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Drought and Domestic Violence: Evidence from Rural Chile

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Comisión

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Drought and Domestic Violence: Evidence from rural Chile

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Abstract

The present work explores the effects of drought on the rate of domestic violence complaints in rural districts of Chile using (i) a Differences-in-Differences with fixed-effects approach, (ii) a Dose Treatment that hinges on the districts' primary crops growing season, and (iii) a Triple Differences approach exploiting the crop's water need period. Also, I present an intra-household bargaining model with information asymmetries. It suggests that in the event of a negative income shock to the husband, the rate of domestic violence complaints should decrease, while if the same shock hits the wife, the rate increases. My results show that domestic violence complaints diminish between 2% and 8% when drought hits a location, consistent with the instrumental value theory predictions. In Chile, a drought shock translates into less violence because agriculture is a strongly men-labor intensive industry, which implies, household-wise, that more husbands than wives could suffer a negative income shock under a drought context.

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I Introduction

By March of the present year, the General Directorate of Water (DGA for its initials in Spanish) decreed 136 (39,3%) counties[1] of Chile as areas with water scarcity. According to the Center for Climate and Resiliance Research (2015), almost a quarter of the Chilean mega-drought precipitation deficit is due to anthropic climate change and, with non-negligible probability, is likely to become more frequent. Furthermore, the world is consistently showing a rising interest in climate change and its consequences on global agriculture and the income of developing countries (Damania et al., 2017). Thus, given that previous climate literature has found a clear relationship between weather shocks and conflict (Miguel et al., 2004; Blakeslee & Fishman, 2013; Burke et al., 2015), and domestic violence economic research proposes that income effects translate into violent situations inside the household (Aizer, 2010; Sekhri & Storeygard, 2014; Anderberg et al., 2015); it is in the interest of this work to explore if the drought in rural Chile has affected the number of domestic violence complaints.

International evidence suggests that drought generates both monetary and psychological costs for individuals living in rural areas (Edwards et al., 2009; Sartore et al., 2007; Carroll et al., 2009). The uncertainty, the consequences of drought over the future capacity of the soil, and the underemployment have adverse impacts over the household's well-being and financial position. Sartore et al. (2007) claim that drought can affect family relationships, increasing the household's irritability through stress and worry. They propose that, if these factors become persistent over time, there is a rising probability of developing mental disorders like depression and anxiety.

[1] Known in Chile as *Comunas*.

At a national level, the Centro de Cambio Global UC (2011) suggests that the interannual variability of the supply of water resources is closely related to the fluctuation of production and explains the crops' productive behavior. Additionally, owners of agricultural land in the face of drought tend to reduce their costs, reduce the maintenance of their equipment and machinery, and fire their employees, decreasing the labor opportunities of seasonal workers and the income of farmers (Meza et al., 2010). Particularly, in Chile, drier seasons affect a considerable proportion of the country: approximately 45% of the rural Chilean counties rely economically on agriculture as their primary source of income[2] (Berdegué et al., 2010), and 10.1% of the employment generated in 2019 at the national level came from the agricultural sector - in some regions, such as Maule, O'Higgins, and Araucania, it reached rates higher than 20% (Office of Agricultural Studies and Policies, 2019) -.

Under previous climate literature findings, and considering the Chilean agricultural context, we would expect a positive relationship between drought and intrafamilial abuse. For instance, Sekhri & Storeygard (2014) propose that rainfall shocks (negative or positive) produce negative income effects that lead to increased violence against women. Likewise, under a sociological scope, there is this an underlying belief that unemployment "triggers" violent situations at home (Anderberg et al., 2015). In this line, some sociocultural models of "male backlash" predict that domestic violence would increase if men feel that their traditional gender role gets threatened. For example, under a case where the husband loses his job and cannot provide money to the household, but his partner can (Aizer, 2010).

In contrast to climate or sociocultural literature, domestic violence economic research

[2] Berdegué et al. (2010) study analyzes 288 out of the 346 counties present in Chile (90% of the Chilean population lives in these 288 counties). Their results suggest that Chile has 223 rural counties, from which 101 depend economically on agriculture.

suggests that the abuse depends on the couple's relative salaries. In this vein, Aizer (2010) indicates that violence against women depends on the difference between husband and wife wages. In particular, a reduction in the wage gap should lead to less violence, as women have more bargaining power within the households than before. Angelucci (2008) results also support this idea, given that violence against women reduced in light of a welfare program directed to wives in Mexico. Furthermore, Anderberg et al. (2015) propose that domestic violence hinges on idiosyncratic unemployment risks and the potential salaries of each partner, in line with Aizer (2010)'s intra-household bargaining model scope. Their model predicts that in the face of a negative income shock to the husband, domestic violence decreases, while if the same shock hits the wife, it increases.

To the best of my knowledge, there are no previous studies relating climate and domestic violence using Latin American data and much less regarding drought and domestic abuse. In this sense, Chile presents a scenario worth exploring: among the OECD countries, it has the third-highest prevalence of violence against women[3] (OECD, 2014) and its a country under a ten-year mega-drought (Center for Climate and Resiliance Research, 2015) with a significant agricultural sector.

To investigate how drought could be affecting the rate of domestic violence complaints in rural areas, I constructed a unique geo-referenced database with information from the "Center of Analysis and Crime Studies." This base contains the rate of domestic violence complaints, the location's total population, monthly drought indexes, and the three most important crops and their growing seasons for each census district. Furthermore, I present

[3] 36% of Chilean women population has suffered, at least once in their lifetime, physical or psychological abuse from their partner.

an intra-household bargaining model with information asymmetries, based on Anderberg et al. (2015)'s work, which includes exogenous drought shocks that can affect the households' income, explaining how in equilibrium, violence depends on the recipient of the shock. Then, I empirically address this question using (i) a differences-in-differences with fixed-effects approach, (ii) a dose treatment that hinges on the districts' primary crops growing season, and (iii) a triple differences approach exploiting the crop's water need period. Specifically, strategies (ii) and (iii) focus on the climate variability crucial for agriculture, elucidating if drought affects domestic violence complaints through its negative impact on agriculture. My results suggest that the rate of domestic violence complaints diminishes between 2% and 8% - depending on the empirical strategy approach - when drought hits a location.

The sign of my results proposes that domestic abuse depends on who gets affected by the drought. In Chile's particular case, drought translates into less violence because agriculture is a men-labor intensive industry, which implies, household-wise, more husbands than wives suffer a negative income shock when drought hits a location. Hence, my findings support domestic violence economic literature claims, annihilating the sociocultural literature's underlying belives.

II Literature Review

II.1 *Climate Literature*

This work is related to the recently developed literature on climate and conflict. As Burke et al. (2015)'s work points out, this is a matter that has at least been studied since 1986, starting with Kendrick and MacFarlane's investigation on how temperature could affect road rage in the United States.

At first, climate literature concentrated mostly on how extreme weather could affect violence through income shocks. In this vein, Miguel (2005) uses rainfall variation to understand how the income shocks of a bad harvest could increment the number of witch murders in Tanzania. Yet, they note that there could be sociocultural explanations at play too since it is the religious-type violence that increases. Considering they do not have access to household income data, instead of using an instrumental variables approach, they study the impact of rainfall through a reduced-form, as most of the later climate literature does. In this manner, as Sarsons (2011) and Burke et al. (2015) suggest, using instrumental variables would not be correct since weather or rainfall shocks do not only affect conflict through income, making the fundamental identification assumption of this strategy not plausible ($\mathbb{E}(z'\varepsilon) \neq 0$). Thus, Burke et al. (2015) propose to "interpret the reduced-form as the net effect of climate on conflict operating through numerous potential channels."

As the authors mentioned above, Harari & La Ferrara (2018) also estimate a reduced-form relationship, but they use a maximum likelihood approach instead. They focus on civil conflict in Africa and drought, measured by the Standardized Precipitation-Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al. (2012), proposing that a negative agricultural shock should lead to more violence. In this regard, they built a dose treatment focusing on the weather of the cell's main crop growing season. Given that weather outside the growing season does not affect the dependent variable, their results propose that low agricultural earnings - or negative income shocks - increase civil conflict. Conversely, Baysan et al. (2019) argue that income shocks are not enough to model violence, and other non-economic variables must be considered, like "taste for violence" or "individual emotional state." Their study suggests that some economic variables, such as income or inequality, could have a limited impact on crime and suicides in Mexico.

Furthermore, there is a strand of papers within climate literature, focusing on how climate affects other elements besides income. For example, Deschênes & Greenstone (2011)'s work analyzes the relationship between daily temperatures and annual mortality rates and yearly residential energy consumption. They suggest that exposure to extreme temperatures has detrimental consequences on human health, increasing premature mortality in the United States. They also find that at both extremes of the temperature distribution, people expend more in air conditioning, trying to adapt to these high or low temperatures. In this regard, Deschênes & Greenstone (2011) exhibit evidence on the possible nonlinearities present in the effects of climate. As Deschênes & Greenstone (2011), Burke et al. (2018) also investigate how temperature impacts mental well-being using data from Mexico and the United States. They suggest that suicide rates increment 2.1% and 0.7%, respectively, at an increase in the monthly temperature average of 1°C, surprisingly with no differences between hotter and colder regions. Contrary to Deschênes & Greenstone (2011), Burke et al. (2018) provide evidence of little historical adaptation to extreme temperatures, at least in the temperature-suicide relationship.

Nevertheless, the recently developed economic literature on climate and crime has not focused extensively on domestic violence or on its relationship with drought. Auliciems & DiBartolo (1995) and Sekhri & Storeygard (2014) provide some evidence on how other climate shocks relate to domestic abuse. In particular, Auliciems & DiBartolo (1995) focus on how high temperatures increase the number of domestic violence cases, and Sekhri &

Storeygard (2014) provide evidence on how rainfall shocks during agriculturally relevant periods increase dowry deaths in India. Thus, I contribute to this strand of literature by focusing on two matters that have not been highlighted until now.

II.2 *Domestic Violence Literature*

This work also relates to domestic violence literature. In general, there are two hypotheses provided to explain the existence of this type of violence: (i) the *intrinsic value theory* and (ii) the *instrumental value theory* (Aizer, 2010; Card & Dahl, 2011; Angelucci, 2008). While the first proposes that violence has an underlying positive utility for some men, the second suggests that men use this kind of behavior to dominate their partners and resources. Depending on which of the two drivers dominates, in the scenario of an increase in women's income or an improvement in a possible "exit option" for her, I expect to see different risks of violence occurring: increasing for the first hypothesis, diminishing for the second (Angelucci, 2008).

The results of Card & Dahl (2011) are consistent with the *intrinsic value theory* predictions. In their research, they acknowledge the significant role of emotional cues when modeling family violence, particularly in the context of the National Football League of the United States. The results of their Poisson count model estimation suggests that "upset-losses" (that is to say, the team expected to win, lost) lead to a 10% increase in the number of policy reports in a narrow time window after the game ended. Thus, the risk of violence or the appearance of an emotional cue depends on a gain-loss utility that rests on a rationally expected reference point.

Conversely, the results of Angelucci (2008), Aizer (2010) and Anderberg et al. (2015) are consistent with the *instrumental value theory* predictions. Specifically, Angelucci (2008) studies how alcohol abuse and alcohol-induced violence decreases by 15% and 21%, respectively, with permanent increases in wives' income through the welfare program "Oportunidades" in rural Mexico. She suggests that the conditional cash transfer to women changes their relative bargaining power inside the household, increasing the wive's freedom and security.

Moreover, Aizer (2010) analyzes how the gender wage gap in the United States determines the risk of violence, exploiting exogenous changes in the demand for female-dominated industries. She proposes that it is not the actual wage that matters; it is the relative wage between husband and wife that determines the household's bargaining powers, and if the woman's relative income increases, we should expect less violence against her.

In this same line, Anderberg et al. (2015) examine the relationship between unemployment and domestic abuse in the UK. They develop a theoretical framework including intra-household bargaining powers and emotional shocks as a function of the partner's maltreatment, in which the male with a violent predisposition can reveal it or not depending on this function. Their results suggest that violence hinges on gender-specific unemployment rates: while male unemployment reduces abuse, female unemployment increases it.

III Theoretical Framework

The empirical predictions presented in this section are based on Anderberg et al. (2015) work, and adapted to consider droughts as the exogenous shocks changing labor opportunities and salaries in rural Chile. The framework is derived from an intra-household bargaining model, where the abuse is non-intentional, and marriage is a non-market institution that works as insurance against income risks (if the couple remains married, each spouse obtains a monetary pay-off that depends on total household income. If they divorce, each individual's financial pay-off depends on their personal earnings). Yet, there exist information asymmetries: wives do not have perfect information about their husbands' type amongst violence.[4] A crucial characteristic of the framework is that the male may or may not have a predisposition to violence, and his partner can infer his *type* from his behavioral effort. For instance, he may reduce his alcohol consumption to minimize the probability of future violent interactions (Angelucci, 2008), signaling his wife that he does not have a violent predisposition. Still, making this effort costs the husband, so, in equilibrium, a male with a propensity towards violence can reveal or hide his *type* depending on each partner's future earnings. Thus, the wife rationally decides whether to remain married considering her husband's behavior as well as the expected incomes due to the drought shocks:

1. **"When-drought-hits-men":** In this scenario, the wife knows with certainty that her husband is getting the negative income shock, and she is not, leading to an increase in her bargaining power inside the household. Additionally, she observes that her husband is not making a behavioral effort, so she understands that he has a predisposition to violence. Consequently, her expected utility of getting a divorce increases against remaining married.

[4] With no loss of generality, the model considers violence against women perpetrated by men, consistent with the existing empirical evidence (Angelucci, 2008).

2. **"When-drought-hits-women":** If the wife observes that her husband is not making a behavioral effort, she understands that he has a predisposition to violence. However, she knows with certainty that she is getting a negative income shock, and her husband is not, in which case, her expected utility of remaining married increases relative to the option of divorcing.

III.1 *Empirical Prediction*

Under the assumption that a drought shock may change the household's bargaining powers through income, the model predicts:

(i) In the face of a negative income shock to the husband, the violent-men will conceal their type to avoid divorce (pooling equilibrium), and I would expect a decrease in domestic violence complaints, in line with Aizer (2010) and Anderberg et al. (2015)'s predictions.

(ii) In the face of a negative income shock to the wife, the violent-men will be less encouraged to hide their type (separating equilibrium), and I would expect an increase in domestic violence complaints, as Aizer (2010) and Anderberg et al. (2015)'s models predict.

See Appendix A for further information on the signaling model and equilibrium proposed by Anderberg et al. (2015).

IV Data Sources and Summary Statistics

IV.1 *Data Sources*

To address the empirical question of whether drought affects domestic violence complaints, I drew information from the "Center of Analysis and Crime Studies" (CEAD for its initials in Spanish). It contains daily geo-referenced information on complaints and detentions due to domestic violence to women, from January 2013 to September 2019. This base includes the time of the day of the event, the location, if it occurred on public roads or in a private home, if the injuries were psychological or physical, the extent of these injuries, and the local police court and police station the case was prosecuted. Using the district level population information from the 2017 Chilean Census, I constructed a domestic violence complaint rate per 10,000 inhabitants for the 2761 census districts.

Second, to measure drought, I retrieved geo-referenced data of the Standardized Precipitation Index (SPI) from the "Climate Data Library" with a 0.5×0.5-degree resolution (Ministerio de Agricultura, Gobierno de Chile, 2019) and the Standardized Precipitation-Evapotranspiration Index (SPEI), developed by Vicente-Serrano et al. (2012), from the "SPEI Global Drought Monitor" with a 1-degree spatial resolution.[5] As shown in Table 1, a drought event is defined as a period in which the index falls below zero.

According to Svoboda et al. (2012), the SPI is an index that represents the probability of precipitation on any time scale (1-, 3-, 6-, 12-, 24- and 48-month timescales), and more than 70 countries around the world use it to characterize drought both for operational and research purposes. An N-month SPI compares the precipitation over a specific N-month

[5] Near the equator, 1-degree spatial resolution or 1×1-degree resolution is equivalent to 111km $\times$ 111km.

period with the precipitation totals from the same N-month period for all the years in the historical record (Svoboda et al., 2012). For example, a 3-month SPI at the end of February 2010 compares the total precipitation of the December-January-February period of 2010 with the average precipitation totals of the December-January-February period of all the years on record for that location.

However, one of the SPI's weaknesses is that it is only based on precipitation and has no soil water-balance component (Svoboda et al., 2012). Consequently, to approach this weakness, the SPEI (a variation of the SPI) includes temperature and potential evapotranspiration (PET). Given that McKee et al. (1993) suggest using shorter timescales to represent agricultural droughts (anywhere from 1-month to 6-month), I retrieved geo-referenced information of 1-month SPEI and 3-month SPEI on a monthly frequency from 2013 to 2019. Also, I have 1-month SPI and 3-month SPI information, from 2014 to 2017 for the first, and from 2013 to 2019 for the second.

Third, I use the Chilean 2007 "Agricultural and Livestock Census" (its latest version) to identify the three primary crops of each county and census district, based on the number of hectares cultivated. Given the concern that farmers could have adapted to the mega-drought that has taken place in Chile since 2010 (Center for Climate and Resiliance Research, 2015) by modifying their agricultural activity, using a Census previous to 2010 can help me, in some extension, to diminish this possible bias.

With the "Agricultural and Livestock Census" information, I believe it is relevant to consider the time of need for water for each of these primary crops, i.e., their growing season, as climate literature usually does. It is crucial to notice that Chile, according to the ODEPA, has five major agro-climatic zones:

1. *Norte Grande*: I, II, III, and XV regions.
2. *Norte Chico*: IV and V regions.
3. *Central Zone*: VI, VII, and XIII (RM) regions.
4. *South-Central Zone*: VIII, IX, and XVI regions.
5. *South Zone*: X, XI, XII, and XIV regions.

thus, the growing season for a crop can be different depending on which zone it is cultivated. For example, zucchini's growing season at Norte Grade goes from March to October, while at Norte Chico goes from October to January (Office of Agricultural Studies and Policies, 2017). Considering the former, I drew growing season data from "The Agricultural Development Institute" (INDAP for its initials in Spanish) for each district's primary crop, taking into account its agro-climatic zone (Olivares, 2019). In the case that the INDAP did not have information on a specific crop, I retrieved the missing data from the Office of Agricultural Studies and Policies (2017) (ODEPA for its initials in Spanish).

Since all the datasets described above are geo-referenced, I constructed a unique database joining each of these layers by location. Figure 1 illustrates the granularity of the data, using the census districts and the SPEI layers of the five major agro-climatic zones. For each census district, the base contains the number of domestic violence complaints, the location's total population, the monthly drought indexes, and the three most important crops and their growing seasons.

IV.2 *Summary Statistics*

Drought Statistics. - Table 2 reports some summary statistics on the different drought indexes for the entire data period. These are expressed in units of standard deviation from the location's historical average, so, by construction, they have a zero mean over the entire historical sample (Harari & La Ferrara, 2018). Still, since my data is a subsample of the historical sample, the indexes' mean could differ from zero, as shown in Table 2. In this case, the majority of the drought indexes have a negative mean, indicating that Chile has been under drier conditions on average than its historical standard, which is consistent with the Center for Climate and Resiliance Research (2015) results on the Chilean mega-drought.

Conversely, Table 2 also shows that the SPI1 is the only index with a positive mean, accumulating more than 70% of its observations on the "wet side" of the scale. Instead, SPI3, SPEI1, and SPEI3's observations concentrate in the middle of the scale, with a tendency to the "dry side". In the same vein, Table 3 reports the yearly drought statistics. Consistent with Table 2, the SPI1's mean indicates humid conditions for every year that there is information available. In contrast, the other indexes' annual mean is generally negative during the same period (except for 2017). The former suggests that SPI1 observations do not fit with the rest of the indexes' statistics and the Center for Climate and Resiliance Research (2015) results.

Bearing in mind the above, I decided to use the SPEI instead of the SPI for several reasons. First, temperature and precipitation are correlated, and the magnitude of that correlation depends on each geographical location (Auffhammer et al., 2013), and as meteorological studies show, temperature is critical when assessing drought conditions (Beguería et al., 2020). Nevertheless, the SPI only considers the variability of precipitation of each location and gives no temporal trend to temperature and potential evapotranspiration, contrary to the SPEI. Second, Beguería et al. (2020) suggests that the SPEI works better in the context of global warming since it accounts for the effects of temperature variability and its extremes, which implies that it is a better fit for my data. Third, according to Harari & La Ferrara (2018), when it comes to predicting crop yields, the SPEI surpasses other indexes. Fourth, although I have better spatial resolution using the SPI, in this particular case, a better spatial resolution does not imply much higher variability. That is, a 1x1-degree spatial resolution, such as the SPEI has, sounds reasonable to measure Chilean drought. Finally, as mentioned before, I do not have access to SPI1's 2013, 2018, and 2019 data, and its distribution seems to be inconsistent with the rest of the indexes and the Center for Climate and Resiliance Research (2015) results. Thus, I am concerned about the existence of a larger classic measurement error than what is usually found in climate variables (Auffhammer et al., 2013), and, as a consequence, magnify the attenuation bias.

Domestic Violence Statistics - As shown in Table 4 and Figure 2, between January 2013 and September 2019, domestic violence complaints increased by 0.22% with a significance of at least 5% and its average per 10,000 habitants was 2.94 (dotted line of the Figure 2). Moreover, Table 4 reports significant changes at a 95% confidence level between 2015 and 2016, 2016 and 2017, and 2018 and 2019. Thus, there is an upward trend of domestic violence complaints against women over the years.

Figure 3 disaggregates domestic violence complaints between physical abuse (Figure 3(a)) and psychological abuse (Figure 3(b)), and the dotted lines represent their mean values. On average, there were 1.01 physical complaints per 10,000 habitants with a standard deviation of 1.9, while the average of psychological complaints was 1.93, with a standard deviation of 2.7 in the 2013-2019 period. Furthermore, the upward trend is steeper for physical abuse than psychological abuse, despite the higher rate for the second.

A common problem with police complaints is that they are usually underreported, in which case, the empirical results represent a lower bound of the actual effect (Card & Dahl, 2011). To explore the magnitude and sign of this bias, I compare my data with the National Domestic Violence and Sexual Offenses Victimization Survey from 2012 and 2017 (ENVIF for its initials in Spanish). These are face-to-face surveys (self-applied for sexual violence), in which the interviewers are women, and their results are statistically representative at the regional and country level (Gfk Adimark, 2013; Subsecretaría de Prevensión del Delito, 2018).

For 2012's ENVIF, more women reported experiencing, during the last 12 months, psychological violence than physical, in line with what we see in Figure 3. On the contrary, in 2017, more women stated having suffered physical abuse, which is discrepant with my data. According to 2017's ENVIF, psychological violence against women raised from 16.8% in 2012 to 20.2% in 2017. Yet, the percentage of women psychologically abused who presented a complaint was only 28% for 2012 and 23% for 2017. In the case of physical violence, the number of women suffering from it decreased over the 2012-2017 period, from 5.8% to 4.3%. Only 36% of these women denounced their aggressor, who 66% of the times was their partner or ex-partner. As reported by the surveys, women do not report that they have suffered this types of incidents due to fear, shame, or the probability others would not believe them. Also, some perceive that contacting to the Police does not work, or decided to stay quiet because things got better at home.

Hence, in Chile, underreporting is sizeable, and it has increased in magnitude over time. Yet, this will only affect my results if drought shocks alter the difficulty of the complaint process - and, therefore, correlate with the error term -. If the latter happened, the results presented in section VI would not suggest causality, but correlation.

The process of reporting domestic violence in Chile can be carried out by the victim or by a third party (the latter may choose to reserve its identity). This complaint can be made to the Police, the Family Court, or the Public Ministry in person, and the Police or SERNAM by phone. If drought shocks negatively affect labor opportunities, couples may raise the time they spend at their households and could potentially challenge the reporting occasions, as evidence from the COVID-19 pandemic lockdown suggests (Ravindran & Shah, 2020). Nevertheless, the reader should consider that Ravindran & Shah (2020)'s results are embedded in a context of complete lockdown due to the pandemic, where, by law, women were forced to stay at home.

In contrast to Ravindran & Shah (2020), the results presented in section VI use data from a period with no mobility restrictions within the population. Thereby, even if husbands did spend more time at home because of the drought, it did not imply that wives would stay at home the twenty-four hours of the day. During this period (January 2013 to September 2019), women in Chile could still carry out their regular activities, such as going to work, visiting a friend, or going grocery shopping. Consequently, if the victim did not have privacy at home to call the Police and present a complaint, she had the opportunity to inform the Police by phone from anywhere else or submit the complaint in person. Additionally, if women did not feel safe approaching this matter themselves, they could ask a friend, a family member, or a neighbor to help them anonymously (for instance, by sending a text message to a friend from the restroom).

Given the above, drought should not have changed the difficulty of the complaint process, at least in Chile during the studied period. Therefore, I should only expect to have the typical measurement error presented in this kind of literature as Card & Dahl (2011) indicate. Thus, the results of section VI should provide evidence of causal effects, and the fixed-effects used on the empirical strategy should capture the "usual" underreporting problem (Angrist & Pischke, 2008).

V Empirical Strategy

Recent studies that estimate the effect of climate on conflict use a time-series variation identification, utilizing panel data (Harari & La Ferrara, 2018; Burke et al., 2018; Baysan et al., 2019; Deschênes & Greenstone, 2011). The previous means that I use the same population as the control group (i.e., just before a change in drought conditions) and as the treated group (i.e., just after a change in drought conditions).

With no loss of generality, for an outcome, Y_t, conditional on climate conditions C_t, estimating the effect of C on Y after some time Δt is $\hat{\beta} = \mathbb{E}[Y_{t+\Delta t}|C_{t+\Delta t}] - \mathbb{E}[Y_t|C_t]$, where $\hat{\beta}$ aproaches the true parameter, β, as long as Y_t is comparable to $Y_{t+\Delta t}|C_{t+\Delta t}$ (Burke et al., 2015). Since the length of the panel is seven years, Y_t and $Y_{t+\Delta t}|C_{t+\Delta t}$ should not differ much. Yet, it can not be ruled out that the take up of the drought shock is endogenous,[6] implying that the results presented in this work may be a local bound.

Following Burke et al. (2015) and Angrist & Pischke (2008) advice on "Bad Control,"

[6]For instance, people may migrated to different locations due to changes in climate or decide to grow different drought-resistant-crops.

for all the empirical strategies presented below, I do not use control variables different from the independent variable lags and, time and location fixed-effects. Specifically, when it comes to climate and violence specifications, they suggest that controls can be endogenously determined as well as modified by the weather.[7] Additionally, as Deschênes & Greenstone (2011) proposes, the value of the coefficient of interest's point estimate should not change by including controls.

Furthermore, according to Burke et al. (2015, 2018, 2020) and Baysan et al. (2019), adding the independent variable lags is important to capture the full effect of climate on conflict. In this specific case, drought could displace domestic violence over time, i.e., some domestic abuse cases had a 100% probability of happening, but drought could have triggered them to occur earlier or later (by changing the households' bargaining powers, for instance). Likewise, drought could have a persistent or delayed effect on violence. For example, drought in $t-2$ and $t-1$ could affect the harvest in t and $t+1$, displacing the income shock a few periods from the climate one. Thereby, Burke et al. (2020) suggest studying the combined effect of climate over time (that is, add the effect of the lags). By doing so, I can differentiate the cases that were going to happen anyway, sooner or later, from the "additional" ones triggered by the drought.

V.1 *Differences in Differences*

As Burke et al. (2015)'s work suggests, drought can be understood as an exogenous treatment to domestic violence complaints that vary in location and timing. Therefore, I approach

[7] For example, using the district's sex ratio as control could introduce bias to the estimations if this ratio hinges on the district's prevalence of domestic violence or the different labor opportunities altered by drought.

the empirical question with a differences-in-differences analysis with time and location fixed-effects:

$$DV_{d,t} = \sum_{i=0}^{n} \beta_i SPEI_{d,t-i} + \gamma_d + \lambda_t + \upsilon_{d,t} \tag{1}$$

Here $DV_{d,t}$ denotes the rate of domestic violence complaints per 10,000 habitants in the district d and month t. SPEI is the drought index present at month t and district d. γ_d is a district fixed-effect (takes into account institutional differences, for example), λ_t is a time fixed-effect which accounts for time-trending variables (economic growth or demographic changes, for example) and $\upsilon_{d,t}$ is the error term. β_i is the differences-in-differences estimator, which will inform us about the effect of the drought on the rate of domestic violence complaints per 10,000 habitants on period $t-i$. At the same time, $\sum_{i=0}^{n} \beta_i$ represents the drought's net effect, understanding that drought can displace violence over time or have persistent and delayed effects over it (Burke et al., 2015). Further, standard errors are corrected with clusters at the county level to control for serial autocorrelation.

V.2 *Dose Treatment: "Agricultural Drought Shock"*

Secondly, I use an "Agricultural Drought Shock", inspired on Depetris-Chauvin (2015) and Harari & La Ferrara (2018)'s work. By isolating the climate variability that is important for agriculture, this treatment allows us to understand if drought affects the rate of domestic violence complaints through an agricultural channel.

$$AgriculturalDroughtShock_{d,t} = \sum_{c=1}^{3} \alpha_{c,d} \times \left(\frac{\sum_{\text{Growing Season}_{c,d}} \text{SPEI}_d}{\text{N° Months Growing Season}_{c,d}} \right)_t \tag{2}$$

where:

$$\alpha_{c,d}^{(a)} = \frac{ha_{c,d}}{\sum_{i=1}^{3} ha_{i,d}} \qquad \text{or} \qquad \alpha_{c,d}^{(b)} = \frac{ha_{c,d}}{\text{Total arable hectares}_d}$$

In particular, the treatment focuses on the growing season of the three most popular crops c of the district d, based on their number of hectares cultivated ($ha_{c,d}$). It averages the monthly SPEI over the growing season months of each of the crops, and weights this average with $\alpha_{c,d}$, which I define as: (a) the hectares cultivated of crop c in district d, divided by the sum of the hectares of the main three crops of the same district, or (b) the hectares cultivated of c in district d, divided by the district's total arable hectares. Thus, this treatment considers the importance of each crop for each district and should account for the relevance of a drier month during the primary crops' growing season. Hence, replacing $SPEI_{d,t}$ from equation (1):

$$DV_{d,t} = \sum_{i=0}^{n} \beta_i AgriculturalDroughtShock_{d,t-i} + \gamma_d + \lambda_t + \upsilon_{d,t} \tag{3}$$

where β_i is the differences-in-differences estimator of the "Agricultural Drought Shock" on $t-i$, and $\sum_{i=0}^{n} \beta_i$ is the net effect of the treatment on the rate of domestic violence complaints per 10,000 habitants.

V.3 *Triple Differences*

As a third source of variation, I use the need for water of the different crops at various districts and dates. Thus, by exploiting the timing, the location, the crops' cycle, and their importance measured by hectares cultivated, I perform a Tripple-Differences analysis with fixed-effects, such as Schofield (2014) did with the impact of Ramadan on agriculture production in India.

$$DV_{c,d,t} = \sum_{i=0}^{n} \sum_{c=1}^{3} \beta_{i,c} \Big(SPEI_{d,t-i} \times GrowingSeason_{c,d,t-i} \times \alpha_{c,d} \Big) + \gamma_{d,c} + \lambda_{t,c} + \theta_{d,t} + \upsilon_{c,d,t} \quad (4)$$

Here $DV_{c,d,t}$ denotes the rate of domestic violence complaints per 10,000 habitants for a crop-district-month. $GrowingSeason$ is a dummy variable that takes the value of 1 if the month $t - i$ corresponds to the growing season of crop c of district d. Furthermore, $\gamma_{d,c}$ is a district-crop fixed-effect, $\lambda_{t,c}$ a month-crop fixed-effect, $\theta_{d,t}$ a district-month fixed-effect and $\upsilon_{c,d,t}$ is the error term. $\sum_{c=1}^{3} \beta_c$ is the differences-in-differences-in-differences estimator, which will inform us about the effect of the drought on the rate of domestic violence complaints per 10,000 habitants in $t - i$ for the three main crops of the district, and $\sum_{i=0}^{n} \sum_{c=1}^{3} \beta_{i,c}$ represents the net effect of drought. Standard errors are corrected with clusters at the month-county level to control for serial autocorrelation, following Schofield (2014).

VI Results

There are a couple of things to consider when analyzing the results presented in this section. First, the SPEI (henceforth, drought) is expressed in units of standard deviation from the location's historical average. Table 5 reports the summary statistics for the dose treatment and the triple differences approaches as inputs to interpret the results of this section, following Harari & La Ferrara (2018)'s work. Second, as shown in Table 1, the interpretation of an increase in one standard deviation of the index implies less drought. To understand the impact of a drier period on domestic violence, I interpret the results as a decrease in one standard deviation. Third, given that (i) drought can displace domestic violence over time or (ii) have persistent or delayed effects, I concentrate on its net impact, i.e., the sum of the lag structure coefficients.

Differences in Differences - Table 6 presents the results of the differences-in-differences approach, using both SPEI indexes and clusters at different levels. As observed, all the lags across specifications go in the same direction as the net effect, yet the only one consistently significant across columns is $Drought_{t-1}$ while using the SPEI1. The former suggests that drought has delayed effects over violence.

Furthermore, the net effect of drought over the rate of domestic violence complaints is always negative,[8] regardless of the index used. Moreover, it is significant, at least at a 10% level, when using more exacting clusters. Additionally, Figure 4 graphically represents the confidence intervals of the lags and the combined effects of columns (2) and (7) of Table 6.

The net results of Table 6 report that a decrease in one standard deviation of the index implies a reduction in 0.06 to 0.09 complaints per 10,000 habitants, or, 2% to 3.1% of the unconditional mean of the rate of domestic violence complaints. Thus, these results suggest that intrafamilial violence complaints diminish when drought hits a location, and as the confidence intervals indicate, this effect changes the dependent variable's mean at most 5.14%.

Dose Treatment - In this empirical approach, I only compare districts that reported cultivating land during the 2007 "Agricultural and Livestock Census". Thus, I do not include

[8]The net effect of the index over the rate of domestic violence complaints is positive.

22.6% of them in this analysis. Table 7 reports the results of the dose treatment using both drought indexes and treatments: panel A presents the Agricultural Drought Shock $\alpha^{(a)}_{c,d}$, while panel B the Agricultural Drought Shock $\alpha^{(b)}_{c,d}$.

As shown in columns (2) to (5), regardless of the treatment, the first lag is significant at a 5% level. These results also support the idea that a climate shock and a violence response do not necessarily happen simultaneously. That is, drought from $t-1$ is affecting domestic violence in t. Furthermore, from columns (2) to (5) and (7) to (10), the combined effect of drought is only significant when using treatment (a). These should be the "additional" violence cases triggered by an increase in the index, as mentioned in Section V.

Specifically, an increase in drought by one standard deviation reduces the number of complaints per 10,000 habitants by 0.06 to 0.08, i.e., it is 1.9% to 2.6% of its mean. As with the differences-in-differences approach, in the face of drought, domestic violence complaints should decrease, but not more than a 4% as the 95% CI suggests. In this vein, Figure 5 shows the intervals of the lags and the combined effects of the dose treatments, using column (2) and (7)'s specifications.

Triple Differences - Tables 8 shows the results of the triple differences approach using month-county and month-province cluster levels, both drought indexes and both treatments. Panel A presents the results using $\alpha^{(a)}_{c,d}$, while panel B, $\alpha^{(b)}_{c,d}$.

As observed in Table 8, despite the index or the treatment used, the first lag of this specification is significant at a 1% level, as well as the drought's combined effect. Hence, these results suggest that drought has a delayed impact on violence and that this is not only a displacement of domestic abuse over time.

The net effect of a decrease in one standard deviation, when using treatment $\alpha^{(a)}_{c,d}$, implies a reduction in 0.19 to 0.21 complaints per 10,000 inhabitants. Hence, a 6.5% to 7.3% of the unconditional mean of the rate of domestic violence complaints. Moreover, when using $\alpha_{c,d}^{(b)}$, the effect grows. The reduction lies between 0.21 to 0.23 complaints per 10,000 habitants, or, 7% to 7.9% of the dependent variable's unconditional mean. However, as the 95% confidence intervals suggest, drought could reduce the rate of domestic violence complaints' mean at least 0.14%, and at most 13.8%.

Thus, these results also suggest that domestic violence complaints diminish when drought hits a location, but to a greater extent than those found with the differences-in-differences strategy and the dose treatment. Nevertheless, the reader should consider that these results have a lower external validity than the previous ones presented in this section because they report how the domestic violence complaint rate changes under a complete overlap between drought, and the growing season of each of the district's three principal crops. Perhaps, if the crops cultivated or the size of areas of the crops grown were different from those found in the data, the magnitude of the results could differ, i.e., the extent of findings is valid for these districts' main crops and their arable hectares.

Lastly, as shown in Table 9, all the results presented in this section are explained by an extensive margin change; that is, by districts in which the number of cases increased from zero to at least one. Columns (1) to (4) display the results of equation (1), but as a linear probability model, where the dependent variable is a domestic violence complaint dummy variable that takes the value of 1 if the district had at least one complaint that month. Here, a decrease of the index in one standard deviation results in a reduction of the dependent variable mean by approximately 0.01 percentage points or 0.012%.

Agricultural Channel - The results of the reduced-form implemented in this work shed light on the net effect of drought over domestic abuse through diverse mechanisms (Burke et al., 2015). Yet, previous literature has shown that climate shocks affect agricultural outcomes, and consequently, households' incomes too (Miguel, 2005; Edwards et al., 2009; Meza et al., 2010; Centro de Cambio Global UC, 2011; Blakeslee & Fishman, 2013; Harari & La Ferrara, 2018). For that reason, equations (3) and (4) propose specifications that focus on the effects of drought on Chilean agriculture. The estimated impact of using these two strategies is larger than the one found with the differences-in-differences approach, proposing that drought affects violence through agricultural and economic outcomes.

Nevertheless, to ensure that these results are due to agriculture, I compare the effects of drought in agricultural and non-agricultural districts, defining the last ones as districts with zero arable hectares, using equation (1). Table 10 reports that the net impact of drought over domestic violence is not significant in non-agricultural areas, while a decrease in one standard deviation of the indexes in agricultural districts implies a reduction in 0.11 to 0.14 complaints per 10,000 habitants; hence, a 3.7% and 4.8% of the rate of domestic violence complaints. These results provide strong evidence that one of the channels in which drought impacts domestic violence is through agriculture, triggering "less" cases than the ones that were expected to happen. Figure 6 graphically represents the lags and the combined effects of columns (1) and (3) of Table 10.

Additionally, Table 11 compares the effects of drought during the growing and non-growing season to better understand any temporal heterogeneities. As shown, the net impact of drought over domestic abuse does depend on the season. In comparison with the non-growing season, the number of complaints per 10,000 habitants increases between 0.08 to 0.16 during the growing season. That is by 2.7% to 5.4% of the unconditional mean of the rate of domestic violence complaints. Lastly, Figure 7 graphically represents the 95% confidence intervals of the lags and the combined effects of columns (1) and (3) of Table 11.

Women, Chilean Agriculture, and Violence - Even though women were 51.1% of the Chilean population and 41.3% of the country's workforce in 2017, they only represented 24.8% of the agriculture's workforce that same year (Office of Agricultural Studies and Policies, 2019). Additionally, Perticará & Bueno (2009) suggests that the gender wage gap in Chile reaches 18%, favoring males, across all the economy. Nevertheless, according to the 2017 National Socioeconomic Characterization Survey (CASEN, henceforth), it is usually the women who receive household subsidies, which may increment their bargaining power inside the relationship, as Angelucci (2008) proposes.

Furthermore, according to the National Employment Survey information from January 2013 to September 2019, agriculture has been a men-labor intensive industry, regardless of the type of contract or month of the year. Therefore, given that I propose that drought works to some extent through agriculture, a climate shock of this kind should affect more men, in absolute terms, concerning wages and unemployment. The former implies that household-wise, there are more households where the husbands suffer the negative income shock instead of the wives. Labor-wise, there are approximately three men per woman. Still, in the household composition, there is one husband and one wife.

Hence, the Chilean agriculture context under a drought scenario is particularly similar to the first assumption of the theoretical model (Section III), in which the husband gets the negative income shock with some certainty, and the wife does not. Following Aizer (2010), in this scenario, the relative wage gap in rural regions between husband and wife gets smaller in drought periods than in non-drought periods, producing an increase in the woman's relative bargaining power.[9] Additionally, a man with a violent predisposition would make an effort to hide his type in this scenario, as the pooling equilibrium predicts. Thus, the husband will not reveal his violent nature while receiving a negative income shock because that will imply that his wife will be willing to divorce him. Furthermore, he knows that if the couple gets immersed in a violent situation, his wife will be more willing to go to the police and ask him to leave the house, given that he is not contributing as much to the household's economy (Aizer, 2010), in comparison with a non-drought season.[10] Given the above, it sounds plausible that drought shocks may decrease the rate of domestic violence complaints as Tables 6, 7, and 8 suggest.

On the other hand, Table 11 reports that the number of complaints is higher during the growing season compared to the non-growing season. Perhaps, in the case of a non-drought-growing season, the wage gap between husband and wife increases, reducing the woman's bargaining power relative to the one she had during the non-growing season. In this scenario, men with violent predispositions do not have incentives to make an effort, given that it is costly. However, the wage gap in a drought-growing season should be smaller than the wage gap in a non-drought-growing season, increasing the wife's bargaining power and increasing the husband's incentive to hide his type, which explains why there are fewer complaints in drier times.

Furthermore, Table 12 reports the results using districts that belong to the first and

[9] According to Pollak (2005), the wife's bargaining power relates to her well-being at her threat point - in this case, divorcing - rather than her well-being while being married. So, he proposes that even a woman who does not work would decide to enter the labor market in the case of getting a divorce.

[10] Once the victim or a third party reports the domestic violence abuse case, the police will force the abuser to leave the household immediately, at least for six months. Then, the Family Court will decide if it is necessary to extend the previous sanction and add others. Also, the victim earns the right to initiate a fault-based divorce process.

last quintiles within the distribution of men in the agricultural labor force.[11] When using SPEI1, the results are mixed. Still, in the case of SPEI3, all the specifications suggest that in demographics with a higher proportion of men working in agriculture, drought should generate a greater impact on domestic abuse.

The results presented above suggest that drought is playing a role over the rate of domestic violence complaints through agriculture. In particular, these results are consistent with the empirical prediction (i) of the theoretical model. There exists a pooling equilibrium where husbands have incentives to hide their nature in the face of a drought shock. By making an effort, they reduce the probability of being immersed in a violent situation with their wives, and consequently, reduce the rate of domestic violence complaints.

VII Robustness

Identification Assumption - Baysan et al. (2019) propose that if the leads in the regression analysis are statistically different from zero, this suggests that the identification assumption is reasonable. In consequence, future drought events should not explain domestic violence today.

Figure 8 reports the 95% confidence intervals of the four leads and the combined effect of these for the differences-in-differences approach, including population weights and cluster standard errors at the county level. As observed in both panels of the figure, some leads are significant at a 5% level. Yet, this may be due to the climatological variables' correlation over time (Auffhammer et al., 2013). Nevertheless, the net effect of the coefficients is

[11] See Appendix C.

not significant in either case. Hence, overall, future drought events do not impact today's domestic violence complaints, fulfilling the identification assumption.

Furthermore, the dose treatment results with population weights and cluster standard errors at the county level are presented in Figure 9. Here, only the first lead $t + 1$ of the estimation with SPEI1 and the type (a) treatment is significant at a 5% level. All the rest, including the combined effect of the leads, are not statistically significant.

Lastly, the lead of the triple differences approach is not significant with either drought index or treatment. The SPEI1's coefficient is 0.01 with a standard deviation of 0.02, while in the SPEI3 regression, it is 0.02 with a 0.03 standard deviation using a type (a) $\alpha_{c,d}$. The results are still not significant when using (b). With treatment $\alpha^{(b)}_{c,d}$, the point estimates change to 0.00 and 0.01, respectively, and the standard deviations remain the same. Thus, all the approaches presented in Section V satisfy the identification assumption.

Spurious Correlation?: Randomizing drought - To examine the possibility that drought is not necessarily changing the rate of domestic violence complaints in rural Chile, I implement a falsification test for the differences-in-differences approach inspired in Rau et al. (2015)'s work.

For each date (month-year) of the whole sample - January 2013 to September 2019 -, I randomize the real drought realizations between the 2761 districts and re-estimate equation (3) using the same specifications as columns (2) and (7) of Table 6. I repeat this process 10,000 times and graph the new estimated coefficients' distributions using a kernel density estimate. Figures 10, 11, and 12 display the results of this falsification test, where the red vertical line represents the original coefficients' point estimates.

The red lines of Figure 10 suggest that the original contemporaneous effect of drought may be a spurious correlation, given how close they are to kernel distributions' mean. However, as displayed in Figures 11 and 12, the point estimates of the lags and the combined effects are far from the randomization's mean, suggesting that the findings presented in Section VI imply causality and not only correlation.

VIII Conclusion

Recently, the world is consistently showing a rising interest in climate change and its consequences, particularly on how it is impacting global agriculture and the income of developing countries. On one hand, climate literature suggests a relationship between climate shocks and violence; on the other hand, domestic abuse economic literature proposes a relationship between income effects and intrafamilial violence. In this vein, Chile presents a scenario worth studying given the mega-drought it is facing, the importance of its agricultural sector as a source of employment, and its high prevalence of violence against women compared to other OECD countries.

To explore if the drought in rural Chile has affected the number of domestic violence complaints, I used a unique geo-referenced database constructed with information from the "Center of Analysis and Crime Studies." Then, I address the empirical question with (i) a differences-in-differences with fixed-effects approach, (ii) a dose treatment that hinges on the districts' primary crops growing season, and (iii) a triple differences approach exploiting the crop's water need period. Specifically, strategies (ii) and (iii) focus on the climate variability crucial for agriculture, elucidating if drought affects domestic violence complaints through its negative impact on agriculture. My results suggest that the rate of domestic violence complaints diminishes between 2% and 8% in the face of drought. The sign of the results proposes that domestic abuse hinges on who gets affected by the drought, as the theoretical model predicts.

One of the limitations of my results is that since I do not have information about the individuals' jobs and house addresses, the domestic violence complaints of one district could capture the effect of the agricultural shock that happened on another. Furthermore, a usual limitation within this literature is the underreporting of domestic violence complaints (Card & Dahl, 2011), which in the case of Chile reaches approximately a 70% (Gfk Adimark, 2013; Subsecretaría de Prevensión del Delito, 2018).

Yet, the main caveat of these results is that they depend on Chile's particular agricultural labor force context; that is, I can not conclude that drought always reduces domestic violence. In Chile, a drought shock translates into less violence because agriculture is a strongly men-labor intensive industry (3 men to one woman), which implies, household-wise, that more husbands than wives could suffer a negative income shock when drought hits a location. Hence, in a country where the ratios are inverse or similar between men and women, the results could perfectly be the opposite.

Future research should explore different mechanisms from the one introduced in this work, such as stress or alcohol consumption, and check for heterogeneities between the Chilean agro-climatic zones. It would also be interesting to examine if farmers can minimize the impact by adapting to the drought conditions, namely, by using more modern irrigation techniques or by planting crops resistant to drier weather. Moreover, further studies could consider the possible nonlinearities of the effect of drought, which are plausible given previous climate literature results. Lastly, future research should explore if these results are robust if the men-women ratio in agriculture flips.

The results presented in this work support the *instrumental value theory* predictions, going beyond the drought context. Thus, policymakers should consider the recommendations previous literature has done in this vein, such as improving women's labor opportunities and employment security, promoting policies that close the gender wage gap, making women the recipients of the household subsidies, among others. Finally, this work suggests that men have some power to reduce the likelihood of violent situations at home. Hence, under a public policy scope, Governments could also implement programs that generate incentives to "make an effort"—for instance, a healthy alcohol consumption campaign.

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IX Tables

Table 1: SPI and SPEI Drought Categories

Index Value	Drought Category
≥ 2.00	Extremely wet
1.50 to 1.99	Severely wet
1.00 to 1.49	Moderately wet
0 to 0.99	Midly wet
-0.99 to 0	Mild drought
-1.49 to -1.00	Moderate drought
-1.99 to -1.50	Severe drought
≤ -2.00	Extreme drought

Source: McKee et al. (1993)

Table 2: Chilean Drought's Statistics

	SPEI1	SPEI3	SPI1	SPI3
Mean	-0.3776	-0.4696	0.2318	-0.4702
Min	-5.0000	-5.0000	-6.0631	-3.0902
Max	5.0000	5.0000	3.9557	2.6955
SD	1.0079	0.9854	0.8591	1.1149
Drought Category Frequencies				
Extremely wet	1.4%	0.8%	41.6%	1.0%
Severely wet	1.7%	0.8%	1.7%	2.1%
Moderately wet	5.6%	5.5%	6.4%	6.6 %
Midly wet	26.4%	21.1%	31.7 %	25.4 %
Midly drought	34.7 %	38.9%	13.7 %	33.3%
Moderate drought	18.4 %	20.8%	2.2 %	15.0 %
Severe drought	8.4%	8.2%	1.6%	9.1 %
Extreme drought	3.3%	3.9%	1.0%	7.5 %

Information of SPI3, SPEI1 and SPEI3 is available from 2013 to 2019.
Information of SPI1 is available from 2014 to 2017.

Table 3: Chilean Drought's Statistics per Year

	SPEI1	SPEI3	SPI1	SPI3
2013				
Mean	-0.78353	-0.84181	.	-0.67739
Min	-2.92654	-2.51589	.	-3.09023
Max	2.13638	2.22090	.	2.32288
SD	0.72294	0.74405	.	1.23576
2014				
Mean	-0.21218	-0.45576	0.21112	-0.49015
Min	-5.00000	-5.00000	-5.47203	-3.09023
Max	5.00000	3.33461	2.60055	2.26256
SD	0.79308	0.64437	0.90215	0.89275
2015				
Mean	-0.41276	-0.53408	0.27749	-0.22026
Min	-5.00000	-5.00000	-6.06310	-3.09023
Max	3.54844	3.03432	3.95574	2.63694
SD	1.11329	1.14269	0.92806	1.31056
2016				
Mean	-0.28015	-0.29468	0.09658	-0.46378
Min	-5.00000	-5.00000	-4.69406	-3.09023
Max	5.00000	5.00000	2.32558	2.21425
SD	1.14263	1.08441	0.89134	1.14968
2017				
Mean	-0.00415	0.04256	0.34197	0.16962
Min	-5.00000	-5.00000	-3.18307	-3.09023
Max	5.00000	5.00000	3.06915	2.69550
SD	1.19456	1.01047	0.67128	0.75582
2018				
Mean	-0.15632	-0.17429	.	-0.55336
Min	-5.00000	-5.00000	.	-3.09023
Max	5.00000	5.00000	.	2.34122
SD	0.91741	0.92154	.	0.83339
2019				
Mean	-0.93162	-1.21324	.	-1.24809
Min	-5.00000	-5.00000	.	-3.09023
Max	2.62666	5.00000	.	1.83343
SD	0.60183	0.62831	.	1.02240

Information of SPI3, SPEI1 and SPEI3 is available from 2013 to 2019. Information of SPI1 is available from 2014 to 2017.

Table 4: Domestic Violence Complaints' Statistics

Year	Mean	Min	Max	SD	N	SE	Confidence Interval at 95% level	Change $\Delta_{(t+1)-(t)}$
2013	2.79	0.00	10,000	3.57	32,588	0.02	[2.75 ; 2.83]	
								-0.06%
2014	2.62	0.00	10,000	3.58	32,588	0.02	[2.59 ; 2.66]	
								+0.05%
2015	2.75	0.00	16,000	4.73	32,588	0.03	[2.70 ; 2.80]	
								+0.06%
2016	2.92	0.00	6,000	3.48	32,588	0.02	[2.88 ; 2.95]	
								+0.07%
2017	3.12	0.00	10,000	3.58	32,589	0.02	[3.08 ; 3.16]	
								-0.02%
2018	3.06	0.00	8,000	3.36	32,588	0.02	[3.03 ; 3.10]	
								+0.11%
2019	3.41	0.00	8,000	3.98	24.503	0.03	[3.36 ; 3.46]	
2013-2019	2.94	0.00	16,000	3.78	220,032	0.01	[2.92 ; 2.95]	+0.22%

Statistics of the rate of domestic violence complaints per 10,000 habitants. District population weights used.

Table 5: Agricultural Shock and Triple Differences' Statistics

	Mean	Min	Max	SD
Dose Treatment				
Agricultural Shock (a) SPEI1	-0.27471	-3.30295	2.51545	0.40846
Agricultural Shock (a) SPEI3	-0.31901	-3.10575	2.93855	0.50557
Agricultural Shock (b) SPEI1	-0.19979	-2.52578	2.44619	0.32682
Agricultural Shock (b) SPEI3	-0.23375	-2.90311	2.85763	0.40216
Triple Differences				
$\sum_{c=1}^{3} \text{SPEI1} \times GrowingSeason_{c,d} \times \alpha^{a}_{c,d}$	-0.12944	-5.00000	5.00000	0.54553
$\sum_{c=1}^{3} \text{SPEI3} \times GrowingSeason_{c,d} \times \alpha^{a}_{c,d}$	-0.15031	-5.00000	5.00000	0.52355
$\sum_{c=1}^{3} \text{SPEI1} \times GrowingSeason_{c,d} \times \alpha^{b}_{c,d}$	-0.09414	-5.00000	5.00000	0.41855
$\sum_{c=1}^{3} \text{SPEI3} \times GrowingSeason_{c,d} \times \alpha^{b}_{c,d}$	-0.11014	-4.67376	5.00000	0.40785

District population weights used. Agricultural Shock averages the monthly SPEI over the growing season months of each of the three main crops of the census district, using as weight $\alpha^{(a)}$ or $\alpha^{(b)}$. *GrowingSeason* is a dummy variable that takes the value of 1 if the month t corresponds to the growing season of crop c of district d, using as weight $\alpha^{(a)}$ or $\alpha^{(b)}$.

Table 6: *Diff-in-Diff*: Domestic Violence Complaints per 10,000 habitants and Drought

	SPEI1					SPEI3				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Drought_t$	0.0052	-0.0133	-0.0133	-0.0133	-0.0133	0.015	0.00328	0.00328	0.00328	0.00328
	(0.0124)	(0.0109)	(0.0164)	(0.0164)	(0.0176)	(0.0154)	(0.0217)	(0.0288)	(0.0205)	(0.0311)
$Drought_{t-1}$		0.0371***	0.0371**	0.0371**	0.0371**		0.0291	0.0291	0.0291	0.0291
		(0.0118)	(0.0145)	(0.0145)	(0.0185)		(0.0254)	(0.0271)	(0.0272)	(0.0382)
$Drought_{t-2}$		0.0181*	0.0181	0.0181	0.0181		0.000702	0.000702	0.000702	0.000702
		(0.0105)	(0.0164)	(0.0164)	(0.0193)		(0.0175)	(0.0233)	(0.0239)	(0.0336)
$Drought_{t-3}$		0.0189	0.0189	0.0189	0.0189		0.0189	0.0189	0.0189	0.0189
		(0.0124)	(0.0151)	(0.0151)	(0.0198)		(0.0182)	(0.0223)	(0.0263)	(0.0405)
$Drought_{t-4}$		0.0268**	0.0268*	0.0268*	0.0268		0.00629	0.00629	0.00629	0.00629
		(0.0120)	(0.0141)	(0.0141)	(0.0171)		(0.0193)	(0.0254)	(0.0209)	(0.0313)
$\sum_{i=0}^{4} Drought_{t-i}$		0.09***	0.09*	0.09***	0.09***		0.06**	0.06	0.06***	0.06**
		(0.030)	(0.050)	(0.020)	(0.030)		(0.030)	(0.040)	(0.020)	(0.030)
Effect Size 95% CI		(0.02; 0.15)	(-0.01; 0.19)	(0.05; 0.13)	(0.02; 0.15)		(0; 0.12)	(-0.02; 0.13)	(0.02; 0.1)	(0; 0.12)
Observations	220,032	204,464	204,464	204,464	204,464	220,032	204,464	204,464	204,464	204,464
Adjusted R^2	0.4678	0.4716	0.4716	0.4716	0.4716	0.4678	0.4715	0.4715	0.4715	0.4715
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
VCE estimation	County level SE	County level SE	Province level SE	Month-County level SE	Month-Province level SE	County level SE	County level SE	Province level SE	Month-County level SE	Month-Province level SE

Standard errors in parentheses. Differences-in-Differences strategy, with the rate of domestic violence complaints per 10,000 habitants as dependent variable, and SPEI1 or SPEI3 as independent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: *Dose Treatment*: Domestic Violence Complaints per 10,000 habitants and Drought

	SPEI1					SPEI3				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: *Treatment (a)*										
$AgriculturalDroughtShock_t$	0.142**	-0.0396	-0.0396	-0.0396	-0.0396	0.0798*	0.0381	0.0381	0.0381	0.0381
	(0.0602)	(0.0765)	(0.0961)	(0.0614)	(0.0730)	(0.0460)	(0.0632)	(0.0764)	(0.0513)	(0.0595)
$AgriculturalDroughtShock_{t-1}$		0.187**	0.187**	0.187**	0.187**		0.0722	0.0722	0.0722	0.0722
		(0.079)	(0.0753)	(0.0802)	(0.0920)		(0.0652)	(0.0578)	(0.0714)	(0.0809)
$AgriculturalDroughtShock_{t-2}$		0.042	0.042	0.042	0.042		0.00363	0.00363	0.00363	0.00363
		(0.0760)	(0.1070)	(0.0652)	(0.0733)		(0.0529)	(0.0743)	(0.0554)	(0.0665)
$\sum_{i=0}^{2} AgriculturalDroughtShock_{t-i}$		0.19**	0.19	0.19***	0.19***		0.11*	0.11	0.11***	0.11**
		(0.080)	(0.130)	(0.050)	(0.060)		(0.060)	(0.090)	(0.040)	(0.050)
Effect Size 95% CI		(0.03; 0.35)	(-0.06; 0.44)	(0.1; 0.28)	(0.07; 0.31)		(-0.01; 0.23)	(-0.07; 0.3)	(0.04; 0.18)	(0.02; 0.21)
Panel B: *Treatment (b)*										
$AgriculturalDroughtShock_t$	0.085	-0.0819	-0.0819	-0.0819	-0.0819	0.0355	0.0157	0.0157	0.0157	0.0157
	(0.0795)	(0.1010)	(0.1230)	(0.0778)	(0.0893)	(0.0614)	(0.0840)	(0.0977)	(0.0640)	(0.0721)
$AgriculturalDroughtShock_{t-1}$		0.250**	0.250**	0.250**	0.250**		0.107	0.107	0.107	0.107
		(0.1030)	(0.0993)	(0.0998)	(0.1120)		(0.0818)	(0.0743)	(0.0858)	(0.0950)
$AgriculturalDroughtShock_{t-2}$		-0.0565	-0.0565	-0.0565	-0.0565		-0.0721	-0.0721	-0.0721	-0.0721
		(0.0963)	(0.1250)	(0.0806)	(0.0884)		(0.0651)	(0.0881)	(0.0662)	(0.0783)
$\sum_{i=0}^{2} AgriculturalDroughtShock_{t-i}$		0.11	0.11	0.11**	0.11		0.05	0.05	0.05	0.05
		(0.110)	(0.150)	(0.060)	(0.070)		(0.080)	(0.110)	(0.040)	(0.060)
Effect Size 95% CI		(-0.11; 0.33)	(-0.19; 0.41)	(0; 0.23)	(-0.03; 0.25)		(-0.11; 0.21)	(-0.17; 0.27)	(-0.04; 0.14)	(-0.06; 0.16)
Observations	142,515	123,745	123,745	123,745	123,745	142,515	123,745	123,745	123,745	123,745
Adjusted R^2	0.3395	0.3432	0.3432	0.3432	0.3432	0.3394	0.343	0.343	0.343	0.3430
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
VCE estimation	County level SE	County level SE	Province level SE	Month-County level SE	Month-Province level SE	County level SE	County level SE	Province level SE	Month-County level SE	Month-Province level SE

Standard errors in parentheses. Dose treatment strategy, with the rate of domestic violence complaints per 10,000 habitants as dependent variable. *AgriculturalDroughtShock* averages the monthly SPEI over the growing season months of each of the three main crops of the census district, using as weight $\alpha^{(a)}$ or $\alpha^{(b)}$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: *Triple Differences*: Domestic Violence Complaints per 10,000 habitants and Drought

	SPEI1				SPEI3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: *Treatment (a)*								
$\sum_{c=1}^{3} SPEI_t \times GrowingSeason_{c,d} \times \alpha_{c,d}$	0.03	-0.05	0.13	-0.05	0.24***	0.10	0.24*	0.1
	(0.080)	(0.080)	(0.120)	(0.120)	(0.080)	(0.110)	(0.120)	(0.180)
$\sum_{c=1}^{3} SPEI_{t-1} \times GrowingSeason_{c,d} \times \alpha_{c,d}$		0.40***		0.40***		0.31***		0.31***
		(0.090)		(0.130)		(0.110)		-0.18
$\sum_{i=0}^{1}\sum_{c=1}^{3} SPEI_{t-i} \times GrowingSeason_{c,d} \times \alpha_{c,d}$		0.35***		0.35**		0.41***		0.41***
		(0.110)		(0.160)		(0.100)		(0.140)
Effect Size 95% CI		(0.13; 0.56)		(0.03; 0.67)		(0.22; 0.6)		(0.13; 0.69)
Panel B: *Treatment (b)*								
$\sum_{c=1}^{3} SPEI_t \times GrowingSeason_{c,d} \times \alpha_{c,d}$	0.03	-0.09	0.03	-0.09	0.32***	0.13	0.32*	0.13
	(0.130)	(0.130)	(0.180)	(0.180)	(0.120)	(0.160)	(0.180)	(0.270)
$\sum_{c=1}^{3} SPEI_{t-1} \times GrowingSeason_{c,d} \times \alpha_{c,d}$		0.58***		0.58***		0.45***		0.45
		(0.140)		(0.190)		(0.170)		(0.280)
$\sum_{i=0}^{1}\sum_{c=1}^{3} SPEI_{t-i} \times GrowingSeason_{c,d} \times \alpha_{c,d}$		0.49***		0.49**		0.57***		0.57***
		(0.160)		(0.240)		(0.150)		(0.220)
Effect Size 95% CI		(0.17; 0.81)		(0.01; 0.97)		(0.29; 0.86)		(0.15; 1)
Observations	220,023	216,085	220,023	216,085	220,023	216,085	220,023	216,085
Adjusted R^2	0.4001	0.3963	0.4001	0.3963	0.4001	0.3963	0.4001	0.3963
Month-District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-Crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
VCE estimation	Month-County level SE	Month-County level SE	Month-Province level SE	Month-Province level SE	Month-County level SE	Month-County level SE	Month-Province level SE	Month-Province level SE

Standard errors in parentheses. Triple differences strategy, with the rate of domestic violence complaints per 10,000 habitants as dependent variable. *GrowingSeason* is a dummy variable that takes the value of 1 if the month t corresponds to the growing season of crop c of district d. Uses as weight $\alpha^{(a)}$ or $\alpha^{(b)}$ to average the effect of each crop c of district d. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Extensive and Intensive Margins

	Extensive Margin				Intensive Margin			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: SPEI1								
$Drought_t$	0.00281**	0.00195*	0.00281*	0.00195	-0.00567	-0.0243**	-0.00567	-0.0243
	(0.0011)	(0.0011)	(0.0016)	(0.0015)	(0.0126)	(0.0116)	(0.0168)	(0.0148)
$Drought_{t-1}$		0.00279***		0.00279***		0.0326**		0.0326**
		(0.0008)		(0.0008)		(0.0133)		(0.0149)
$Drought_{t-2}$		0.00293***		0.00293**		0.00566		0.00566
		(0.0009)		(0.0014)		(0.0120)		(0.0156)
$Drought_{t-3}$		0.00227*		0.00227		0.011		0.011
		(0.0012)		(0.0017)		(0.0130)		(0.0142)
$Drought_{t-4}$		0.00309**		0.00309**		0.017		0.017
		(0.0012)		(0.0015)		(0.0123)		(0.0127)
$\sum_{i=0}^{4} Drought_{t-i}$		0.01***		0.01***		0.04		0.04
		(0.000)		(0.000)		(0.030)		(0.040)
Effect Size 95% CI		(0.01; 0.02)		(0; 0.02)		(-0.02; 0.1)		(-0.04; 0.12)
Panel B: SPEI3								
$Drought_t$	0.00249**	0.00247	0.00249	0.00247	0.0103	-0.00887	0.0103	-0.00887
	(0.0013)	(0.0017)	(0.0016)	(0.0024)	(0.0150)	(0.0218)	(0.0196)	(0.0252)
$Drought_{t-1}$		0.00129		0.00129		0.0327		0.0327
		(0.0018)		(0.0026)		(0.0287)		(0.0295)
$Drought_{t-2}$		0.00433***		0.00433**		-0.0209		-0.0209
		(0.0016)		(0.0021)		(0.0205)		(0.0255)
$Drought_{t-3}$		-0.00127		-0.00127		0.0262		0.0262
		(0.0016)		(0.0014)		(0.0219)		(0.0261)
$Drought_{t-4}$		0.000746		0.000746		0.00622		0.00622
		(0.0018)		(0.0024)		(0.0207)		(0.0255)
$\sum_{i=0}^{4} Drought_{t-i}$		0.01***		0.01**		0.04		0.04
		(0.000)		(0.000)		(0.030)		(0.030)
Effect Size 95% CI		(0; 0.01)		(0; 0.01)		(-0.02; 0.09)		(-0.03; 0.1)
Mean of dep. variable	85.06%	85.06%	85.06%	85.06%	2.94	2.94	2.94	2.94
SD of dep. variable	(0.36)	(0.36)	(0.36)	(0.36)	(3.78)	(3.78)	(3.78)	(3.78)
Observations	220,032	204,464	220,032	204,464	92,220	86,839	92,220	86,839
Adjusted R^2	0.5311	0.5241	0.5311	0.5241	0.6509	0.6503	0.6509	0.6503
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
VCE estimation	County level SE	County level SE	Province level SE	Province level SE	County level SE	County level SE	Province level SE	Province level SE

Standard errors in parentheses. Columns (1) and (2) present the results of a linear probability model, with domestic violence complaint dummy as dependent variable, that takes the value of 1 if the census district had a least one complaint in t. Columns (3) and (4) use the rate of domestic violence complaints per 10,000 habitants as dependent variable, and contains all the observations where the domestic complaint dummy is equal to 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: *Diff-in-Diff*: Agricultural and Non-Agricultural District

	Agricultural District		**Non-Agricultural District**	
	(1)	(2)	(3)	(4)
Panel A: SPEI1				
$Drought_t$	0.0109	0.0109	-0.0503***	-0.0503***
	(0.0155)	(0.0208)	(0.0135)	(0.0157)
$Drought_{t-1}$	0.0422***	0.0422**	0.025	0.025
	(0.0139)	(0.0163)	(0.0162)	(0.0167)
$Drought_{t-2}$	0.0228*	0.0228	0.00651	0.00651
	(0.0130)	(0.0177)	(0.0154)	(0.0218)
$Drought_{t-3}$	0.0208	0.0208	0.0312**	0.0312***
	(0.0147)	(0.0184)	(0.0121)	(0.0109)
$Drought_{t-4}$	0.0433***	0.0433***	0.012	0.012
	(0.0139)	(0.0158)	(0.0147)	(0.0160)
$\sum_{i=0}^{4} Drought_{t-i}$	0.14***	0.14**	0.02	0.02
	(0.040)	(0.060)	(0.040)	(0.040)
Effect Size 95% CI	(0.06; 0.22)	(0.02; 0.26)	(-0.05; 0.1)	(-0.06; 0.11)
Panel B: SPEI3				
$Drought_t$	0.0387	0.0387	-0.0611***	-0.0611***
	(0.0257)	(0.0347)	(0.0210)	(0.0197)
$Drought_{t-1}$	0.0237	0.0237	0.0578*	0.0578*
	(0.0264)	(0.0273)	(0.0318)	(0.0298)
$Drought_{t-2}$	-0.00298	-0.00298	-0.0114	-0.0114
	(0.0229)	(0.0269)	(0.0248)	(0.0407)
$Drought_{t-3}$	0.0078	0.0078	0.0435	0.0435
	(0.0227)	(0.0279)	(0.0294)	(0.0375)
$Drought_{t-4}$	0.0467**	0.0467	-0.0183	-0.0183
	(0.0227)	(0.0295)	(0.0228)	(0.0304)
$\sum_{i=0}^{4} Drought_{t-i}$	0.11***	0.11**	0.01	0.01
	(0.040)	(0.050)	(0.030)	(0.030)
Effect Size 95% CI	(0.04; 0.18)	(0.01; 0.21)	(-0.05; 0.07)	(-0.05; 0.07)
Observations	159,486	159,486	44,978	44,978
Adjusted R^2	0.3395	0.3395	0.548	0.548
Time FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes
VCE estimation	County level SE	Province level SE	County level SE	Province level SE

Standard errors in parentheses. Differences-in-differences strategy, with the rate of domestic violence complaints per 10,000 habitants as dependent variable, and SPEI1 or SPEI3 as independent variable. A non-agricultural district is defined as a census district with zero arable hectares reported in the "Agricultural and Livestock Census" of 2007. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: *Diff-in-Diff*: Growing and Non-Growing Season

	Growing Season		**Non-Growing Season**	
	(1)	(2)	(3)	(4)
Panel A: SPEI1				
$Drought_t$	-0.0103	-0.0103	-0.0344	-0.0344
	(0.0109)	(0.0158)	(0.0301)	(0.0317)
$Drought_{t-1}$	0.0348***	0.0348**	0.0583	0.0583
	(0.0124)	(0.0148)	(0.0389)	(0.0435)
$Drought_{t-2}$	0.0238**	0.0238	-0.0206	-0.0206
	(0.0100)	(0.0150)	(0.0434)	(0.0496)
$Drought_{t-3}$	0.0162	0.0162	0.047	0.047
	(0.0124)	(0.0144)	(0.0298)	(0.0414)
$Drought_{t-4}$	0.0191	0.0191	0.109***	0.109*
	(0.0133)	(0.0163)	(0.0387)	(0.0564)
$\sum_{i=0}^{4} Drought_{t-i}$	0.08**	0.08	0.16**	0.16**
	(0.030)	(0.050)	(0.080)	(0.080)
Effect Size 95% CI	(0.02; 0.15)	(-0.02; 0.19)	(0.01; 0.31)	(0; 0.32)
Panel B: SPEI3				
$Drought_t$	-0.00427	-0.00427	0.0378	0.0378
	(0.0226)	(0.0277)	(0.0505)	(0.0526)
$Drought_{t-1}$	0.0401	0.0401	-0.047	-0.0470
	(0.0259)	(0.0267)	(0.0576)	(0.0664)
$Drought_{t-2}$	-0.0029	-0.0029	0.089	0.0890
	(0.0186)	(0.0283)	(0.0599)	(0.0559)
$Drought_{t-3}$	0.00748	0.00748	0.0458	0.0458
	(0.0224)	(0.0262)	(0.0583)	(0.0659)
$Drought_{t-4}$	0.00968	0.00968	0.0332	0.0332
	(0.0203)	(0.0262)	(0.0424)	(0.0516)
$\sum_{i=0}^{4} Drought_{t-i}$	0.05	0.05	0.16***	0.16***
	(0.030)	(0.040)	(0.050)	(0.060)
Effect Size 95% CI	(-0.01; 0.11)	(-0.04; 0.14)	(0.05; 0.27)	(0.04; 0.27)
Observations	172,411	172,411	32,053	32,053
Adjusted R^2	0.4757	0.4757	0.454	0.454
Time FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes
VCE estimation	County level SE	Province level SE	County level SE	Province level SE

Standard errors in parentheses. Differences-in-differences strategy, with the rate of domestic violence complaints per 10,000 habitants as dependent variable, and SPEI1 or SPEI3 as independent variable. A month is considered growing season if at least one of the crops in the district is in its growing period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: *Diff-in-Diff*: Domestic Violence and Men in Agriculture

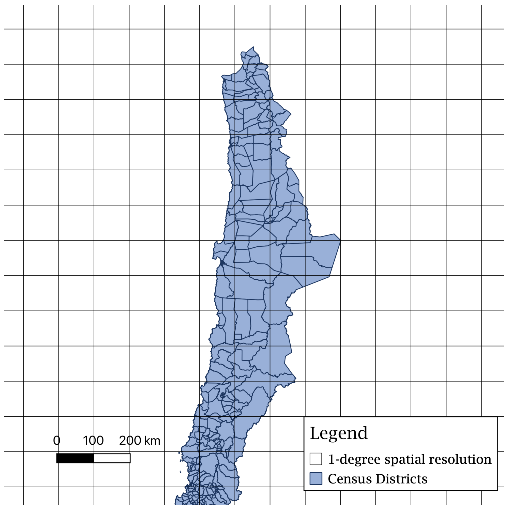
	1st Quintile				5th Quintile			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: SPEI1								
$Drought_t$	0.0122	0.0122	0.0122	0.0122	0.00767	0.00767	0.00767	0.00767
	(0.0347)	(0.0339)	(0.0274)	(0.0271)	(0.0227)	(0.0266)	(0.0335)	(0.0353)
$Drought_{t-1}$	0.0284	0.0284	0.0284	0.0284	0.0112	0.0112	0.0112	0.0112
	(0.0273)	(0.0250)	(0.0269)	(0.0298)	(0.0267)	(0.0279)	(0.0382)	(0.0397)
$Drought_{t-2}$	0.0642^{***}	0.0642^{***}	0.0642^{**}	0.0642^{**}	0.0244	0.0244	0.0244	0.0244
	(0.0207)	(0.0211)	(0.0272)	(0.0293)	(0.0230)	(0.0238)	(0.0321)	(0.0341)
$Drought_{t-3}$	0.0407	0.0407	0.0407	0.0407	0.0387	0.0387	0.0387	0.0387
	(0.0263)	(0.0279)	(0.0265)	(0.0299)	(0.0238)	(0.0245)	(0.0325)	(0.0346)
$Drought_{t-4}$	0.000252	0.000252	0.000252	0.000252	0.0282	0.0282	0.0282	0.0282
	(0.0254)	(0.0279)	(0.0248)	(0.0286)	(0.0245)	(0.0245)	(0.0300)	(0.0317)
$\sum_{i=0}^{4} Drought_{t-i}$	0.15	0.15	0.15^{***}	0.15^{***}	0.11^{*}	0.11^{*}	0.11^{**}	0.11^{**}
	(0.09)	(0.10)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
Effect Size 95% CI	(-0.03; 0.32)	(-0.06; 0.35)	(0.05; 0.24)	(0.04; 0.25)	(0; 0.22)	(-0.01; 0.23)	(0; 0.22)	(0; 0.22)
Panel B: SPEI3								
$Drought_t$	0.0386	0.0386	0.0386	0.0386	-0.0609	-0.0609	-0.0609	-0.0609
	(0.0451)	(0.0456)	(0.0414)	(0.0508)	(0.0545)	(0.0581)	(0.0566)	(0.0591)
$Drought_{t-1}$	0.00947	0.00947	0.00947	0.00947	0.190^{***}	0.190^{***}	0.190^{***}	0.190^{**}
	(0.0398)	(0.0324)	(0.0566)	(0.0668)	(0.0465)	(0.0494)	(0.0731)	(0.0773)
$Drought_{t-2}$	0.0363	0.0363	0.0363	0.0363	-0.0904	-0.0904	-0.0904	-0.0904
	(0.0412)	(0.0392)	(0.0486)	(0.0533)	(0.0591)	(0.0608)	(0.0614)	(0.0633)
$Drought_{t-3}$	0.00479	0.00479	0.00479	0.00479	-0.0731^{**}	-0.0731^{**}	-0.0731	-0.0731
	(0.0417)	(0.0422)	(0.0520)	(0.0619)	(0.0330)	(0.0334)	(0.0641)	(0.0660)
$Drought_{t-4}$	-0.016	-0.016	-0.016	-0.0160	0.141^{***}	0.141^{***}	0.141^{**}	0.141^{**}
	(0.0292)	(0.0270)	(0.0366)	(0.0447)	(0.0442)	(0.0458)	(0.0595)	(0.0615)
$\sum_{i=0}^{4} Drought_{t-i}$	0.07	0.07	0.07^{*}	0.07	0.11^{*}	0.11	0.11^{**}	0.11^{*}
	(0.07)	(0.07)	(0.04)	(0.05)	(0.06)	(0.07)	(0.05)	(0.06)
Effect Size 95% CI	(-0.06; 0.21)	(-0.08; 0.23)	(-0.01; 0.15)	(-0.02; 0.17)	(-0.02; 0.24)	(-0.03; 0.24)	(0; 0.21)	(0; 0.22)
Observations	39,034	39,034	39,034	39,034	30,243	30,243	30,243	30,243
Adjusted R^2	0.4311	0.4311	0.4311	0.4311	0.2526	0.2526	0.2526	0.2526
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population Weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
VCE estimation	County level SE	Province level SE	Month-County level SE	Month-Province level SE	County level SE	Province level SE	Month-County level SE	Month-Province level SE

Differences-in-differences strategy, with the rate of domestic violence complaints per 10,000 habitants as dependent variable, and SPEI1 or SPEI3 as independent variable. The regressions only consider agricultural districts. An agricultural district is defined as a census district with more than zero arable hectares reported in the "Agricultural and Livestock Census" of 2007. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

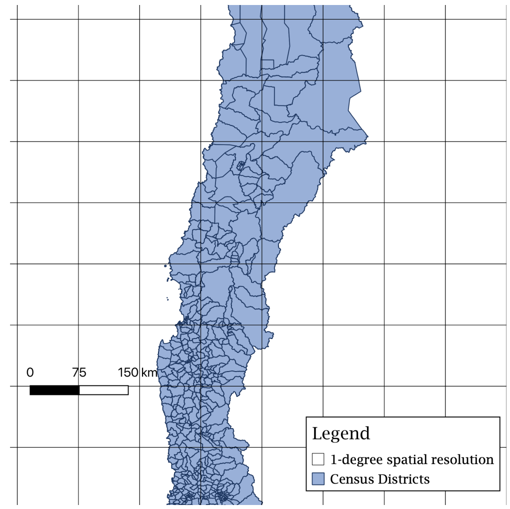
X Figures

Figure 1: Data's granularity

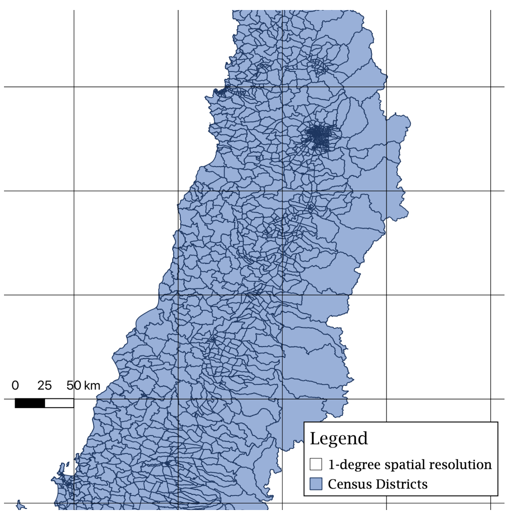
"Agricultural and Livestock Census" districts and SPEI 1 × 1-degree resolution



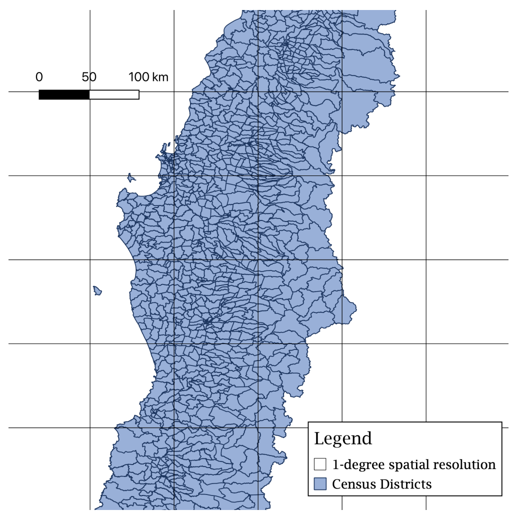
(a) Norte Grande



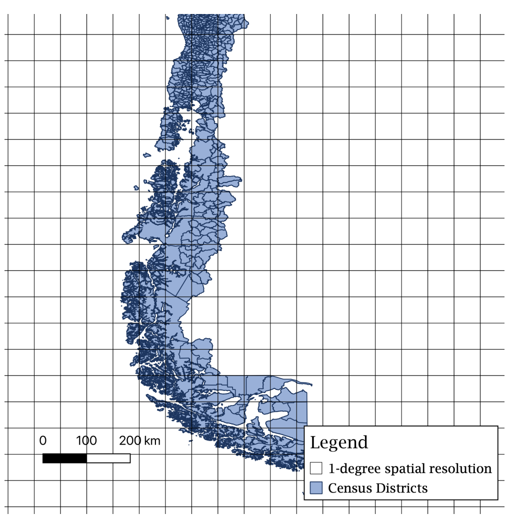
(b) Norte Chico



(c) Central Zone



(d) South Central Zone



(e) South Zone

Figure 2: Rate of Domestic Violence Complaints per 10,000 habitants over time

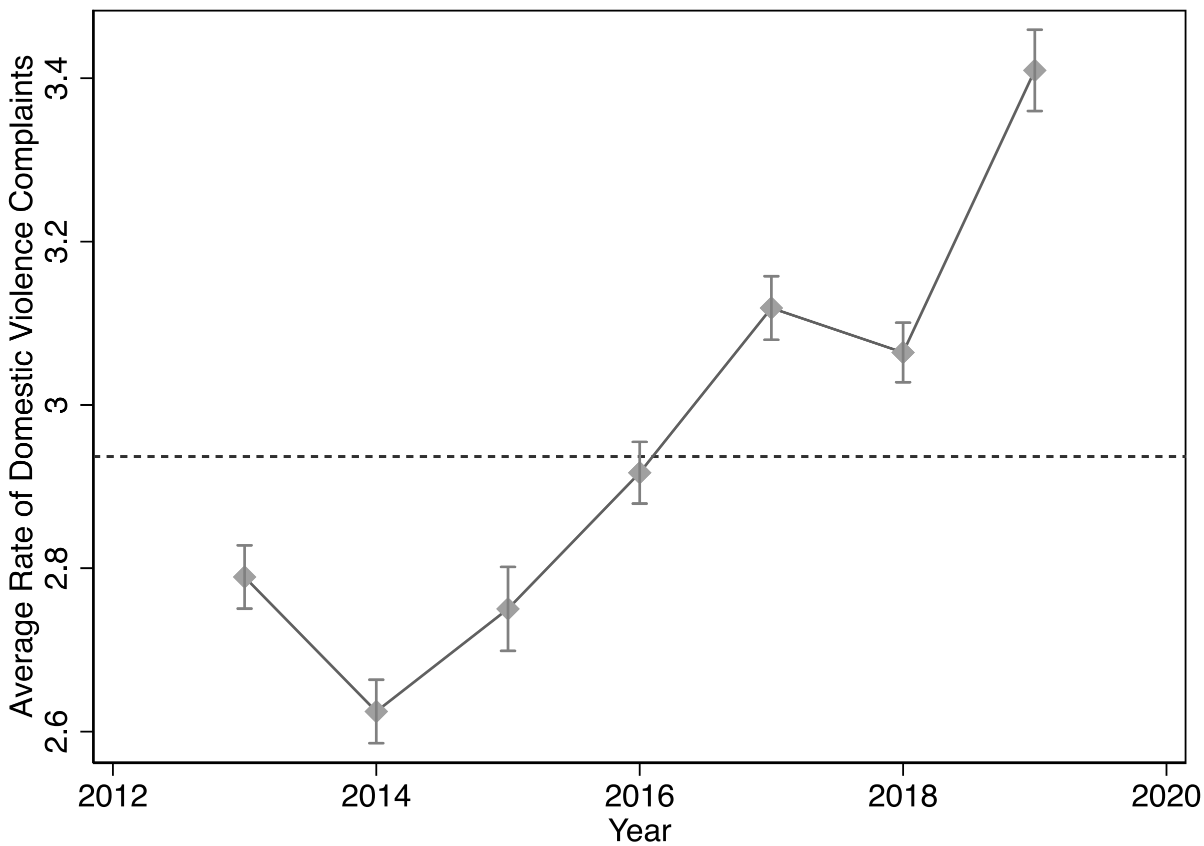
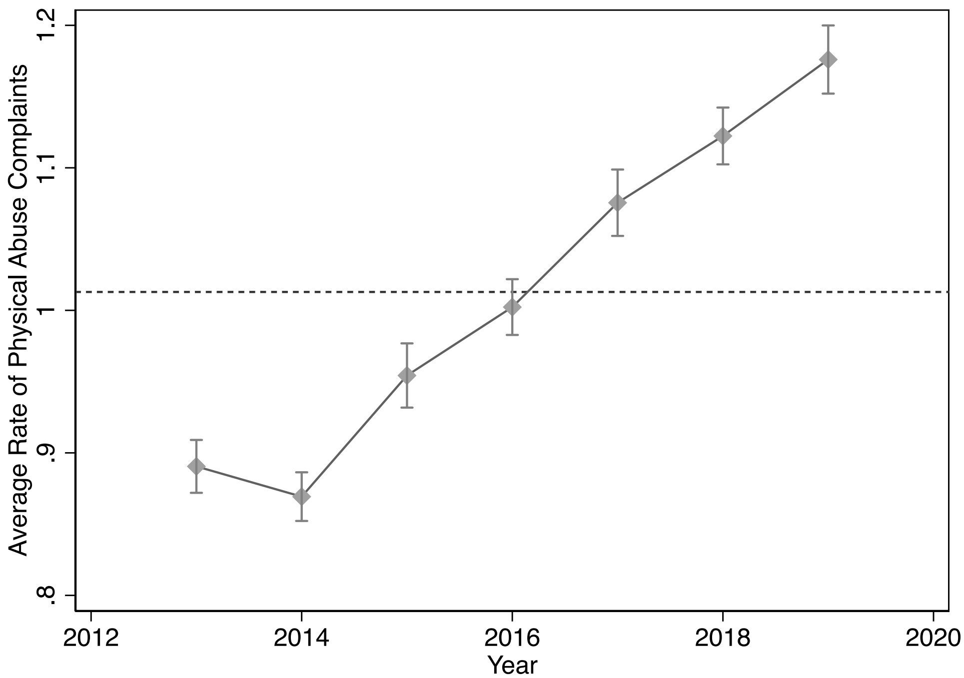
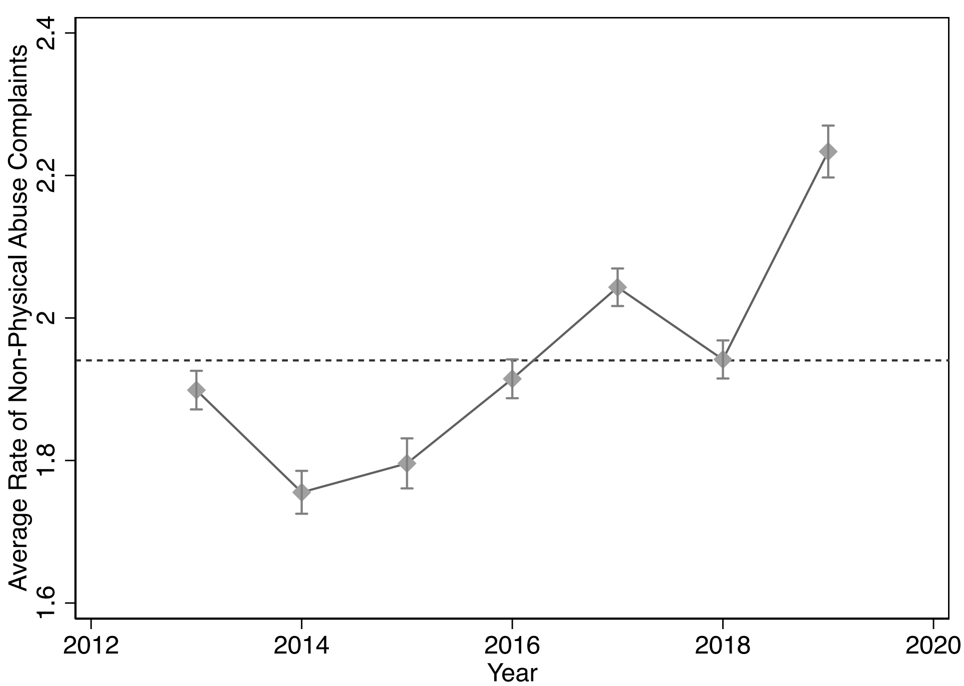


Figure 3: Rate of Domestic Violence Complaints per 10,000 habitants over time disaggregated by type.



(a) Evolution of Physical Abuse Complaints per 10,000 habitants
Dotted line represents mean value 1.01



(b) Evolution of Non-Physical Abuse Complaints per 10,000 habitants
Dotted line represents mean value 1.93

Figure 4: *Lags Differences in Differences*

95% Confidence Interval, Population Weights & County level SE

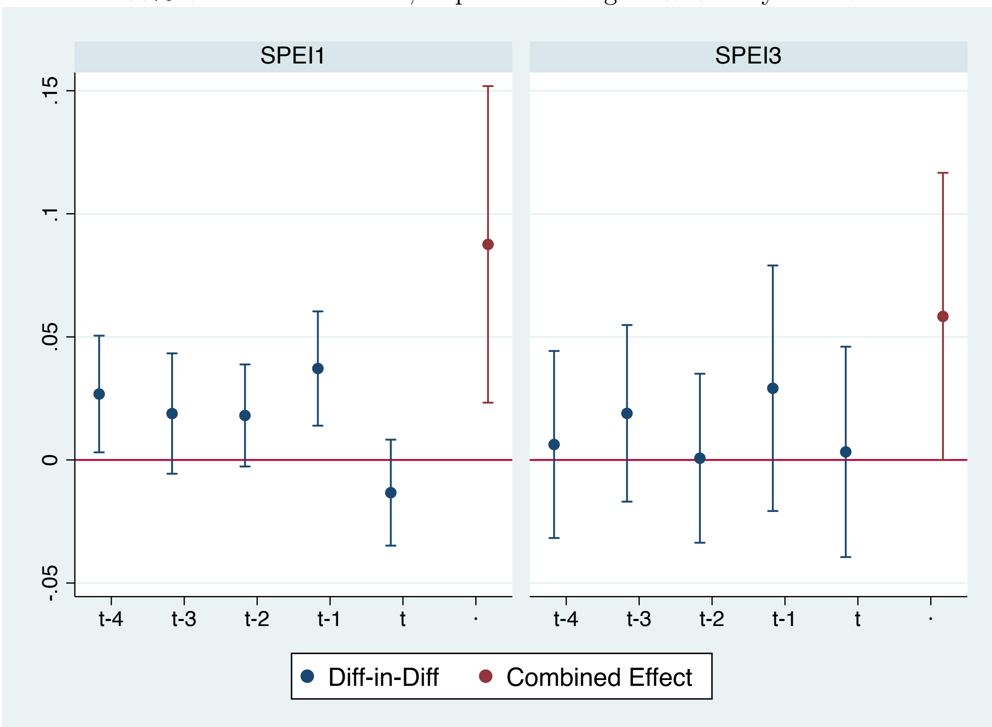


Figure 5: *Lags Dose Treatment*

95% Confidence Interval, Population Weights & County level SE

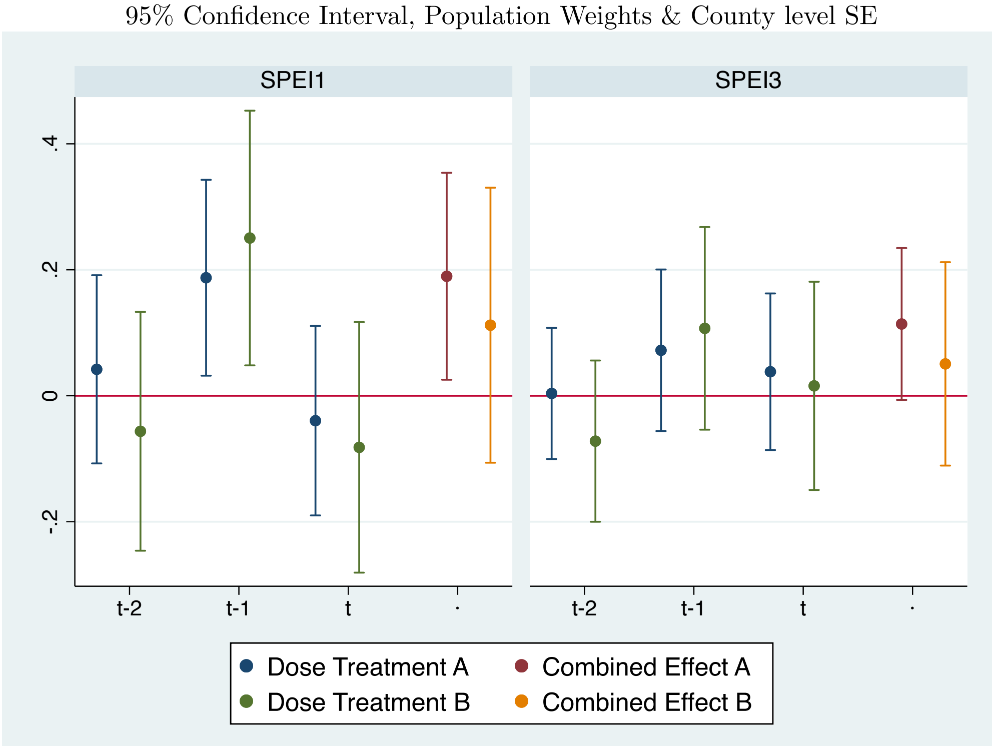


Figure 6: *Lags Agricultural and Non-Agricultural Districts*

95% Confidence Interval, Population Weights & County level SE

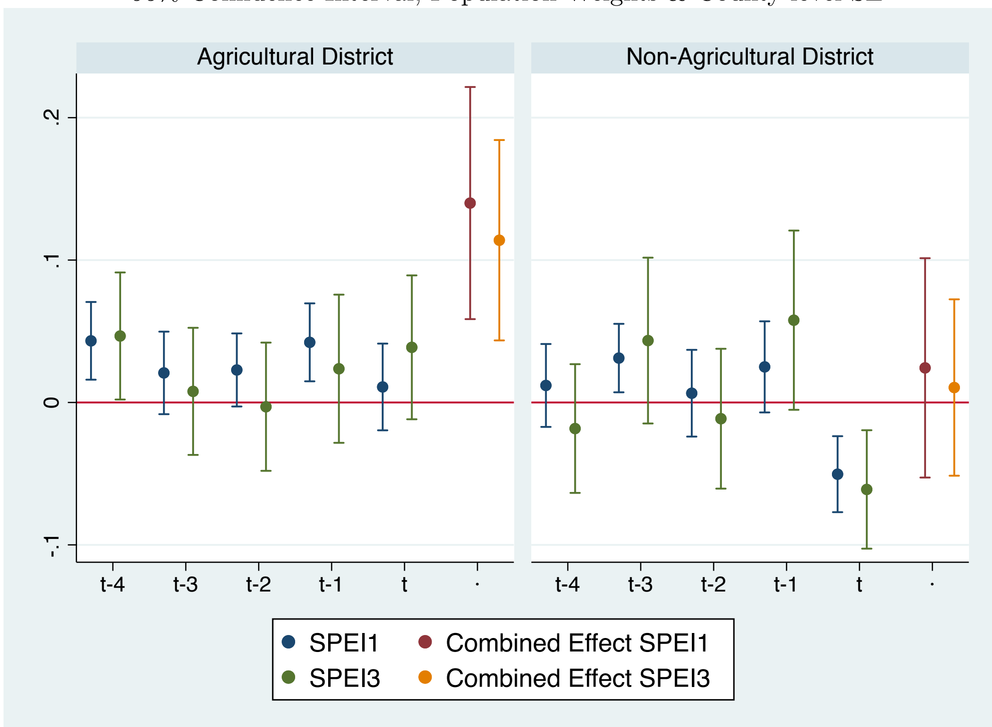


Figure 7: *Lags Growing and Non-Growing Season*

95% Confidence Interval, Population Weights & County level SE

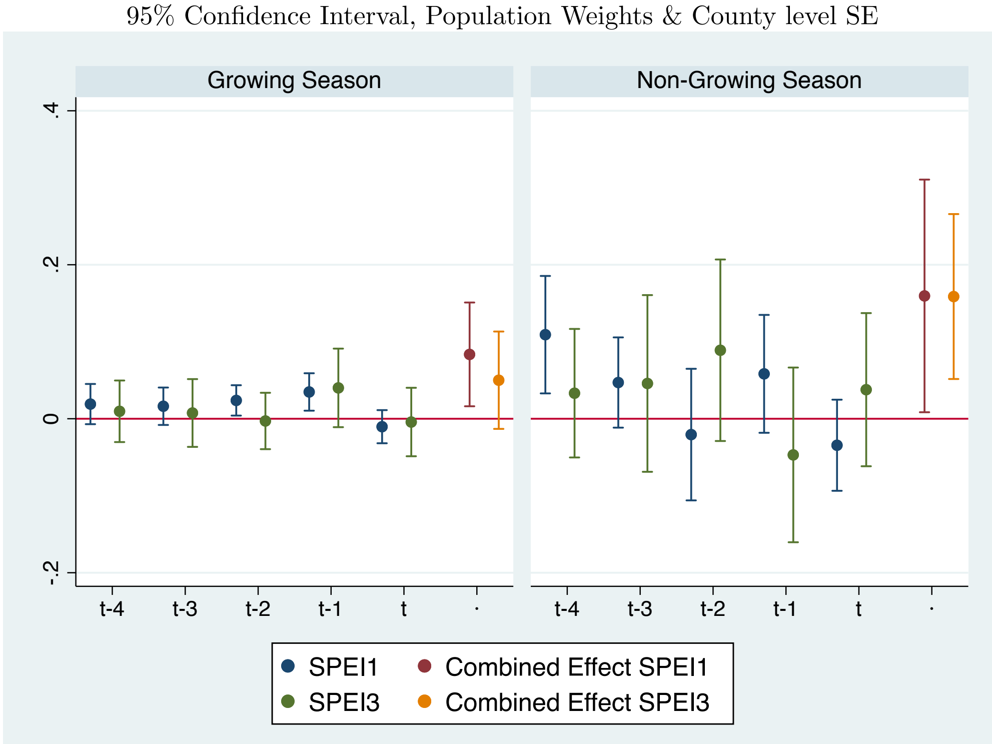


Figure 8: *Leads Differences in Differences*

95% Confidence Interval, Population Weights & County level SE

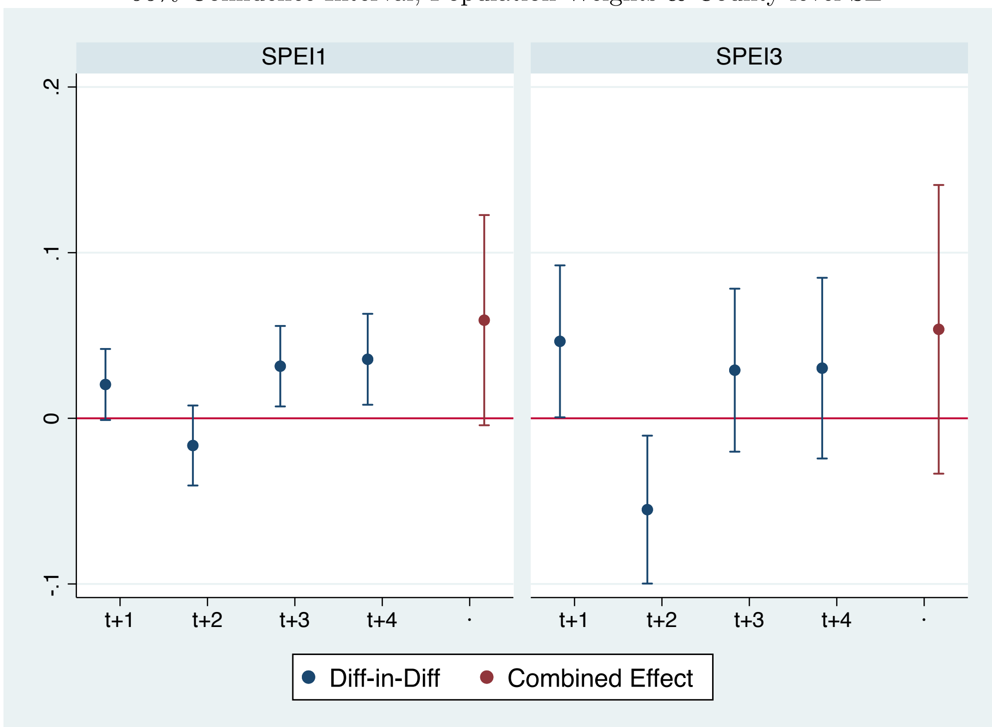


Figure 9: *Leads Dose Treatment*

95% Confidence Interval, Population Weights & County level SE

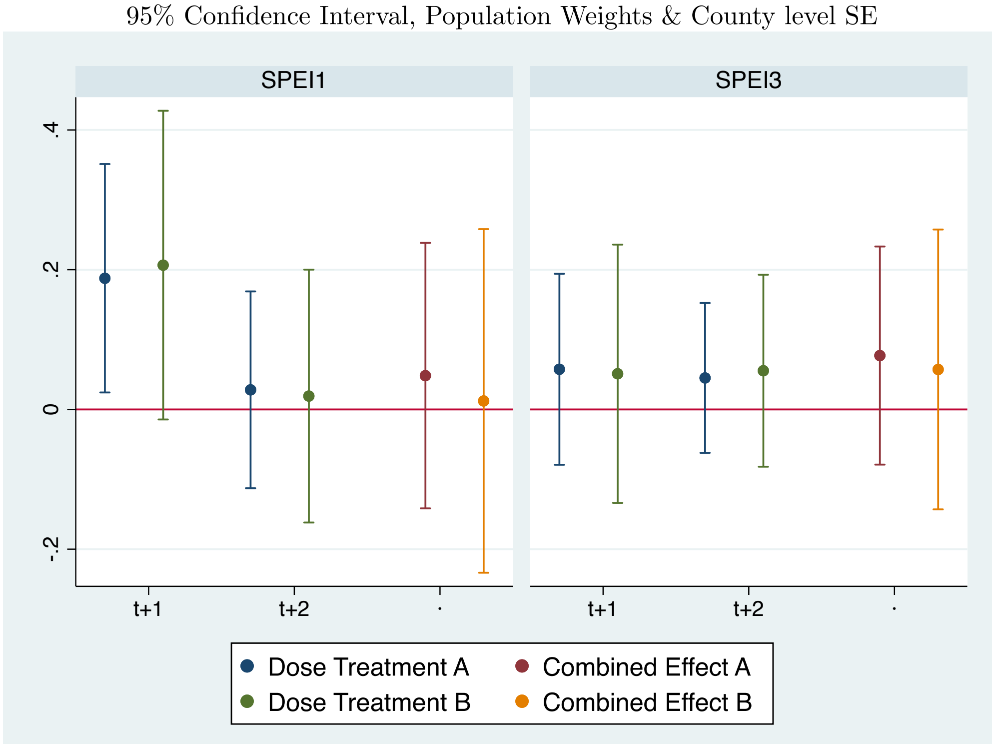
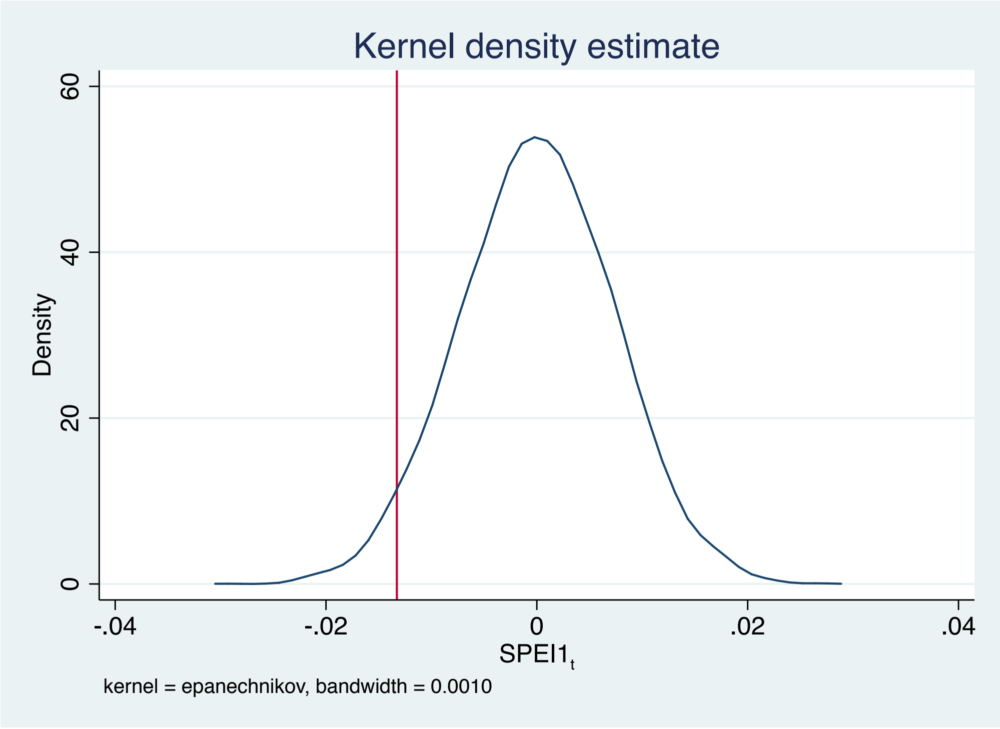
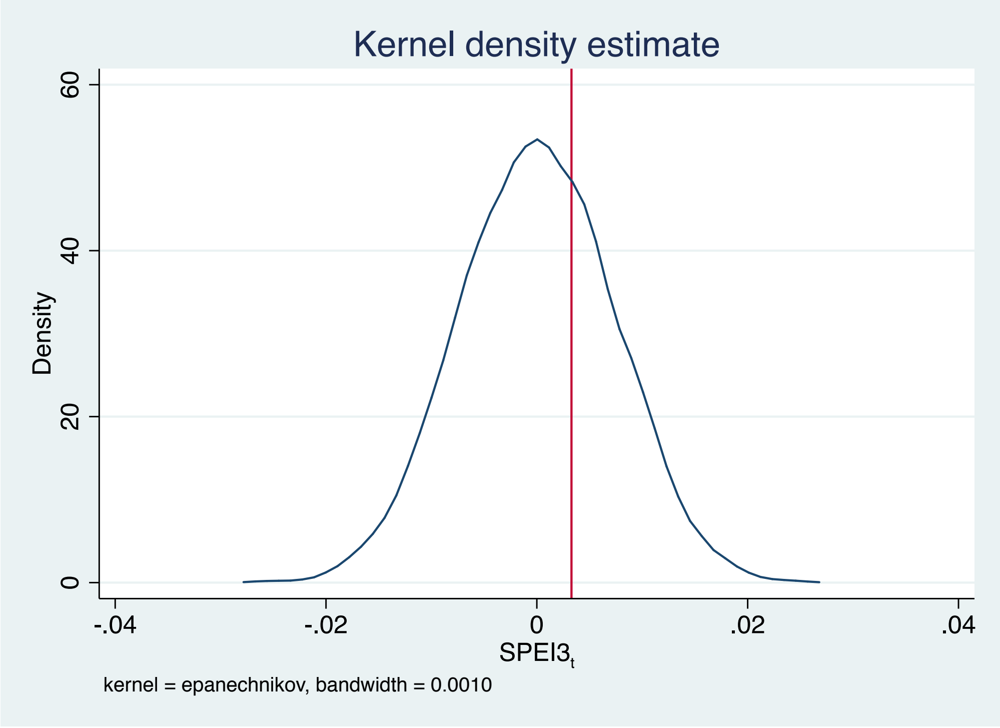


Figure 10: Differences-in-Differences Robustness

Effect in $t = 0$



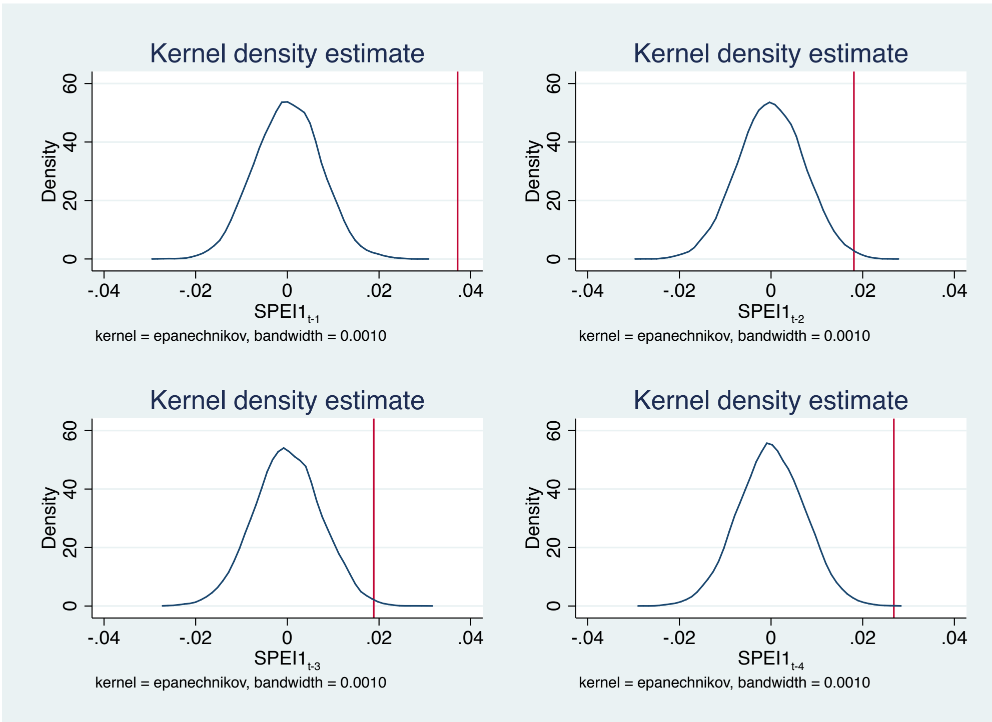
(a) SPEI1



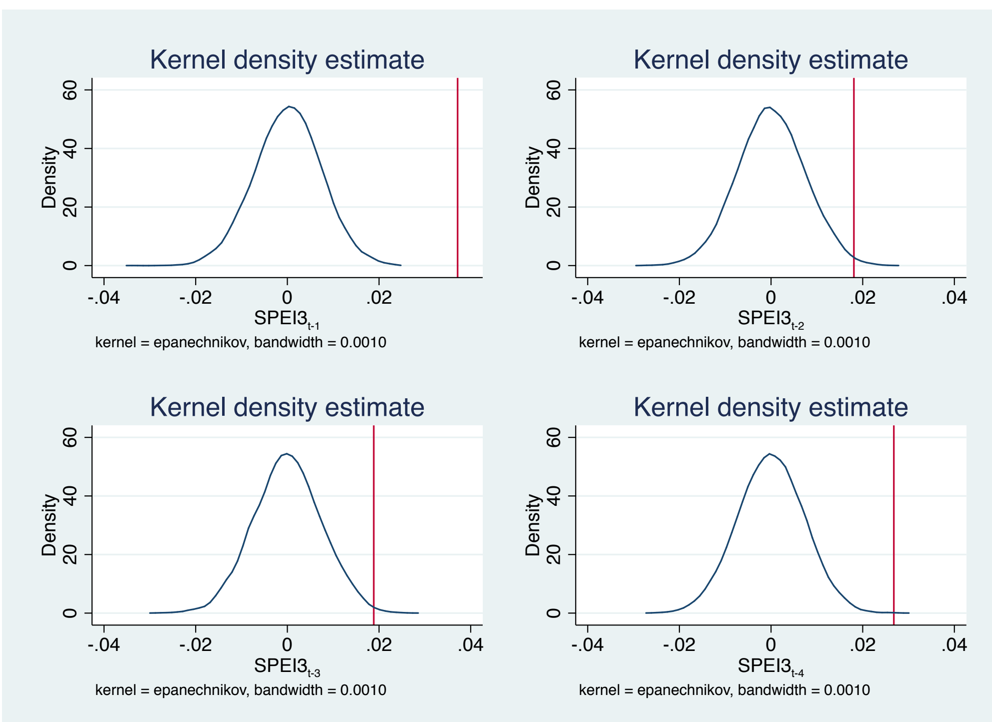
(b) SPEI3

Figure 11: Differences-in-Differences Robustness

Lags $t-1$, $t-2$, $t-3$ & $t-4$



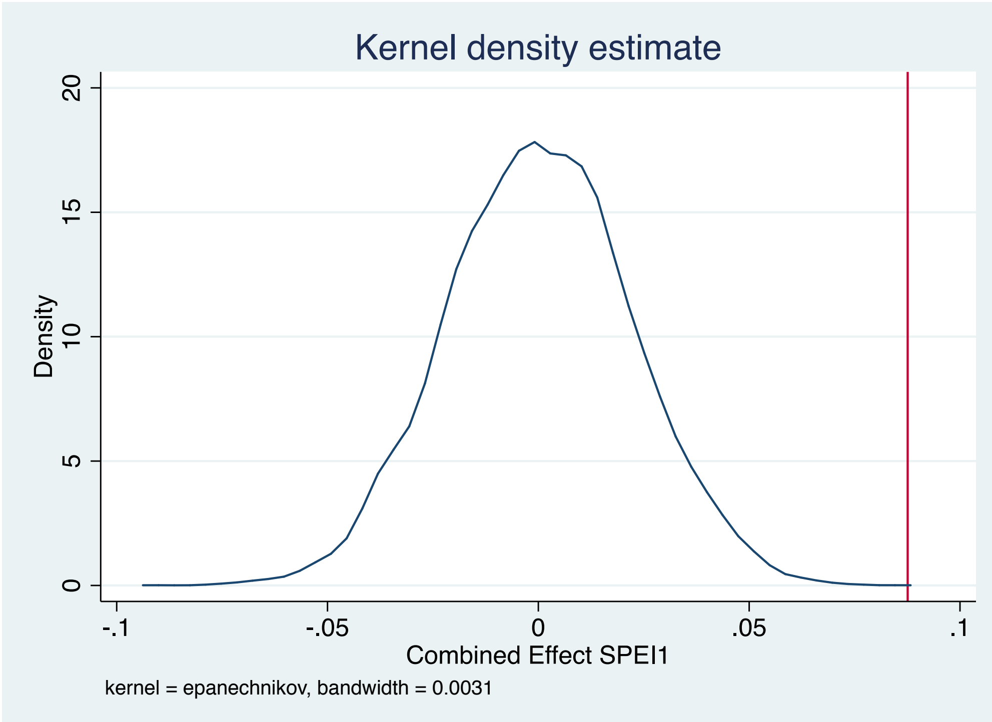
(a) SPEI1



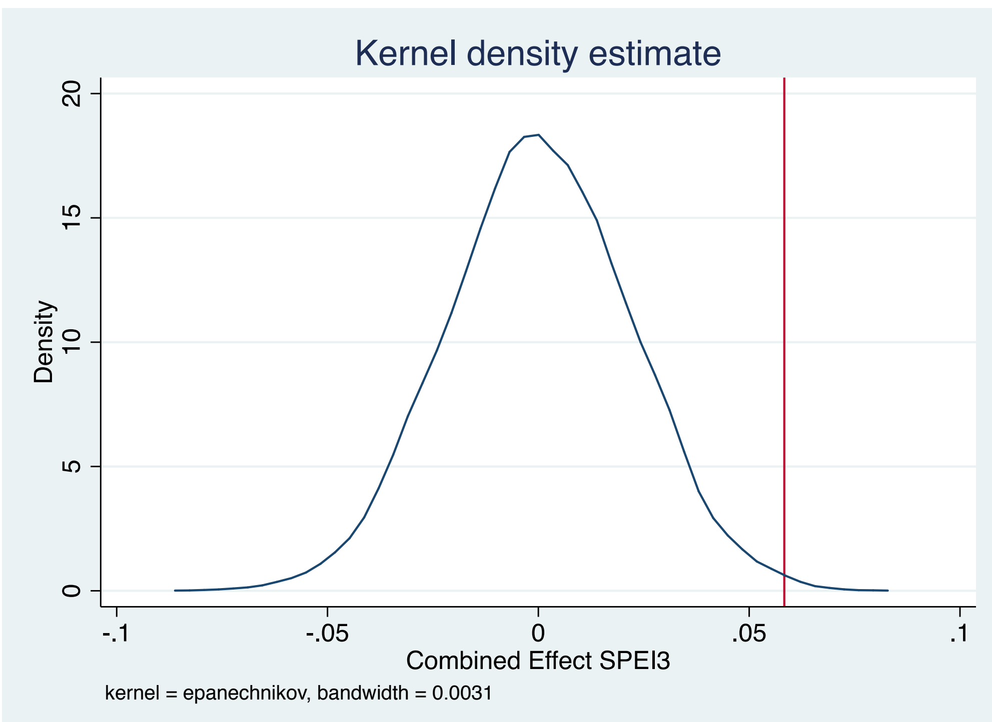
(b) SPEI3

Figure 12: Differences-in-Differences Robustness

Combined Effect



(a) SPEI1



(b) SPEI3

Appendix A Theoretical Framework

The theoretical framework developed in this section is based on Anderberg et al. (2015) work, and adapted to consider droughts as the exogenous shocks changing labor opportunities in rural Chile. The framework is derived from an intra-household bargaining model, where the abuse is non-intentional. I will presume that someone assumes a dominant role inside every couple, while the other is dominated. With no loss of generality, the model considers the male as the dominant sex inside the relationship, consistent with the existing empirical evidence (Angelucci, 2008).

Yet, there exist information asymmetries: wives do not have perfect information about their husbands' type. In this model, marriage is a non-market institution that works as insurance against income risks. A crucial characteristic of the framework is that the male may or may not have a predisposition to violence, and his partner can infer his type from his behavior. In equilibrium, a male with a preference for violence can reveal or hide his kind. His incentives depend on each partner's future earnings, which hinge on drought idiosyncratic risks and potential salaries.

A.1 *Signaling Model with Forward-looking Males*

Anderberg et al. (2015) consider a dynamic game with incomplete information including a wife (w) and a husband (h). The game proceeds as follows:

(i) Nature plays and chooses the husband's type between $\theta \in \{N, V\}$, where N denotes aversion to violence, and V predisposition to it. The probability that $\theta = V$ is denoted by $\phi \in (0, 1)$, i.e., $P(\theta = V) = \phi \in (0, 1)$.

(ii) The husband learns his type θ and chooses a behavioral effort from the set $\varepsilon \in \{0, 1\}$. The probability of occurrence of violence depends on values of θ and ε, and it is denoted by $\kappa(\theta, \varepsilon) \in [0, 1]$. The authors propose two assumptions: first, if $\varepsilon = 1$, the likelihood of violence occurring decreases; second, a husband type N is less prone to violence than a husband type V. From the above can be deduced that:

(a) $\kappa(\theta, 1) < \kappa(\theta, 0)$ for each $\theta \in \{N, V\}$.

(b) $\kappa(N, \varepsilon) < \kappa(V, \varepsilon)$ for each $\varepsilon \in \{0, 1\}$.

Additionally, ξ represents the cost (in utils) of making an effort $\varepsilon = 1$, namely, there exists a "costly action" that the husband can perform to reduce the probability of losing control. Following Angelucci (2008), he could reduce his alcohol consumption, for example.

(iii) The wife observes ε, but not θ, ergo, she sees the effort but not her husband's type. Thus, she updates her beliefs about her husband's kind to $\hat{\phi}(\varepsilon)$. Given her updated information, she decides to stay married (m) or to get a divorce (d), which is represented by $\chi = \{m, d\}$. The cost of getting a divorce, for each partner, i, is $\alpha_i \geq 0$ (which could be emotional).

(iv) Nature plays again and decides whether there will be drought or not. In the event of drought, and understanding that rural areas mostly have economies dependent on agriculture (Berdegué et al., 2010), each partner i ($i = h, w$) can suffer a negative income effect with a probability π_i. The former can happen via unemployment, or through a decrease in their variable wage (if they get paid per kilo harvested, for example), or by a decline in the production for self-consumption, among others. Therefore, if the couple remains married, each spouse obtains a monetary pay-off that depends on total household income. If they divorce, each individual's financial pay-off depends on their personal earnings.

(v) If the couple is still married, with a probability of $\kappa(\theta, \varepsilon)$, they will get involved in a violent situation. In case of violence:

  (a) Wife suffers a disutility $\delta_w > 0$.

  (b) Type N husband has a disutility $\delta_N > 0$.

  (c) Type V husband has no disutility, i.e. $\delta_V = 0$.

A.2 *Equilibrium*

The wife rationally decides whether or not to remain married, depending on the expected pay-offs of each situation. Let M and D represent the expected utility of being married and getting a divorce, respectively. Anderberg et al. (2015) proposes that the wife's expected utility of remaining married is decreasing in $\hat{\phi}(\varepsilon)$, i.e., in her perceived probability that her husband has a violent predisposition. The equilibrium hinges on a series of assumptions:

Assumption 1. ("when-drought-hits-men") The wife observes that her husband is not making an effort ($\varepsilon = 0$), so she updates her beliefs to $\hat{\phi} = 1$, understanding that her husband has a predisposition to violence. Furthermore, she knows with certainty that her husband is getting the negative income shock, and she is not ($\pi_h = 1$ and $\pi_w = 0$), which leads to an increase in her bargaining power inside the household. Consequently, her expected utility of remaining married is smaller than getting a divorce ($\boldsymbol{M < D}$).

Assumption 2. ("when-drought-hits-women") The wife observes that her husband is not making an effort ($\varepsilon = 0$), so she updates her beliefs to $\hat{\phi} = 1$. However, she knows with certainty that she is getting the negative income shock, and her husband is not ($\pi_h = 0$ and $\pi_w = 1$). In this case, her expected utility of remaining married is higher than the one of getting a divorce ($\boldsymbol{M} > \boldsymbol{D}$) because she is an economically dependent woman who depends on her abusive partner.

Assumption 3. ("nothing-new-under-the-sun") If the expected utility of remaining married has not changed, she will remain married ($\boldsymbol{M} > \boldsymbol{D}$) regardless of the probabilities of an income shock ($(\pi_h, \pi_w) \in [0, 1]^2$) and her husband's actions ($\varepsilon \in \{0, 1\}$). That is, she will be consistent with her decision to get married in the first place if the information available does not change.

Assumption 4. Husband type N values the reduction in violence, related to an effort $\varepsilon = 1$, more than its cost ξ.

Assumption 5. At any level of effort $\varepsilon \in \{0, 1\}$, for any husband $\theta \in \{N, V\}$, it is preferable to continue married than to get a divorce. Therefore, the husband has no incentives to choose a behavioral effort that leads to divorce.

Following the "intuitive criterion" of Cho-Kreps (Cho & Kreps, 1987), two types of equilibriums exist:

(i) Pooling Equilibrium : It occurs when both types of husbands make a costly effort to reduce violence. Husband N makes an effort because he values the reduction of violence more than its costs. Husband V strives not to reveal his type since this will lead to divorce (in the face of $\varepsilon = 0$, his wife updates her beliefs to $\hat{\phi} = 1$, i.e., she will believe he has a violent predisposition).

(ii) Separating Equilibrium: The husband observes his wife is economically vulnerable, and even though she updates her beliefs to $\hat{\phi} = 1$, she would not leave him. In this scenario, a husband with a violent predisposition has no incentives to make an effort that would reduce the risk of violence. On the contrary, a husband reluctant to violence chooses $\varepsilon = 1$, given that he values the reduction of violence more than its costs. The wife updates her beliefs and remains married since she received a negative income shock.

A.3 *Empirical Prediction*

Under the assumption that a drought shock may change the household's bargaining powers through income, the model predicts:

(i) In the face of a negative income shock to the husband, the violent-men will conceal their type, and I would expect a decrease in domestic violence complaints, in line with Aizer (2010) and Anderberg et al. (2015) predictions.

(ii) In the face of a negative income shock to the wife, the violent-men will be less encouraged to hide their type, and I would expect an increase in domestic violence complaints, as Aizer (2010) and Anderberg et al. (2015) 's models predict.

Appendix B

Figure B1 shows how the rate of domestic violence complaints move over time compared to the different drought indexes. As an exemplification, in case drought increases domestic abuse, I should expect to see the complaints go up when the index drops. However, figure B1 does not show a clear relationship between these two variables.

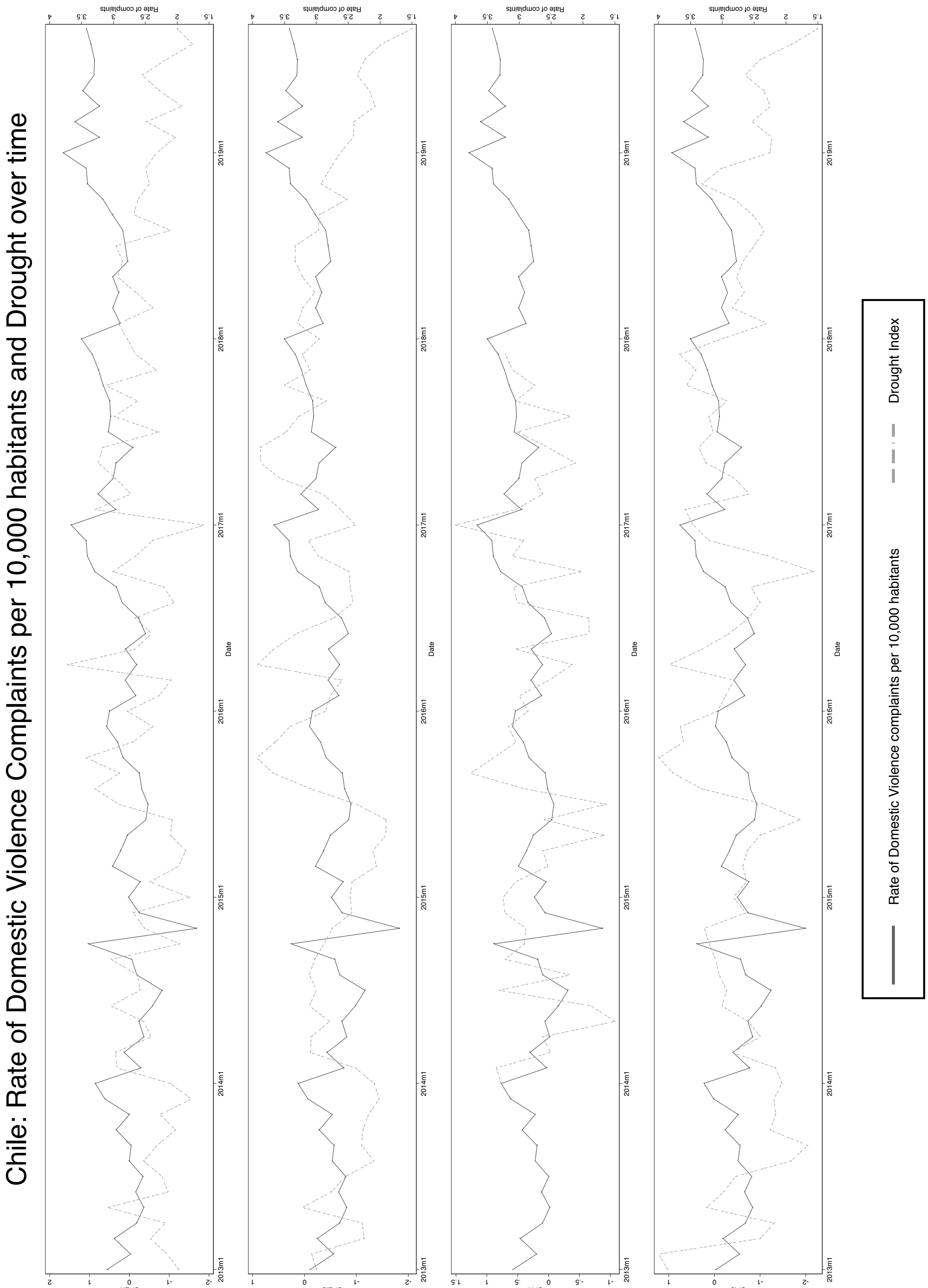


Figure B1: Rate of Domestic Violence Complaints per 10,000 habitants and Drought over time

Appendix C

Table C1: Proportion of Men in Agriculture Statistics

Quintile	N	Mean	Min	Max	SD	Median
1	42,481	0.720	0.000	0.797	0.100	0.751
2	30,082	0.827	0.798	0.847	0.017	0.830
3	29,202	0.877	0.849	0.892	0.012	0.879
4	23,081	0.913	0.892	0.929	0.011	0.911
5	32,540	0.965	0.929	1.000	0.023	0.961
Total	157,386	0.858	0.000	1.000	0.097	0.878

Statistics of the proportion of men belonging to the agricultural labor force according to the National Employment Survey information from January 2013 to September 2019. It includes data only from agricultural census districts. District population weights used.

I use data from the National Employment Survey (ENE for its initials in Spanish), from January 2013 to September 2019 at a county level. I only have data for 300 counties (or 2,562 census districts), from which 275 (or 1,962 census districts) have more than zero arable hectares. I calculated each county's mean proportion of men in the agricultural labor force using the entire data period. Then, I attributed the county's mean percentage of men found at ENE to the corresponding census districts of that county, weighted by their district's population.