural stock returns to ENSO shocks. In particular, impulse response functions reveal that La Niña shocks, in general, are associated with an increase returns, while the responses to El Niño shocks are typically negative or insignificant. We further quantify the magnitude and significance of this asymmetry, and show that the difference in the stock return responses to El Niño shocks and La Niña shocks are significantly different from zero for seven of the twelve returns considered. These findings are robust to the use of lower frequency (monthly) data, as well as to controlling for the effect of macroeconomic conditions. The analysis, thus, emphasizes the need to disentangle ENSO shocks into corresponding El Niño, and La Niña shocks, as failure to do so might result in misleading conclusions about the effect of ENSO on U.S. food and agricultural stock returns.

The remainder of the paper is as follows. The next section discusses the data and presents the empirical methodology. Section 3 discusses the empirical results. Section 4 concludes.

2 Data and Methodology

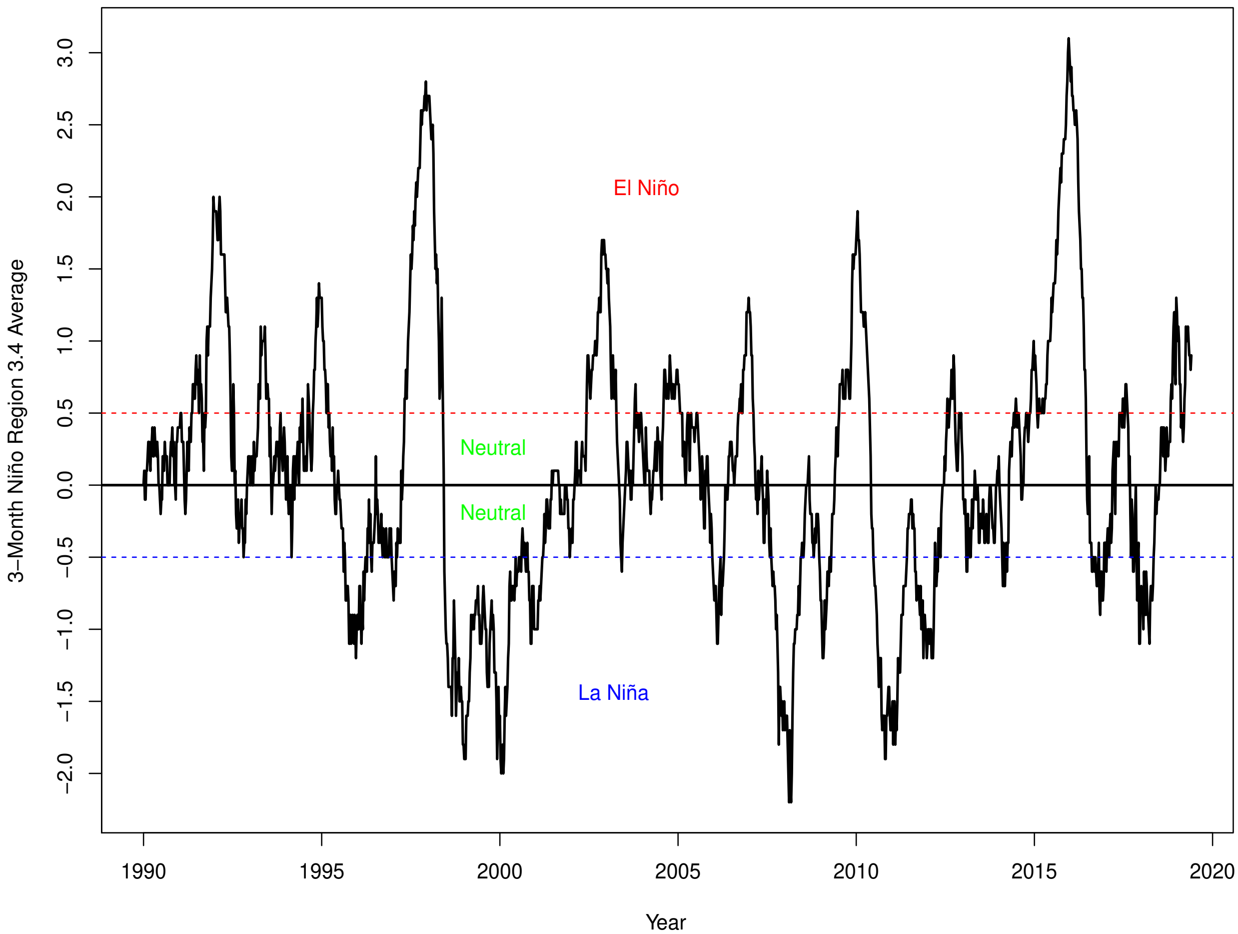
2.1 Data

This paper uses weekly observations on the measure of ENSO intensity and the closing values of the stock prices of twelve U.S. food and agricultural companies covering the period January 1990 to April 2019. We use sea surface temperature anomalies (SSTA) for the "Niño 3.4" region - the region between 5°N-5°S and 120°W-170°W) - as our measure of ENSO intensity. While other measures of ENSO intensity, such as the Southern Oscillation Index (SOI) anomalies, have sometimes been used in the literature, the use of SSTA is more prevalent (see e.g. Hansen et al., 1998; Brunner, 2002; Ubilava, 2017).[3] The data on weekly SSTA come from the Climate Prediction Center (National Oceanic and Atmospheric Administration (NOAA)). An El Niño event is defined as three consecutive months of SSTA of 0.5°C (0.9°F) or higher, while a La Niña episode is defined as three consecutive months of SSTA of -0.5°C (-0.9°F) or less. SSTA between 0.5°C (0.9°F) and -0.5°C (-0.9°F) are referred to as neutral ENSO events. Figure 1 shows the weekly SSTA values over our entire sample period. It is apparent that whereas neutral ENSO events are more prevalent, a nontrivial number of ENSO events have been El Niño and La Niña episodes.

We collect data on the stock prices of twelve publicly traded U.S. food and agricultural

[3]See Atems et al. (2019) for further discussion on the advantages of using SST anomalies over the SOI anomalies to measure ENSO intensity

Figure 1: Weekly El Niño Southern Oscillation (ENSO): 1990:1-2019:04



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

companies from the Center for Research in Security Prices (CRSP). The companies considered are listed in Table 1. We chose these companies because they are among the largest food and agricultural companies trading in U.S. stock markets. All the twelve firms, in fact, are included in the S&P index. We narrowed the number of companies to twelve by first using the Global Industry Classification Standard (GICS) to identify companies in the Consumer Staples, and Materials sectors. As it is not possible to consider the stock returns of all firms in these sectors, and it is unlikely that the output, prices, and therefore stock returns of all these firms respond to ENSO shocks, we consider only those firms in the Packaged Foods

Table 1: Variable Names and Descriptions

Variable	Description	Source	Sample Period
SSTA	Sea surface temperature anomalies: Niño 3.4 region	NOAA	1990:01-2019:04
CPI	Consumer price index for all urban consumers	FRED	1990:01-2019:04
Output	Industrial Production Index	FRED	1990:01-2019:04
Archer Daniels	The Archer Daniels Company stock prices	CRSP	1990:01-2019:04
Campbell's	The Campbell Soup Company stock prices	CRSP	1990:01-2019:04
Conagra	Conagra Brands, Inc. stock prices	CRSP	1990:01-2019:04
FMC	The FMC Corporation stock prices	CRSP	1990:01-2019:04
General Mills	General Mills, Inc. stock prices	CRSP	1990:01-2019:04
Hershey's	The Hershey Company stock prices	CRSP	1990:01-2019:04
Hormel	Hormel Foods Corporation stock prices	CRSP	1990:01-2019:04
McCormick	McCormick and Company stock prices	CRSP	1990:01-2019:04
Mosaic	The Mosaic Company stock prices	CRSP	1990:01-2019:04
Smucker	The J.M. Smucker Company stock prices	CRSP	1994:11-2019:04
Sysco	Sysco Corporation stock prices	CRSP	1990:01-2019:04
Tyson Foods	Tyson Foods, Inc. stock prices	CRSP	1990:01-2019:04

Notes: Full meanings of the 'Source' acronyms are found in the text.

and Meats, and the Fertilizers and Agricultural Chemicals GICS Subsectors. This leaves us with sixteen of the largest publicly traded U.S. food and agribusiness firms. Given the importance of long enough time series for our empirical methodology, we only consider twelve of these sixteen companies with long enough data.

The main results of the paper are based on weekly data. In a robustness section, however, we also utilize monthly data on SSTA and stock returns. In addition, monthly data on the U.S. consumer price index (CPI) for all urban consumers and the U.S. industrial production index (output), both collected from the Federal Reserve Economic Database (FRED) are used in some specifications. Variable descriptions are provided in Table 1.

In Table 2 are results of a battery of unit root and stationarity tests performed on all the variables in log levels and log first differences. The table first reports results of the augmented Dickey-Fuller (ADF) test (see Dickey and Fuller, 1981). The low power of the ADF test against relevant trend stationary alternatives is well documented (see e.g. DeJong

Table 2: Unit Root and Stationarity Tests

A. Tests for Variables in Levels

Variables	*ADF*	*ERS*	*PP*	*KPSS*
SSTA*	-3.4258	-3.7560	-3.7677	0.3737
The Archer Daniels Company	-3.2612	-2.9226	-3.2745	1.1714
The Campbell Soup Company	-2.2772	-1.8840	-2.2995	1.0055
Conagra Brands, Inc.	-2.9377	-2.6754	-2.8934	1.6881
The FMC Corporation	-1.3352	-1.1177	-1.3550	3.2270
General Mills, Inc.	-2.6526	-2.6733	-2.8066	2.2847
The Hershey Company	-1.7918	-1.5420	-1.8139	2.0565
Hormel Foods Corporation	-1.0802	-0.6475	-1.0534	3.7714
McCormick and Company	1.1986	0.8372	1.1150	3.4195
The Mosaic Company	-2.5879	-2.7084	-2.6554	1.0164
The J.M. Smucker Company	-2.9581	-1.9279	-2.9515	2.1468
Sysco Corporation	-1.6570	-1.3985	-1.5828	1.2706
Tyson Foods, Inc.	-0.6964	-0.9917	-0.7789	3.2585

B. Tests for Variables in Log First Differences

Variables	*ADF*	*ERS*	*PP*	*KPSS*
SSTA*	-28.6417	-12.1366	-39.9541	0.0188
The Archer Daniels Company	-27.8557	-14.1648	-41.1783	0.0301
The Campbell Soup Company	-28.0371	-8.2142	-42.1599	0.0628
Conagra Brands, Inc.	-26.5184	-17.3770	-38.4228	0.0455
The FMC Corporation	-26.1837	-17.3446	-39.3132	0.0442
General Mills, Inc.	-28.9045	-7.5477	-42.7601	0.0309
The Hershey Company	-28.3221	-8.1135	-44.0361	0.0435
Hormel Foods Corporation	-27.8296	-7.0937	-40.4333	0.0170
McCormick and Company	-30.4455	-3.4513	-43.7667	0.0317
The Mosaic Company	-27.2498	-11.9950	-38.4983	0.0630
The J.M. Smucker Company	-27.2464	-16.6816	-37.0892	0.0404
Sysco Corporation	-29.7601	-7.9562	-42.4773	0.0677
Tyson Foods, Inc.	-28.8343	-8.8293	-38.1075	0.0530

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.

et al., 1992). As a consequence, we also report the Phillips-Perron (Phillips and Perron, 1988) test (PP), the Elliott, Rothenberg and Stock (1996) modified Dickey Fuller (ERS) test, and the Kwiatkowski, Phillips, Schmidt, and Shin (1992) test (KPSS). As is apparent from the table, the null hypothesis of a unit root in the SSTA series in levels (panel A), and in first differences (panel B) is rejected at the 5% level when using the first three tests.

The KPSS test shows that this series is trend stationary in levels and first differences. In addition, the table provides evidence that all the food and agricultural stock returns are nonstationary in levels but stationary after first differencing. We thus estimate the models in this paper with SSTA in levels and the stock returns in first differences.

2.2 Methodology

The impulse response functions of the food and agricultural stock returns to El Niño and La Niña shocks are calculated using state-dependent local projection methods (Jorda, 2005). While this paper represents the first attempt to apply local projections to investigate asymmetries in the effects of ENSO, state-dependent local projection methods are now the state-of-the-art technique used in the macroeconomics literature to study, for instance, the asymmetric effects of fiscal policy shocks (see e.g. Auerbach and Gorodnichenko, 2012, 2013; Owyang et al., 2013; Ramey and Zubairy, 2018; Alpanda and Zubairy, 2018), monetary policy shocks (see e.g. Tenreyro and Thwaites, 2016; Jorda et al., 2019), and oil price shocks (Basher et al., 2012; Choi et al., 2018; Equiza-Goñi and Perez de Gracia, 2019).

The main appeal of local projections is that they are flexible enough to accommodate nonlinear specifications without the need to impose the type of dynamic restrictions generally required in standard VAR and other nonlinear and regime-dependent modeling techniques (Jorda 2005). In addition, it is less sensitive to misspecification since it imposes no constraints on the shape of impulse response functions (Ramey and Zubairy, 2018).[4] Furthermore, unlike VAR models in particular, and other multivariate models, in general, all variables are not required to enter all equations, therefore allowing the researcher to use a more parsimonious specification that can be estimated by simple regression methods and packages. As well, local projections allow for the investigation of state-dependence using all available data, as opposed to estimating a VAR for each regime. It is possible that fewer observations in one of the regimes results in imprecise and unstable estimates (Auerbach and Gorodnichenko, 2012).

[4]See Jorda (2005) for further details on the robustness of local projections to misspecification.

For these reasons, this paper uses local projections to assess the existence of asymmetries in the response of agricultural stock returns to ENSO shocks. The method is described below.

Consider the reduced-form linear model:

$$y_t = \alpha + \sum_{i=1}^{k} \beta_i y_{t-i} + \sum_{i=1}^{k} \gamma_i z_{t-i} + \varepsilon_t \tag{1}$$

where y_t is the variable of interest at time t, z_t is an exogenous shock, ε_t refers to the error term, and k denotes the maximum lag length, which is selected by minimizing the Schwartz Information Criterion (SIC) over $1 \leq k \leq 12$. In our case, y_t denotes the percentage change in the agricultural stock returns, and z_t denotes sea surface temperature anomalies (SSTA). We model the ENSO variable, SSTA, as exogenous because there is no reason to believe that it is caused (in Granger sense) by the agricultural stock returns. Because we use weekly data, the baseline model does not consider other control variables that potentially impact stock returns, such as macroeconomic variables, due to their unavailability at this frequency. In a robustness section, we use monthly data and a multivariate specification that controls for the impact of macroeconomic conditions. The coefficient, γ_i, is the period t response of the stock returns, y to an ENSO shock in period $t-i$. With this approach, impulse response functions are computed as a sequence of γ_i's recovered from estimating sequential regressions of the form (1) for increasingly larger horizons.

Equation (1) can be modified to allow for state-dependence by estimating, for each horizon, sequential regressions of the form:

$$y_t = \alpha + \sum_{i=1}^{k} \beta_i y_{t-i} + \sum_{i=1}^{k} \gamma_i z_{t-i} + \sum_{i=1}^{k} \delta_i inter_{t-i} + \varepsilon_t \tag{2}$$

where the variable $inter_t$ is the interaction term:

$$inter_t = I_t \times z_t$$

and the variable, I_t is an indicator variable, such that

$$I_t = \begin{cases} 1 & z_t > 0.5 \\ 0 & z_t < 0.5 \end{cases} \quad (3)$$

Hence, $I_t = 1$ in El Niño episodes and 0 in non-El Niño episodes. Note then, that non-El Niño episodes contain neutral episodes, as well as La Niña episodes. For the ease of exposition, however, we refer to non-El Niño episodes as La Niña.[5]

The h-period impulse response functions are calculated by first estimating the regression:[6]

$$y_t = \alpha^h + \sum_{i=h}^{h+k-1} \theta_i x_{t-i} + \sum_{i=h}^{h+k-1} \lambda_i z_{t-i} + \sum_{i=h}^{h+k-1} \rho_i inter_{t-i} + \nu_t^h \quad (4)$$

where α^h, θ_i, λ_i, and ρ_i are parameters to be estimated, and $h = 1, \ldots, 12$. Let $\hat{\Phi}_h$ denote the coefficient matrix calculated by sequentially estimating equation (4) for each forecast horizon, and let d_i represent the contemporaneous impulse response vector. Then the contemporaneous stock return responses in the El Niño and La Niña regimes, respectively denoted as d_i^{nino} and d_i^{nina} are:

$$d_i^{nino} = \begin{bmatrix} y_0 & z_0 & inter_0 \end{bmatrix} \quad (5)$$

$$d_i^{nina} = \begin{bmatrix} y_0 & z_0 & 0 \end{bmatrix} \quad (6)$$

where y_0 is the contemporaneous response of stock returns to an ENSO shock, and z_0 is the one time SSTA shock. Using equations (5) and (6), the h-period responses in both regimes can now be computed as:

$$\widehat{IR}_h^{nino} = \Phi_h d_i^{nino} = \hat{\lambda}_h z_0 + \hat{\rho}_h inter_0 \quad (7)$$

$$\widehat{IR}_h^{nina} = \Phi_h d_i^{nina} = \hat{\lambda}_h z_0 \quad (8)$$

[5]We have divided the data into two regimes. In our robustness check, we redefine the threshold to make sure that our results are not driven by neutral shocks. La Niña episodes are defined as one regime and non La Niña episodes as the other. Our results do not change which suggests that the fluctuation in agricultural stock returns are driven only by changes in SSTA during El Niño and La Niña. We conclude that our results are not sensitive to how we define our threshold.

[6]This corresponds to equation (2) in Jorda (2005).

where $\Phi_h = \begin{bmatrix} \hat{\theta}_i & \hat{\lambda}_i & \hat{\rho}_i \end{bmatrix}$.

The responses resulting from equations (7) and (8) will converge to zero over time, since the agricultural stock returns are expressed in log first differences (to achieve stationarity). To measure persistence of the responses, we construct h-period cumulative impulse responses:

$$CIR_h^{nino} = \sum_{j=0}^{h} \widehat{IR}_j^{nino} \tag{9}$$

$$CIR_h^{nina} = \sum_{j=0}^{h} \widehat{IR}_j^{nina}. \tag{10}$$

Evidently, the cumulative impulse response functions, (9) and (10), show the accumulation of the effects of a shock to El Niño and La Niña through time, rather than its impact at one point in time, thus, allowing us to trace out the deviation of the food and agricultural stock returns from their long-run level.

The primary purpose of this paper is to explore asymmetries in the stock return responses to El Niño and La Niña shocks. While impulse responses constructed from equations (9) and (10) may suffice for this purpose, an alternative approach is to ask whether the difference between the stock return responses across the El Niño and La Niña regimes are significantly different from zero. For the purpose of exposition, we refer to this difference in responses between the regimes as "cumulative difference responses", and is calculated as:

$$\Delta CIR_h = \sum_{j=0}^{h} \left(\hat{IR}_j^{nino} - \hat{IR}_j^{nina} \right) \tag{11}$$

where $\Delta CIR_h = CIR_h^{nino} - CIR_h^{nina}$. A value of $\Delta CIR_h < 0$ indicates that the response to an El Niño shock is larger than that to a La Niña shock. To gauge statistical significance, we compute 90% confidence bands for the impulse responses. Due to serial correlation in the error terms induced by successive leading of the dependent variable, we apply the Newey-West correction to the standard errors (Ramey and Zubairy, 2018). If zero lies within the 90% confidence intervals, the response is not statistically different from zero.

3 Results and Discussion

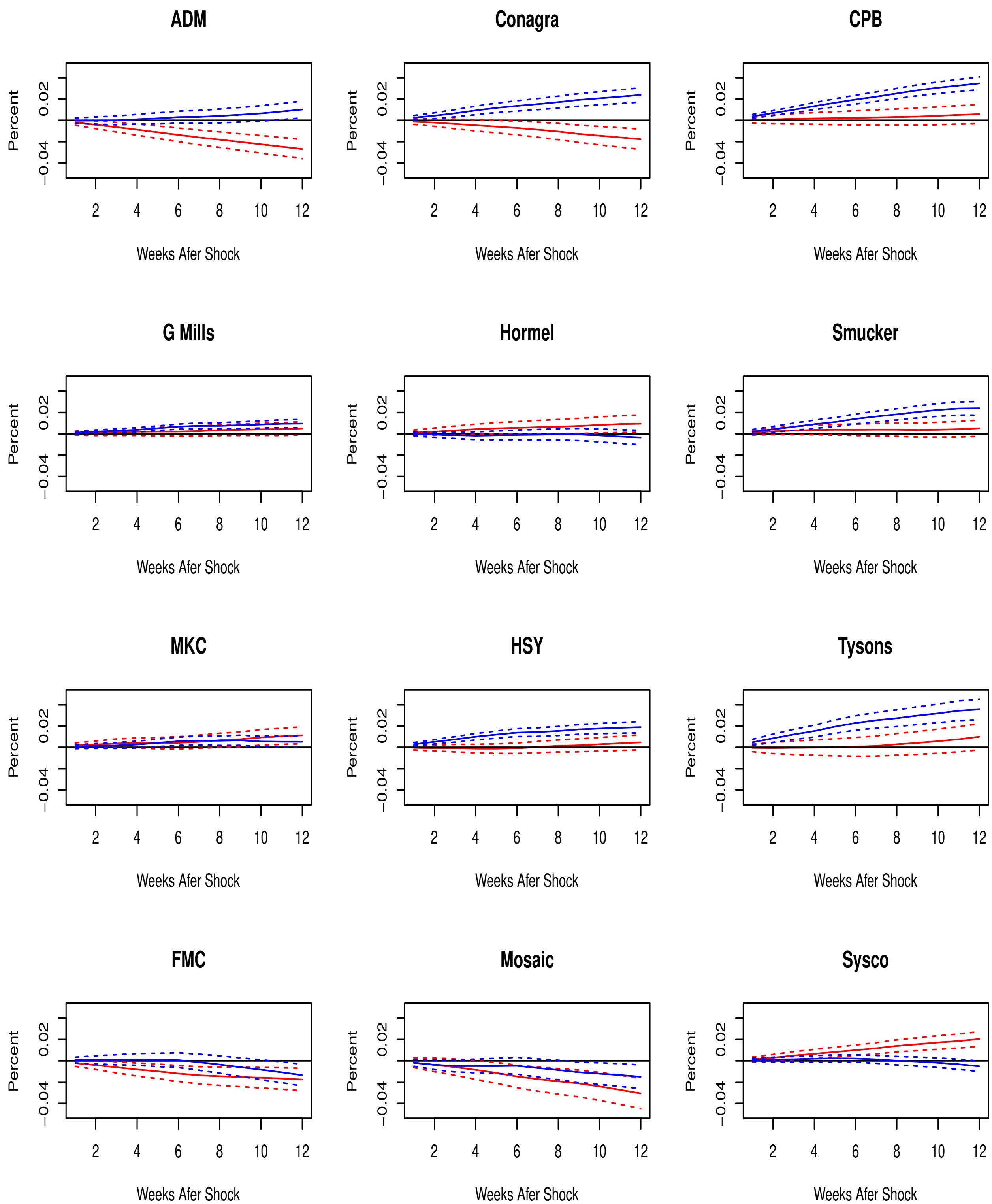
In this section, we present the results of the analysis. Section 3.1 reports and discusses the main findings, while results of several sensitivity analyses are presented in Section 3.2.

3.1 Main Results

Figure 2 shows how the twelve food and agricultural returns respond to the distinct ENSO shocks. In particular, it shows the cumulative responses of the stock returns to an El Niño shock (red solid lines) and a La Niña shock (blue solid lines). The corresponding dashed red and blue lines are the 90% confidence bands constructed as described in Section 2.2.

The figure highlights the point that the responses of U.S. agricultural stock returns to an El Niño shock may differ from those of La Niña. For eight of the twelve returns, namely Archer Daniels, Conagra, Campbell's, General Mills, Smucker, McCormick, Hershey's, and Tyson, the response to a La Niña shock is positive and significantly different from zero. For Archer Daniels, General Mills, and McCormick, the positive responses occur after a delay of several weeks, while for the five other stock returns, the contemporaneous and subsequent responses are almost always significantly different from zero. The figure also shows that the responses of two returns - Hormel, and Sysco - are not significantly different from zero at any forecast horizon. The finding that for most food and agricultural returns considered, a shock to La Niña results in a statistically significant increase in these returns is consistent with the related literature on the impact of La Niña on agricultural yields and prices. Several authors have found that agricultural output decreases during or immediately following La Niña events (see e.g. Hansen et al., 1998; Mauget and Upchurch, 1999; Cadson et al., 1996; and Iizumi et al., 2014). This decrease in agricultural output increases prices in the following periods, triggering a rise in firm cash flows, their profitability, and, hence, their stock returns.

Figure 2: Responses of U.S. Food and Agricultural Stock Returns to El Niño and La Niña



Notes: Solid blue and red lines represent the responses to La Niña and El Niño shocks, while the corresponding dashed lines are the 90% confidence intervals.

Regarding the responses to an El Niño shock, Figure 2 shows that the returns of four firms considered, namely Archer Daniels, Conagra, FMC Corporation, and Mosaic exhibit responses that are negative and significantly different from zero. For all four returns, the declines turn significant after a delay of a few weeks. Our findings also demonstrate that the responses of Campbell's, General Mills, Smucker, Hershey's, and Tyson are not different from zero in a statistical sense, while for Hormel, McCormick, and Sysco, an El Niño shock is shown to increase their returns. The finding that the returns of Archer Daniels and Conagra decrease following unanticipated increases in SSTA is not surprising. Archer Daniels operates within four segments, namely, Agricultural Services, Corn Processing, Oilseeds Processing, and Wild Flavors and Specialty Ingredients. Their Agricultural Services division buys, stores, and transports agricultural commodities. The Corn Processing division involves corn milling. Oilseeds Processing involves oilseeds marketing, crushing, and processing. Conagra packages and distributes various food brands to supermarkets and restaurants. Given that these companies are all involved with the food and/or grains industry, and grains constitute the largest cost share of animal feed, the warming of sea surface temperatures may decrease output (or prices). In fact, Iizumi et al. (2014) find that yields of corn, rice and wheat changed by -4.3 to +0.8% following an El Niño event. If this decrease in yields is not accompanied by a corresponding or larger increase in prices, then cash flows to these companies, their profitability, and, consequently, their stock returns are expected to decline, thereby validating the negative responses shown in Figure 2.

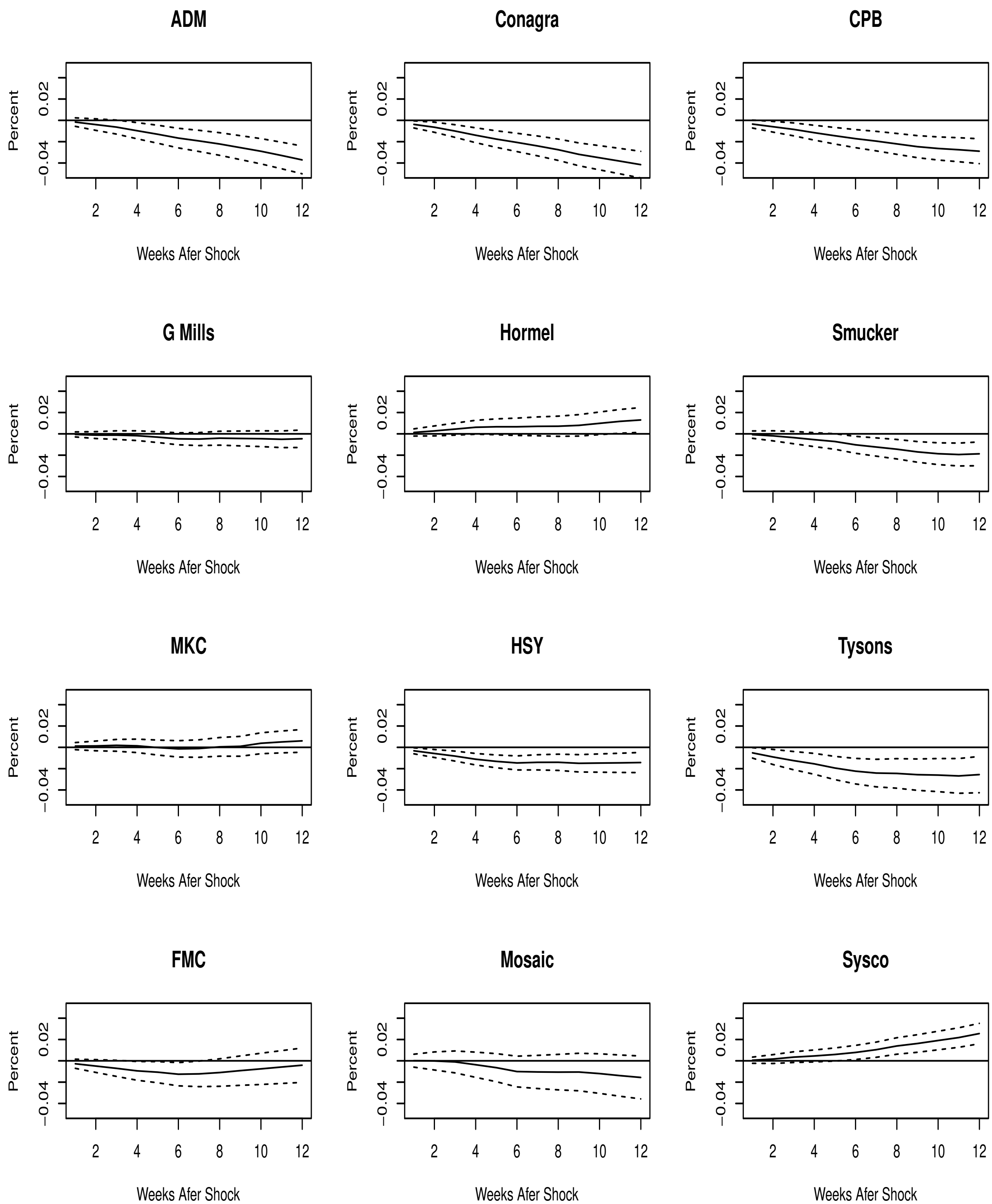
The significantly negative and persistent responses of Mosaic and the FMC Corporation are interesting because the products of these companies are not directly affected by ENSO. Both companies are providers of crop nutrients. Mosaic specifically concentrates in the production of phosphate, potash, and nitrogen nutrients used to maintain healthy and productive soils. The FMC Corporation manufactures herbicides, insecticides, and fungicides. The warming of sea surface temperatures should not directly impact these products. However, an El Niño shock may affect these companies indirectly for at least two reasons.

First, as discussed above El Niño may cause a decrease in agricultural yields, which, in turn may decrease the demand for pesticides and fertilizers. Second, El Niño is often associated with above normal temperatures in the fall and winter in the northern tier of the 48 contiguous U.S. states (Ropelewski and Halpert, 1986). Arizona, California, and western New Mexico generally experience above normal rainfall due to the more southerly, zonal, storm track (Andrade and Sellers, 1988), while greater than usual rainfall in states in the U.S. Gulf coast and Southeast are typically attributed to the stronger than average southerly, subtropical jet stream (Beckage et al., 2003). It is possible that the precipitation and temperature changes in these regions provide favorable conditions for crops, causing a decrease in demand for (and, therefore, price of) crop nutrients produced by the FMC Corporation and Mosaic, lowering their cash flows, and triggering a decline in their stock returns.

While Campbell's, General Mills, Smucker, and Tysons are all considered food and/or agricultural companies, they all produce a wide variety of products. Therefore, the insignificance of their responses of to El Niño shocks should not be surprising. Consider General Mills, for example. The company's main products are consumer foods within the cereal breakfast foods industry, but it also operates a Convenience Stores and Foodservice segment. The company has locations in Asia, Australia, Europe, and Latin America. Given the large literature that shows spatial differences in the impact of El Niño, it is possible that an El Niño shock that is detrimental to the U.S. might be beneficial for General Mills' operations in its other global locations. If this is the case, then the insignificance of the responses of Campbell's, General Mills, Smucker, and Tysons to El Niño shocks is exactly what one would expect. For Hormel, McCormick, and Sysco, we conjecture that the significantly positive responses to an El Niño shock occur due to an increase in the prices of the products of these companies, which trigger an increase in their revenues and overall profitability.

The key question in this paper is whether there exists asymmetries in the stock return responses between El Niño and La Niña. While a look at Figure 2 provides some evidence of asymmetries, a preferred approach is to compute the cumulative difference impulse response

Figure 3: Asymmetric Effects of El Niño and La Niña on U.S. Agricultural Stock Returns



Notes: Solid blue and red lines represent the responses to La Niña and El Niño shocks, while the corresponding dashed lines are the 90% confidence intervals.

functions, as defined in equation (11), together with their 90% confidence bands to examine whether this difference is statistically different from zero. Figure 3 presents these cumulative difference responses. The figure provides support for the proposition that the impacts of El Niño and La Niña on U.S. agricultural stock returns asymmetric. For seven of the twelve returns, namely Archer Daniels, Conagra, Campbell's, Hershey's, Smucker, Tyson, and Sysco, we find significant evidence of asymmetry, with the magnitude of the asymmetries being particularly large for Archer Daniels, Conagra, Campbell's, and Tyson. For the remaining five returns, the evidence of asymmetry is weak.

3.2 Sensitivity Analysis

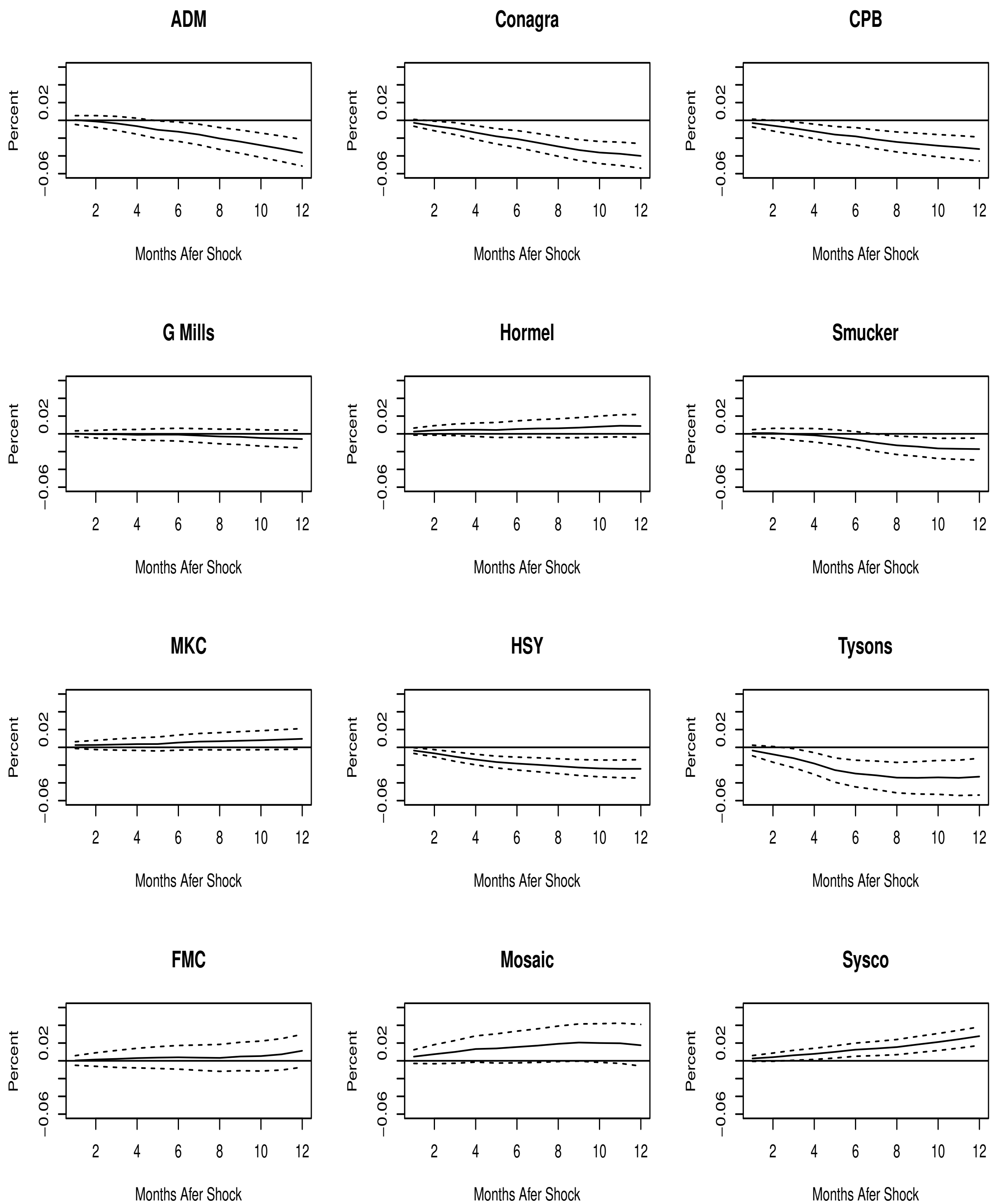
3.2.1 Do Neutral ENSO Shocks Matter?

Thus far, we have referred to non-El Niño events as La Niña events. Recall that an El Niño event is defined as three consecutive months of $SSTA > 0.5$, while La Niña refers to three consecutive months of $SSTA < -0.5$. When $-0.5 < SSTA < 0.5$, this is referred to as neutral ENSO events. By referring to non-El Niño events as La Niña events in our analysis thus far, we implicitly assume that neutral ENSO events have no impact of U.S. food and agricultural stock returns. If neutral shocks, however, have an impact on these returns, then the estimated responses to La Niña shocks displayed in Figure 2 are biased, and the evidence of asymmetry in Figure 3 is misleading. To ensure that neutral shocks have no significant influence on our estimated results, we now define the indicator variable as:

$$I_t = \begin{cases} 1 & SSTA < -0.5 \\ 0 & SSTA > -0.5 \end{cases}$$

That is, $I_t = 1$ for La Niña, and $I_t = 0$ for non-La Niña events. We then estimate impulse response functions of stock returns to La Niña and non-La Niña shocks (results not shown to save space). Since the paper is primarily concerned with the question of asymmetries, we

Figure 4: Asymmetric Effects of El Niño and La Niña on U.S. Agricultural Stock Returns



Notes: Solid blue and red lines represent the responses to La Niña and El Niño shocks, while the corresponding dashed lines are the 90% confidence intervals.

rather show results of the difference impulse responses in Figure 4. The evidence of asymmetry shown in Figure 4 is similar to that shown in Figure 3. This suggests that neutral ENSO shocks have no significant impact of on U.S. agricultural stock returns. Importantly, these results reveal that referring to non-El Niño shocks as La Niña shocks is not fundamentally incorrect, as treating non-El Niño shocks as La Niña shocks has no qualitative or quantitative effects on inference about the impact of La Niña on U.S. agricultural stock returns.

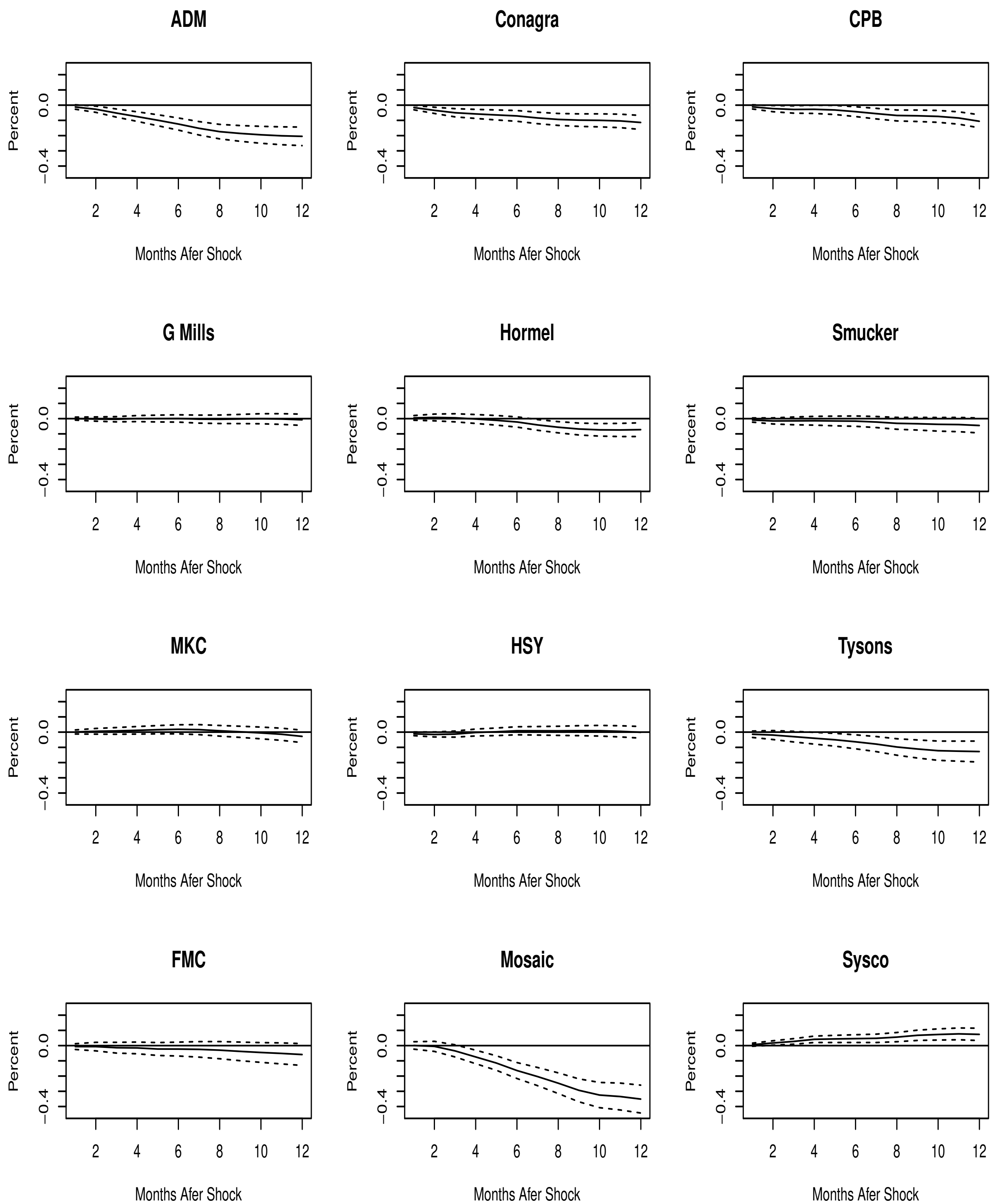
3.2.2 Results When Using Monthly Data and Controlling for Macroeconomic Conditions

The main results discussed in Section 3.1 are based on weekly data and bivariate models of stock returns and SSTA. While our use of weekly data provides a much richer and more appropriate dataset for estimating the asymmetric impacts of ENSO on U.S. food and agricultural stock returns, it prevents us from controlling for other macroeconomic variables that potentially impact stock returns. Failure to account for these variables may result in issues related to omitted variable bias. As another robustness check, we now redo the analysis using monthly data, and control for the impact of output and inflation.[7] As with the analysis using weekly data, the sample spans the period 1990:01-2019:04.

Figure 5 presents the cumulative difference functions. As in Figure 3, we continue to find that seven of the twelve stock returns display considerable evidence of asymmetry. This finding suggests that the impulse response functions resulting from the use weekly data are not significantly contaminated by shocks other than El Niño and La Niña shocks, giving some degree of confidence in the main results of the paper.

[7] In another robustness check, we find that the results remain virtually unchanged when controlling for a number of other variables, including inflation uncertainty, the broad currency real trade weighted U.S. Dollar index to control for the link between stock returns and the foreign exchange rate, the monthly premium of the book-to-market factor, the monthly premium of the size factor, and momentum of the stock market.

Figure 5: Asymmetric Effects of El Niño and La Niña on U.S. Agricultural Stock Returns: Monthly Data



Notes: Solid blue and red lines represent the responses to La Niña and El Niño shocks, while the corresponding dashed lines are the 90% confidence intervals.

4 Conclusion

The goal of this paper is to explore whether El Niño-Southern Oscillation has asymmetric impacts on U.S. food and agricultural stock returns. In particular, using weekly data over the period 1990:01-2019:04 and the method of local projections, we study whether the magnitude, sign, significance, and persistence of the responses of U.S. food and agricultural stock returns to El Niño and La Niña are significantly different from each other. For seven of the twelve returns considered, we find significant evidence of asymmetries. This finding is robust to a number of robustness tests, including the use of monthly data, and controlling for the effect of macroeconomic conditions on stock returns.

References

[1] Adams, R., C. Chen, B. McCall, and R. Wei her (1999). The Economic Consequences of ENSO Events for Agriculture. *Climate Research* 13 (3), 165–172.

[2] Alpanda, S., Zubairy, S. (2019). Household Debt Overhang and Transmission of Monetary Policy. *Journal of Money, Credit and Banking*, 1-25.

[3] Auerbach, A., Gorodnichenko, Y. (2012). Measuring the Output Responses to Fiscal Policy. *American Economic Journal: Macroeconomics* 4(2), 1-27.

[4] Auerbach, A., Gorodnichenko, Y. (2013). Fiscal Multipliers in Recession and Expansion. In Fiscal Policy After the Financial Crisis, edited by Alberto Alesina and Francesco Giavazzi, pp. 63–98. University of Chicago Press.

[5] Basher, S., Haug, A., Sadorsky, P. (2012). Oil Prices, Exchange Rates, and Emerging Stock Markets. *Energy Economics* 34, 227-240.

[6] Beckage, B., W. J. Platte, M. G. Slocum, B. Pinko (2003). Influence of the El Niño Southern Oscillation on Fire Regimes in the Florida Everglades. *Ecology* 84 (12), 3124-3130.

[7] Brunner, A. (2002). El Niño and World Primary Commodity Prices: Warm Water or Hot Air? *Review of Economics and Statistics* 84 (1), 176–183.

[8] Cadson, R., D. Toyed, and S. Taylor (1996). Midwestern Corn Yield and Weather in Relation to Extremes of the Southern Oscillation. *Journal of Production Agriculture* 9 (3), 347–352.

[9] Choi, S., Furceri, D., Loungani, P., Mishra, S., Poplawski-Ribeiro. (2018). Oil Prices and Inflation Dynamics: Evidence from Advanced and Developing Economies. *Journal of International Money and Finance* 82, 71-96.

[10] DeJong, D. N., J. C. Bernanke, N. E. Sivan, C. H. Whitman (1992). The Power Problems of Unit Root Test in Time Series with Auto regressive Errors. *Journal of Econometrics* 53 (1-3), 323-343.

[11] Dickey, D. and W. Fuller (1979). Distribution of the Estimators for Auto regressive Time Series With a Unit Root. *Journal of the American Statistical Association* 74 (366), 427-431.

[12] Elliott, G., T. Nuremberg, J. Stock (1996). Efficient Tests for an Auto regressive Unit Root. *Econometrica* 64 (4), 813-836.

[13] Equiza-Goñi, J., Perez de Gracia, F. (2019). Impact of State-Dependent Oil Price on U.S. Stock Returns Using Local Projections. *Applied Economics Letters* 26(11), 919-926.

[14] Geweke, J. (1978). Temporal Aggregation in the Multiple Regression Model. *Econometrica* 46 (3), 643-661.

[15] Hall, A., Skalin, J. and Terasvirta, T. (2001). A Nonlinear Time Series Model of El Niño. *Environmental Modelling and Software* 16(2), 139-146.

[16] Hansen, J., A. Hodges, and J. Jones (1998). ENSO Influences on Agriculture in the Southeastern United States. *Journal of Climate* 11 (3), 404–411.

[17] Iizumi T., J. J. Lou, A. J. Challis, G. Samurai, M. Yokohama, H. Satsuma, M. E. Brown, T. Yamagata, (2014). Impacts of El Niño Southern Oscillation on the Global Yields of Major Crops. *Nature Communications* 5, 1-7.

[18] Jordà, Ò. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review* 95(1), 161–182.

[19] Jordà, Ò., Schularick, M., Taylor, A. (2019). The Effects of Quazi-Random Monetary Experiments. Journal of Monetary Economics

[20] Kwiatkowski, D., P. Phillips, P. Schmidt, and Shin, Y. (1992). 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? *Journal of Econometric* 54 (1-3), 159-178.

[21] L'Heureux, M. (2014). What is the El Niño–Southern Oscillation (ENSO) in a Nutshell? National Oceanic and Atmospheric Administration, https://www.climate.gov/news-features/blogs/enso/what-el-ni%C3%B1o%E2%80%93southern-oscillation-enso-nutshell

[22] Mauget, S. A., Upchurch, D. R. (1999). El Niño and La Niña Related Climate and Agricultural Impacts Over the Great Plains and Midwest. *Journal of Production Agriculture* 12 (2), 203-215.

[23] Owyang, M., Ramey, V., Zubairy, S. (2013). Are Government Spending Multipliers Greater During Times of Slack? Evidence from 20th Century Historical Data. *American Economic Review* 103(2), 129-34.

[24] Phillips, P. and P. Perron (1988). Testing for Unit Root in Time Series Regression. *Barometric* 75 (2), 335-346.

[25] Ramey, V., Zubairy, S. (2018). Government Spending Multipliers in Good Times and in Bad: Evidence from U.S. Historical Data. *Journal of Political Economy* 126(2), 850-901.

[26] Ropelewski, C. F. and M. S. Halpert (1986). North American Precipitation and Temperature Patterns Associated with the El Niño/Southern Oscillation (ENSO). *Monthly Weather Review* 114, 2352-2362.

[27] Schlenker, W. and M. Roberts (2006). Nonlinear Effects of Weather on Corn Yields. *Applied Economic Perspectives and Policy* 28 (3), 391.

[28] Smith, S. C. and D. Ubilava (2017). The El Niño-Southern Oscillation and Economic Growth in the Developing World. Global Environmental Change 45, 151-164.

[29] Tenreyro, S., Thwaites, G. (2016). Pushing on a String: US Monetary Policy Is Less Powerful in Recessions. American Economic Journal: Macroeconomics 8(4), 43-74.

[30] Ubilava, D. and M. Holt (2013). El Niño Southern Oscillation and Its Effects on World Vegetable Oil Prices: Assessing Asymmetries Using Smooth Transition Models. *Australian Journal of Agricultural and Resource Economics* 57, 2273-297.

[31] Ubilava, D. (2012a). El Niño, La Niña, and World Coffee Price Dynamics. *Agricultural Economics* 43(1), 17–26.

[32] Ubilava, D. (2012b). Modeling Nonlinearities in the U.S. Soybean-to-Corn Price Ratio: A Smooth Transition Autoregression Approach. *Agribusiness: an International Journal* 28(1), 29-41.

[33] Ubilava, D. (2014). El Niño-Southern Oscillation and the Fishmeal-Soya Bean Meal Price Ratio: Regime-Dependent Dynamics Revisited. *European Review of Agricultural Economics* 41(4), 583–604.

[34] Ubilava, D. (2017). The ENSO Effect and Asymmetries in Wheat Price Dynamics. *World Development* 96, 490-502.