Instrumental variable network difference-in-differences (IV-NDID) estimator: model and application

Abstract: The difference-in-difference (DID) framework is now a well-accepted method in quasi-experimental research. However, DID does not consider treatment-induced changes to a network linking treated and control units. Our instrumental variable network DID methodology controls first for the endogeneity of the network to the treatment and, second, for the direct and indirect role of the treatment on any network member. Monte Carlo simulations and an estimation of the drought impact on global wheat trade and production demonstrate the performance of our new estimator. Results show that DID disregarding the network and its changes leads to significant underestimates of overall treatment effects.

KEY WORDS: Difference-in-difference, Network, International Trade, Climate Change.
JEL codes: C21, F14, Q54

1. Introduction

Difference-in-differences (DID) is a standard quasi-experimental method for estimating treatment effects in applied econometrics (Lechner, 2010; Card, 1990; Card and Krueger, 1994; Athey and Imbens, 2006; Abadie *et al.*, 2010, 2014; Stuart, 2021). Over the last few years, the literature has highlighted the importance of incorporating spatial dependence within the DID framework. For instance, when observations are geographical units fixed in space, the treatments are likely to be spatially correlated and/or the individuals' responses to the treatment are prone to spatial autocorrelation (Delgado and Florax, 2015; Chagas *et al*., 2016; Dubé *et al*., 2014). Spatially autocorrelated treatments do not violate the stable unit treatment value assumption (SUTVA), a standard DID assumption that assumes potential outcome for a unit is unrelated to the treatment status of another unit. However, spatially autocorrelated responses violate the SUTVA, leading to potentially biased and inconsistent DID estimates of treatment effects when spillovers are disregarded (Kolak and Anselin, 2019). Delgado and Florax (2015) formalize this result and conduct a simulation analysis to show the biases arising from ignoring the spatial correlation in treatment response. In addition, they measure the presence and magnitude of the indirect effect of the treatment on the control units (spillover) and on the treated units (spillover and feedback effects). Based on this development, Lima and Barbosa (2019) apply a spatial DID (SDID) model to estimate the effect of flash floods. They discover that municipalities directly affected by these events experienced an average 8.9% decline in per capita GDP while those affected indirectly experienced a 1.09% decline. Chagas *et al*. (2016) further account for spatial interactions between treated and untreated regions when measuring the effect of burning sugarcane before harvest on hospitalization due to respiratory problems in Brazil. They find that the presence of sugarcane production in treated regions causes an increase of 1.49 cases per thousand people compared to the control group and that the influence on the neighboring untreated regions is 1.34 cases per thousand people.

In this paper, we extend SDID by considering the case where regions are connected in an economic network that is prone to changes in response to the treatment. SDID relies on a network that is exogenous, constant in time, and purely based on the geographical proximity of the spatial units. However, the capacity of geographical proximity to subsume all forms of interregional interactions has been challenged multiple times (Corrado and Fingleton, 2012; Kang and Dall'erba, 2016). A large amount of literature has already highlighted the main pull and push factors that drive networks based on socio-economic processes such as trade (e.g. Anderson, 1979; Eaton and Kortum, 2002; Yotov *et al.*, 2016), migration (Cullinan and Duggan, 2016; Cooke and Boyle, 2011; Mahajan and Yang, 2020), knowledge flows (Peri, 2005; Jaffe, 1986) and peer effects (Mayer and Puller, 2008; Jackson and Yariv, 2010; Kelejian and Piras, 2014; Hsieh and Lee, 2016). As such, this paper offers the methodological framework and an application that correspond to the case of DID with a network structure affected by the treatment. We name it the instrumental variable network difference-in-difference process, or IV-NDID for short. This framework accounts for endogeneity of the network to the treatment in a first-stage regression while the role of the treatment on the treated areas and on any member of the network is measured in the second stage. As such, our approach differs from other contributions in which the network is endogenous but is time-invariant (Elhorst, 2010; Kelejian and Piras, 2014; Bramoullé *et al.*, 2009).

To our knowledge, the only study that is closely related to our contribution is Comola and Prina (2020) as the authors also adopt a two-stage approach and dynamic interactions following a treatment. However, their identification strategy might suffer from several challenges. First, their network variable is subject to confounding factors because their network focuses only on repeated financial exchanges across households within the same village while other forms of interaction might be present. Second, the authors follow the standard statistical approach suggested by Kelejian and Prucha (1998) and adopt the spatial lag of the covariates and their cross-product as excluded instruments for the first-stage estimation of the peer effect. As we will demonstrate in this paper, we believe that choosing excluded instruments based on economic theory is more appropriate. Finally, Comola and Prina (2020) adopt an approach in which the same network strucuture is applied to both the dependent and exogenous variables to capture peer-effects. Yet, Gibbons and Overman

(2012) and Pace and Zhu (2012) indicate that this setting can be inappropriate as it does not allow for the quantification of distinct coefficients for the peer effects and the autoregressive interaction among the error terms.

We describe in section 2 the conceptual framework that extends the basic DID setting to the IV-NDID case. Section 3 offers Monte Carlo simulations over various sample sizes in order to demonstrate the bias in the estimates that disregard interregional externalities and the endogeneity of their network structure. Section 4 focuses on an application of the IV-NDID framework that measures how drought events affect the international production and trade of wheat. Without a doubt, drought achieves the identification conditions of a treatment variable as its exogeneity and random distribution are unquestionable. Our focus on climate change, and its impacts embodied by severe drought events, is driven by its global scale, urgency, and potential consequences on our society. Indeed, the most recent report of the Intergovernmental Panel on Climate Change predicts that the current warming trend and an increase in the frequency and intensity of extreme weather events (IPCC, 2021) will put additional pressure on arid regions, where water shortages are already occurring and agriculture accounts for the large majority of all water consumption (Richter *et al*., 2017; Bae and Dall'erba, 2018). In addition, future weather conditions and extremes are expected to deeply reduce the yield of most crops (Dall'erba and Dominguez, 2016; Deschênes and Greenstone, 2007; Schlenker *et al*., 2005) and create new challenges in terms of food safety and food security (Wilhite, 2000; Ziska *et al*., 2016).

Our results suggest that failing to account for the transmission of the treatment effect through the trade network, as well as the adjustment of the trade network itself in response to the treatment, leads to underestimates of the impact of drought on agriculture. This finding allows us to contribute not only to the nascent literature on DID with endogenous networks (Comola and Prina, 2020; Dieye *et al.*, 2015) but also to the fairly small literature focusing on the impact of weather events on agricultural trade (Jones and Olken, 2010; Dallman, 2019; see Magalhães *et al.*, 2021 for a review). In the latter, only two contributions have studied how weather-induced changes in trade might affect an outcome variable. The first one, Costinot *et al.* (2016), finds that after accounting for the trade and production adjustments, climate change is estimated to have an impact on agriculture equivalent to a 0.26% decrease in global GDP. The second one, Dall'erba *et al.* (2021), concludes that the capacity of the U.S. interstate trade of crops to mitigate the impact of climate change on agricultural profit is worth $14.5 billion. Additional research in this area as well as applications of IV-NDID to other network structures such as peer-effects (Arieli *et al*., 2020), alliances (König *et al*., 2017), supply-chains (Acemoglu and Azar, 2020) and migration flows (Mahajan and Yang, 2020) are therefore needed.

2. The IV-NDID: conceptual framework

The SUTVA assumption that underpins the validity of DID estimates relies on the idea that the potential outcome observed in one or a group of units (the control group) is unaffected by the treatment taking place in other units. Recent contributions in statistics and regional and urban economics (Sobel, 2006; Delgado and Florax, 2015; Chagas *et al.*, 2016; Kolak and Anselin, 2019) have demonstrated that the neutrality of the treatment in untreated areas is likely to be violated when the units of observations are spatially dependent. As indicated in Sobel (2006), failure to recognize externalities in space can result in a universally harmful treatment being estimated as beneficial.

The traditional DID considers two groups of regions, the treated group and the untreated one (control group), and it focuses on their outcome before (*b*) and after (*a*) the treatment. If both groups are in their steady state before the treatment, it is reasonable that their outcomes are similar conditional on each group's individual characteristics (Card, 1990). Because some of the characteristics cannot be observed, it is common to control for unit fixed effects in addition to observables. Furthermore, common shocks impacting all regions are traditionally modeled through a time fixed effect. Therefore, the before and after treatment outcomes in the control group (region 0) and in the treated group (region 1) can be described as:

Before treatment:

$$y_{it,0}^{b} = \mu_i + \theta_t + \varphi(\mathrm{x}_{it}, \beta) + \epsilon_{it} \qquad (1)$$

$$y_{it,1}^{b} = y_{it,0}^{b} \qquad (2)$$

After treatment:

$$y_{it,0}^{a} = y_{it,0}^{b} \qquad (3)$$

$$y_{it,1}^{a} = y_{it,0}^{a} + \alpha \qquad (4)$$

where y_{it} is the dependent variable, μ_i and θ_t represent the individual and time fixed effects respectively, x_{it} is a vector of observable individual characteristic, $\varphi(\cdot)$ is a generic function linear in the parameters (β), and ϵ_{it} is an idiosyncratic error term with the usual *i.i.d.* properties which support the SUTVA assumption and allow proper estimation of the treatment effect α.

Based on (1)-(4), we obtain the Average Treatment Effect (ATE) as:

$$\mathrm{ATE} = \mathrm{E}\left[y^a_{it,1} - y^b_{it,1}\right] - E\left[y^a_{it,0} - y^b_{it,0}\right] = \alpha \tag{5}$$

Defining D_{it} as region i's indicator of treatment in time $t \geq \tau_i$, where τ_i represents the time when region *i* receives the treatment, then we can write:

$$y_{it} = (1 - D_{it})y_{it,0} + D_{it}y_{it,1} \tag{6}$$

$$D_{it} = \mathbb{I}(t \geq \tau_i, i = 1, \dots, n) \tag{7}$$

where $\mathbb{I}(.)$ is an indicator variable equal to 1 if the condition is satisfied and zero otherwise.

A panel data regression allows us to identify the ATE using D_{it} as the treatment on the treated regions in the treated period:

$$y_{it} = \alpha D_{it} + \mu_i + \theta_t + \varphi(\mathrm{x}_{it}, \beta) + \epsilon_{it} \tag{8}$$

Let $\bar{y}_1 = \frac{1}{n}\sum_i y_{it,1}$ and $\bar{y}_0 = \frac{1}{n}\sum_i y_{it,0}$ be the sample average for the treated and nontreated regions respectively; then the panel data estimator is:

$$\hat{\alpha} = \Delta\, \bar{y}_1 - \Delta\, \bar{y}_0 = \left(\bar{y}^a_1 - \bar{y}^b_1\right) - \left(\bar{y}^a_0 - \bar{y}^b_0\right) \tag{9}$$

As indicated above, identification relies on the assumption that one, and only one, of the potential outcomes is observable for every member of the population. This requirement is called the observation rule and it implies that the potential outcome in one unit, whether treated or not, is not affected by the assignment of treatment in other units (Cox, 1958; Rosenbaum, 2010). Yet, empirical evidence and a large amount of econometric literature have shown that network externalities are more often the rule than the exception when dealing with geographically referenced units (e.g., Anselin, 1988; LeSage and Pace, 2009). Considering proximity-based spillovers (or spillovers based on a W that is not affected by the treatment) obliges us to reformulate Eq. (1)-(4) as follows:

Before treatment:		After treatment:	
$y_{it,0}^{b} = \mu_i + \theta_t + \varphi(\mathrm{x}_{it}, \beta) + \epsilon_{it}$	(1')	$y_{it,0}^{a} = y_{it,0}^{b} + w_i' D_{it}\gamma$	(3')
$y_{it,1}^{b} = y_{it,0}^{b}$	(2')	$y_{it,1}^{a} = y_{it,0}^{a} + \alpha$	(4')

While the direct effect α of the treatment (4') has not changed compared to the previous case (4), the outcome is now subject to the indirect effect of the treatment on all regions conditional on the neighborhood of the treated region as captured by $w_i' D_{it}$ where w_i is the i^{th} vector of the W network matrix. Based on (1')-(4'), we can compute three difference effects: the Average Treatment Effect (ATE), the Average Treatment Effect on the Treated (ATET), and the Average Treatment Effect on the Nontreated (ATENT):

$$\text{ATE} = \mathrm{E}\left[y_{it,1}^{a} - y_{it,1}^{b}\right] - E\left[y_{it,0}^{a} - y_{it,0}^{b}\right] = \frac{1}{n}\sum_{i=1}^{n} \alpha \tag{10}$$

$$\text{ATET} = \mathrm{E}\left[y_{it,1}^{a} - y_{it,1}^{b}\right] = \frac{1}{n_{i\in D}}\left[\sum_{i=1}^{n_{i\in D}} (\alpha + w_i' D_{it}\gamma)\right] \tag{11}$$

$$\text{ATENT} = \mathrm{E}\left[y_{it,0}^{a} - y_{it,0}^{b}\right] = \frac{1}{n_{i\in ND}}\left[\sum_{i=1}^{n_{i\in ND}} (w_i' D_{it}\gamma)\right] \tag{12}$$

Where $n_{i\in D}$ and $n_{i\in ND}$ are the number of treated and non-treated regions, respectively.

The reduced form model that derives from (3')-(4') is:

$$y_{it} = (1 - D_{it})y_{it,0} + D_{it}y_{it,1} = \alpha D_{it} + w_i' d_{it}\gamma + \mu_i + \theta_t + \varphi(\mathrm{x}_{it}, \beta) + \epsilon_{it} \tag{13}$$

or, in matrix format:

$$\mathrm{Y}_t = \mu + \theta_t + \beta(\mathrm{X}_t) + (\alpha + W\gamma)\mathrm{D}_t + \mathrm{E}_t \tag{14}$$

where Y_t is a $n \times 1$ vector of observable dependent variables in t, μ is a $n \times 1$ vector of non-observable spatial fixed effect, θ_t is a scalar time fixed effect, D_t is a $n \times 1$ vector reflecting the treatment status of each region in time t, and X_t is a $n \times k$ matrix of independent variables linked to the dependent variable by the parameters β. As in DID, α

captures the effect of the treatment on the treated regions; however, compared to DID, the element $W\gamma$ represents the indirect effect of the treatment on both the treated and the non-treated regions.

As is traditional in the spatial econometric literature, Equations (10)-(14) consider the network relationships as purely exogenous; hence, they are not affected by the treatment. However, endogenous network structures such as migration, trade, or social and professional networks can be affected by the treatment. While the econometric literature is increasingly focusing on models and applications with endogenous interregional structures (e.g. Elhorst, 2010; Qu and Lee, 2015; Qu *et al.*, 2020), the latter have never been introduced in a network DID setting until now. Considering the response of the network structure to the treatment effect allows us to extend (1')-(4') as follows:

Before treatment:

$$w_{ijt,0}^{b} = \psi\left(x_{it}, x_{jt} | \rho, \mu_i^w + \mu_j^w + \theta_t^w\right) + \epsilon_{ijt} \quad (15)$$

$$w_{ijt,1}^{b} = w_{ijt,0}^{b} \quad (16)$$

$$y_{it,0}^{b} = \mu_i^y + \theta_t^y + \varphi(\mathrm{x}_{it}, \beta) + \varepsilon_{it} \quad (17)$$

$$y_{it,1}^{b} = y_{it,0}^{b} \quad (18)$$

After treatment:

$$w_{ijt,0}^{a} = w_{ijt,0}^{b} + \alpha_{i\in D}^{w} + \alpha_{j\in D}^{w} \quad (19)$$

$$w_{ijt,1}^{a} = w_{ijt,0}^{a} \quad (20)$$

$$y_{it,0}^{a} = y_{it,0}^{b} + \gamma \textstyle\sum_j w_{ijt,0}^{a} D_{jt} \quad (21)$$

$$y_{it,1}^{a} = y_{it,0}^{a} + \alpha^{y} \quad (22)$$

where w_{ijt} represents the network relationship between region i and region j at time t. D_{jt} represents the set of treated regions after treatment so that the parameters α_i^w and α_j^w are the direct impact of the treatment on the regions treated at the origin and destination respectively. γ is the indirect impact of the treatment in the partner regions after the treatment affects the network structure. This approach allows us to capture the time heterogeneity of the individual's characteristics and of the network. Furthermore, the network itself evolves over space through the reallocation of the values and directionality of the origin-destination flows that results from the treatment *D*.

Compared to Equations (1)-(4), it follows from (15)-(22) that the derivative of y_{i} with respect to the treatment does not only equal α^y. Indeed, it is also determined by the *i* or *j* element of the partial derivative matrix **J** below:

$$\mathbf{J} \equiv \frac{\partial \mathbf{Y}}{\partial \mathbf{D}} = \begin{bmatrix} \frac{\partial \mathrm{Y_i}}{\partial \mathrm{D_i}} & \cdots & \frac{\partial \mathrm{Y_i}}{\partial \mathrm{D_n}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \mathrm{Y_n}}{\partial \mathrm{D_i}} & \cdots & \frac{\partial \mathrm{Y_n}}{\partial \mathrm{D_n}} \end{bmatrix}$$

Based on LeSage and Pace (2010), we define the average direct impact of a treatment **D** on **Y** as the average of J_{ii} or $\frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}} \frac{\partial \mathrm{Y_i}}{\partial \mathrm{D_i}} = \frac{1}{\mathrm{n}}\mathrm{tr}(\mathbf{J})$. It can also be expressed as:

$$\mathrm{ATE} = \mathrm{E}\left[y_{it,1}^{a} - y_{it,1}^{b}\right] - E\left[y_{it,0}^{a} - y_{it,0}^{b}\right] = \alpha^{y} \tag{23}$$

In addition, because the off-diagonal elements of **J** are non-zero, the overall channel of transmission of treatment *D* on *y* is composed of a direct effect (α^{y}) and of the indirect effect through a change in the network matrix:

$$\begin{aligned} \mathrm{ATET} = \mathrm{E}\left[y_{it,1}^{a} - y_{it,1}^{b}\right] &= \frac{1}{n_{i\in D}}\left[\sum_{i=1}^{n_{i\in D}}\left(\alpha^{y} + \gamma \sum_{i=1}^{n} w_{ijt,0}^{a} D_{jt}\right)\right] \\ &= \frac{1}{n_{i\in D}}\sum_{i=1}^{n_{i\in D}}\left[\alpha^{y} + \gamma \sum_{j} w_{ijt,0}^{b} D_{jt} + \gamma \sum_{j=1}^{n}\left(w_{ijt,0}^{a} - w_{ijt,0}^{b}\right) D_{jt}\right] \\ &= \mathrm{ATDET} + \mathrm{ATIET} \end{aligned} \tag{24}$$

where ATDET (the Average Treatment Direct Effect on the Treated) is $\frac{1}{n_{i\in D}}\sum_{i=1}^{n_{i\in D}}\left[\alpha^{y} + \gamma \sum_{j} w_{ijt,0}^{b} D_{jt}\right]$. This corresponds to the effect of the treatment on the treated region if the treatment does not change the network structure. In addition, the ATIET (Average Treatment Indirect Effect on the Treated) is given by $\frac{1}{n_{i\in D}}\sum_{i=1}^{n_{i\in D}}\left[\gamma \sum_{j=1}^{n}\left(w_{ijt,0}^{a} - w_{ijt,0}^{b}\right) D_{jt}\right]$, which captures the effect of the treatment on the treated region due to the change in the network structure since regions will rearrange their links after the intervention. In the same way, we compute the Average Treatment Effect on the Non-Treated regions as:

$$\begin{aligned} \mathrm{ATENT} = \mathrm{E}\left[y_{it,0}^{a} - y_{it,0}^{b}\right] &= \frac{1}{n_{i\in ND}} \sum_{i=1}^{n_{i\in ND}} \gamma \sum_{j} w_{ijt,0}^{a} D_{jt} \\ &= \frac{1}{n_{i\in ND}}\sum_{i=1}^{n_{i\in ND}} \gamma\left[\sum_{j} w_{ijt,0}^{b} D_{jt} + \gamma \sum_{j}\left(w_{ijt,0}^{a} - w_{ijt,0}^{b}\right) D_{jt}\right] \\ &= \mathrm{ATDENT} + \mathrm{ATIENT} \end{aligned} \tag{25}$$

Where the Average Treatment Direct Effect on the Non-Treated, ATDENT =

$\frac{1}{n_{i \in ND}} \sum_{i=1}^{n_{i \in ND}} \gamma \left[\sum_j w_{ijt,0}^b D_{jt} \right]$, captures the effect of the treatment on the untreated region without the treatment affecting the network structure, while $\text{ATIENT} = \frac{1}{n_{i \in ND}} \sum_{i=1}^{n_{i \in ND}} \gamma \left[\sum_j \left(w_{ijt,0}^a - w_{ijt,0}^b \right) D_{jt} \right]$, the Average Treatment Indirect Effect on the Non-Treated, captures the effect of the treatment on the untreated regions due to a change in the network structure. We note that in this formulation ATIET = ATIENT because the change in the network structure affects indirectly and in the same way both the treated and non-treated regions.

3. The IV-NDID: simulations

This section focuses on a Monte Carlo evaluation of the IV-NDID estimator so that we can test its small sample performance. We assume a world composed of n = 5, 10, 50, or 100 spatial units observed over t = 2, 6, or 10 time periods. We start by dividing the panel before and after treatment. In each simulation, the treatment starts in the second half of the time period. The treated regions are selected according to the proportion $p + \zeta$ where p = 0.1 or 0.2 and ζ is a uniformly distributed pseudo-random number varying between 0 and 0.2. As a result, the share of treated regions varies from 0.1 to 0.3 when p = 0.1 and from 0.2 to 0.4 when p = 0.2.

For each simulation, the network structure is defined by a function that includes a normally distributed exogenous variable x_1 in addition to time and spatial fixed effects. The treatment impacts the network structure as follows:

$$w_{ij,t}^* = \beta_1 x_{1i,t} + \beta_2 x_{1j,t} + \mu_i + \mu_j + \mu_t + \delta_1 D_{i,t \geq \tau} + \delta_2 D_{j,t \geq \tau}$$

$$w_{ij,t} = \exp\left(w_{ij,t}^*\right) \varepsilon_{ij,t} \tag{26}$$

where $w_{ij,t}^*$ is the deterministic part of the network structure between regions i and j at time t, with $w_{ij,t}^* = 0$ when $i = j$. $x_{1i,t}$ and $x_{1j,t}$ are place- and time-specific characteristics. The fixed effects μ_i, μ_j and μ_t are generated as normal and centered variables. The variables $D_{i,t \geq \tau}$ and $D_{j,t \geq \tau}$ are dummy indicators equal to 1 during the period in which the treatment occurs and 0 otherwise. The error term $\varepsilon_{ij,t}$ follows a $Poisson(w_{ij,t}^*)$ distribution as it is the most common estimator in gravity models (Santos Silva and Tenreyro, 2006; Yotov *et* *al.*, 2016). Finally, β_1, β_2, δ_1 and δ_2 are the parameters of the simulation. The next step consists in using $w_{ij,t}$ to build a row-standardized network structure W matrix defined as:

$$W_{ij} = \begin{cases} 0 & \text{if } i = j \\ \frac{w_{ij,t}}{\sum_j w_{ij,t}} & \text{if } i \neq j \end{cases} \tag{27}$$

In the second stage, the variable of interest $y_{i,t}$ is a function of an exogenous and normally distributed variable x_2, spatial and time fixed effects, the local treatment, and the treatment occurring in the partners:

$$y_{i,t} = \beta_3 x_{2i,t} + \mu_i + \mu_t + \delta_3 D_{i,t\geq\tau} + \delta_4 \sum_j W_{ij} D_{j,t\geq\tau} + \epsilon_{i,t} \tag{28}$$

We set the parameters β_1, β_2, β_3, δ_1, δ_2, δ_3, and δ_4 equal to 1 in our simulations. Estimations are based on a Poisson regression with a multiple fixed effects algorithm that is especially adapted to the first-stage simulation and the second-stage panel fixed effect whereby δ_4 reflects the role of W_{ij}. The results of the simulations are reported in Tables 1 and 2 below. In Table 1, we report the results for the parameters of the exogenous characteristics in the first stage (β_1 and β_2) and in the second stage (β_3).

<< Insert table 1 here >>

The results of Table 1 meet with expectations: when it comes to the exogenous variables, the greater the number of observations (both in time and space), the smaller is the bias. The simulation results on the treatment effects at origin and at the destination on the network structure (stage 1) are reported in Table 2 below. This table also reports the results on the treatment effects and the network treatment effect in the second stage.

<< Insert table 2 here >>

As expected, the panel with fewer observations in space or time displays the worst results. This finding is particularly true for the network parameter δ_4. These results are similar to those of Chagas *et al.* (2016) in a SDID context with W exogenous. We also note that the bias diminishes as the spatial dimension of the panel increases, except when the time dimension is small (2 time periods). We believe that the reason comes from the network coefficient being based on a weighted treatment of the partner units. When the number of time observations is small, the IV-NDID parameter is strongly correlated with the time fixed effect. However, as the number of time observations increases, it is possible to accurately identify the IV-NDID parameter. We also note that estimates on each of the other parameters perform well, even when t is small, which meets our expectations.

We complement the exercise above with a comparison of the performance of the IV-NDID estimator with three alternative approaches: the classical DID estimator, the classical SDID estimator using a geographical proximity matrix, and the classical NDID estimator using a biased network matrix (i.e. a network matrix without the first stage regression). For the distance-based weight matrix, we consider a circular world in which each region is bordered by one neighbor on the left and right when $n = 5$; otherwise, the number of neighbors is 3 for $n = 10$ and is 5 when $n = 50$ or 100. Table 3 below reports the results. The results indicate that if the parameter of interest is β_3 (the parameter associated with the exogenous variable on the second stage), then any of the DID methods perform well even though DID displays the largest bias, more especially when $n < 10$. However, if the focus is on the direct treatment effect (δ_3) or on the treatment in locations captured through a network matrix (δ_4), then IV-NDID performs significantly better than any of the alternatives, indicating that they suffer from an omitted variable bias. DID does not generate a measurement of the latter effect, while SDID methods based on exogenous matrices lead to biased results, more especially with small n and/or when the number of treated regions is small.

<< Insert table 3 here >>

Finally, the last set of simulations refers to the change in the network structure due to the treatment D_i and D_j in the first stage regression. In Table 4, the true value corresponds to the difference between the simulated w_{ijt}^a (after the drought occurred) and w_{ijt}^b (the network structure before the treatment): $\gamma \sum_j \left(w_{ijt,0}^a - w_{ijt,0}^b\right) D_{jt}$. The estimated value corresponds to the difference between the estimated $\widehat{w}_{ijt}^a$ and $\widehat{w}_{ijt}^b$. The estimated value highlights the capacity of IV-NDID to estimate how the treatment induces changes in the network. Finally, the remaining columns report the difference between the true and estimated values. For all simulations, the difference between simulated and estimated values is insignificant, showing that the simulated network is close to the observed network after the drought.

<< Insert table 4 here >>

4. Application to the effect of drought events on wheat trade and production

This section applies our IV-NDID estimator to the international trade and production (in volume) of wheat. Wheat is an important staple food crop and is one of the most widely produced and traded agricultural commodities in the world. In 2018, wheat accounted for \$114 billion in production and over \$41 billion of trade (Food and Agriculture Organization of the United Nations, FAO, 2020) and trailed only soybeans in terms of total traded value across agricultural commodities. Wheat is not only traded in large amounts, but is exported by a wide assortment of countries. In 2018, a total of 28 countries undertook wheat exports of \$100 million in value or greater. Compared to the number of similarly large exporters in other major crops (11 countries exporting such volumes in soybeans, 22 in corn, and 18 in rice), it clearly indicates the extent to which wheat is produced and traded across many regions. Similar figures for the number of countries with imports surpassing \$100 million – 69 countries in wheat compared to 36 in soybeans, 52 in corn, and 54 in rice – reflect the crucial importance of international wheat trade in meeting the excess demands of dozens of countries.

Drought events are one of the greatest threats to agricultural productivity and crop yields, particularly for wheat. Wheat production is highly susceptible to stress from drought conditions, more so than corn or soybeans. A meta-analysis of the agronomic literature by Daryanto *et al.* (2016) suggests a typical reduction in wheat yields of 20.6% under drought conditions. While plant breeders have recently begun to develop and introduce drought-resistant wheat varieties (Khadka *et al.*, 2020), technological advances in this direction have been enabled more slowly than for other crops.

An example of the trade-based externalities that we investigate is the 2008 drought that afflicted many Middle Eastern and Central Asian countries, which caused wheat production in the region to decline by nearly 22% relative to the previous year (FAS, 2008). These countries also witnessed a significant contraction of their wheat exports due to production losses. However, the total value of wheat exports from the rest of the world to the Middle Eastern countries increased by 224% relative to the previous year (FAO, 2020). The countries that supplied these exports (mostly the United States, Canada, Russia, and Ukraine) each produced substantially more wheat than they had in years prior, an increase in production that can conceivably be attributed as a response to the increased import demand from the drought-afflicted Middle East.

While the 2008 drought is illustrative of the direct and indirect (trade-based) impacts of drought on wheat trade and production, this episode provides no systematic causal evidence of the phenomenon that we seek to analyze. As a result, we turn to the gravity model to estimate the determinants of bilateral trading relationships, including drought, and thus the economic linkages that determine the scope for spillovers across regions. The gravity model's accuracy in describing the factors that determine trade has made it one of the most successful approaches in empirical economics. Beyond its empirical success, the gravity relationship can be derived based on a wide assortment of theoretical foundations, both demand-based (e.g., Anderson, 1979; Bergstrand, 1985) and supply-based (e.g., Eaton and Kortum, 2002; Chaney, 2008).

Implementing a now standard approach, we estimate our gravity model of bilateral trade using a Poisson pseudo-maximum likelihood (PPML) estimator, as suggested by Santos Silva and Tenreyro (2006), to account for zero trade flows and heteroskedasticity in the error terms. The equation that we estimate is:

$$X_{ijt}=\exp[\boldsymbol{\alpha}_1'\boldsymbol{X}_{it}+\boldsymbol{\alpha}_2'\boldsymbol{X}_{jt}+\alpha_3 D_{it}+\alpha_4 D_{jt}+\alpha_5 FTA_{ijt}+\phi_{ij}+\eta_t+\varepsilon_{ijt}] \quad (29)$$

where X_{ijt} is the value of bilateral wheat exports from i to j in year t. $\boldsymbol{X}_{it}$ is a vector of exporter supply-side factors that includes exporter i's value of wheat production (measured with a three-year lag to avoid simultaneity with the second stage estimation), as well as observed temperature, precipitation and their squared terms to control for their non-linear effects. The latter three are measured during the growing season for wheat and calculated across each country's land area devoted to wheat production.[1] We also control for the extent to which irrigation is used, as the degree to which farmers are able to rely on irrigation versus rainfall as a water source captures the natural resources endowments and the ability of producers to mitigate the negative impacts of drought. Because of the potential simultaneity of drought conditions and irrigation – the countries that have recently experienced drought are conceivably more likely to use irrigation more extensively – we introduce the irrigation variable with a three-year lag (Dall'erba and Dominguez, 2016). Irrigation is measured by the percent of cropland within a country under irrigation and is not wheat specific as crop-specific data are not available for our panel.

Similarly, for importer demand-side factors $\boldsymbol{X}_{jt}$ we include three measures to capture importer j's demand for wheat imports. These include the value added in importer j's food processing sector to reflect j's demand for wheat, the population of j to account for consumer demand, and the combined estimated weight of j's cattle, hog, and chicken stocks to reflect demand for wheat as animal feed. We also include the same temperature, precipitation, and irrigation variables for j as previously described for i, as the seasonal weather conditions in importer j and the ability of producers to mitigate these conditions using irrigation are likely to impact j's productive capacity and thus its demand for imports. FTA_{ijt} in equation (29) is an indicator variable for i and j sharing membership in a free trade agreement to account for time-varying changes in bilateral trade costs, and we also include the pair- and time-specific fixed effects ϕ_{ij} and η_t. The dyadic fixed effect ϕ_{ij} controls for long-run determinants of bilateral trade costs (including commonly used gravity covariates such as distance, contiguity, common language, etc.) as well as exporter-

[1] Appendix 1 provides details on how these data are calculated for the growing area(s) of each country.

and importer-specific features, while the time fixed effect accounts for year-specific shocks to the international trading environment such as changes in commodity prices.

The variables of primary interest here are the drought measures for the exporter and importer – the treatment, in the context of the difference-in-differences setting.[2] D_{it} and D_{jt} are indicator variables equal to one if the average drought conditions in a particular country-year during the growing season for wheat qualified as "moderate drought" or worse as measured by the Standardized Precipitation-Evapotranspiration Index drought measure (SPEI < -0.7), and zero otherwise. The coefficient α_3 thus reflects how i's exports to j are impacted by the presence of drought conditions in i, and since drought in an exporting country is likely to diminish a producer's supply capacity and thus its propensity to export, we expect α_3 to be negative. Analogously, α_4 reflects how drought conditions in j impact its demand for crop imports from i. As drought conditions are similarly likely to diminish j's productive capacity, causing j's excess demand for crops to increase and to be satisfied through imports, α_4 is expected to be positive.

<< Insert table 5 here >>

The data used cover the years 1995-2015 for a panel of 97 exporting countries and 89 importing countries. Table 5 describes each variable used in the analysis and provides basic summary statistics for each. The second-stage analysis, presented further below, includes the same 97 wheat-producing countries as in the first stage.[3]

The estimation results for the first-stage gravity equation (36) are presented in table 6. Significant estimates on the variables reflecting the size of exporters' supply (total wheat production) and importers' demand (population, and total weight of livestock) are positive, in accordance with intuition and the underlying structure of gravity. Likewise, common FTA membership positively influences bilateral trade between partners. As expected from the literature (Magalhães *et al.*, 2021), evidence on the role played by temperature and

[2] Appendix 2 provides details on how the drought variable is calculated.
[3] Appendix 3 lists the countries included in the analysis.

precipitation on exports and imports is mixed. Estimates on these variables are generally insignificant apart from the negative estimate on the linear temperature term for importers. However, because temperature and precipitation are inherently correlated with the drought treatment dummy, and are also likely to be correlated with how much a particular country exports or imports in a particular year, their inclusion is nonetheless necessary. In addition, we find that the extent of irrigation in both the exporting and importing country in a given trading relationship is negatively associated with the level of trade. We hypothesize that the extent of irrigation is negatively correlated with the quality of the country's natural endowments for wheat production (meaning more efficient producing and exporting countries rely less on irrigation). Alternatively, countries possessing a significant amount of irrigated farmland reflect a relative comparative advantage in crops such as fruits and vegetables that rely more extensively on irrigation than wheat production.

The main variables of interest are the drought indicator variables. The coefficients behave as anticipated: a drought in an exporting country reduces exports by 12.1% (= exp(–0.129) – 1). Dall'erba *et al.* (2021) find a similar result with respect to the impact of a local drought on the domestic export of crops across U.S. states, even though the marginal effect they calculate is not statistically significant. They justify it by indicating that the large producers are likely to compensate the decrease in production by drawing on reserves built over the previous years. They did not find any indication that, following a drought, a state would favor domestic versus foreign markets. Finally, the results confirm our assumption that a drought in an importing country increases its imports. Specifically, the estimate implies a 6.8% (= exp(0.066) – 1) increase in wheat exports to a destination experiencing drought, all other things held constant. In the U.S. interstate case, Dall'erba *et al.* (2021) find an elasticity of $\partial \mathrm{X}_{ijt} / \partial D_{jt}$ between 6.3-9.4% depending on the specification.

<< Insert table 6 here >>

In the second stage, we estimate the impact of drought events on wheat production in terms of both (1) local effects of drought on production in afflicted regions and (2) spillover effects on production that arise when a producing country's export destinations are impacted by drought. From the gravity analysis in the first stage, we can account for the way in which drought events – and the consequent impacts on trade – affect the network linkages connecting trading partners. As trade is the channel through which negative productivity shocks in one locale generate spillover effects on other regions, we use the newly generated trade flows (row-standardized estimated values) in the second stage to account for the endogenous nature of trade with respect to the drought treatment.

The estimating equation for the second stage represents wheat production in i as a function of both local drought (the direct difference-in-differences treatment effect), as well as drought in trading partners (the indirect network difference-in-differences spillover effect):

$$Y_{it} = \boldsymbol{Z}'_{it}\boldsymbol{\beta}_1 + \beta_2 D_{it} + \beta_3 \widehat{\boldsymbol{W}}_{it}\boldsymbol{D}_{jt} + \lambda_i + \eta_t + \nu_{it} \tag{30}$$

where Y_{it} is the outcome variable for country i in year t, which reflects wheat production along three dimensions: the total physical quantity of production, the amount of land area allocated to wheat production in a given year, and yield (production over area). Each of these outcome variables is expressed in logarithms and will be regressed separately. Production is a function of local characteristics $\boldsymbol{Z}_{it}$ which encompass variables for contemporaneous local weather conditions (temperature and precipitation as well as squared terms of each) as well as lagged (t – 3) irrigation capacity to control for its endogeneity (Dall'erba and Dominguez, 2016) as done in the first stage.

We should anticipate local drought conditions to have a negative effect on production, largely because of physical impacts driving lower yields and productivity. Externalities $\widehat{\boldsymbol{W}}_{it}\boldsymbol{D}_{jt}$ should generally evince positive impacts – if export destinations are afflicted by a drought, producers that sell to these destinations are likely to produce more in response, largely through increases in planted area. In this sense we capture both the intensive margins (output per planted area) and extensive margins (how much land area is devoted to production) and delineate the local impact versus the externalities of the drought treatment along these dimensions. Note that $\widehat{\boldsymbol{W}}_{it}\boldsymbol{D}_{jt}$ corresponds to the export-share-weighted indirect treatment from drought in i's export destinations since $\widehat{\boldsymbol{W}}_{it}$ is row-standardized ($\sum_{j\neq i}\widehat{w}_{ijt} = 1$, with $\widehat{w}_{ijt} = 0$ for $i = j$). As such, the extent to which a drought in a trading partner will indirectly impact production in i depends on the importance of a particular destination in exporter i's total exports.

Note one implication of the row-standardization of $\widehat{\boldsymbol{W}}_{it}$: because in the first-stage gravity equation the drought treatment uniformly affects origin i's exports to all of its partners, in this particular setting, a change in the treatment status of i does not alter $\widehat{\boldsymbol{W}}_{it}$. This is because the systematic shock that reduces i's exports to all destinations by the same proportional amount does not change the relative importance of any particular importer as measured by $\widehat{w}_{ijt}$. This adjustment in trade is consistent with the absolute level of i's exports changing as demonstrated in Appendix 4. However, the treatment status of j does alter the structure of $\widehat{\boldsymbol{W}}_{it}$, with the overall marginal impact of D_{jt} on Y_{it} depending on three elements: (1) the importance of j in i's network ($\widehat{w}_{ijt}$), (2) how the importance of j changes as a result of the treatment in j ($\partial\widehat{w}_{ijt}/\ \partial D_{jt}$), and (3) how the importance of regions besides j (and thus the scope for spillovers from these other regions) changes in response to the treatment in j ($\partial\widehat{w}_{ikt}/\ \partial D_{jt}$). The derivation of this result is also given in Appendix 4.[4]

Results from estimating equation (30) are shown in table 7. Because $\widehat{\boldsymbol{W}}_{it}\boldsymbol{D}_{jt}$ is an estimated variable, the standard errors in this estimation are calculated by bootstrap using 200 replications (Monchuk *et al.*, 2011; Jin and Lee, 2015). For comparison purposes, we also calculate an alternative version of the weighted drought measure using an (exogenous) spatial weight matrix $\boldsymbol{W}_t^{dist}$, which is comprised of (row-standardized) weights reflecting the inverse geographical distance between a producer and its trading partners.[5] We find significant evidence for the adverse effect of a domestic drought on production, an effect that, as in the first stage trade analysis, aligns with expectations of a profoundly negative

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[4] Note, however, that all the results presented in Table 7 are consistent with a globally-standardized weight matrix $w_{ijt} = X_{ijt}/\sum_{i\neq j}\sum_j X_{ijt}$ which implies that $\partial\widehat{w}_{ij}/\partial D_i \neq 0$.

[5] Bilateral distances are taken from the U.S. International Trade Commission gravity dataset and are calculated based on population-weighted great circle distance between countries.

impact of drought on wheat production and yields (columns 1 and 3). On the other hand, area planted is not statistically impacted by local drought (column 2). Importantly, we find positive and significant impacts from the estimates on $\widehat{\boldsymbol{W}}_{it}\boldsymbol{D}_{jt}$ in both total production and planted area (columns 1 and 2). When country i's export destinations are afflicted by a drought, wheat production in country i increases and this positive supply response occurs entirely through an expansion in planted area. A possible explanation is that wheat is grown over two seasons, winter and spring, in the large majority of countries; hence a drought in a partner country can lead to more planted area locally within the same year. The fact that none of the estimates based on the exogenous, geographical distance-based spatial weight matrix $\boldsymbol{W}_t^{dist}$ enter significantly (columns 4 through 6) confirms the Monte Carlo simulations of section 3 and suggests that (endogenous) trading relationships are the channel through which these effects are mediated.

The remaining results indicate that the estimates of the coefficients on temperature and precipitation are scattered and largely non-significant for temperature. However, both total production and yield seem to maintain a significant, positive and non-linear relationship with precipitation. The extent of a country's irrigation is again negatively correlated with production (column 1), a relationship that seems to be based on countries with more area under irrigation simply devoting less land to wheat production. Another element that explains this negative marginal effect is that our measure of irrigation is not wheat specific, and as explained in the first-stage analysis, could potentially be positively correlated with unfavorable weather and/or soil conditions for agriculture.

<< Insert table 7 here >>

Finally, we report in table 8 the average treatment on the treated for each of the four versions of W listed in the Monte Carlo results of table 3. The findings of table 8 indicate that the only specification that leads to a significant direct and indirect impact of drought on the (log of) production is through the IV-NDID method. Other approaches generate estimates with the expected sign but suffer from a missing variable bias (DID) or poorly measured interactions (NDID and SDID-geo), hence confirming their lesser performance already measured in table 3. In summary, our results indicate clearly that the estimate of the overall treatment effect would be biased if the units of our sample had been treated as isolated individuals. Indeed, by accounting for the drought-induced changes in trade, we see the indirect effect becomes significant and offsets the direct effect.

<< Insert table 8 here >>

A decomposition of the average treatment effect on the treated (ATET) between the average treatment direct effect on the treated (ATDET) and the network effect on the treated (ATIET) as in Eq. (24) requires the estimated values $\widehat{\alpha^{y}}$ = -0.051 and $\hat{\gamma} = 0.090$ from the results in Table 7 column 1. Defining $\sum_j w_{ijt}^{b} D_{jt}$ as the treatment status of the neighbors weighted by the predicted importance-weight in the absence of treatment (i.e., when D_{jt} = 0 in the first-stage regression) and $\sum_j w_{ijt}^{a} D_{jt}$ as the treatment status of neighbors weighted by the predicted importance-weight based on observed treatment status, we calculate $\overline{\sum_J w_{ijt}^{b} D_{Jt}} = 0.0173$ and $\overline{\sum_J \left(w_{ijt}^{a} - w_{ijt}^{b}\right) D_{Jt}} = 0.0005$ as the sample averages of the weighted treatment-in-neighbors measures. Therefore, drought still has a negative direct effect on wheat production since ATDET is -0.049 (= -0.051+0.090×0.0173). It is counteracted, although to a muted extent, by the positive impact on the network change as ATIET is 4.5×10^{-5} $(= 0.090 \times 0.0005)$. When it comes to the average treatment effect on the non-treated regions (ATENT, Eq. 25), the decomposition leads to an average treatment direct effect on the non-treated of 1.5×10^{-3} while the indirect effect (network change) is also positive and small at 4.5×10^{-5}.

5. Conclusion

There has been a surge in interest in the DID framework over the last decade. However, its increasing application to geographically-referenced data has raised doubts about its capacity to deal with the presence of externalities across units of observations in the context of endogenous networks such as trade, migration and peer-effects that link observations with each other. In the presence of such externalities, the SUTVA assumption upon which this framework relies does not hold, estimates can be biased, and conclusions about the true impacts of a treatment inferred from these estimates are likely to be unreliable.

This manuscript offers the conceptual framework, simulations and application necessary to account for the fact that a large amount of interregional network structures are, in fact, endogenous to a treatment. In such a setting, the actual impact of the treatment takes place not only directly – as expected from the usual DID – but also in the partner units and through the changes it creates in the system-wide network structure. Our Monte Carlo simulations, as well as our application based on the impact of drought events on the international trade and production of wheat, indicate that failure to account for the presence of all three effects leads to underestimates of the true marginal effect of the treatment. This result is related to the fact that the treatment status leads to changes in the network between and across treated and non-treated. Treated countries see a reduction in yield and production that leads to an increase in their imports and thus to an increase in area planted and in production in the non-treated (exporting) countries.

We believe our contribution paves the way for future research avenues as interregional network data – e.g., migration, supply-chains, co-patenting, social networks – continue to grow in availability and detail. Identifying the true nature of the network channel(s) that link units is still a challenge as uncertainty remains over the form of the correct spatial structure(s), its (their) proper measurement and its (their) capacity to encompass all network interactions. However, these data complement the widely available trade flow data which have dominated the library of network data for decades and, in turn, offer researchers the capacity to investigate (or reinvestigate) the impact of a large number of policies, interventions, and shocks of interest.

References

Abadie A., Diamond, A., and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association 105*(490), 493–505.

Abadie A., Diamond A., and Hainmueller, J. (2014) Comparative politics and the synthetic control method. *American Journal of Political Science 59*(2), 495–510.

Acemoglu, D. and Azar, P.D. (2020), Endogenous Production Networks. *Econometrica*, 88: 33-82.

Anderson, J. (1979). A Theoretical Foundation for the Gravity Equation. *American Economic Review 69*(1), 106–116.

Anselin, L. (1988). Spatial Econometrics: Methods and Models. Dordrecht, the Netherlands: Kluwer Academic.

Arieli, I., Babichenko, Y., Peretz, R. and Young, H.P. (2020), The Speed of Innovation Diffusion in Social Networks. E*conometrica*, 88: 569-594.

Athey, S. and Imbens, G.W. (2006), Identification and Inference in Nonlinear Difference-in-Differences Models. Econometrica, 74: 431-497

Bae J., Dall'erba S. (2018) Crop Production, Export of Virtual Water and Water-saving Strategies in Arizona, *Ecological Economics*, 146, 148-156.

Bergstrand, J. (1985). The Gravity Equation in International Trade: Some Microeconomic Foundations and Empirical Evidence. *Review of Economics and Statistics 71*(1), 143–153.

Bramoullé, Y., Djebbari, H., and Fortin, B. (2009). Identification of Peer Effects through Social Networks, *Journal of Econometrics 150*(1), 41–55.

Card, D. (1990). The impact of the Mariel boatlift on the Miami labor market. *Industrial and Labor Relations Review 43*(2), 245–257.

Card, D. and Krueger, A. (1994). Minimum wages and employment: Case study of the fast-food industry in New Jersey and Pennsylvania. *American Economic Review 84*(4), 772–793.

Chagas, A. L. S., Azzoni, C. R., and Almeida, A. N. (2016). A Spatial Difference-in-Differences Analysis of the Impact of Sugarcane Production on Respiratory Diseases. *Regional Science and Urban Economics 59*, 24–36.

Chaney, T. (2008). Distorted Gravity: The Intensive and Extensive Margins of International Trade. *American Economic Review* 98(4), 1707–1721.

Comola, M. and Prina, S. (2020). Treatment Effect Accounting for Network Changes. *Review of Economics and Statistics* 103(3), 597-604.

Cooke, T. J. and Boyle, P. (2011). The Migration of High School Graduates to College. *Educational Evaluation and Policy Analysis 33*(2), 202–213.

Corrado, L. and Fingleton, B. (2012). Where is the economics in spatial econometrics? *Journal of Regional Science 52*(2), 210–239.

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World. *Journal of Political Economy 124*(1), 205–248.

Cox, D.R. (1958). *Planning of Experiments*. Wiley.

Cullinan, J. and Duggan, J. (2016). A School-Level Gravity Model of Student Migration Flows to Higher Education Institutions. *Spatial Economic Analysis 11*(3), 294–314.

Dall'erba, S. and F. Dominguez (2016). The Impact of Climate Change on Agriculture in the Southwestern United States: The Ricardian Approach Revisited. *Spatial Economic Analysis 11*(1), 46–66.

Dall'erba, S., Chen Z., and Nava N. (2021). Interstate Trade Will Mitigate the Negative Impact of Climate Change on Crop Profit. *American Journal of Agricultural Economics*, forthcoming.

Dallman, I. (2019). Weather Variations and International Trade. *Environmental and Resource Economics 72*, 155–206.

Daryanto, S., Wang, L., and Jacinthe, P.-A. (2016). Global Synthesis of Drought Effects on Maize and Wheat Production. *PloS one 11*(5).

Delgado, M. S., and Florax, R. J. G. M. (2015). Difference-in-Differences Techniques for Spatial Data: Local Autocorrelation and Spatial Interaction. *Economics Letters 137*, 123–126.

Deschênes, O. and Greenstone, M. (2007). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *American Economic Review 97*(1), 354–385.

Dieye, R., Djebbari H., and Osario-Barrera, F. (2015). Accounting for Peer Effects in Treatment Response. Unpublished manuscript.

Dubé, J., Legros D., Thériault M., and Des Rosiers F. (2014). A spatial Difference-in-Differences estimator to evaluate the effect of change in public mass transit systems on house prices. *Transportation Research Part B: Methodological 64*, 24–40.

Eaton, J. and Kortum, S. (2002). Technology, Geography, and Trade. *Econometrica 70*(5), 1741–1779.

Elhorst, J.P. (2010). Dynamic panels with endogenous interaction effects when T is small. *Regional Science and Urban Economics 40*(5), 272–282.

FAO (2020). FAOSTAT Statistical Database. Food and Agriculture Organization of the United Nations. Available at http://www.fao.org/faostat/en/#data.

FAS (2008). Middle East and Central Asia: Continued Drought in 2009/10 Threatens Greater Food Grain Shortages. U.S. Department of Agriculture Foreign Agricultural Service. Available at ipad.fas.usda.gov/highlights/2008/09/mideast_cenasia_drought/.

Gaulier, G. and Zignago, S. (2010). BACI: International Trade Database at the Product-level. Munich Personal RePEc Archive Paper No. 31398.

Gibbons, S. and Overman, H.G. (2012). Mostly pointless spatial econometrics? *Journal of Regional Science 52*(2), 172–191.

Gurevich, T. and Herman, P. (2018). The Dynamic Gravity Dataset: 1984-2016. USITC Working Paper 2018-02-A.

Harris, I., Jones, P.D., Osborn, T.J., Lister, D.H. (2014). Updated high - resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology 34*, 623–642.

Head, K. and Mayer, T. (2014). Gravity Equations: Workhorse, Toolkit, and Cookbook. In *Handbook of International Economics Vol. 4*, G. Gopinath, E. Helpman, and K. Rogoff (eds.). Elsevier.

Hsieh, C.-S., and Lee, L.-F. (2015). A Social Interactions Model with Endogenous Friendship Formation and Selectivity. *Journal of Applied Econometrics*, *31*(2), 301–319. http://doi.org/10.1002/jae.2426

IPCC (2021). AR6 Climate Change 2021. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team]. IPCC, Geneva, Switzerland.

Jackson, M., L. Yariv (2010). Diffusion, Strategic Interaction, and Social Structure. In *The Handbook of Social Economics*, 645–678. North Holland Press.

Jaffe, A. (1986). Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value, *American Economic Review 76*(5), 984–1001.

Jin. F. and Lee, L.-F. (2015). On the bootstrap method for Moran's *I* test for spatial dependence. *Journal of Econometrics 184*(2), 295–314.

Jones, B. F. and Olken, B. A. (2010). Climate Shocks and Exports. *American Economic Review 100*(2), 454–459.

Kang, D. and Dall'erba, S. (2016). An Examination of the Role of Local and Distant Knowledge Spillovers on the US Regional Knowledge Creation, *International Regional Science Review 39*(4), 355–385.

Khadka, K., Raizada, M., and Navabi, A. (2020). Recent Progress in Germplasm Evaluation and Gene Mapping to Enable Breeding of Drought-Tolerant Wheat. *Frontiers in Plant Science 11*, 1149.

Kelejian, H.H. and Piras, G. (2014). Estimation of spatial models with endogenous weighting matrices, and an application to a demand model for cigarettes. *Regional Science and Urban Economics 46*, 140–149.

Kelejian, H. and Prucha, I. (1998). A Generalized Spatial Two Stages Least Square Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances. *Journal of Real Estate Finance and Economics*, 17(1): 99–121.

Keyantash, J. and National Center for Atmospheric Research Staff (Eds). Last modified 07 Aug 2018. "The Climate Data Guide: Standardized Precipitation Index (SPI)."

Kolak M. and Anselin L. (2019). A Spatial Perspective on the Econometrics of Program Evaluation, *International Regional Science Review 43***(**1**)**, 128–153.

König, M.D., Rohner, D., Thoenig, M. and Zilibotti, F. (2017), Networks in Conflict: Theory and Evidence From the Great War of Africa. *Econometrica*, 85: 1093-1132.

Lechner, M. (2010). The Estimation of Causal Effects by Difference-in-Difference Methods. *Foundations and Trends in Econometrics 4*(3), 165–224.

LeSage, J. P. and R. K. Pace (2009). *Introduction to Spatial Econometrics*. Boca Raton, FL: CRC Press.

Lima, R. C. d. A. and Barbosa, A. V. B. (2019). Natural Disasters, Economic Growth and Spatial Spillovers: Evidence from a Flash Flood in Brazil. *Papers in Regional Science 98*(2), 905–924.

Magalhães, V. T., Dall'erba, S., Ridley, W., and Wang, X. (2021). The Impact of Weather on Agricultural and Food Trade Flows: A Meta-Analysis. Working paper.

Mahajan P. and Yang D. (2020) Taken by Storm: Hurricanes, Migrant Networks, and US Immigration, *The American Economic Journal: Applied Economics*, 12, 2, 250-277.

Mayer, A. and Puller, S.L. (2008). The old boy (and girl) network: Social network formation on university campuses. *Journal of Public Economics 92*(1-2), 329–347.

Monfreda, C., Ramankutty, N., and Foley, J.A., (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles* 22, 1–19.

Monchuk, D.C., Hayes, D.J., Miranowski, J.A., and Lambert, D.M. (2011). Inference based on alternative bootstrapping methods in spatial models with an application to county income growth in the United States. *Journal of Regional Science 51*(5), 880–896.

Pace, R. K. and Shuang, Z. (2012). Separable Spatial Modeling of Spillovers and Disturbances. *Journal of Geographical Systems 14*(1), 75–90.

Peri, G. (2005). Determinants of Knowledge Flows and Their Effect on Innovation. *The Review of Economics and Statistics 87*:308–322.

Qu, X. and Lee, L.-F. (2015). Estimating a spatial autoregressive model with an endogenous spatial weight matrix. *Journal of Econometrics 184*(2), 209–232.

Qu X., Lee L.-F., and Yang, C. (2020). Estimation of a SAR model with endogenous spatial weights constructed by bilateral variables. *Journal of Econometrics 184*, 209–232.

Richter, B.D., Brown, J.D., DiBenedetto, R., Gorsky, A., Keenan, E., Madray, C., Morris, M., Rowell, D., and Ryu, S. (2017). Opportunities for Saving and Reallocating Agricultural Water to Alleviate Water Scarcity. *Water Policy 19*(5), 886–907.

Rosenbaum, P. (2010). *Design of Observational Studies* (Vol. 10). New York: Springer.

Sacks, W.J., Deryng, D., Foley, J.A., and Ramankutty, N. (2010). Crop planting dates: an analysis of global patterns. *Global Ecology and Biogeography 19*, 607–620.

Santos Silva, J. and Tenreyro S. (2006). The Log of Gravity. *Review of Economics and Statistics*, *88*(4), 641–658.

Schlenker, W., Hanemann, W.M., and Fisher, A.C. (2005). Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *American Economic Review 95*(1), 395–406.

Sobel, M. E. (2006). What Do Randomized Studies of Housing Mobility Demonstrate? Causal Inference in the Face of Interference. *Journal of the American Statistical Association 101*, 1398–1407.

Stuart B. (2021) The Long-Run Effects of Recessions on Education and Income, *The American Economic Journal: Applied Economics*, forthcoming.

Thornthwaite, C. (1948). An Approach toward a Rational Classification of Climate. *Geographical Review 38*(1), 55–94.

Vicente-Serrano, S.M., Beguería, S., and López-Moreno, J.I. (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index – SPEI. *Journal of Climate 23*(7), 1696–1718.

Vicente-Serrano, Sergio M. and National Center for Atmospheric Research Staff (Eds). Last modified 18 Jul 2015. “The Climate Data Guide: Standardized Precipitation Evapotranspiration Index (SPEI).”

Villoria, N. and Chen, B. (2018). Yield risks in global maize markets: Historical evidence and projections in key regions of the world, *Weather and Climate Extremes 19*, 42–48.

Villoria, N., Elliott, J., Müller, C., Shin, J., Zhao, L., and Song, C. (2018). Web-based access, aggregation, and visualization of future climate projections with emphasis on agricultural assessments. *Software X* 7, 15–22.

Wilhite, D.A. (2000). Drought as a natural disaster. In *Drought. Routledge: Routledge Hazards and Disasters Series*, Donald, W. (ed.); pp. 3–19.

World Bank (2020). Total Population by Country. World Development Indicators. Available at https://databank.worldbank.org.

Yotov, Y. V., Larch M., Monteiro J.-A., and Piermartini, R. (2016). An Advanced Guide to Trade Policy Analysis: The Structural Gravity Model. *World Trade Organization Publications*.

Ziska, L., Crimmins, A., Auclair, A., DeGrasse , S., Garofalo, J.F., Khan, A.S., Loladze, I., Pérez de León, A.A., Showler, A., Thurston, J., and Walls, I. (2016). Ch. 7: Food Safety, Nutrition, and Distribution. In *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment*. U.S. Global Change Research Program, Washington, DC, 189–216.

Tables

Table 1 - Monte-Carlo results – exogenous variables

	β_1		β_2		β_3	
	n = 5					
	p = 0.1	p = 0.2	p = 0.1	p = 0.2	p = 0.1	p = 0.2
t = 2	1.0317	1.0848	1.0176	1.0271	0.9541	1.0018
t = 6	1.0030	1.0041	1.0036	1.0017	1.0040	0.9994
t = 10	1.0004	1.0004	1.0004	1.0003	0.9900	1.0053
	n = 10					
	p = 0.1	p = 0.2	p = 0.1	p =0.2	p = 0.1	p = 0.2
t = 2	1.0443	1.0247	1.0042	1.0003	0.9991	1.0230
t = 6	1.0018	1.0009	0.9999	1.0014	0.9983	1.0006
t = 10	1.0001	1.0002	0.9997	0.9995	1.0035	0.9985
	n = 50					
	p = 0.1	p = 0.2	p = 0.1	p = 0.2	p = 0.1	p = 0.2
t = 2	1.0127	1.0208	1.0016	1.0012	1.0073	0.9946
t = 6	1.0010	1.0014	1.0005	1.0005	1.0026	1.0022
t = 10	1.0009	1.0007	1.0007	1.0006	0.9978	0.9990
	n = 100					
	p = 0.1	p = 0.2	p = 0.1	p = 0.2	p = 0.1	p = 0.2
t = 2	1.0379	1.0202	1.0010	1.0019	1.0040	1.0116
t = 6	1.0013	1.0006	1.0012	1.0008	1.0016	1.0016
t = 10	1.0008	1.0009	1.0009	1.0004	1.0009	1.0032

Table 2 - Monte-Carlo results – treatment effects

	δ_1		δ_2		δ_3		δ_4	
	n = 5							
	p = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2
t = 2	1.0571	1.0474	1.0094	1.0020	0.9553	1.0262	0.8157	0.9433
t = 6	0.9971	1.0047	1.0009	1.0033	1.1161	0.9668	1.1465	0.9696
t = 10	1.0032	1.0011	0.9975	0.9994	0.9636	0.9971	0.9406	0.9708
	n = 10							
	p = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2
t = 2	1.0186	1.0084	1.0011	0.9989	1.0647	0.9530	0.9916	0.7745
t = 6	0.9992	1.0004	0.9998	1.0018	0.9300	0.9826	0.9661	0.8810
t = 10	0.9996	1.0011	0.9997	0.9984	1.0025	1.0237	1.0070	1.0544
	n = 50							
	p = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2
t = 2	1.0084	1.0152	0.9992	0.9988	1.0426	0.9971	0.9817	0.8844
t = 6	1.0002	1.0004	1.0003	1.0004	0.9814	1.0100	1.0194	1.0424
t = 10	1.0004	1.0006	1.0005	1.0001	1.0155	0.9993	1.0450	0.9682
	n = 100							
	p = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2	*p* = 0.1	*p* = 0.2
t = 2	1.0084	1.0152	0.9992	0.9988	1.0426	0.9971	0.9817	0.8844
t = 6	1.0002	1.0004	1.0003	1.0004	0.9814	1.0100	1.0194	1.0424
t = 10	1.0004	1.0006	1.0005	1.0001	1.0155	0.9993	1.0450	0.9682

Table 3 - Monte-Carlo results – comparison of selected parameters across DID methods

		β_3				δ_3				δ_4			
t	p	DID	SDID geo	NDID	IV-NDID	DID	SDID geo	NDID	IV-NDID	DID	SDID geo	NDID	IV-NDID
							$n = 5$						
2	0.1	0.946	0.974	0.901	0.954	0.814	0.949	0.861	0.955	0.000	0.210	0.440	0.816
2	0.2	0.987	1.014	1.041	1.002	0.820	0.714	0.898	1.026	0.000	-0.018	0.853	0.943
6	0.1	1.005	1.004	1.004	1.004	0.825	0.851	1.110	1.116	0.000	0.146	1.116	1.147
6	0.2	0.999	0.999	1.001	0.999	0.743	0.754	0.962	0.967	0.000	0.088	0.907	0.970
10	0.1	0.993	0.991	0.991	0.990	0.738	0.751	0.952	0.964	0.000	0.016	0.871	0.941
10	0.2	1.005	1.005	1.006	1.005	0.757	0.774	0.994	0.997	0.000	0.008	0.956	0.971
							$n = 10$						
2	0.1	0.995	0.984	0.994	0.999	0.972	0.993	1.076	1.065	0.000	0.018	0.894	0.992
2	0.2	1.013	1.014	1.025	1.023	0.839	0.830	0.914	0.953	0.000	-0.028	0.635	0.775
6	0.1	0.999	1.001	0.998	0.998	0.825	0.836	0.929	0.930	0.000	0.008	0.964	0.966
6	0.2	1.001	1.002	1.002	1.001	0.897	0.907	0.988	0.983	0.000	0.079	0.854	0.881
10	0.1	1.003	1.003	1.004	1.003	0.895	0.896	0.999	1.002	0.000	-0.028	0.982	1.007
10	0.2	0.999	0.999	0.999	0.998	0.902	0.900	1.010	1.024	0.000	-0.024	0.956	1.054
							$n = 50$						
2	0.1	1.008	1.008	1.008	1.007	1.013	1.015	1.042	1.043	0.000	-0.054	1.055	0.982
2	0.2	0.994	0.993	0.994	0.995	0.980	0.980	0.994	0.997	0.000	-0.032	0.883	0.884
6	0.1	1.003	1.003	1.003	1.003	0.962	0.963	0.984	0.981	0.000	-0.015	1.089	1.019
6	0.2	1.002	1.002	1.002	1.002	0.988	0.987	1.010	1.010	0.000	0.000	0.978	1.042
10	0.1	0.998	0.998	0.998	0.998	0.995	0.995	1.017	1.016	0.000	0.028	1.077	1.045
10	0.2	0.999	0.999	0.999	0.999	0.980	0.979	0.998	0.999	0.000	-0.002	0.960	0.968
							$n = 100$						
2	0.1	1.005	1.005	1.005	1.004	0.985	0.985	1.001	0.999	0.000	0.003	0.814	0.942
2	0.2	1.011	1.011	1.011	1.012	0.989	0.996	1.009	1.007	0.000	0.014	0.865	0.815

6	0.1	1.002	1.002	1.002	1.002	1.002	1.000	1.022	1.022	0.000	0.000	0.953	0.989
6	0.2	1.002	1.002	1.002	1.002	0.973	0.972	0.995	0.994	0.000	0.014	1.082	1.086
10	0.1	1.001	1.001	1.001	1.001	0.974	0.974	0.995	0.994	0.000	-0.001	1.008	1.037
10	0.2	1.003	1.003	1.003	1.003	0.979	0.979	0.999	0.999	0.000	-0.013	0.977	0.988

Table 4 - Monte-Carlo results – comparison between observed and simulated network after the treatment.

t	p	true	estimated	difference	true	estimated	difference
		$n = 5$			$n = 50$		
2	0.1	0.0704	0.0702	0.0001	0.0086	0.0085	0.0001
2	0.2	0.0609	0.0619	0.0001	0.0071	0.0070	0.0001
6	0.1	0.0248	0.0257	-0.0002	0.0048	0.0048	0.0000
6	0.2	0.0259	0.0264	-0.0001	0.0022	0.0022	0.0000
10	0.1	0.0123	0.0122	0.0001	0.0021	0.0021	0.0000
10	0.2	0.0047	0.0058	-0.0002	0.0017	0.0017	0.0000
		$n = 10$			$n = 100$		
2	0.1	0.0418	0.0423	0.0000	0.0089	0.0094	-0.0001
2	0.2	0.0386	0.0393	0.0000	0.0069	0.0066	0.0000
6	0.1	0.0213	0.0215	0.0000	0.0048	0.0048	0.0000
6	0.2	0.0157	0.0159	-0.0001	0.0021	0.0021	0.0000
10	0.1	0.0122	0.0123	0.0000	0.0015	0.0015	0.0000
10	0.2	0.0070	0.0070	0.0000	0.0010	0.0010	0.0000

Table 5 – Variable descriptions and summary statistics

Variable	Description	Source	Mean	Std. Dev.
X_{ijt}	Bilateral wheat trade flows (1,000 USD)	CEPII's BACI	8,085.6	55,426.6
Production $value_{it}$	Value of wheat production (million USD)	FAO (2020)	1532.2	3821.4
Pop_{jt}	Population (millions)	World Bank, 2020	57.8	176.0
Food $proc_{jt}$	Value added in food processing (million USD)	Eora database	15,604.0	36,081.8
$Livestock_{jt}$	Weight of combined livestock (tons)	FAO (2020)	6,589.1	15,710.0
$Irrigation_{it/jt}$	Percentage of cropland under irrigation	FAO (2020)	2.88	3.01
FTA_{ijt}	Shared free trade agreement membership	Gurevich and Herman (2018)	0.43	0.50
$Temp_{it/jt}$	Temperature in wheat-growing areas (10 °C)	CRU	1.95	0.48
$Precip_{it/jt}$	Precipitation in wheat-growing areas (10 cm)	CRU	0.78	0.67
$D_{it/jt}$	Indicator of average SPEI < –0.7 in wheat growing areas	CRU	0.20	0.40
$\widehat{W}_{it}D_{jt}$	Export-share-weighted average of drought in partners		0.19	0.27
$Production_{it}$	Wheat production (1,000 metric tons)	FAO (2020)	6,450.6	16,111.7

$Area_{it}$	Wheat area planted (1,000 hectares)	FAO (2020)	2,236.2	5,216.0
$Yield_{it}$	Wheat yield (100 grams/hectare)	FAO (2020)	28,623.2	17,675.4

Note: FAO is the Food and Agriculture Organization. CEPII's BACI is the International Trade Database (BACI in French) of the Center for Research and Expertise of the World Economy (CEPII in French). The CRU data (Climatic Research Unit, version 3.26) have been treated by Villoria and Chen (2018) and Villoria *et al.* (2018).

Table 6 – Gravity estimation of wheat trade

Exporter variables		**Importer variables**	
log(Prod.$_{i,t-3}$)	0.290**	log(Food proc.$_{jt}$)	–0.085
	(0.115)		(0.082)
		log(Pop$_{jt}$)	1.400***
			(0.364)
		log(Livestock$_{jt}$)	0.578***
			(0.167)
Irrigation$_{i,t-3}$	–0.457***	Irrigation$_{j,t-3}$	–0.059**
	(0.120)		(0.029)
Temperature$_{it}$	2.501	Temperature$_{jt}$	–1.655**
	(2.599)		(0.764)
Temperature$_{it}^2$	–0.431	Temperature$_{jt}^2$	0.362*
	(0.759)		(0.217)
Precip$_{it}$	–0.158	Precip$_{jt}$	0.088
	(0.617)		(0.156)
Precip$_{it}^2$	0.006	Precip$_{jt}^2$	–0.031
	(0.281)		(0.031)
D$_{it}$	–0.129**	D$_{jt}$	0.066*
	(0.063)		(0.035)
FTA$_{ijt}$		0.122**	
		(0.061)	
Observations		53,497	
Pseudo R^2		0.888	
Pair FEs		Y	
Year FEs		Y	

Notes: Dependent variable is the unidirectional value of bilateral trade. Estimation method is PPML. D_{it} = mean value of SPEI in growing season < –0.7. Standard errors clustered by importer–year and exporter-year reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7- Wheat production as a function of local and international drought

	IV-NDID: Export-Share-Weighted W			SDID-geo: Inverse-Distance-Weighted W		
	Production	Area	Yield	Production	Area	Yield
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{Temperature}_{it}$	–0.272	0.436	–0.708*	–0.296	0.412	–0.709*
	(0.733)	(0.609)	(0.384)	(0.696)	(0.658)	(0.395)
$\mathrm{Temperature}^2_{it}$	–0.111	–0.249	0.138	–0.094	–0.232	0.139
	(0.214)	(0.182)	(0.112)	(0.201)	(0.197)	(0.114)
$\mathrm{Precipitation}_{it}$	0.319*	0.263*	0.056	0.307*	0.252*	0.055
	(0.166)	(0.154)	(0.058)	(0.163)	(0.147)	(0.055)
$\mathrm{Precipitation}^2_{it}$	–0.090*	–0.063	–0.027**	–0.089*	–0.062	–0.027**
	(0.052)	(0.046)	(0.012)	(0.049)	(0.046)	(0.012)
$\mathrm{Irrigation}_{i,t-3}$	–0.191***	–0.187***	–0.005	–0.191***	–0.186***	–0.005
	(0.021)	(0.021)	(0.008)	(0.023)	(0.021)	(0.008)
D_{it}	–0.051*	0.029	–0.079***	–0.045	0.033	–0.079***
	(0.027)	(0.025)	(0.015)	(0.028)	(0.024)	(0.016)
$\widehat{\mathbf{W}}_i \mathrm{D}_{jt}$	0.090**	0.085**	0.005			
	(0.043)	(0.034)	(0.022)			
$\mathbf{W}_i^{\mathrm{dist}} \mathrm{D}_{jt}$				0.045	0.045	0.001
				(0.117)	(0.096)	(0.052)
Observations	2,037	2,037	2,037	2,037	2,037	2,037
R^2	0.981	0.984	0.902	0.981	0.983	0.902
Country FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y

Notes: Dependent variables expressed in logarithms. Estimation method is OLS. Bootstrapped standard errors reported in parentheses. D_{it} = mean value of SPEI in growing season < –0.7. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table 8 – Average treatment effect on the treated – differences across DID specifications

	IV-NDID (1)	NDID (2)	SDID-geo (3)	DID (4)
D_{it}	–0.051*	–0.046*	–0.045	–0.044
	(0.027)	(0.028)	(0.028)	(0.031)
$\mathbf{W}_i D_{jt}$	0.090**	0.032	0.045	
	(0.043)	(0.039)	(0.117)	
Observations	2,037	2,037	2,037	2,037
R^2	0.981	0.981	0.981	0.981
Country FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y

Notes: Dependent variable is log production by country. Estimation method is OLS. Bootstrapped standard errors reported in parentheses. Drought = mean value of SPEI in growing season < –0.7. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$