Difference-in-Differences with endogenous externalities: model and application to climate econometrics

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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. The endogenous network DID methodology we offer here (ENDID) controls for the direct and indirect role of the treatment on any network member. In addition, we control for the sensitivity of the network to the treatment and its endogeneity on the outcome variable. 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 a DID that disregards 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

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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, 2022). 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 the potential outcome for a unit is unrelated to the treatment status of another unit. However, when the responses to the treatment lead to spillovers and when the latter are disregarded, it leads to potentially biased and inconsistent DID estimates of treatment effects (Kolak and Anselin, 2019; An, 2018; An and VanderWeele, 2019; Hudgens and Halloran, 2019; Forastiere *et al*., 2020; Sun and Delgado, 2024; Hyun, 2025). 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, the neighbors, 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 hospitalization 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 (or upwind-downwind relationships in the case of Chagas *et al*., 2016). 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; 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 endogenous network difference-in-difference process, or ENDID for short. This framework accounts, first, for endogeneity of the network in a first-stage regression. Endogeneity comes from the sensitivity of the network to the treatment as well as from the correlation between the network and the error terms in the structural equation. Once the estimated value of the network is measured in stage one, the second stage estimates the role of the treatment on the treated areas and on any member of the network. As such, our approach differs from other contributions such as Elhorst (2010), Kelejian and Piras (2014), Bramoullé *et al.* (2009) in which the network is endogenous but is time-invariant.

Our contribution is more closely related to the one of Comola and Prina (2020) even though our approach differs on several grounds. First, our network of choice, trade, allows us to avoid any confounding factors[6]. Second, we do not follow the standard statistical approach suggested by Kelejian and Prucha (1998) that consists in adopting 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.

[6] Their network variable may be subject to confounding factors because their network is exclusively based on repeated financial exchanges across households within the same village while other forms of interaction, such as social and family links, might be present.

As such, this paper is structured as follows: in Section 2, we describe the conceptual framework that extends the basic DID setting to the ENDID 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 ENDID 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, 2023) 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 (Bramoullé *et al*., 2020; Braun and Verdier, 2023; Griffith, 2024) but also to the fairly small literature focusing on the impact of weather events on agricultural trade (Dall'erba et al., 2021; Magalhães *et al*., 2022; Jones and Olken, 2010; Dallman, 2019; Yim and Dall'erba, 2025). In that literature, only three contributions have studied how weather-induced changes in trade will, in turn, affect another outcome variable. The first one by Costinot *et al.* (2016) is the only one based on simulations. It finds that after accounting for trade adjustments, climate change is estimated to have an impact on agricultural production equivalent to a 0.26% decrease in global GDP. The second one, Dall'erba *et al.* (2021), estimates gravity model parameters and 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 by 2070. The third one, Yim and Dall'erba (2025), shows that the U.S. agrifood manufacturing sector always adapts to a weather-induced shock on agricultural inputs but, depending on the location of the latter, it leads to either an increase or a decrease in a State's food manufacturing production. For instance, food manufacturing in California is very sensitive to drought events in Nebraska, where it imports grains from.

In sum, we believe that applications of ENDID could easily be extended to other network structures such as peer-effects (Arieli *et al*., 2020), alliances (König *et al*., 2017), supply-chains (Pei *et al*., 2017; Acemoglu and Azar, 2020), patenting (Innocenti et al., 2020; Kekezi *et al*., 2022) and migration flows (Walters, 1994; Mahajan and Yang, 2020; Gao and Sam, 2019).

2. The ENDID: conceptual framework

2.1. Classical DID estimator

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; Jackson *et al*., 2017; Bramoullé *et al*., 2020; Banerjee *et al*., 2024) 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 even 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 follows:

Assumption 1: Homogeneity

$$E\,[Y_{i,t}(1)|D_i = 1] = E\,[Y_{j,t}(1)|D_j = 1] \quad \text{for all } (i,j) \qquad (1)$$

All treated regions are exposed to the same treatment level. It means that the potential $Y_{i,t}$ value for a region in the treated group is the same for all regions. The assumption 1 refers to the homogeneity of the effect over different regions. Usually, this assumption is not explicitly stated in causal inference works.

Assumption 2: No interference

$$E\left[Y_{i,t}(D)\middle|D_i = D_i, D_j = D_j\right] = E\left[Y_{j,t}(D)\middle|D_i = D_i\right] \tag{2}$$

Each unit's outcome depends only on its own treatment status, not on the treatment status of others. Assumptions 1 and 2 are often referred to as SUTVA, the Stable Unit Treatment Value Assumption (Imbens and Rubin, 2015).

Assumption 3: Parallel Trends

Another key assumption is the parallel trends assumption, which intuitively states that the average outcome for the treated and untreated populations would have evolved in parallel if the treatment had not occurred.

$$E\left[Y_{i,2}(0) - Y_{i,1}(0)\middle|D_i = 1\right] = E\left[Y_{i,2}(0) - Y_{i,1}(0)\middle|D_i = 0\right] \tag{3}$$

Assumption 4: No anticipatory effects

$$Y_{i,1}(0) = Y_{i,1}(1), \qquad \text{for all } i \text{ with } D_i = 1 \tag{4}$$

The no-anticipation assumption states that the treatment has no causal effect prior to its implementation. Without this assumption, the changes in the outcome for the treated group between periods 1 and 2 could reflect not just the causal effect in period $t = 2$ but also the anticipatory effect in period $t = 1$ (Roth *et al.*, 2023).

Proposition 1: Under assumptions 1-4, the ATET (Average Treatment Effect on the Treated) in period 2 (noted τ) is identified.

Proof: Rearranging the terms in the parallel trends assumption (3), we obtain

$$E\left[Y_{i,2}(0)\middle|D_i = 1\right] = E\left[Y_{i,1}(0)\middle|D_i = 1\right] + E\left[Y_{i,2}(0) - Y_{i,1}(0)\middle|D_i = 0\right]$$

Furthermore, based on the assumption of no anticipation:

$$E\left[Y_{i,1}(0)\middle|D_i = 1\right] = E\left[Y_{i,1}(1)\middle|D_i = 1\right]$$

It follows that:

$$\begin{aligned} E\left[Y_{i,2}(0)\middle|D_i = 1\right] &= E\left[Y_{i,1}(1)\middle|D_i = 1\right] + E\left[Y_{i,2}(0) - Y_{i,1}(0)\middle|D_i = 0\right] \\ &= E\left[Y_{i,1}\middle|D_i = 1\right] + E\left[Y_{i,2} - Y_{i,1}\middle|D_i = 0\right] \end{aligned} \tag{5}$$

where the second equality uses the fact that we observe $Y(1)$ for the treated units and $Y(0)$ for the untreated units. The previous display shows that we can infer the counterfactual average outcome for the treated group by taking its observed pre-treatment mean and adding the change in mean for the untreated group. Since we observe (1) for the treated group directly, it follows that:

$$\tau = E\left[Y_{i,2}(1) - Y_{i,2}(0)|D_i = 1\right]$$

is identified as:

$$\tau = \underbrace{E\left[Y_{i,2} - Y_{i,1}\middle|D_i = 1\right]}_{\text{Change for } D_i = 1} - \underbrace{E\left[Y_{i,2} - Y_{i,1}\middle|D_i = 0\right]}_{\text{Change for } D_i = 0} \tag{6}$$

which corresponds to the “difference-in-differences” of population means.

Equation (6) gives us an expression for τ in terms of a “difference-in-differences” of population expectations. Therefore, a natural way to estimate τ is to replace the expectations with their sample analogs,

$$\hat{\tau} = \left(\bar{Y}_{t=2,D=1} - \bar{Y}_{t=1,D=1}\right) - \left(\bar{Y}_{t=2,D=0} - \bar{Y}_{t=1,D=0}\right)$$

where $\bar{Y}_{t=t',D=d}$ is the sample mean of Y for treatment group d in period t'.

Although these sample means could be computed “by hand”, an analogous way of computing $\hat{\tau}$ is to use the following two-way fixed effects (TWFE) regression specification:

$$Y_{i,t} = \alpha_i + \phi_t + (1[t = 2] \cdot D_i)\beta + \epsilon_{i,t} \tag{7}$$

which regresses the outcome $Y_{i,t}$ on an individual fixed effect, a time-fixed effect, and an interaction of a post-treatment indicator with treatment status.

In this canonical DID setup, it is straightforward to show that the ordinary least squares (OLS) coefficient $\hat{\beta}$ is equivalent to $\hat{\tau}$. OLS estimates of $\hat{\beta}$ from (7) provide consistent estimates and asymptotically valid confidence intervals of τ when assumptions 1-4 are combined with the assumption of independent sampling.

2.2 Treatment and Spillover

2.2.1. A single neighbor

Results change when we relax the SUTVA assumption, i.e. when the outcome of an area depends on its own treatment status and on the treatment status of others. For simplicity purposes, consider the situation in which a region has only one neighbor j.

Let $Y_{i,t}(D_i = 0, D_j = 0)$ denote unit i's potential outcome in period t if i and its neighbor j remains untreated in both periods. Similarly, $Y_{i,t}(D_i = 1, D_j = 0)$ denotes unit i's potential outcome in period t if i is exposed to treatment at the second period and its neighbor j is untreated in both periods. The remaining two cases are $Y_{i,t}(D_i = 0, D_j = 1)$ and $Y_{i,t}(D_i = 1, D_j = 1)$. We denote these situations as $Y_{i,t}(00)$, $Y_{i,t}(10)$, $Y_{i,t}(01)$ and $Y_{i,t}(11)$ respectively. Let D_i be a dummy variable identifying if region i is treated and D_j a dummy variable identifying if the neighbor region j is treated. The observed outcome is now given by:

$$\begin{aligned} Y_{i,t} &= D_i D_j Y_{i,t}(11) + D_i(1 - D_j) Y_{i,t}(10) + (1 - D_i) D_j Y_{i,t}(01) \\ &\quad + (1 - D_i)(1 - D_j) Y_{i,t}(00) \end{aligned} \tag{8}$$

We are interested in the Average Treatment Effect on the Treated (ATET) in period t=2. Given that the neighbor j is untreated, the direct treatment effect on i is:

$$\tau_{10} = E\left[Y_{i,2}(10) - Y_{i,2}(00) \middle| D_i = 1, D_j = 0\right]$$

We can also measure the Average Spillover Effect on the Untreated (ASEUT), i.e. the spillover effect (or indirect effect) on i when j is treated compared to the situation where both are untreated:

$$\tau_{01} = E\left[Y_{i,2}(01) - Y_{i,2}(00) \middle| D_i = 0, D_j = 1\right]$$

Furthermore, we can calculate a total effect, composed of the direct and indirect effects, when both regions are treated compared to the situation where both are untreated:

$$\tilde{\tau}_{11} = E\left[Y_{i,2}(11) - Y_{i,2}(00) \middle| D_i = 1, D_j = 1\right]$$

The Average Spillover Effect on the Treated (ASET) corresponds to the difference between the total effect and the direct effect:

$$\tau_{11} = \tilde{\tau}_{11} - \tau_{10}$$

Assumption 3a below rewrites the parallel trend assumption 3 above for the current case. It states that the average outcome for the treated and untreated populations would evolve in parallel if no treatment takes place in either *i* or *j*.

Assumption 3a Parallel trend with spillover

$$E\left[Y_{i,2}(00) - Y_{i,1}(00) \middle| D_i = 1, D_j = 1\right] = E\left[Y_{i,2}(00) - Y_{i,1}(00) \middle| D_i = 0, D_j = 0\right] \tag{9a}$$

$$E\left[Y_{i,2}(00) - Y_{i,1}(00) \middle| D_i = 1, D_j = 0\right] = E\left[Y_{i,2}(00) - Y_{i,1}(00) \middle| D_i = 0, D_j = 0\right] \tag{9b}$$

$$E\left[Y_{i,2}(00) - Y_{i,1}(00) \middle| D_i = 0, D_j = 1\right] = E\left[Y_{i,2}(00) - Y_{i,1}(00) \middle| D_i = 0, D_j = 0\right] \tag{9c}$$

Assumption 4a: No anticipatory effects with spillover

$$\begin{gathered} Y_{i,1}(00) = Y_{i,1}(01) = Y_{i,1}(10) = Y_{i,1}(11) \\ \text{for all } i \text{ and } j \text{ with } D_i = 1 \text{ and / or } D_j = 1 \end{gathered} \tag{10}$$

Proposition 2: Under the assumptions 1, 3a and 4a, the ATET (τ_{10}), ASEUT (τ_{01}) and ASET (τ_{11}) are identified in period 2. The proof of this proposition is in apprendix 1.

2.2.2. Multiple neighbors

In settings with multiple neighbors, additional assumptions about the network structure and the nature of the treatment effect are required. For example, in some cases, a single treated region may be enough to generate a full spillover effect to its neighbors. In others, spillovers occur only when a certain threshold of neighboring regions—say 70%—are treated. Alternatively, the spillover effect may scale proportionally with the share of treated neighbors. In all previous cases, we can determine a vector $\boldsymbol{D}_j$ indicating the treatment status of the neighbors. We introduce in our notations $Y_{i,t}(0\boldsymbol{D}_j)$ and $Y_{i,t}(1\boldsymbol{D}_j)$ which represent the situations where the region *i* is untreated (respectively treated) and $\boldsymbol{D}_j$ is a vector indicating the treated/untreated status of each neighbor *j* of the *i* region. They allow us to consider additional assumptions.

Assumption 5: Isotropy

The spillover effect depends only on the neighborhood structure, not the direction of the spillover. For instance, in a three region setting, region 1 is influenced by the treatment in region 2 (region 3 being untreated, case noted as 110) in the same way that region 1 is influenced by the treatment in region 3 (region 2 being untreated, case noted as 101):

$$Y_{i,t}(110) = Y_{i,t}(101) \tag{11a}$$
$$Y_{i,t}(010) = Y_{i,t}(001) \tag{11b}$$

This assumption can be generalized to a situation with more than two neighbors:

$$Y_{i,t}(1, D_{ij}) = Y_{i,t}(1, D_{ik}) \tag{12a}$$
$$Y_{i,t}(0, D_{ij}) = Y_{i,t}(0, D_{ik}) \tag{12b}$$

where D_{ij} and D_{ik} capture different arrangements of the neighbors of i.

Assumption 6: Spillover Structure

Let $W = w_{ij}, i, j = 1, \dots N$ be the row-standardized neighborhood matrix (so that each row sums to one and $w_{ii} = 0$). Note as $D_{i,t}$ the treatment indicator for the region i in period t, $D_t = (D_{1,t}, D_{2,t}, \dots, D_{N,t})$ as the vector of all regions' assignments at time t, and $S_{i,t} = \sum_{j=1}^{N} w_{ij} D_{i,t}$ is the total spillover exposure of region i at time t.

We assume:

a) Additivity. Each treated neighbor contributes independently to $S_{i,t}$ so that regions with more treated neighbors receive a larger total spillover impact.

b) Proportionality. Spillover effects are linear in the weighted count of treated neighbors, i.e. for every $i \neq j$,
$$\frac{\partial S_{i,t}}{\partial D_{i,t}} = w_{ij}$$

c) Weight-matrix standardization. The matrix W satisfies:

1. $w_{ii} = 0$ for all i (no self-spillover),

2. $\sum_{j=1}^{N} w_{ij} = 1$ for all i (each row sums to one), and

3. all entries of W are uniformly bounded in absolute value.

Proposition 3: Under Assumptions 1 (homogeneity), 3a (parallel trends with spillover), 4a (no anticipatory effects), 5 (isotropy), and 6 (spillover structure), every region's observed outcome $Y_{i,t}$ can be decomposed into the sum of direct treatment effects and all possible indirect (spillover) effects as follows:

$$Y_{i,t} = D_{i,t}[\boldsymbol{w}_{i\cdot} \boldsymbol{D}_t Y_t] + D_{i,t}[\boldsymbol{w}_{i\cdot} (\boldsymbol{1_N} - \boldsymbol{D}_t) Y_t] + (1 - D_{i,t})[\boldsymbol{w}_{i\cdot} \boldsymbol{D}_t Y_t] + (1 - D_{i,t})[\boldsymbol{w}_{i\cdot} (\boldsymbol{1_N} - \boldsymbol{D}_t) Y_t] \tag{13}$$

where $\boldsymbol{1_N}$ is a vector of one's of dimension t, D_t is the vector of all regions' treatment statuses at t, $w_{i\cdot}$ is the ith row of the normalized weight matrix, and Y_t is the vector of all regions' potential outcomes. The proof of proposition 3 is in appendix 1.

As a consequence of Proposition 3, a spatial two-ways fixed effect can be used to estimate the treatment and the spillover effect:

$$Y_{i,t} = \beta^d D_{i,t} + \beta^t \sum_j w_{ij,t} D_{i,t} D_{j,t} + \beta^u \sum_j w_{ij,t} (1 - D_{i,t}) D_{j,t} + \mu_i + \delta_t + u_{i,t} \tag{14}$$

Proposition 4: Under the assumptions 1, 3a, 4a, 5-8 and Proposition 3,

a) the ATET (τ_{10}) is equal to β^d

b) the ASET (τ_{11}) is equal to β^t.

c) the ASEUT (τ_{01}) is equal to β^u.

The proof of proposition 4 is in the appendix 1.

2.3. Network endogeneity

Traditionally, the spatial econometric literature qualifies any W matrix that is not based on pure geographical distance as endogenous. That is because only geographical distance is not affected by the outcome variable and/or economic or behavioral relationships. This characteristic holds true in our definition of the network as the latter is based on trade flows. However, the endogeneity of W is also defined in the more traditional econometric sense: the absence of W from the main specification would lead to an uncontrolled confounding effect as W is correlated with both the second-stage dependent variable and the explanatory variable $D_{i,t}$. Reverse causality comes from the fact that the second-stage dependent variable, production in i noted as Y_{it}, is one of the main determinants of the trade flows W (see section 4). Furthermore, drought in the trade partners increase local production Y_{it} (see Dall'erba *et al*., 2021, and section 4). Correlation with the explanatory variable $D_{i,t}$ is due to empirical evidence showing that a local drought reduces yield and the flows of export captured in W. To illustrate this point, assume that the model estimated is the classical DID:

$$Y_{it} = \beta^d D_{i,t} + \mu_i + \delta_t + \varepsilon_{it}$$

where $\varepsilon_{it} = \beta^t \sum_j w_{ij,t} D_{i,t} D_{j,t} + \beta^u \sum_j w_{ij,t} (1 - D_{i,t}) D_{j,t} + u_{i,t}$. As discussed above, the omitted terms $\sum_j w_{ij,t} D_{i,t} D_{j,t}$ and $\sum_j w_{ij,t} (1 - D_{i,t}) D_{j,t}$ are correlated with $D_{i,t}$, which makes the classical two-way fixed effect estimation to ATE biased.

As the model contains an endogenous weighting matrix, we need to consider an IV procedure for its estimation. Some elements of W, $w_{ij,t}$, are zero and others are positive. Denote as $w^*_{ij,t}$ the subset of W formed by the non-zero elements. We assume that the mean of $w^*_{ij,t}$ exists and is an unknown function of exogenous variables, $h_{ij,t}$, which are observable and known. Suppose that $h_{ij,t}$ is a $1 \times r$ vector, then the elements of $w^*_{ij,t}$ can be estimated as:

$$w^*_{ij,t} \approx \alpha_1 h_{1ij,t} + \alpha_2 h_{2ij,t} + \cdots + \alpha_r h_{rij,t} + \zeta_{ij,t} \tag{15}$$

where $E(\zeta_{ij,t}) = 0$ and $\alpha_1, \ldots, \alpha_r$ are parameters which can be estimated using the non-zero elements of W. Let $H_{S,t}$ be the $N \times N$ matrix whose zero elements are in the same positions as those of W, and whose non-zero elements are obtained by replacing $w^*_{ij,t}$ with $h_{s,ij,t}$. Using the approximation (15), the estimated value of W is:

$$\widehat{W_t} = \widehat{\alpha_1} H_{1ij,t} + \widehat{\alpha_2} H_{2ij,t} + \cdots + \widehat{\alpha_r} H_{rij,t} \tag{16}$$

Assumption 7: In (16), we assume $\mathrm{E}(u_{i,t} | H_{\mathrm{s,t}}) = 0$ and $\mathrm{E}(W_t | H_{\mathrm{s,t}}) \neq 0$.

Proposition 5: Under assumptions 1, 3a, 4a, 5-9, the ATET, ASET, and ASEUT can be estimated using a two-stage procedure where the first stage estimates $\widehat{W_t}$ and the second stage measures expression (14) with W_t substituted for $\widehat{W_t}$. The proof is in appendix 1.

3. The ENDID: simulations

This section focuses on a Monte Carlo evaluation of the ENDID 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:

$$w^*_{ij,t} = \beta_1 x_{1i,t} + \beta_2 x_{1j,t} + \mu_i + \mu_j + \mu_t + \delta_1 D_{i,t\geq\tau} + \delta_2 D_{j,t\geq\tau}$$
$$w_{ij,t} = \exp(w^*_{ij,t})\varepsilon_{ij,t} \tag{17}$$

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 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:

$$W_{ij} = \begin{cases} 0 & \text{if } i = j \\ \frac{w_{ij,t}}{\sum_j w_{ij,t}} & \text{if } i \neq j \end{cases} \tag{18}$$

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:

$$y_{i,t} = \beta_3 x_{2i,t} + \mu_i + \mu_t + \delta_3 D_{i,t\geq\tau} + \delta_4 \sum_j W_{ij} D_{j,t\geq\tau} + \epsilon_{i,t} \tag{19}$$

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 ENDID parameter is strongly correlated with the time fixed effect. However, as the number of time observations increases, it is possible to accurately identify the ENDID 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 ENDID 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 ENDID performs significantly better than any of the alternatives, indicating that these alternatives 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 ENDID 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 ENDID 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; it is also 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 release drought-resistant wheat varieties (Khadka *et al.*, 2020), technological progress for wheat has lagged behind that of 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. It 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. As a result, these countries had no choice but to increase wheat imports from the rest of the world. They increased by 224% relative to the previous year in spite of the world wheat prices being 27% higher than in the previous year (FAO, 2020; Wiggins *et al*., 2010). The countries that supplied these exports (mostly the United States, Canada, Russia, and Ukraine) each produced substantially more wheat than they did in years prior. We attribute the increase in production they experienced to the increase in exports towards the drought-afflicted Middle Eastern countries.

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 trade, including drought, and thus the economic linkages that determine the scope for spillovers across regions. While our focus is on the role of drought as a treatment, we control for variations in the network coming from other exogenous factors, such as supply and demand, by including them as covariates (e.g., Anderson, 1979; Bergstrand, 1985; Eaton and Kortum, 2002; Chaney, 2008).

Implementing an approach that is now standard, 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:

$$W_{ijt}=\exp[\boldsymbol{\alpha}'_1\boldsymbol{X}_{it}+\boldsymbol{\alpha}'_2\boldsymbol{X}_{jt}+\alpha_3 D_{it}+\alpha_4 D_{jt}+\alpha_5 FTA_{ijt}+\phi_{ij}+\eta_t+\varepsilon_{ijt}] \qquad (20)$$

where W_{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.[7] 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 (20) 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

[7] Appendix 2 provides details on how these data are calculated for the growing area(s) of each country.

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- 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.[8] 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 qualify 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.

As indicated in section 2.3., the matrix of trade flows is endogenous to the outcome variables we will study in stage 2. As such, we need to define a set of instrumental variables (IV) in the first stage that the gravity model represents. These instruments shall be relevant (they have direct impact on the endogenous variable in the first-stage regression) and exogenous (they should not be directly correlated with the error term in the second stage equation). In the case of our first-stage equation, the choice of IVs is driven by the structural gravity model equations. These are all the j-specific covariates (Food proc._{jt}, Pop_{jt}, Livestock_{jt}, $\text{Irrigation}_{j,t-3}$, Temperature_{jt}, Precip_{jt}, Drought D_{jt}) as well as the i-j covariates (FTA_{ijt} and the pair fixed effects). All these variables affect trade, the first-stage dependent variable (see table 6), and the only way they affect the second-stage dependent variables is through the endogenous variable. Furthermore, we also use $\text{Prod.}_{i,t-3}$ (production in the country of origin lagged three years) as an instrument in the first stage as contemporaneous production will be one of the dependent variables used in the second stage.

<< 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 of them. The second-stage analysis, presented further below, includes the same 97 wheat-producing countries as in the first stage.[9]

The estimation results for the first-stage gravity equation (20) are presented in table 6. Significant estimates on the variables reflecting the size of the 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 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. They

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[8] Appendix 3 provides details on how the drought variable is calculated.

[9] Appendix 4 lists the countries included in the analysis.

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 $\partial X_{ijt}/\ \partial D_{jt}$ 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 country generate spillover effects on other countries, we use the estimated trade flows (row-standardized estimated values) in the second stage to account for the endogenous nature of trade.

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) and drought in trading partners (the indirect network difference-in-differences spillover effect):

$$Y_{it} = \boldsymbol{Z}'_{it}\boldsymbol{\beta}_1 + \beta_2 D_{it} + \beta_3 \widehat{\boldsymbol{W}}_{it}\boldsymbol{D}_{jt} + \lambda_i + \eta_t + \nu_{it} \tag{21}$$

where Y_{it} is the outcome variable for country *i* in year *t* which reflects wheat production along three dimensions: i) the total physical quantity of production, ii) the amount of land area allocated to wheat production in a given year, and iii) 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 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 display a positive marginal effect: 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 that the row-standardization of $\widehat{\boldsymbol{W}}_{it}$ has one interesting implication. Since the drought treatment uniformly affects origin *i*'s exports to all of its partners in the first-stage gravity equation, then 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 5. 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: i) the importance of *j* in *i*'s network ($\widehat{w}_{ijt}$), ii) how the importance of *j* changes as a result of the treatment in *j* ($\partial\widehat{w}_{ijt}/\ \partial D_{jt}$), and iii) 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 5.[10]

[10] 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 $\partial\widehat{w}_{ij}/\partial D_i \neq 0$.

Results from estimating equation (21) are shown in table 7. Note that because $\widehat{\boldsymbol{W}}_{it}\boldsymbol{D}_{jt}$ is an estimated variable, we choose to bootstrap the standard error of all the coefficients 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.[11] 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 impact of drought on wheat production and yields (columns 1 and 3). On the other hand, the area planted is not statistically impacted by a local drought (column 2). It is a result we expected given that the decision to plant is taken a year prior. 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. This response likely stems from the rise in exports triggered by the foreign drought, which depletes domestic reserves. To replenish these stocks and safeguard against potential domestic shortages in the event of a future drought, the country increases its planting efforts.

The remaining results of table 7 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 because of unfavorable weather and/or soil conditions.

Furthermore, note in table 7 that columns 4-6 show that none of the estimates based on the exogenous, geographical distance-based spatial weight matrix $\boldsymbol{W}_t^{dist}$ are significant, which confirms the Monte Carlo simulations of section 3 and suggests that endogenous trading relationships are the channel through which the detrimental effects of drought are mediated.

<< Insert table 7 here >>

As a robustness check, we tested in table 8 whether the results would change when we add a one-year time lag of the local (D_{it-1}) and trade-based drought ($\widehat{\mathbf{W}}_i D_{jt-1}$). The idea is to account for cases where drought events take place towards the end of the year, say November-December, and hence affect the outcome variables the following year. The results remain consistent and show that a drought in the trade partners countries occurring in the current or in the past year will increase production locally. While the negative impact of a local drought on local production and yield matches the results of table 7, we also find that a past drought increases the current year's area planted and production, which confirms our expectations that stocks need to be replenished after a drought.

<< Insert table 8 here >>

Finally, we report in table 9 the average treatment on the treated for each of the four versions of W listed in the Monte Carlo results of table 3: i) ENDID, ii) NDID where the network is trade measured at the initial period only (hence it is not affected by changes in any of the covariates), iii) SDID where the network is based on geographical proximity, hence is also constant and iv) DID without network. In all cases the standard errors are bootstrapped so that differences in the coefficients' significance level do not come from differences in standard error calculations.

The findings of table 9 indicate that the only specification that leads to a significant direct and indirect impact of drought on the (log of) production is through the ENDID method. Other approaches generate estimates with the expected sign but suffer from a missing variable bias (DID) or poorly measured externalities (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 i) the units of our sample had been treated as isolated individuals (as in DID), ii) if we had used a misspecified network matrix (as in SDID) or iii) if the

[11] 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.

matrix were correctly specified but insensitive to the treatment (as in NDID). Indeed, by accounting for the drought-induced changes in trade through ENDID, we see the indirect effect becomes significant and offsets the direct effect.

<< Insert table 9 here >>

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 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 on does not hold, estimates are 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, sensitive 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 countries. 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 the same year as well as the following year.

We believe our contribution paves the way for several future research venues 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 natural shocks of interest.

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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	ENDID	DID	SDID geo	NDID	ENDID	DID	SDID geo	NDID	ENDID
		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.**
W_{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_{it}	Population (millions)	World Bank, 2020	57.8	176.0
Food $proc_{it}$	Value added in food processing (million USD)	Eora database	15,604.0	36,081.8
$Livestock_{it}$	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)
Drought D_{it}	–0.129**	Drought 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

	ENDID: Export-Share-Weighted W			SDID-geo: Inverse-Distance-Weighted W		
	Production	Area	Yield	Production	Area	Yield
	(1)	(2)	(3)	(4)	(5)	(6)
$Temperature_{it}$	–0.272	0.436	–0.708*	–0.296	0.412	–0.709*
	(0.733)	(0.609)	(0.384)	(0.696)	(0.658)	(0.395)
$Temperature_{it}^2$	–0.111	–0.249	0.138	–0.094	–0.232	0.139
	(0.214)	(0.182)	(0.112)	(0.201)	(0.197)	(0.114)
$Precipitation_{it}$	0.319*	0.263*	0.056	0.307*	0.252*	0.055
	(0.166)	(0.154)	(0.058)	(0.163)	(0.147)	(0.055)
$Precipitation_{it}^2$	–0.090*	–0.063	–0.027**	–0.089*	–0.062	–0.027**
	(0.052)	(0.046)	(0.012)	(0.049)	(0.046)	(0.012)
$Irrigation_{i,t-3}$	–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)
$\widehat{\mathbf{W}}_i D_{jt}$	0.090**	0.085**	0.005			
	(0.043)	(0.034)	(0.022)			
$\mathbf{W}_i^{dist} D_{jt}$				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- Wheat production as a function of local and international Drought at time t and t-1

	ENDID: Export-Share-Weighted *W*		
	Production	Area	Yield
	(1)	(2)	(3)
Temperature_{it}	–0.368	0.417	–0.785*
	(0.828)	(0.629)	(0.464)
$\text{Temperature}^2_{it}$	–0.060	–0.203	0.143
	(0.233)	(0.172)	(0.134)
$\text{Precipitation}_{it}$	0.267	0.223	0.045
	(0.186)	(0.147)	(0.070)
$\text{Precipitation}^2_{it}$	–0.085	–0.061	–0.024*
	(0.067)	(0.055)	(0.014)
$\text{Irrigation}_{i,t-3}$	–0.138***	–0.128***	–0.010
	(0.025)	(0.020)	(0.010)
D_{it}	–0.080**	0.010	–0.090***
	(0.032)	(0.025)	(0.019)
D_{it-1}	0.060**	0.039**	0.021
	(0.027)	(0.019)	(0.016)
$\widehat{\mathbf{W}}_i D_{jt}$	0.086*	0.088**	-0.001
	(0.051)	(0.042)	(0.028)
$\widehat{\mathbf{W}}_i D_{jt-1}$	0.116*	0.046	0.070**
	(0.060)	(0.049)	(0.028)
Observations	1,512	1,512	1,512
R^2	0.981	0.986	0.888
Country FEs	Y	Y	Y
Year FEs	Y	Y	Y

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

Table 9 – Average treatment effect on the treated – differences across DID specifications

	ENDID	NDID	SDID-geo	DID
	(1)	(2)	(3)	(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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$