

Job Displacement and Reallocation Failure

Evidence from Climate Shocks in Morocco

Federica Alfani

Vasco Molini

Giacomo Pallante

Alessandro Palma



WORLD BANK GROUP

Poverty and Equity Global Practice

January 2023

Abstract

This paper investigates the effects of severe drought shocks in Morocco's agriculture sector. Using a staggered difference-in-differences design, the estimates show that climatic shocks produced job displacement of about 6.5 percentage points for workers who were exposed to severe drought

events. Overall, about 45 percent of these workers remained unemployed, generating a partial reallocation failure. The effects are significant only for severe and extreme shocks; they last for at least five years, and are more pronounced among females and the least educated workers.

This paper is a product of the Poverty and Equity Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at <http://www.worldbank.org/prwp>. The authors may be contacted at falfani@worldbank.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

Job Displacement and Reallocation Failure: Evidence from Climate Shocks in Morocco*

Federica Alfani[†] Vasco Molini[‡]
Giacomo Pallante[§] Alessandro Palma[¶]

J.E.L. codes: Q1, Q54, J21

Keywords: Drought, Climate change, Job displacement, SPEI, Unemployment.

*The authors acknowledge financial support from the World Bank. We thank colleagues from the Haut Commissariat au Plan of Morocco (HCP) for their excellent data preparation. We also wish to thank the participants at the IAERE 2022 and IFAD 2022 conferences for their suggestions. We also benefited from useful discussions with Luca Citino, Daniele Curzi, Salvatore Di Falco, and Giuseppe Maggio.

[†]World Bank, E-mail: falfani@worldbank.org

[‡]World Bank E-mail: vmolini@worldbank.org

[§]School of International Studies, University of Trento, E-mail: giacomo.pallante@unitn.it

[¶]Corresponding author. Gran Sasso Science Institute (GSSI), Via Francesco Crispi 7, 67100 L'Aquila, Italy; CEIS Tor Vergata, E-mail: alessandro.palma@gssi.it

1 Introduction

Climate change is generating unprecedented pressure on the agriculture sector as the increased variability of weather translates into extreme events that are largely responsible for short- and medium-term impacts ([Day et al., 2019](#); [Stevanović et al., 2016](#); [Key and Sneeringer, 2014](#)). The frequency, duration, and intensity of these events, in particular droughts, are expected to dramatically intensify in the future ([Fischer et al., 2021](#); [Chiang et al., 2021](#)). Recent estimates point at a reduction in the global agricultural total factor productivity by 22 percent ([Ortiz-Bobea et al., 2021](#)). However, the regional distribution of these impacts is largely heterogeneous. In the Middle East and North Africa (MENA) region, it is projected that surface water availability will be reduced by 5-40 percent during 2030-2065 compared to the availability during 1976-2005, with decreases in runoff of 10-63 percent by mid-century in Morocco and Tunisia ([Pörtner et al., 2022](#)). In addition, climate conditions strongly interact with the local socioeconomic context; therefore, economies that are heavily dependent on the agriculture sector, with weaker institutions and poor safety nets, are those paying the highest toll ([Hallegatte et al., 2018](#)). These interactions are already manifesting with a greater intensity on the African continent, an area that is considered a climate hotspot ([Blunden and Arndt, 2020](#); [Niang et al., 2014](#)). While the direct impacts of weather variability on land productivity are well documented ([Schleussner et al., 2018](#); [Dell et al., 2014](#); [Deschênes and Greenstone, 2007](#); [Di Falco et al., 2011](#), among others), we know much less about how these impacts spill over into the labor markets. This gap is particularly evident in MENA countries, where the limited availability of data leaves policy makers with little guidance ([Cramer et al., 2018](#)).

In this paper we contribute to address this gap by investigating the effects of severe drought shocks on the Moroccan labor market using individual labor-force surveys aligned with granular weather data at the provincial level. In a staggered difference-in-difference setting, we

test whether agricultural workers—who are the most exposed to climate variability—faced a job displacement as a consequence of severe drought events that occurred in Morocco from 2000 to 2009, and—by looking at the employment rate of other economic sectors and the unemployment dynamic—a reallocation effect took place.¹ In industrialized countries, the employment loss in sectors largely exposed to climate shocks (for example, agriculture and tourism) can be compensated by employment gains obtained in less exposed, or even new sectors of the “green economy” (ILO, 2018b). However, in less developed countries, the risk of job displacement increases dramatically when climate-exposed activities account for a big portion of the GDP and labor force. Therefore, while industrialized countries are experiencing an adaptation process oriented towards transition to a green-economy, developing economies are struggling to adapt because they do not have the economic and institutional capacities needed to address these challenges; at the same time they are burdened with structural factors that increase the risk of adaptation deficit (Asfaw et al., 2018; Barrett et al., 2001). As a result, climate shocks can be accompanied by a reallocation failure and a dramatic increase in unemployment. Morocco is an interesting case in this regard, and is quite representative of the typical socioeconomic and climatic conditions of many other MENA countries (Clementi et al., 2019; Belhaj et al., 2022). Morocco has experienced sustained economic growth over the last two decades; however, this has not been accompanied by the effective structural transformation needed to respond to a higher demand for high-skilled workers. Labor productivity remains low; an illiterate workforce accounts for about one-third of the total and the agri-food sector, which is mostly low value added, still absorbs more than 30 percent of the total workforce (Lopez-Acevedo et al., 2021). In addition, over the years informality has remained stubbornly high, especially among women and youth. Finally, the labor market is not very inclusive: Morocco posts one of the lowest female labor force participation rates in

¹ ¹Reallocation occurs when the job destruction rate is lower than the job creation rate (Haltiwanger et al., 2014). In our setting, we consider job destruction deriving from the displacement of agricultural workers who are not reallocated into other sectors

the developing world (Belhaj et al., 2022). From a climatic point of view, Morocco and most of the MENA region countries are largely prone to recurrent arid conditions and drought events are dramatically increasing. The recent Sixth IPCC Assessment Report points to an average GDP loss of about 11 percent in a scenario with the temperature increase of 4.8 that has been projected for 2100, while in Morocco GDP projected impacts range from -3 to +0.4 percent by 2050 relative to 2003 (Pörtner et al., 2022). Recently, Morocco's Ministry of Equipment and Water has declared that the country experienced the fourth consecutive year of low rainfall and climatic disruptions and is currently facing the worst drought in 30 years.² Therefore, the agriculture sector will be continuously exposed to climate shocks that will make production outcomes highly uncertain (Moriando et al., 2016). Moreover, individuals living in rural areas face a large socioeconomic and cultural divide with respect to those living in urban areas, a situation that can strongly sharpen the climate impacts (Burgess et al., 2014). The literature has largely documented how in developing economies international migration represents an important margin of adjustment for workers to cope with different types of climatic shocks (Gray and Mueller, 2012; Mueller et al., 2014; Dillon et al., 2011; Marchiori et al., 2012; Kaczan and Orgill-Meyer, 2020). Nevertheless, the cost-opportunity offered by migration is largely heterogeneous (Cattaneo and Peri, 2016), and is more likely to take place with moderate but persistent shocks (Di Falco et al., 2022). Crop and local labor diversification also constitute two well-known adaptation strategies in rural areas. However, while crop diversification is often adopted as an *ex ante* practice (Asfaw et al., 2018; Alfani et al., 2021; Aragón et al., 2021), labor diversification represents an *ex post* coping strategy used to face unexpected and severe climatic events such as droughts or floods. By and large, a negative shock in agricultural productivity is expected to drive farmers to allocate more time to economic sectors that are less climate-sensitive, generating an agricultural job displacement

² Source: Morocco's Ministry of Equipment and Water. For further details, see <https://www.reuters.com/business/environment/catastrophic-moroccan-drought-boost-import-subsidy-costs-2022-02-18/> and <https://joint-research-centre.ec.europa.eu/jrc-news/agricultural-production-threatened-combination-drought-an>.

that may be associated with a local rural-to-urban migration (for a recent review of this phenomenon, see [Cattaneo et al. \(2020\)](#)). In such cases, workers could search for seasonal or new permanent local off-farm wages to compensate for their loss of agricultural income ([Gröger and Zylberberg, 2016](#)). Still, when markets are not perfectly developed, a climate-induced reduction of the agricultural productivity depresses the aggregate demand, preventing the nontradable economic sectors from absorbing the excess of rural labor supply ([Foster and Rosenzweig, 2007](#)). This effect is more likely to hit low-skilled workers, most of whom are employed in the agriculture sector ([Emerick, 2018](#)).

Despite the increasing debate among institutions and policy makers about the “winners” and “losers” of a changing climate era ([ILO, 2018a](#)), we have little evidence of the consequences of extreme climate events on the local labor markets. In Brazil, [Albert et al. \(2021\)](#) found that areas affected by abnormal dryness experienced a sharp reduction in population and employment in agriculture and services, with manufacturing absorbing only a small portion of the displaced workers. In West Africa, [Elmallakh and Wodon \(2021\)](#) have shown that climatic shocks led to an increase in female labor force participation. In China, [Li and Pan \(2021\)](#) found no impacts on employment status caused by higher temperatures, even though they observed that workers do leave the agriculture sector and engage in other occupations as a response to abnormal temperatures. [Jessoe et al. \(2018\)](#) have found that hotter temperatures reduce labor opportunities in rural Mexico, and [Branco and Feres \(2021\)](#) have documented similar effects due to water scarcity in Brazil. Finally, in India, [Emerick \(2018\)](#) has estimated a modest increase in the non-agricultural labor share due to exogenous increases in agricultural output, while [Colmer \(2021\)](#) found that a temperature-driven decrease of agricultural labor demand is attenuated by a job reallocation in non-agriculture sectors. While we have immensely benefited from these studies, [Jessoe et al. \(2018\)](#) highlight that *“apart from the channel of migration, little is known about the effect of rising temperatures on rural employment in less developed countries.”*

Building on previous studies, our paper offers three main contributions. Firstly, we explore the effect of severe drought conditions on the labor market. Using the Standardized Evapotranspiration Precipitation Index (SPEI), we identify the Moroccan provinces that have been hit by extreme drought events and frame the analysis in a staggered difference-in-differences setting in order to estimate the effects on three outcomes: the employment rate in the agri- culture sector (including the most climate-sensitive activities); the employment rate in other sectors; and the unemployment rate. This provides an overall picture of the labor market dynamics at the local level for a period of up to five years after the drought's shock.

Secondly, we have conducted a rich analysis of the effects of heterogeneity by disentangling the impacts across age, gender, educational levels and formal/informal work participation for each of the three outcomes considered. Therefore, our analysis also speaks to the important strand of literature on climate injustice, which highlights how climatic shocks tend to have a significant distributional impact with unequal effects among the most vulnerable and most exposed population groups ([Sovacool, 2013](#)). Finally, we explore how drought events of different intensities affect the labor market; this provides a useful picture for understanding how the market responds to drought shocks of increasing severity, and how the policy response should be targeted accordingly.

Our estimates show that in Morocco severe drought events, measured by a 12-month SPEI lower than -2 s.d., caused a drop of up to 6.5 percentage points (p.p.) in the agricultural employment rate compared to provinces that were not affected by severe drought. In the same period, we also observe a non-significant increase of 4.8 p.p in the employment rate of other economic sectors, and a significant increase in the unemployment rate of nearly 2.5 p.p. Even though our data do not allow observing the same workers over time, overall, those figures provide strong evidence of a large displacement of agricultural workers and a

partial reallocation failure, considering that about 38 percent of displaced workers remain unemployed.

We also find that these climate-induced impacts are unequally distributed across educational levels and gender, with workers with no education, females and informal workers the most affected. In addition, the sensitivity analysis, based on an increasing treatment intensity, shows a sharp increase in the magnitude and significance of the impacts when drought shocks become severe, corresponding to SPEI values lower than -1.8 s.d. in all three labor market outcomes. Overall, our results are robust to various specifications and falsification tests.

The remainder of the paper proceeds as follows. [Section 2](#) presents the data, our measures of drought shocks and some descriptive analysis. [Section 3](#) outlines our empirical strategy, [Section 4](#) presents the results, and [Section 5](#) presents a set of robustness checks. [Section 6](#) offers a discussion of the findings and some policy implications, and [Section 7](#) concludes. Additional information on the data employed and empirical analysis can be found in the Appendix.

2 Data

We employed two data sources. First, we used the Enquête Nationale sur l'Emploi (ENE), which provides nationally representative socioeconomic information at the individual level from 2000 to 2009. The ENE is conducted by the Haut Commissariat au Plan (HCP) and consists of demographics and labor market data. The sampling follows a two-phase stratification approach with an urban-rural strata and a regional strata. Our analysis is restricted to the period from 2000 to 2009 since the provincial identifier was not provided in the survey rounds from 2010 to 2019.³ Despite the richness of the available information, the survey consists of repeated cross-sections, which does not allow for tracking individuals over time. We started with an initial sample of nearly 2.7 million observations across 54 provinces.

³ While from 2000 to 2005 around 40,000 households and 230,000 individuals were sampled, from 2006 these numbers increased to around 60,000 and 270,000, respectively.

After restricting the sample to working age individuals (between 15 and 59 years old),⁴ since our treatment is at the provincial level, we collapsed the data into province×year cells to obtain yearly outcomes of the labor markets since our treatment is at the province level.

Considering the non-panel

structure of our survey data, this aggregation does not come at the cost of losing information.

Therefore, in order to identify the impact of a drought shock on labor markets, we leveraged its within-province variation across years. Exploiting the details of employment status and the economic sector codes (NACE classification) for employed individuals, we focused on three labor market outcomes at the provincial level: the share of employment in the agriculture sector; the share of employment in the other economic sectors; and the unemployment rate. Other information at the provincial level includes the share of population across five age groups; the gender of the workforce; the share of educational levels across the population; the share of informal jobs; and the share of the workforce population living in urban areas.

We aligned ENE socioeconomic data with detailed weather information that we obtained from the Agri-4-Cast database. These data are provided by the Food Security Unit of the Joint Research Center (JRC.D.5) and were specifically employed for identifying the climate change impacts in the agriculture sector. The data consists of gridded meteorological observations from weather stations interpolated on a 25×25 km grid. They are available on a daily basis from 1979 in the European Union and its neighboring countries, including Morocco. We selected variables for maximum, minimum, and mean air temperature (in Celsius degrees); mean daily wind speed at 10m (m/s); and sum of precipitation (mm/day) to calculate the Standardized Precipitation Evapotranspiration Index (SPEI), our treatment measure. The SPEI represents a state-of-the-science indicator for measuring the impact of increased temperatures on water demand (Vicente-Serrano et al., 2010; Chiang et al., 2021). Since climate grids come at a finer spatial resolution than our administrative unit of analysis, we calculated

⁴ Retirement age in Morocco was 60 up to 2015.

SPEI values for each grid point falling within each administrative unit. We then collapsed the data to obtain medians of minimum SPEI values in each province $\times$ year cell; considering the large density of point measures in each province (see Appendix), this procedure minimizes the risk of assigning drought shocks to provinces that had only a negligible portion of territory exposed to extreme shocks.

We considered SPEIs at two different time scales, 12 and 3 months, since SPEIs that are calculated at different accumulation periods capture different types of drought shocks. Specifically, an accumulation period of three months captures short- and medium-term moisture conditions and represents a good early warning, since drought usually takes a season or more to develop. SPEI at longer duration scales, for example 12-months, are more appropriate to account for interseasonal precipitation patterns over a medium duration timescale (Svoboda et al., 2012). As mentioned in Section 1, the duration of drought also affects the response of the local labor markets differently: longer and more severe drought periods are likely to generate more significant and persistent effects.

Unlike McGuirk and Burke (2020), who considered moderate and severe shocks, in order to identify our treatment group on both 12-month and 3-month SPEIs, we calculated binary variables with SPEI values ≤ -2 s.d. According to Table A1, this threshold identifies extremely severe droughts, corresponding on average to an event probability of one in 50 years. The low probability of occurrence of these events makes them plausibly interpretable as as-good-as-random, allowing us to minimize the bias due to the sorting of workers into less exposed areas. Conversely, we do not expect long-lasting displacement effects in the labor market for moderate shocks; such shocks may, however, affect worker productivity, as has been documented by Emerick (2018). We successfully test this assumption in Section 4, where we show that weaker drought events, classified at least as ‘moderate’, have no impact on either job displacement of agricultural workers or overall unemployment.

Figure 1 shows the national average (the dashed line) and the minimum value (the solid line)

of the 12-month SPEI observed over the period 2000-2009. The national average SPEI ranges around -0.5; when we consider the extreme negative values, at least five periods of severe drought have taken place. To better characterize our empirical setting, we considered SPEIs at the provincial level, and the associated classification of drought intensity is reported in [Table A1](#). Accordingly, we classified as treated provinces in which the SPEI value assumed a value lower than -2 s.d. over the period 2000-2009; this threshold corresponds to “severe” drought events. Provinces that never experienced severe droughts constituted our control group. The distributions across years of these groups are reported in [Table 1](#). Finally, [Table 2](#) shows the summary statistics, for the treated and untreated provinces, for all the socioeconomic and climatic variables described above.

3 Empirical Strategy

Our goal was to estimate the causal effect of a drought shock on various labor market outcomes at the provincial level in Morocco. Since drought occurs at different points in time across provinces, we have framed the analysis in a staggered difference-in-difference (DiD) setting that exploits two sources of variation: the cross-sectional variation in the probability of experiencing an SPEI lower than -2; and the variation in timing of the observed years when the drought hits a province. In a standard dynamic two-way fixed effect (TWFE), the following specification is estimated:

$$y_{p,t} = \alpha_t + \gamma_p + \sum_{e=-K}^{-2} \delta_e \times D_{p,t}^e + \sum_{e=0}^L \beta_e \times D_{p,t}^e + \varepsilon_{p,t} \quad (1)$$

where $y_{p,t}$ is one of the three outcomes considered, i.e., the employment rate in the agriculture sector, the employment rate in other sectors and the unemployment rate in province p and year t , α_t are year fixed effects, γ_p are province fixed effects and $\varepsilon_{p,t}$ is an idiosyncratic error term. $D_{p,t}^e$ is a distance-to-event indicator being e periods away from the

year when the province p experienced for the first time a severe drought event over the observed period. We considered absorbing treatment processes, assuming that once a province is shocked it remains treated for the remainder of the panel length. β_e are the parameters of interest that measure the marginal difference in the labor outcomes between treated and control provinces after e years of exposure to the treatment, relative to the same difference in $e = -1$.

Recent studies have demonstrated that when units are treated at different points in time, as in our case, estimates from a TWFE can be biased because of the *negative weight problem*.⁵ Among the alternative methods used to address these limitations, we follow [Callaway and Sant'Anna \(2021\)](#), who developed a disaggregated causal parameter, the group-time average treatment effect ($ATT(g, t)$), in which the group is defined by the provinces that receive the first shock in a common year. Under parallel trends and without anticipation effect, the $ATT(g, t)$ is identified by comparing the expected change in outcome for group g between periods $g - 1$ and t to that for a control group, as follows:

$$ATT(g, t) = E[y_{p,t} - y_{p,g-1} | G_p = g] - E[y_{p,t} - y_{p,g-1} | G_p \in \mathcal{G}] \quad (2)$$

where the control group space $\mathcal{G}$ can include either the never-treated or the not-yet treated provinces. Building on the $ATT(g, t)$, it is possible to obtain several aggregate parameters of interest such as the weighted average, by group size, of the $ATT(g, t)$ across all groups and periods, or the simple average ATT for all groups across all periods. Further, the dynamic $ATTs$, by the length of exposure e , can be estimated in an event study setting with the proper weighting:

⁵ β represents a weighted average of some underlying treatment effect parameters but some of the weights on these parameters can be negative leading to an extreme case in which the treatment effect is positive for all the provinces but the TWFE results in a negative β ([Sun and Abraham, 2021](#); [Goodman-Bacon, 2021](#)). This occurs when the dynamic TWFE does not aggregate natural comparisons of units and allows bad comparisons between always, earlier, later, and never-treated provinces.

$$\beta_e^w = \sum_g w_g ATT(g, g + e) \quad (2)$$

where w_g weights the groups equally or according to their relative frequencies in the sample of treated provinces. The associated event study plots can be used to see whether treated and control provinces were in parallel trends in the period before the shock.

All of our estimates were obtained using a doubly-robust inverse probability weighting ([Sant'Anna and Zhao, 2020](#)) over a balanced panel of provinces with a maximum length of time, e , of five years around the first drought shock. We used clustered bootstrapped standard errors at the provincial level and accounted for autocorrelation in the data ([Kline and Santos, 2012](#)).

4 Results

4.1 Main Estimates

We begin by presenting plots of the dynamic ATT s in an event study setting. Our preferred estimation focuses on the 12-month SPEI shock as the treatment, and the never-treated provinces as the control group. Panel A in [Figure 2](#) shows the effect on workers employed in the agriculture sector, the sector most exposed to climate change and therefore the sector in which most of the workers are at risk when there is a drought shock. The ATT s support our hypothesis. We observe a significant drop in the share of agricultural workers after the drought shock, which remains statistically significant at 5 percent in all the post-event periods. The magnitude of the impacts increases over time up to the fourth year, when it reaches about 6.5 p.p, then it loses in intensity in the fifth year dropping back down to 5 p.p. Importantly, we also observe the absence of a significant trend in the pre-treatment period; this strengthens the causal interpretation of our results.

We now present the results on the employment rate in other sectors, and on the unemployment rate, which helps to explain the labor market dynamic concurrent with the displacement of

workers employed in the agriculture sector. Panel b) and Panel c) report, respectively, the effect of experiencing a drought shock on the employment share in less-climate sensitive sectors, and on the unemployment rate. We observe a larger, though barely significant, increase in the share of workers employed in non-agriculture sectors (up to 4.5 p.p. after four years) and a smaller but highly significant increase in the share of unemployed, which reaches a maximum and remains stable at about 2.5 p.p. after the third year. This increase highlights that 38 percent of the displaced agricultural workers remain unemployed.

Finally, for the sake of comparison, in [Table 3](#) we present a few aggregated *ATT* measures obtained starting from the group-specific *ATT* and for several control groups, as explained in [Section 3](#). In Panel A, we show the *ATTs* using the never treated provinces as control group, while in Panel B we report *ATTs* when the not-yet-treated provinces are included. In both cases, we show the simple group-weighted *ATT* observed over all groups and periods⁶ and an aggregation of all the point estimates for the post and pre-treatment periods obtained in the event study setting.⁷

The aggregated parameters in Panel A confirm what we observed above. Considering all periods and groups, we observe that the share of employment in agriculture in the treated provinces is about 4.3 p.p. lower, with respect to the difference with the never treated provinces in the pre-shock period, than it would have been if the drought had not occurred. At the same time, there is a nonsignificant larger share of 2.5 p.p. in the employment rate in other economic sectors. We also show that the unemployment rate of shocked provinces is significantly larger by about 1.7 p.p. The aggregation of *ATT* parameters represented in the event study plots points to the same direction and magnitude as the simple *ATT*. Importantly, we observe an average of virtually-zero and non-significant effects over the entire pre-treatment period, which supports the causal interpretation of our treatment effects. In the same manner, parameters

⁶ The *ATTGs* are available from the authors upon request.

⁷ For the estimations with the never treated provinces, these correspond to an average of the dynamic parameters observed in [Figure 2](#).

in Panel B confirm that, even including the not yet treated provinces as the control group, the magnitude and direction of *ATTs* do not change, except for the aggregate *ATTs* of the event study, which are slightly larger for both employment in the agriculture sector and the unemployment rate.

4.2 Effects of Heterogeneity

In this section we explore the effects of heterogeneity by analyzing the impacts along four important margins, i.e. age, gender, educational level and formal vs. informal jobs.

Age – To begin with, [Figure 3](#) shows the heterogeneous effects across five different age groups. The drought impact appears much stronger and significant among middle-aged workers (18-50), among whom we observe a drop of about 2.5 p.p. in the agricultural employment rate in the second year, reaching about 7 p.p. in the fourth year. At the same time, the employment rate in other sectors moves in the opposite direction, though with a nonsignificant magnitude. We also observe an increase in the unemployment rate, with a coefficient that becomes significant and stable at about 2.5 p.p. after the third year, which signals a reallocation failure for only a small share of middle-aged workers. We find nonsignificant effects both for workers under the legal age (15-17) and for workers close to retirement (51-60), with the exception of a sharp but temporary increase in the unemployment rate in the group of very young workers in the first year after the shock.

Gender – [Figure 4](#) shows the heterogeneous effects by gender. While overall we find significant effects in both females and males, the temporal dynamic appears very different. The drop in the agricultural employment rate is U-shaped for female workers, reaching 9.8 p.p. in the fourth year, vis-à-vis 6 p.p. for males. However, among female workers the effect decreases to about 5.1 p.p. after five years, while it steadily increases for males. As a consequence of the lack of significant evidence for reallocation in other sectors, the unemployment rate for females increases up to 4.9 p.p., more than twice what is observed for males.

Education – Figure 5 shows the heterogeneous effects by educational level. Despite less robust results, we find that most of the effects are delayed and driven by workers without a formal educational qualification. In this group, we observe a large and temporary decrease in the agricultural employment rate, which reached a maximum in the fourth year (about 8 p.p.). Interestingly, for this group, we also estimated a symmetric dynamic for the employment rate in other sectors (about 9 p.p.). There is no evidence of a sizable change in the unemployment rate, which suggests that although these workers are the most exposed to agricultural job displacement, because they are low-skilled, they can easily relocate themselves. The results for the other levels of education are imprecise, with pre-trends that appear less aligned to zero.

Formal vs. informal employment – One of the most heterogeneous effects emerges when we look at formal and informal workers, reported in Figure 6. We observe that formal agricultural workers are only weakly and non-significantly affected by drought shocks. Consequently, we do not find any evidence of reallocation of these workers to other sectors. On the contrary, we observe a strong and highly significant drop of workers informally employed in agriculture, and a reallocation effect of similar magnitude and temporal dynamic toward the other economic sectors. More specifically, the drop in the agriculture employment rate is about -2.5

p.p. already during the first year after the shock and reaches a maximum of about -8 p.p. after four years, with a symmetric dynamic of the employment rate in other sectors.

4.3 Treatment Intensity

A relevant issue for policy makers and scholars is whether there is a threshold in the intensity of the shock that significantly affects the labor market. Additional knowledge about such a potential threshold could indeed help better set and target policy response and reduce the underlying uncertainty involved in addressing climate impacts. In this section we address this

important point by looking at how local labor markets in Morocco have responded to droughts of different severity as measured by varying SPEI values. We calculate dummy indicators for SPEI bins of 0.05 s.d. in a range $-2.3 - 1.3$ s.d. According to the classification reported in [Table A1](#), this range captures droughts from very moderate to extreme intensity. [Figure 7](#) plots the effects by treatment intensity in the three outcomes of interest: the employment rate in agriculture (Panel A); the employment rate in other sectors (Panel B); and the overall unemployment rate (Panel C). The first important evidence emerging from these figures is the absence of effects for drought classified as ‘moderate’ (SPEI ranging from -1.5 to -1 s.d.). As the shock increases in intensity, we observe a rapid and significant decline in the agricultural employment rate (Panel A). Specifically, for SPEI values lower than about -1.8 s.d., we observe a drop of about 5 p.p., which remains stable and significant for shocks of greater intensity. At the same time, for similar SPEI values, we observe a corresponding increase in the unemployment rate of about 2 p.p., which then steadily increases up to about 3.5 p.p. as the shock becomes more severe. With SPEI values lower than -2 s.d.,⁸ the number of shocks becomes lower or even absent in many provinces, and we lose precision in the estimates: both the drop in the agricultural employment rate and the unemployment rate show larger standard errors.

5 Robustness Checks

Effects of short-term drought – The impacts of drought can be different depending on the timescale considered. In the previous section, we presented the effects of medium-term drought shocks using an SPEI calculated at 12 months. In this section, we replicate the main analysis using a 3-month SPEI to test the robustness of our findings when considering drought shocks of shorter duration. [Figure A1](#) shows that estimates with a treatment of a 3-month SPEI produce a very similar pattern of results in magnitude, but they are much less precise.

⁸ It is worth noting that an SPEI value of -2 s.d. is associated with a drought event occurring globally once every 50 years.

We observe a maximum decrease of about -0.8 p.p. in the agricultural employment rate after four years (significant at 10 percent) and an increase in the employment rate of 0.75 p.p. after six years (significant at 1 percent), while the employment rate in other sectors reaches a maximum increase of about 0.04 p.p. in the fourth year. Overall, the analysis of drought shocks of the same magnitude but shorter duration confirms the findings we obtained using a 12-month SPEI, though with less significant impacts.

Reshuffling of shocks – An additional check we present is a falsification test that alters the combinations of shocks across years. We therefore run our preferred regression specification on a set of randomized shock years, maintaining the same composition of treated and control provinces that were used in the original sample. Since drought occurs in specific years, by altering the time of onset one would expect to find non statistically significant effects. In [Figure 8](#) we report event study results for the three outcomes considered, from which we observe the absence of significant effects after the shock occurs. In addition, estimates of aggregate *ATT*s, reported in [Table A2](#), confirm that the placebo results using both 3- and 12-month SPEIs, do not statistically differ from zero. Altogether, these tests provide evidence that our main estimates are not driven by some underlying systematic trend in the data, and that the validity of our identification strategy is warranted.

Conditional parallel trend estimates – Our estimates in [Section 4](#) assume that the parallel trend assumption holds unconditionally. We therefore present conditional parallel trend parameters, controlling for a set of observed provincial characteristics of the working age population, that is age, female population, educational level and urban population. Comparing those *ATT*s with the parameters in [Table 3](#), we observe no differences in the *ATT* of employment in the agriculture sector, while slightly less evidence is detectable for the unemployment rate. To strengthen the causal interpretation of our conditional estimates, [Table A3](#) shows a balancing test of the covariates adopted in the conditional estimates, in which we regress each control variable on the treatment; that is, the drought shocks measured

with the 12-month SPEI values lower than -2 s.d., controlling for year and province fixed effects, and regional-specific time trends. With the exception of educational level, which, however, is only weakly statistically significant, none of the estimated coefficients are significant, confirming that the characteristics for which we controlled are predetermined and are only contributing to increasing the precision of our estimates.

6 Discussion and Policy Implications

Our estimates assess the negative effect of severe drought on the labor force in Morocco from 2000 to 2009. The obtained results should be interpreted as a lower bound of the stronger displacement effect and reallocation failure, accompanied by higher unemployment, which may occur in the future as a combination of demographic expansion, greater climate variability and a large dependence on climate-exposed sectors. This is for two main reasons. First, our study considers a period during which climate variability has been more limited, both in Morocco and, generally in the MENA region, than it has been in the subsequent decade, and compared to recent estimates of future trends ([Pörtner et al., 2022](#)). Secondly, Morocco—like other MENA countries—has not experienced a gradual shift of labor and capital from agriculture to manufacturing and services, and the industry value added has remained largely unchanged over the past 20 years ([Moussir and Chatri, 2020](#)).

Another important consideration comes from the significant heterogeneity in the effects we have found, which strongly penalizes women and, to a lesser extent, less educated, younger, and informal workers. This evidence signals the presence of pronounced climate injustice in the labor markets of Morocco. In particular, women—who are primarily informally employed—represent the population group for which we observe the largest displacement effect and the weakest adjustment mechanism in terms of reallocation to other economic sectors. Middle-aged workers (ages 18-50) also face significant displacement but, at the same time, they seem to experience limited market frictions when looking for a job in other sectors. A similar

dynamic is observed for workers without formal education, who mainly represent the low-skilled labor force. Considering the ‘premature de-industrialization’, industry is not able to absorb the excess of labor supply from the agriculture sector. Therefore, displaced workers are more likely to relocate in the tertiary sector, mainly in tourism, which does not rely on local demand. On the contrary, we observe an effective relocation process in informal employment, in which the dynamic between the employment rate in the agriculture and the other sectors is perfectly symmetric. This evidence is in line with empirical studies that show that informal workers react counter-cyclically during market shocks ([Johannes et al., 2009](#); [Loayza and Rigolini, 2011](#)); this represents a safety net for displaced workers, who benefit from a greater flexibility in finding jobs in alternative economic activities. Still, even though informal employment may represent a temporary asset for displaced workers in agriculture, in the mid- and long-run perspective this translates into a weaker labor market attachment and a considerable obstacle to the necessary structural transformation of the labor market ([Lopez-Acevedo et al., 2021](#)).

The last consideration relates to the analysis of shock intensity and the associated effects. This set of results can help policy makers address the impact of droughts on the basis of a standard classification of shock intensity, which has been observed to produce significant effects in the labor market due to specific intensity thresholds. In particular, we find significant and negative effects in the labor market only for severe and extreme drought shocks —those corresponding to SPEI values lower than about -1.8 s.d. At these intensities, we observe a substantial drop in the share of workers employed in agriculture and a simultaneous increase in the unemployment rate. On the contrary, we do not detect significant negative effects for drought shocks classified as moderate (SPEI values greater than 1.7 s.d.). In light of this evidence and considering the increasing trend in drought events in MENA, policy makers should consider interventions to mitigate the displacement effect of the most extreme events; it should be noted however, that previous studies have documented that milder events do not

come without costs in terms of loss of productivity ([Bedi et al., 2021](#)).

7 Conclusions

In this paper we have explored the impact of severe drought in the local labor markets of Moroccan provinces during the period 2000-2009. We used nationally representative labor force surveys and the SPEI, a state-of-the-art climate indicator, to estimate the causal effects of severe drought shocks on labor market dynamics by observing the employment rate in agriculture and in other less-exposed sectors and the unemployment rate. Our staggered diff-in-diff estimates shed light on the effects occurring in Morocco, which is considered a climate hotspot and for which little evidence is available. Importantly, Morocco is a good case study to investigate the interacted effects of climate change on the local labor markets in a socioeconomic context characterized by high demographic expansion, a growing labor force and structural market frictions.

We found that in provinces that experienced a severe and prolonged drought, measured by a 12-month SPEI value lower than -2 s.d., the share of employment in agriculture decreased by about 4.3 p.p. on average. The effect took place in the aftermath of the shock and was long-lasting: the coefficients remain significant and negative up to 5 years after the drought occurred. Moreover, we observed a contemporaneous and significant increase in the unemployment rate, which signals that those shocked workers found difficulty in accessing alternative jobs in less climate-exposed sectors. These figures point to general reallocation failure as a consequence of severe drought shocks, a failure which is more pronounced for the most vulnerable workers. This generates concerns about an exacerbation of climate injustice in the future, if we also consider the historical trend in MENA countries characterized by large unemployment among youth and females ([Alfani et al., 2020](#)). However, our study needs to be hedged with some caveats. First, the results rely on a time period (2000-2009) that is only relatively recent, because of missing information on workers' location in the

subsequent labor force surveys. Therefore, we cannot extend the validity of the results to more recent years, in which the impact of drought events became more frequent and intense. In this respect, our estimates should be interpreted as an early evaluation of the effects that severe droughts may have in the mid-run. Second, the individual data employed in this study do not allow for tracking individuals over time. This hinders the possibility to directly observe individual out-migration as a response to shock; nevertheless, our outcome variables are normalized to the local labor force and therefore represent the net of migration effects. Despite these limitations, our results deliver important implications for policy makers as, to the best of our knowledge, this is the first quasi-experimental study that explores the labor market effects of severe drought shocks.

In Morocco, where structural transformation of the economy is slow, and low growth of industry prevents the labor force from being efficiently reallocated, recurrent droughts may accelerate the detrimental interaction between a changing climate and the local socioeconomic context. Our study offers new evidence to help policy makers properly tackle and assess the expected climate impacts by planning and developing safety-net measures and reforms. The latter should be targeted towards the most vulnerable population groups, i.e., women and informal workers, in order to create the conditions for a more even distribution of the impacts and costs of climate change.

References

- Albert, C., Bustos, P., and Ponticelli, J. (2021). The effects of climate change on labor and capital reallocation. Technical report, National Bureau of Economic Research.
- Alfani, F., Arslan, A., McCarthy, N., Cavatassi, R., and Sitko, N. (2021). Climate resilience in rural Zambia: evaluating farmers' response to El Nino-induced drought. *Environment and Development Economics*, 26(5-6):582–604.
- Alfani, F., Clementi, F., Fabiani, M., Molini, V., and Valentini, E. (2020). Once NEET, always NEET? A synthetic panel approach to analyze the Moroccan labor market. *World Bank Policy Research Working Paper*, (9238).
- Aragón, F. M., Oteiza, F., and Rud, J. P. (2021). Climate change and agriculture: Subsistence farmers' response to extreme heat. *American Economic Journal: Economic Policy*, 13(1):1– 35.
- Asfaw, S., Pallante, G., and Palma, A. (2018). Diversification strategies and adaptation deficit: Evidence from rural communities in Niger. *World Development*, 101:219–234.
- Barrett, C. B., Reardon, T., and Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food policy*, 26(4):315–331.
- Bedi, S. M., Azzarri, C., Kotu, B. H., Kornher, L., and von Braun, J. (2021). Scaling- up agricultural technologies: who should be targeted? *European Review of Agricultural Economics*.
- Belhaj, F., Gatti, R., Lederman, D., Sergenti, E. J., Assen, H., Lotfi, R., and Mousa, M. E. (2022). A new state of mind.

- Blunden, J. and Arndt, D. (2020). State of the climate in 2019. *Bulletin of the American Meteorological Society*, 101(8):S1–S429.
- Branco, D. and Feres, J. (2021). Weather shocks and labor allocation: evidence from rural brazil. *American Journal of Agricultural Economics*, 103(4):1359–1377.
- Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2014). The unequal effects of weather and climate change: Evidence from mortality in India. *Cambridge, United States: Massachusetts Institute of Technology, Department of Economics. Manuscript.*
- Callaway, B. and Sant’Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.
- Cattaneo, C., Beine, M., Fröhlich, C. J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., Millock, K., Piguet, E., and Schraven, B. (2020). Human migration in the era of climate change. *Review of Environmental Economics and Policy*.
- Cattaneo, C. and Peri, G. (2016). The migration response to increasing temperatures. *Journal of Development Economics*, 122:127–146.
- Chiang, F., Mazdidasni, O., and AghaKouchak, A. (2021). Evidence of anthropogenic impacts on global drought frequency, duration, and intensity. *Nature communications*, 12(1):1–10.
- Clementi, F., Khan, H. A. D., Molini, V., Schettino, F., and Soudi, K. (2019). Polarization and its discontents: Morocco before and after the Arab spring. *World Bank Policy Research Working Paper*, (9049).
- Colmer, J. (2021). Temperature, labor reallocation, and industrial production: Evidence from india. *American Economic Journal: Applied Economics*, 13(4):101–24.
- Cramer, W., Guiot, J., Fader, M., Garrabou, J., Gattuso, J.-P., Iglesias, A., Lange, M. A., Lionello, P., Llasat, M. C., Paz, S., et al. (2018). Climate change and interconnected risks to sustainable development in the Mediterranean. *Nature Climate Change*, 8(11):972–980.

- Day, E., Fankhauser, S., Kingsmill, N., Costa, H., and Mavrogianni, A. (2019). Upholding labour productivity under climate change: an assessment of adaptation options. *Climate policy*, 19(3):367–385.
- Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, 52(3):740–98.
- 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.
- Di Falco, S., B Kis, A., and Viarengo, M. (2022). Cumulative climate shocks and migratory flows: Evidence from sub-Saharan Africa.
- Di Falco, S., Veronesi, M., and Yesuf, M. (2011). Does adaptation to climate change provide food security? a micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3):829–846.
- Dillon, A., Mueller, V., and Salau, S. (2011). Migratory responses to agricultural risk in northern Nigeria. *American Journal of Agricultural Economics*, 93(4):1048–1061.
- Elmallakh, N. and Wodon, Q. (2021). Climate shocks, migration, and labor markets: A gender analysis from west Africa. Technical report, GLO Discussion Paper.
- Emerick, K. (2018). Agricultural productivity and the sectoral reallocation of labor in rural India. *Journal of Development Economics*, 135:488–503.
- Fischer, E., Sippel, S., and Knutti, R. (2021). Increasing probability of record-shattering climate extremes. *Nature Climate Change*, 11(8):689–695.
- Foster, A. D. and Rosenzweig, M. R. (2007). Economic development and the decline of agricultural employment. *Handbook of development economics*, 4:3051–3083.

- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.
- Gray, C. and Mueller, V. (2012). Drought and population mobility in rural ethiopia. *World development*, 40(1):134–145.
- Gröger, A. and Zylberberg, Y. (2016). Internal labor migration as a shock coping strategy: Evidence from a typhoon. *American Economic Journal: Applied Economics*, 8(2):123–53.
- Hallegatte, S., Fay, M., and Barbier, E. B. (2018). Poverty and climate change: Introduction. *Environment and Development Economics*, 23(3):217–233.
- Haltiwanger, J., Scarpetta, S., and Schweiger, H. (2014). Cross country differences in job reallocation: The role of industry, firm size and regulations. *Labour Economics*, 26:11–25.
- ILO (2018a). The employment impact of climate change adaptation - g20 report.
- ILO (2018b). World employment and social outlook 2018: Greening with jobs.
- Jessoe, K., Manning, D. T., and Taylor, J. E. (2018). Climate change and labour allocation in rural Mexico: Evidence from annual fluctuations in weather. *The Economic Journal*, 128(608):230–261.
- Johannes, J. et al. (2009). *Development Centre Studies Is Informal Normal? Towards More and Better Jobs in Developing Countries: Towards More and Better Jobs in Developing Countries*. OECD Publishing.
- Kaczan, D. J. and Orgill-Meyer, J. (2020). The impact of climate change on migration: a synthesis of recent empirical insights. *Climatic Change*, 158(3):281–300.
- Key, N. and Sneeringer, S. (2014). Potential effects of climate change on the productivity of us dairies. *American Journal of Agricultural Economics*, 96(4):1136–1156.

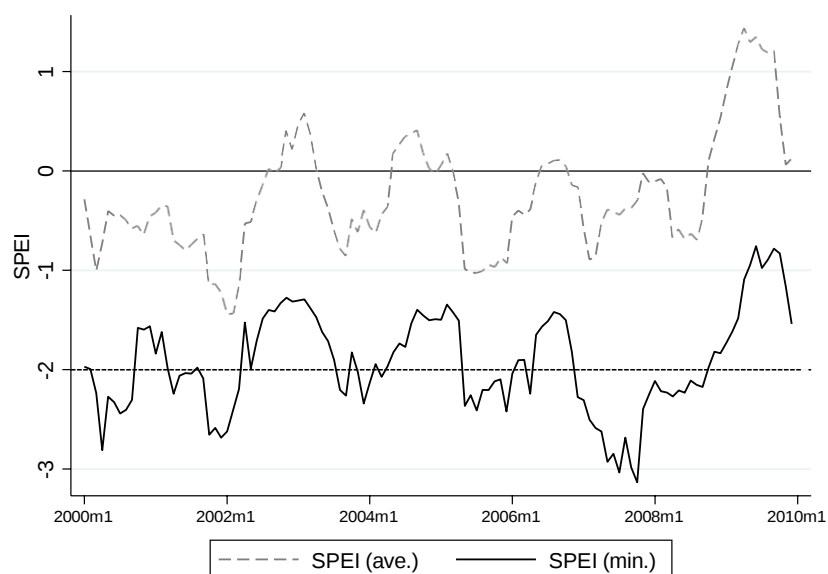
- Kline, P. and Santos, A. (2012). A score based approach to wild bootstrap inference. *Journal of Econometric Methods*, 1(1):23–41.
- Li, C. and Pan, Z. (2021). How do extremely high temperatures affect labor market performance? evidence from rural China. *Empirical Economics*, 61(4):2265–2291.
- Loayza, N. V. and Rigolini, J. (2011). Informal employment: safety net or growth engine? *World Development*, 39(9):1503–1515.
- Lopez-Acevedo, G., Betcherman, G., Khellaf, A., and Molini, V. (2021). *Morocco's Jobs Landscape: Identifying Constraints to an Inclusive Labor Market*. World Bank Publications.
- Marchiori, L., Maystadt, J.-F., and Schumacher, I. (2012). The impact of weather anomalies on migration in sub-Saharan Africa. *Journal of Environmental Economics and Management*, 63(3):355–374.
- McGuirk, E. and Burke, M. (2020). The economic origins of conflict in africa. *Journal of Political Economy*, 128(10):3940–3997.
- Moriondo, M., Argenti, G., Ferrise, R., Dibari, C., Trombi, G., and Bindi, M. (2016). Heat stress and crop yields in the Mediterranean basin: impact on expected insurance payouts. *Regional Environmental Change*, 16(7):1877–1890.
- Moussir, C.-E. and Chatri, A. (2020). Structural change and labour productivity growth in morocco. *Structural Change and Economic Dynamics*, 53:353–358.
- Mueller, V., Gray, C., and Kosec, K. (2014). Heat stress increases long-term human migration in rural Pakistan. *Nature climate change*, 4(3):182–185.
- Niang, I., Ruppel, O. C., Abdrabo, M. A., Essel, A., Lennard, C., Padgham, J., and Urquhart, P. (2014). Africa. climate change 2014: impacts, adaptation, and vulnerability. part b: regional aspects. contribution of working group ii to the fifth assessment report of the intergovernmental panel on climate change. *Climate Change 2014: Impacts, Adaptation*

- and Vulnerability: Part B: Regional Aspects: Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, pages 1199–1266.
- Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., and Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, 11(4):306–312.
- Pörtner, H.-O., Roberts, D. C., Adams, H., Adler, C., Aldunce, P., Ali, E., Begum, R. A., Betts, R., Kerr, R. B., Biesbroek, R., et al. (2022). Climate change 2022: Impacts, adaptation and vulnerability. *IPCC Sixth Assessment Report*.
- Sant’Anna, P. H. and Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics*, 219(1):101–122.
- Schleussner, C.-F., Deryng, D., Müller, C., Elliott, J., Saeed, F., Folberth, C., Liu, W., Wang, X., Pugh, T. A., Thiery, W., et al. (2018). Crop productivity changes in 1.5 c and 2 c worlds under climate sensitivity uncertainty. *Environmental Research Letters*, 13(6):064007.
- Sovacool, B. K. (2013). The complexity of climate justice. *Nature Climate Change*, 3(11):959–960.
- Stevanović, M., Popp, A., Lotze-Campen, H., Dietrich, J. P., Müller, C., Bonsch, M., Schmitz, C., Bodirsky, B. L., Humpenöder, F., and Weindl, I. (2016). The impact of high-end climate change on agricultural welfare. *Science advances*, 2(8):e1501452.
- Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.
- Svoboda, M., Hayes, M., Wood, D. A., et al. (2012). Standardized precipitation index user guide.
- 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.

Journal of climate, 23(7):1696–1718.

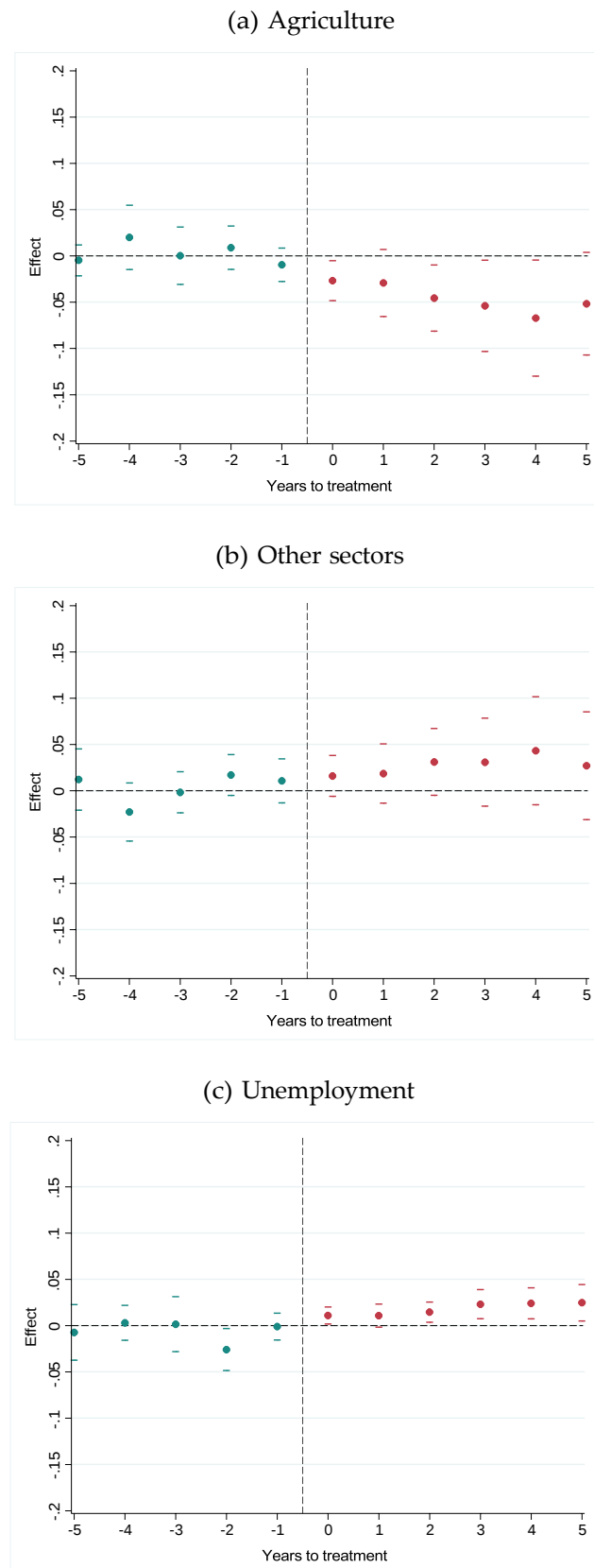
Figures

Figure 1: 12-Month SPEI Trends



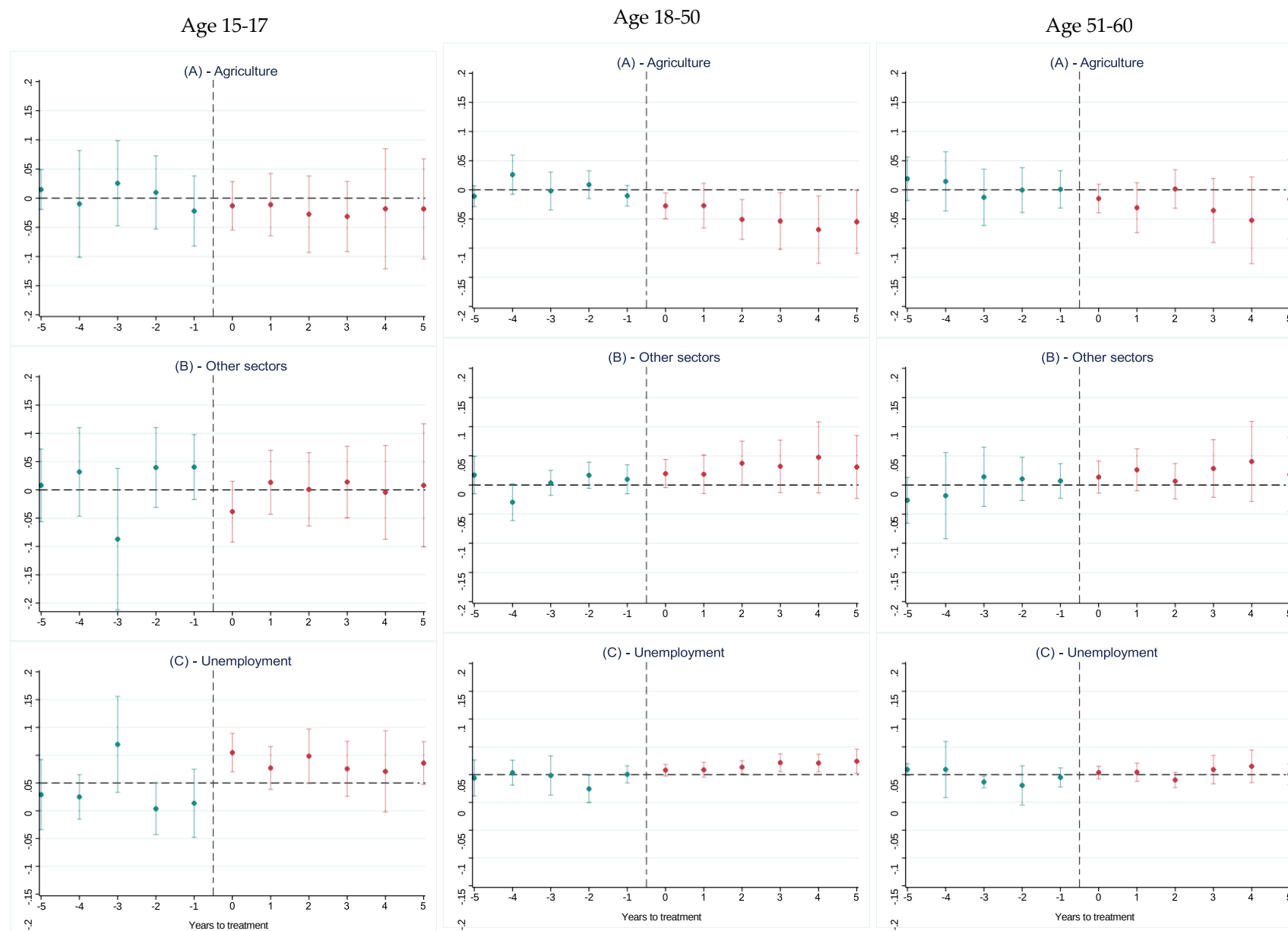
Notes : The figure shows average and minimum SPEI values averaged at the national level from 2000 to 2009.

Figure 2: Effect of Drought Shocks on the Labor Market



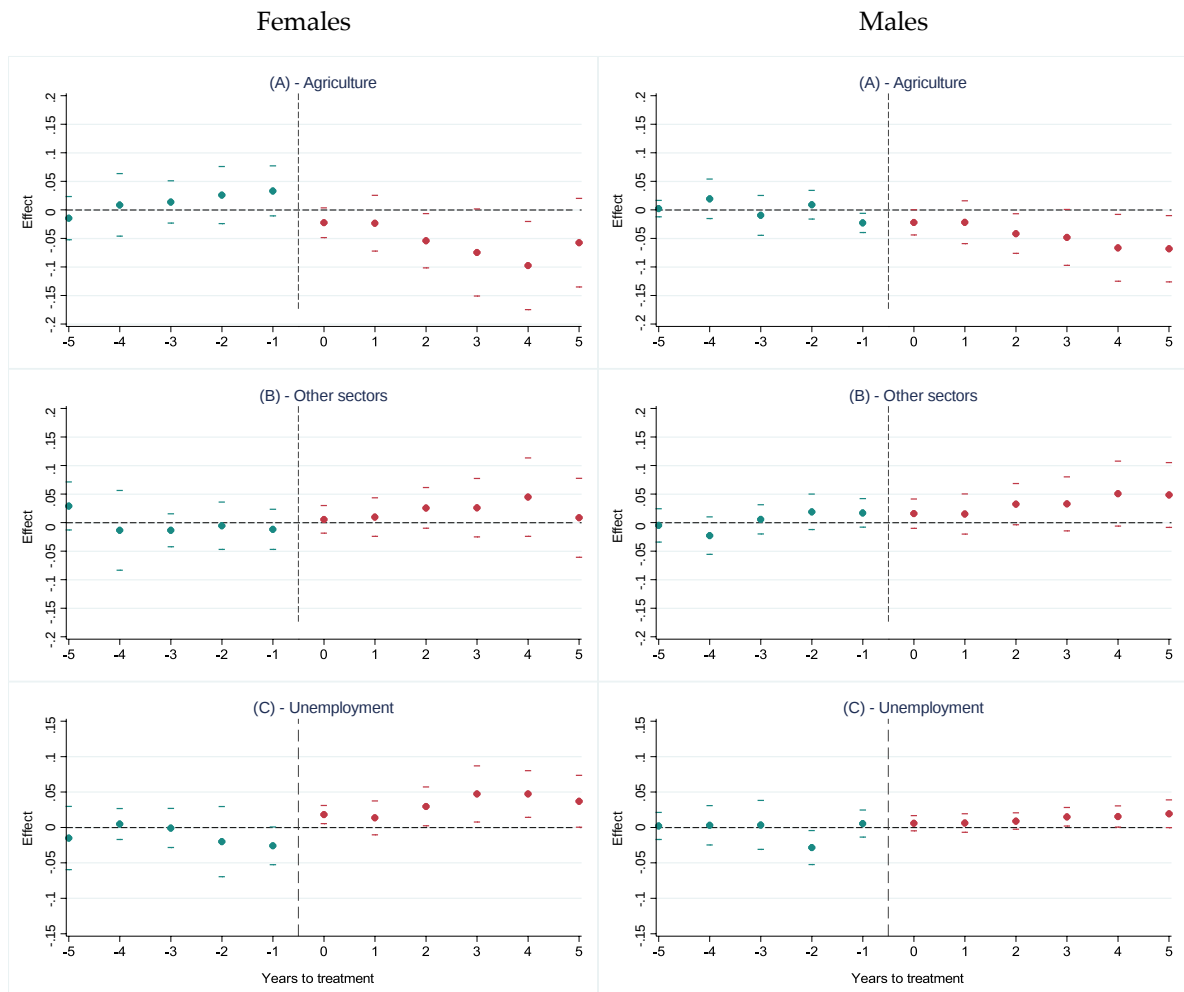
Notes: The figure shows event study estimates of the effect of drought shocks (12-month SPEI ≤ -2 s.d.) on the employment rate in agriculture (panel A), in other sectors (panel B) and the unemployment rate (panel C), over the period 2000-2009. Estimates are obtained using the csdid Stata command by [Callaway and Sant'Anna \(2021\)](#). Bootstrapped (1000 reps.) confidence intervals are at 95 percent.

Figure 3: Effects of Drought Shocks Across Age Groups



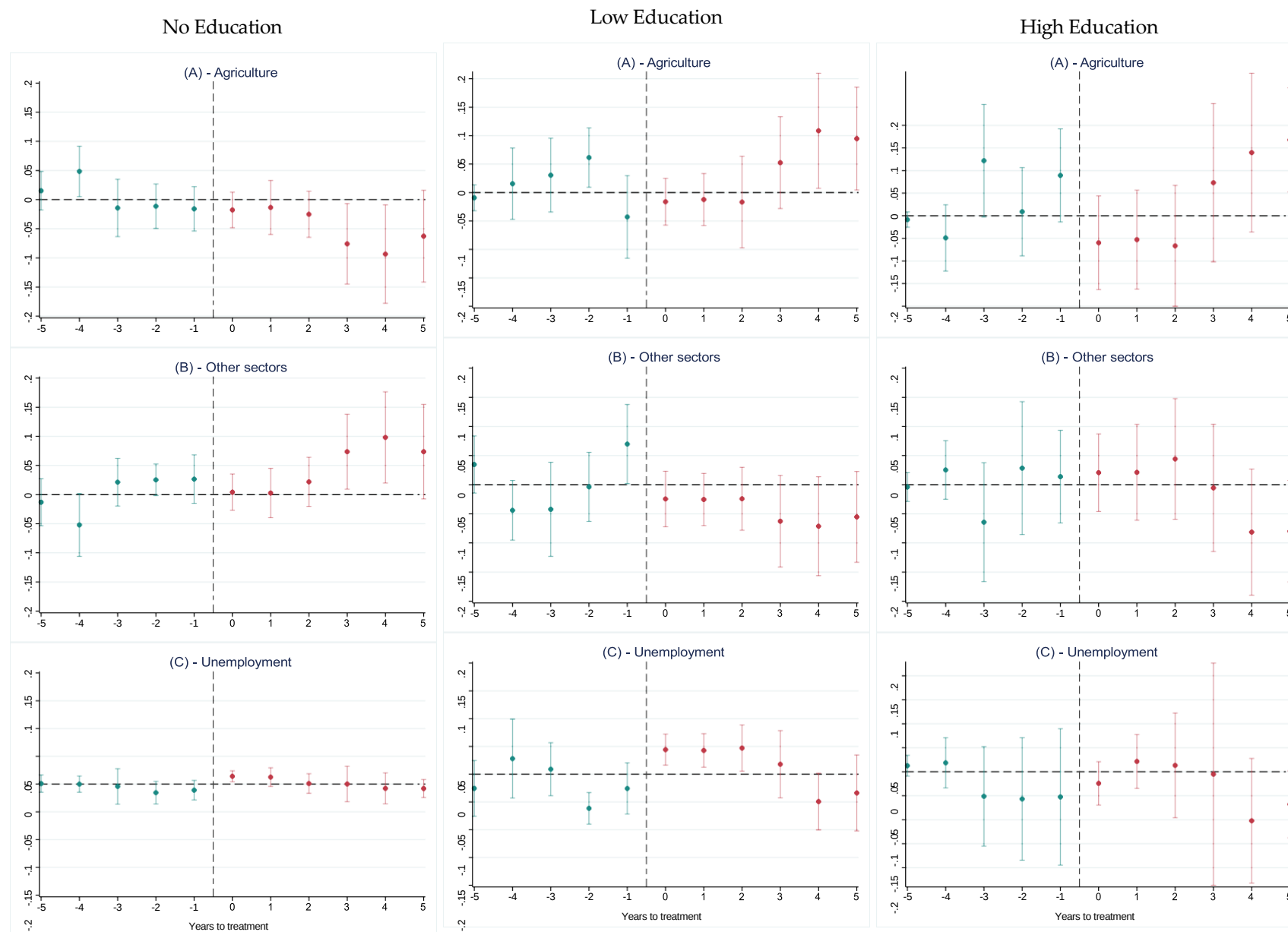
Notes: The figure shows event study estimates of the effect of drought shocks (12-month SPEI ≤ -2 s.d.) on the unemployment rate in the agriculture sector (panel A), in other sectors (panel B) and the unemployment rate (panel C) across three different age groups. Estimates are obtained using the csdid Stata command by [Callaway and Sant'Anna \(2021\)](#). Bootstrapped (1000 reps.) confidence intervals are at 95 percent.

Figure 4: Effects of Drought Shocks by Gender



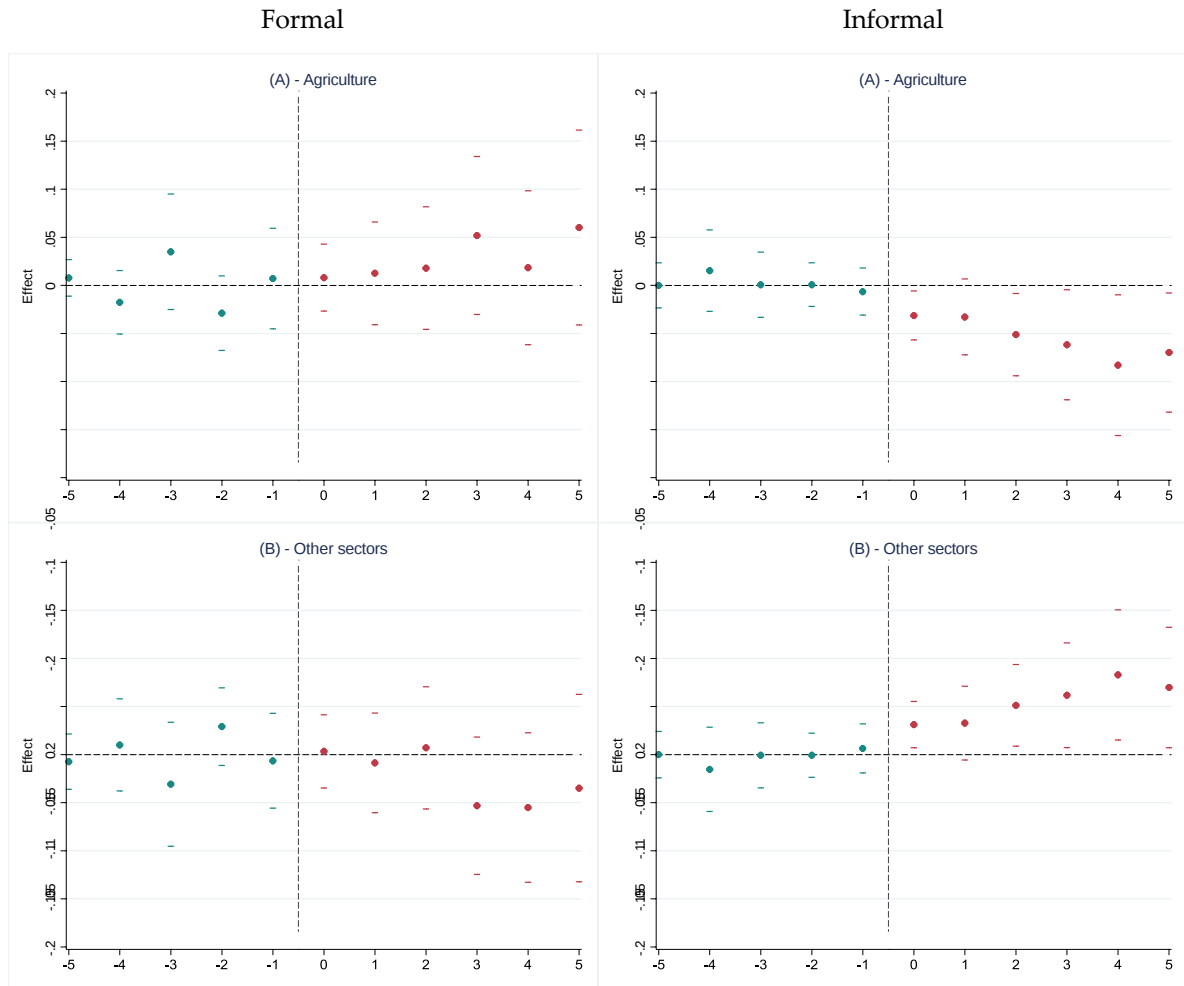
Notes: The figure shows event study estimates of the effect of drought shocks (12-month SPEI ≤ -2 s.d.) on the unemployment rate in the agriculture sector (panel A), in other sectors (panel B) and the unemployment rate (panel C). Estimates are obtained using the csdid Stata command by Callaway and Sant'Anna (2021). Bootstrapped (1000 reps.) confidence intervals are at 95 percent.

Figure 5: Effects of Drought Shocks Across Education Levels



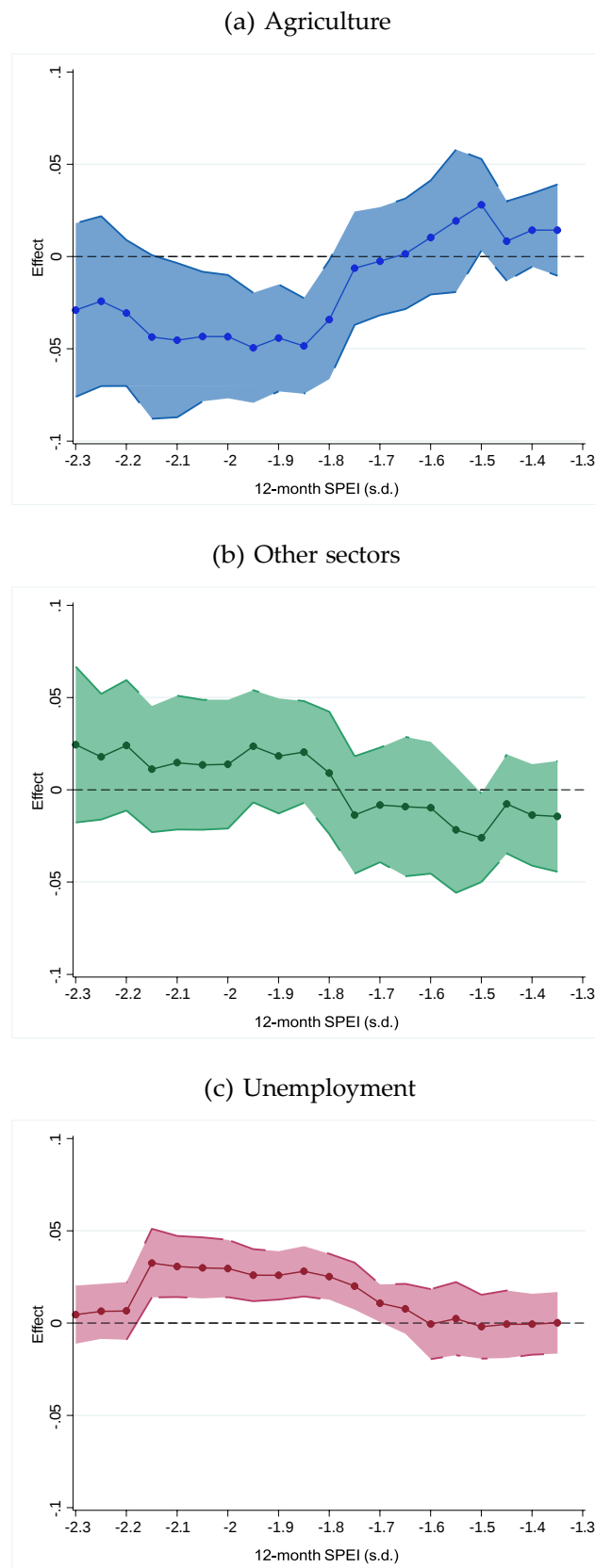
Notes: The figure shows event study estimates of the effect of drought shocks (12-month SPEI ≤ -2 s.d.) on the unemployment rate in the agriculture sector, in other sectors and the unemployment rate over the period 2000-2009 across three different education levels. Estimates are obtained using the csdid Stata command by [Callaway and Sant'Anna \(2021\)](#). Bootstrapped (1000 reps.) confidence intervals are at 95 percent.

Figure 6: Effects of Drought Shocks on Formal and Informal Workers



Notes: The figure shows event study estimates of the effect of drought shocks (12-month SPEI ≤ -2 s.d.) on the employment rate in the agriculture sector (panel A) and in other sectors (panel B) across formal and informal workers. Estimates are obtained using the csdid Stata command by [Callaway and Sant'Anna \(2021\)](#). Bootstrapped (1000 reps.) confidence intervals are at 95 percent.

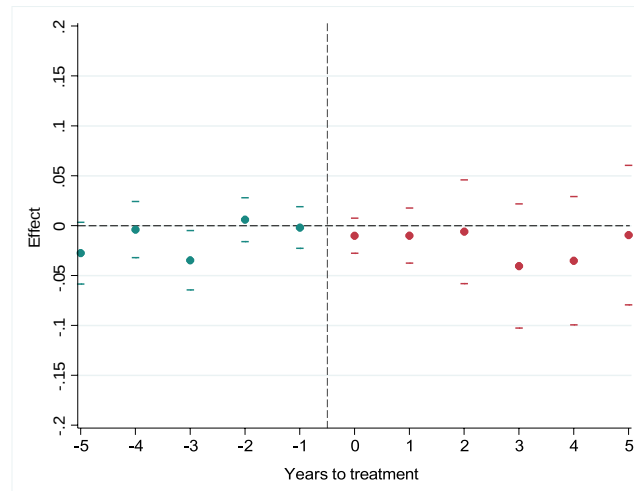
Figure 7: Effects by Intensity of Drought Shock Measured by SPEI



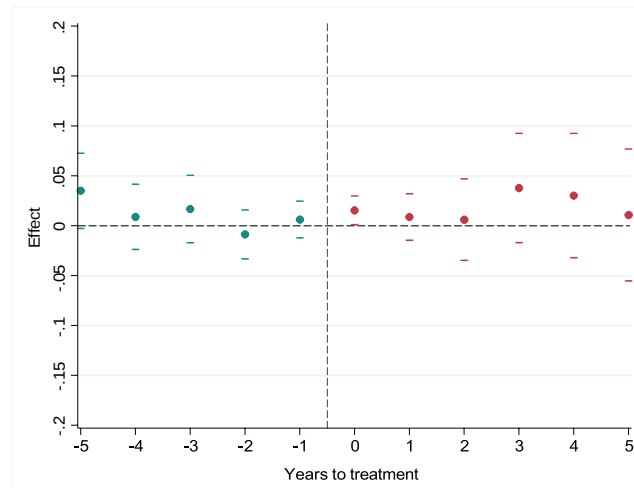
Notes: The figure displays the effects of drought shocks of different intensity, measured by the SPEI, on the employment rate in the agriculture sector (in blue), in other sectors (in green) and the unemployment rate (in red). All diff-in-diffs estimates are obtained by separately regressing the outcomes on binary indicators of SPEI bins of 0.05 s.d. from -2.3 to -1.3 s.d. Estimates are obtained using the `csdid` Stata command by [Callaway and Sant'Anna \(2021\)](#). Bootstrapped (1000 reps.) confidence intervals are at 95 percent.

Figure 8: Placebo estimates

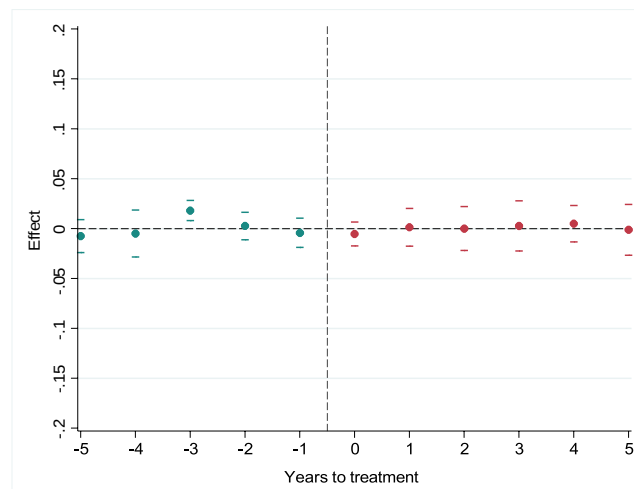
(a) Agriculture



(b) Other sectors



(c) Unemployment



Notes: The figure shows placebo estimates of the effect of drought shocks (12-month SPEI ≤ -2 s.d.) on the unemployment rate in the agriculture sector, in other sectors and on the unemployment rate over the period 2000-2009. Placebo treatments are assigned by reshuffling drought years in each treated province. Estimates are obtained using the `csdid` Stata command by [Callaway and Sant'Anna \(2021\)](#). Bootstrapped (1000 reps.) confidence intervals are at 95 percent.

Tables

Table 1: Treated and Control Provinces Across Years

SPEI ≤ -2 s.d.	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Total
No. of treated provinces	4	8	5	2	0	3	2	3	1	0	28
No. of control provinces	50	42	37	35	35	32	30	27	26	26	26
% of treated provinces/year	8%	19%	14%	6%	0%	9%	7%	11%	4%	0%	54

Notes: Sample size is 540 (54 province $\times$ 10 year cells).

Table 2: Summary Statistics

Variable	Description	Control	Treated	Total
Agriculture	Employment rate in Agriculture	0.37 (0.25)	0.48 (0.19)	0.38 (0.24)
Other Sectors	Employment rate in other sectors	0.51 (0.20)	0.42 (0.13)	0.50 (0.20)
Unemployment	Unemployment rate	0.12 (0.07)	0.10 (0.07)	0.12 (0.07)
Females	Share of active females	0.28 (0.09)	0.32 (0.07)	0.28 (0.09)
Age 15-17	Share of population ages 15-17	0.02 (0.01)	0.02 (0.01)	0.02 (0.01)
Age 18-50	Share of population ages 18-50	0.26 (0.04)	0.25 (0.03)	0.26 (0.04)
Age 51-60	Share of population ages 51-60	0.04 (0.01)	0.04 (0.01)	0.04 (0.01)
No education	Share of working age population without education	0.55 (0.30)	0.58 (0.24)	0.56 (0.30)
Low education	Share of working age population with at least secondary education	0.32 (0.21)	0.32 (0.18)	0.32 (0.21)
High education	Share of working age population with at least tertiary education	0.12 (0.11)	0.10 (0.08)	0.12 (0.11)
Informal job	Share of employees without formal contract	0.85 (0.12)	0.91 (0.06)	0.86 (0.11)
Urban	Share of working age population in urban areas	0.56 (0.28)	0.42 (0.23)	0.55 (0.28)
SPEI at 3 months	Average value of SPEI at 3 months	-0.13 (0.40)	-0.47 (0.52)	-0.17 (0.43)
SPEI at 12 months	Average value of SPEI at 12 months	-0.16 (0.73)	-1.01 (0.51)	-0.25 (0.76)

Notes: Sample size is 540 (54 province $\times$ 10 year cells); Standard deviation in parenthesis.

Table 3: Effect of Drought Shocks on the Labor Market

	(1) Agriculture	(2) Other sectors	(3) Unemployed
<i>Panel A - Control group: never treated provinces</i>			
- Group weighted <i>ATT</i>	-0.043** (0.020)	0.025 (0.019)	0.017*** (0.006)
- Event study <i>ATT</i>	-0.044** (0.019)	0.027 (0.018)	0.017*** (0.006)
- Event study pre treatment	-0.007 (0.005)	0.008 (0.006)	-0.001 (0.003)
<i>Panel B - Control group: never and not-yet treated provinces</i>			
- Group weighted <i>ATT</i>	-0.043** (0.020)	0.026 (0.019)	0.018*** (0.006)
- Event study <i>ATT</i>	-0.047** (0.019)	0.024 (0.029)	0.024*** (0.009)
- Event study pre treatment	-0.002 (0.006)	0.004 (0.006)	-0.007 (0.005)
Obs.	500	500	500

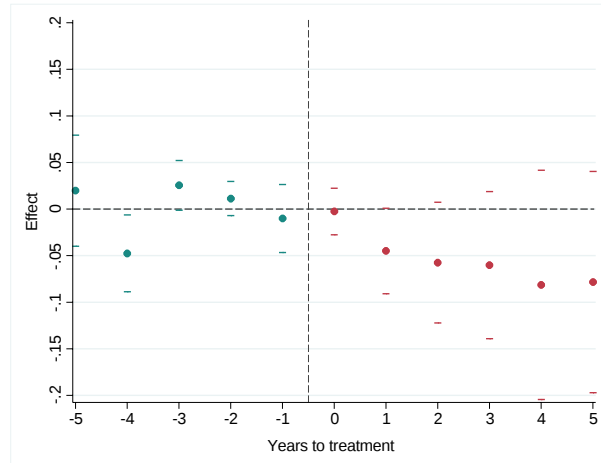
Notes: The table reports panel diff-in-diffs estimates of the effect of drought shocks (12-month SPEI ≤ -2 s.d.) on the employment rate in agriculture (1), in other sectors (2) and the unemployment rate (3), over the period 2000-2009. Panel A shows aggregated parameters when the control group comprises never treated provinces, while Panel B includes not-yet treated provinces. In both the panels, we report the weighted average (by group size) of *ATT* for all groups across all periods, an aggregate parameter of the *ATT*s estimated in the dynamic diff-in-diff (event study) and the average value of the pre-treatment parameters. Estimates are obtained using the *csdid* Stata command by [Callaway and Sant'Anna \(2021\)](#) with double-robust inverse probability (*driptw*) estimand. Always treated provinces are excluded. Aggregation method for *ATT* is based on *wildbootstrap* standard errors with 1000 replications. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix

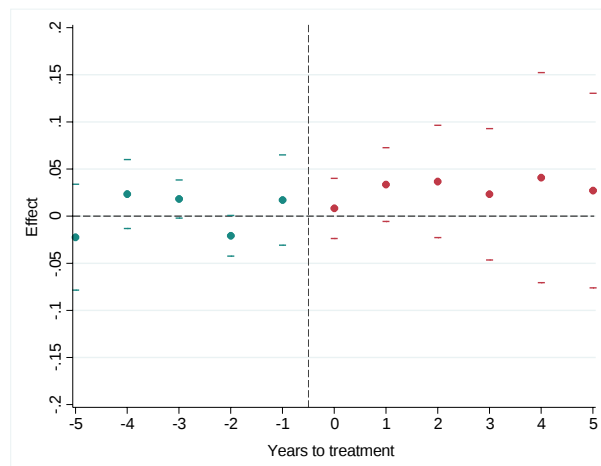
Appendix Figures

Figure A1: Effect of Drought Shocks on Labor Demand - 3-month SPEI

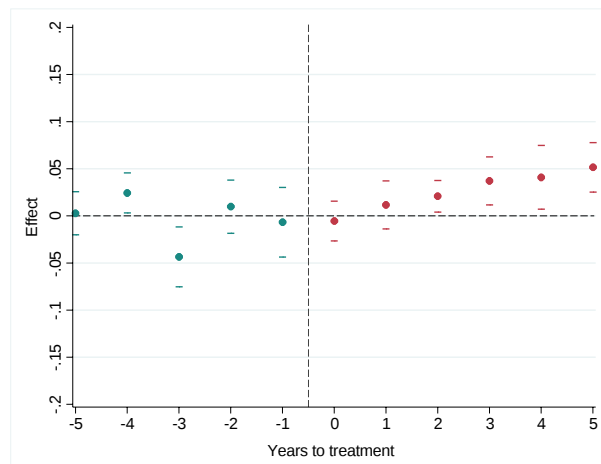
(a) Agriculture



(b) Other sectors



(c) Unemployment



Notes : The figure shows event study estimates of the effect of drought shocks (3-month SPEI ≤ -2 s.d.) on the employment rate in agriculture (panel A), in other sectors (panel B) and the unemployment rate (panel C), over the period 2000-2009. Estimates are obtained using the csdid Stata command by [Callaway and Sant'Anna \(2021\)](#). Bootstrapped (1000 reps.) confidence intervals are at 95 percent.

Appendix Tables

Table A1: Drought Classification Based on the SPEI

Drought category	SPEI range
Extreme wet	$\text{SPEI} \geq 2.0$
Severe wet	$1.5 \leq \text{SPEI} < 2$
Moderate wet	$1.0 \leq \text{SPEI} < 1.5$
Normal	$-1.0 < \text{SPEI} < 1.0$
Moderate drought	$-1.5 < \text{SPEI} \leq -1.0$
Severe drought	$-2.0 < \text{SPEI} \leq -1.5$
Extreme drought	$\text{SPEI} \leq -2.0$

Notes: Source: <https://olc.worldbank.org/system/files/Drought%20Indices-EO4SD%20CR%20SPEI%20index%20products.pdf>

Table A2: Placebo Estimates of the Effect of Drought Shocks

	(1) Agriculture	(2) Other sectors	(3) Unemployment
Panel A: <i>ATT</i> (12-month SPEI)	-0.017 (0.020)	0.018 (0.020)	-0.000 (0.009)
Obs.	480	480	480
Panel B: <i>ATT</i> (3-month SPEI)	-0.017 (0.022)	0.018 (0.019)	-0.000 (0.010)
Obs.	480	480	480

Notes: The table reports placebo diff-in-diffs estimates of the effect of drought shocks using 12-month SPEI (Panel A) and 3-month SPEI (Panel B) with shock set at -2 s.d. on the employment rate in agriculture (1), in other sectors (2) and the unemployment rate (3), over the period 2000-2009. *ATT* is the overall average treatment effect on the treated. Placebo treatments are assigned by reshuffling drought years in each treated province. Estimates are obtained using the *csdid* Stata command by Callaway and Sant'Anna (2021) with double-robust inverse probability (*dripw*) treatment model. Always treated provinces are excluded. Aggregation method for ATT is based on *wildbootstrap* standard errors with 1000 replications. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A3: Balancing Test of Population Characteristics

	(1) Age	(2) Female	(3) Education	(4) Urban	(5) Informal
SPEI at 12 months	0.010 (0.088)	-0.011 (0.008)	-0.080* (0.044)	-0.003 (0.005)	0.001 (0.003)
Obs.	540	540	540	540	540
R-squared	0.939	0.882	0.933	0.969	0.944
Province FEs	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES
Region×Year Trend	YES	YES	YES	YES	YES

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%; Standard errors, in parentheses, are clustered on provinces.

Table A4: Effect of Drought Shocks on the Labor Market - Conditional Estimates

	(1) Agriculture	(2) Other sectors	(3) Unemployed
<i>Panel A - Control group: never treated provinces</i>			
- Group weighted <i>ATT</i>	-0.041** (0.023)	0.033 (0.022)	0.008 (0.007)
- Event study <i>ATT</i>	-0.040** (0.021)	0.027 (0.019)	0.013* (0.007)
- Event study pre-treatment	0.001 (0.007)	0.006 (0.007)	0.008 (0.006)
<i>Panel B - Control group: never and not-yet treated provinces</i>			
- Group weighted <i>ATT</i>	-0.042** (0.019)	0.033* (0.019)	0.006 (0.007)
- Event study <i>ATT</i>	-0.041** (0.017)	0.029 (0.024)	0.012 (0.008)
- Event study pre treatment	-0.002 (0.005)	0.007 (0.007)	-0.008 (0.005)
Obs.	500	500	500

Notes: The table reports panel conditional diff-in-diffs estimates of aggregate parameters of the effect of drought shocks (12-month SPEI ≤ -2 s.d.) on the employment rate in agriculture (1), in other sectors (2) and the unemployment rate (3), over the period 2000-2009. Panel A shows aggregated parameters when the control group comprises never treated provinces, while Panel B includes not-yet treated provinces. In both the panels, we report the weighted average (by group size) of *ATT* for all groups across all periods, an aggregate parameter of the *ATT*s estimated in the dynamic diff-in-diff (event study) and the average value of the pre-treatment parameters. The models include the average education level, the female shares, the share of urban areas and the share of informal workers in the province. Estimates are obtained using the *csdid* Stata command by [Callaway and Sant'Anna \(2021\)](#) with double-robust inverse probability (*dripw*) estimand. Always treated provinces are excluded. Aggregation method for *ATT* is based on *wildbootstrap* standard errors with 1000 replications. * significant at 10%; ** significant at 5%; *** significant at 1%.

Data construction

Drought shocks – To build our climate shock measures, we use daily weather data from the Agri-4-Cast (A4C) database described in [Section 2](#). Total rainfall precipitation, minimum and maximum temperatures are input variables to calculate SPEIs at different time scales using the `SPEI` R package. As A4C data come on a grid of 25×25 km, we first calculate SPEIs at 12 and 3 months in each grid point in order to reduce noise due to spatial interpolation. This implies that each province initially has multiple SPEI measures. To obtain province-year shock indicators, we calculate dummy variables to detect SPEI values ≤ -2 s.d. in each grid point, corresponding to severe drought events, and collapse data at province-year cells calculating the maximum value of each point-dummy indicator. The final climate data set is composed of a balanced panel of 54 provinces observed over 10 years with dummy indicators equal to one when a province experiences a severe drought shock in each year. Since shocks occur at different points in time, in our empirical setting we account for variation in the timing of treatment by considering a staggered design, but we do not consider that a province can be exposed to the same shock for multiple periods. This implies that we only consider the first shock.