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Agricultural Shocks, Coping Policies and Deforestation: Evidence from the Coffee Leaf Rust Epidemic in Mexico*

Isabelle Chort† Berk Öktem‡

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Abstract

Deforestation in the tropics is a critical issue that interacts with global environmental changes, and the mediating role of negative agricultural shocks is ambiguous. We investigate the impact of the massive epidemic of coffee leaf rust (CLR) that affected Mexico from 2012 on deforestation. CLR is a fungal disease that negatively affects coffee production. We exploit the gradual spread of the epidemic across coffee-growing municipalities and estimate a difference-in-difference model. We find that deforestation increased by 32% in CLR-affected municipalities but we find no increase in agricultural land. Effects are driven by municipalities with low coffee yields, characterizing shade coffee systems, and states where rustic coffee systems were predominant. These results suggest that deforestation occurred within coffee cultivation areas and point out the concurrent role of government subsidies and incentives through the PROCAFE program, launched in 2014, that promoted the replacement of traditional coffee trees by CLR-resistant hybrids. We study the dynamic effects of CLR and exploit the delayed launch of PROCAFE to try to disentangle the impact of the epidemic from that of the policy response. Our results emphasize the vulnerability of agroforestry systems to exogenous shocks and suggest that PROCAFE, as a short-term response to CLR, contributed to increasing deforestation and accelerating the transition of Mexican traditional coffee landscapes to monoculture.

Keywords : deforestation; coffee; Mexico; climate change; land use; agroforestry systems; government policies

JEL classification : O13; Q23 ; Q57; Q58

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1 Introduction

Forest preservation is rightly perceived as a key dimension to limit climate change, but the role of forests, particularly in tropical areas, is not limited to carbon sequestration. The 2019 IPBES-IPCC assessment report on biodiversity (Brondizio et al., 2019) points out the urgency to reduce its unprecedented decline before reaching the tipping point which would have catastrophic consequences, particularly on the developing world. Tropical forests support two-thirds of the world's species (Bradshaw et al., 2009) and they are constantly under pressure due to agricultural expansion and urbanization. Mexico is particularly concerned, since one of these tropical forest areas, the Mesoamerica biodiversity hotspot, covering the Southern part of Mexico, Guatemala, and Honduras, lost 7% of tree cover between 1992 and 2015 (Hu et al., 2021). Agricultural expansion is by far the main driver of deforestation in tropical and sub-tropical areas. In the 2000s, more than 90% of forest loss in Latin America is due to agriculture (Kissinger et al., 2012).

On the other hand, agriculture in those areas is increasingly vulnerable to shocks due to the rise in temperatures and greater climate variability which are already visible consequences of climate change. It is thus key to better understand the interrelations between negative shocks and land conversion. The economic literature demonstrates that shocks on agricultural yields affect land use, but their impacts on deforestation are ambiguous as they are channeled by different mechanisms. For instance, a reduction of yields caused by repeated droughts has been found to increase deforestation due to the expansion of cropland to reach pre-shock production levels (Zaveri et al., 2020). But shocks may also encourage off-farm work and enhance migration, thus lowering the pressure on forests (Rodriguez-Solorzano, 2014). Repeated shocks, by signalling an increase in the risk associated with agricultural production may also reduce incentives for risk-averse farmers to extend agricultural land (Desbureaux and Damania, 2018).

Our paper explores a rather undocumented issue in the literature - the mixed consequences of both negative agricultural shocks and the short-term policy responses that they generate, on deforestation. By shaping incentives, government policies may distort household responses to an adverse shock and modify equilibrium outcomes. However, the impact of a policy designed to cope with a negative shock is most often hard to disentangle from the impact of the initial shock itself.

We investigate the impact of the recent outbreak of a fungal disease affecting coffee, the coffee leaf rust (CLR), on deforestation in Mexico. This massive outbreak spread gradually since 2012 in Central America and Mexico and caused severe decreases in Arabica coffee yields. The severity of the epidemic can be related to favourable weather conditions associated with climate change (Libert Amico et al., 2020), such as an increase in minimum temperatures (Avelino et al., 2015; Merle et al., 2020).

The Mexican government responded to this shock with a support program called PROCAFE, which started in 2014. Part of the program was targeted at the replacement of traditional coffee trees by CLR-resistant hybrids. While coffee in Mexico is traditionally produced under shade trees in agroforestry systems, the hybrid Arabica varieties promoted by the program are adapted to sunlight and do not need tree cover.

Although several environmental factors are believed to influence the intensity of the disease, such as altitude, precipitation patterns, or temperatures, they interact in such a complex manner that the local outbreaks of the CLR within Mexico from 2012 onwards proved highly unpredictable (Avelino et al., 2015). We first exploit the quasi-random nature of the CLR spread and intensity and provide estimates of the impact of the epidemic on deforestation in Mexico in a difference-in-difference framework. Using deforestation data from Hansen et al. (2013), we find that deforestation increased by 32 percent in

CLR-affected municipalities compared to municipalities that were not affected by the disease. Focusing on land use, based on municipal level statistics provided by the Mexican Ministry of Agriculture, we find that CLR had no significant impact on pastures and non-coffee agricultural area and, if any, a small negative impact on coffee area. Matching our dataset with land use data from the Mexican statistical institute, we find that CLR increased deforestation in agricultural land. An heterogeneity analysis reveals that CLR-induced deforestation increased more in municipalities with initially low coffee yields. Taken together, these findings suggest that CLR-induced deforestation cannot be explained by agricultural expansion, but rather affects traditional coffee agroforestry systems, which invites us to question the role played by the PROCAFE program launched in 2014. We take advantage of the late implementation of PROCAFE, to try to disentangle the effects of CLR and PROCAFE on deforestation. We find that the impact of CLR on deforestation was larger after 2014, and that deforestation increased to the same extent in coffee municipalities whether affected or not by the disease compared to non-coffee municipalities. An event-study analysis reveals that in municipalities affected by the disease in 2012 and 2013, deforestation increased significantly only two to three years after the outbreak, while deforestation jumped simultaneously with the CLR outbreak for municipalities that were affected by CLR after 2014. These convergent results suggest that PROCAFE contributed to the observed increase in deforestation following the CLR crisis in Mexico: by publicly advertising CLR-resistant hybrid varieties and increasing their availability to coffee farmers most probably contributed to accelerate the intensification of the coffee sector, at the expense of forest conservation and biodiversity.

Our study first relates to the literature that investigates the determinants of deforestation and the impact of diverse environment-oriented policy responses. The prevailing message that emerges from a review of recent studies in Latin America is the disappointingly weak efficiency of classic programs or legal instruments specifically designed as a mean to preserve forests. Results are at best ambiguous, or dependent on the local context, for example as regards property rights. Baragwanath and Bayi (2020) find that property rights limit deforestation in the Brazilian Amazon, but Lipscomb and Prabakaran (2020) find no overall impact of the Terra Legal property right reform in the same geographic area. As regards payments for ecosystems services (PES), Alix-Garcia et al. (2012) find evidence an impact of PES on deforestation in Mexico that is moderate to low, partly due to spillover effects reducing the effectiveness of the program. In a different context, Jayachandran (2013) emphasizes the role of credit constraints that limit the effectiveness of such schemes providing periodic payments of limited amounts. Although promising, eco-certification does not prove efficient in the case of Mexico, Blackman et al. (2018) finding no impact of the Forest Stewardship Council (FSC) certification on deforestation. In the same context, regulation, taking the form of timber extraction permits, has no significant impact on national-level deforestation (Blackman and Villalobos, 2021). In a different context, the success of a community management program in Nepal (Libois et al., 2021) contrasts with previous findings and advocates for local rather than centralized response. The fact that specifically designed tools fail to curb deforestation invites us to reconsider the prime driver of deforestation, which is by far agriculture. We show in this paper that agricultural shocks and policies interact to increase deforestation in a particularly vulnerable agroforestry ecosystem.

In this specific context, the classical intensification *vs* expansion tradeoff (Koch et al., 2019; Abman and Carney, 2020) does not apply. Whereas the study by Koch et al. (2019), focused on the Priority List program implemented in the Brazilian Amazon, suggests that anti-deforestation programs are compatible with increased agricultural production and yields through intensification, our results confirm that in agroforestry systems, intensification leads to deforestation (Somarriba and López-Sampson, 2018). Our results emphasize the need to account for diversity in forest environments. Rustic shade coffee systems,

although they represent a non-negligible environmental degradation compared to native forests, perform much better than intensified plantations in preserving biodiversity and ecosystems services (De Beenhouwer et al., 2013; Jha et al., 2014; Davidson, 2004). Our findings suggest that an agricultural crisis addressed with short-term oriented policy response may hasten environmental degradation, that in turn, may prove detrimental to communities' capacity to face future shocks. Indeed, as emphasized by Noack et al. (2019), biodiversity and forests play a stabilizing role and contribute to limit income losses caused by droughts.

Our work also relate to the debate on the environmental Kuznets curve Foster and Rosenzweig (2003) and its recent developments uncovering the linkages between environment protection and poverty reduction. As illustrated in the case of Mexico by Alix-Garcia et al. (2015) and Alix-Garcia et al. (2013), or Heß et al. (2021) in Gambia, environment preservation and poverty are two intertwined issues. Alix-Garcia et al. (2015) show that a federal environmental program had positive effects on poverty reduction, but proved more efficient in low poverty areas. Still in the case of Mexico, Alix-Garcia et al. (2013) find that the large cash-transfer program, PROGRESA, aimed at alleviating poverty, resulted in an increase in deforestation. Consistent with this literature, our findings suggest that non-environmental programs may generate negative spillovers. The PROCAFE program designed to help the coffee sector overcome the CLR crisis has most probably directly contributed to increasing deforestation and indirectly resulted in a greater vulnerability of coffee farmers and local communities to future shocks. These results call for a global, preventive and long-term approach of negative agricultural shocks.

The paper is organized as follows. Section 2 introduces the characteristics of coffee production in Mexico, presents the coffee leaf rust, and the main features of the PROCAFE program. Section 3 describes the data and the estimation strategy. Section 4 presents estimates of the static and dynamic effects of CLR on deforestation. Section 5 investigates the channels through which CLR affects deforestation and intends to disentangle the impact of CLR and PROCAFE by exploiting the late implementation of PROCAFE. Finally, Section 6 concludes and discusses the implications of our findings for policy design.

2 Coffee production and coffee leaf rust in Mexico

2.1 Characteristics of coffee production in Mexico

Historically, world coffee production is concentrated in three regions: Southeast Asia, Africa, and Latin America. The sector has been exposed to various crises caused by pests and diseases, volatile prices, climate change, and institutional arrangements (Rhiney et al., 2021), and has passed through landscape transformations (Jha et al., 2014; Rhiney et al., 2021).

Latin America accounts for 21% of global Arabica production (International Coffee Organization, 2020), and was known for high-quality beans and certified organic production before the 2012 CLR crisis. Mexico was the 9th largest producer in 2011, Mexican coffee production accounting for 3.4% of world coffee production.

Coffee-growing landscape falls into two broad categories: shade-grown agroforests, and open-sun systems.(Moguel and Toledo, 1999; Toledo and Moguel, 2012) In rustic, traditional shade systems with a high-density of shade trees, coffee is cultivated within the thinned native forest that covers most of the land. At the opposite end of the spectrum, open-sun systems consist of coffee monoculture, or intensified production with very little or no shade trees and high coffee tree density. In between, low-density shade systems associate coffee to other productive crops or activities (banana cultivation, timber activity)

or service trees that preserved or planted to provide shade to coffee plants. Traditional cultivation in agroforests is associated with higher quality coffee and lower yields (Vaast et al., 2006; Jezeer et al., 2017), is richer in terms of biodiversity and provide ecosystems services such as carbon sequestration, pollination, and erosion control (Jha et al., 2014; Somarriba and López-Sampson, 2018; Davidson, 2004).

In most part of the world, open-sun coffee areas tend to grow at the expense of shade coffee systems. In Latin America, between the 1970s and 1990s, nearly 50% of the rustic canopy was converted to a low shade system (Jha et al., 2014), illustrating the intensification of coffee cultivation and its transition towards monoculture.

In 2012, the Mexican coffee-growing landscape consisted of 80% of agroforestry (with 30% rustic and 50% low-diversity shade) and 20% of open-sun systems Jha et al. (2014). The coffee sector provides livelihoods to three million individuals in ethnically diverse regions of Southern Mexico, with a majority of smallholders and family production (92% of producers cultivate less than 5 hectares of coffee) (International Coffee Organization, 2020; Harvey et al., 2021).

2.2 The 2012 coffee leaf rust epidemic

Coffee leaf rust (CLR) is a well-known disease in the coffee sector. Previous spreads devastated the coffee industry in East Asia between 1870 and 1950. The disease particularly affected Ceylon since 1870 and forced 90% of the coffee farmers to stop production and turn into other agricultural products (Rhiney et al., 2021). After spreading to West Africa through the 1950s and 1960s, the CLR arrived in America in the late 1960s but only in the 2000s did massive outbreaks caused losses comparable to those of the 1870s Ceylon outbreak (Rhiney et al., 2021). In particular, Colombia was severely affected in 2008-2013 (Avelino et al., 2015), and Mexico from 2012.

The disease is caused by a fungus called *Hemileia vastatrix*. The development of the fungus provokes defoliation and reduces the plant's photosynthesis capacity (Avelino et al., 2015), which negatively impacts production levels. CLR continues to alter coffee production years after the initial infection by causing the death of productive branches. In an experimental parcel in Costa Rica, Cerda et al. (2017) find a 57% reduction in yields two years after the infection.

The pathogens are carried by wind, rain, animals, and humans. Weather conditions, and in particular temperatures, are known to influence intensity of CLR outbreaks. Moreover, different coffee varieties naturally present heterogeneous resistance to CLR, Arabica being more vulnerable than Robusta species. Latin America, that is mostly producing Arabica coffee is more at risk of an epidemic. However, until the 2012 epidemic, the mountainous, high-altitude characteristics of coffee producing regions in Latin America contributed to limit the intensity of CLR (Avelino et al., 2015). Climate change plays an important role through the increase in temperatures that favors fungal growth (Avelino et al., 2015; Merle et al., 2020), and global warming contributes to explaining that previously intact high-altitude regions were affected by the 2012 outbreak.[1] Unlike temperatures, precipitations have an ambiguous impact on CLR. The disease seems to be favored by wetness but is washed-off by intense rainfall (Merle et al., 2020; Lasso et al., 2020). The timing of precipitations also matters, as suggested by Avelino et al. (2015) who observe positive early rainfall anomalies before the CLR epidemic in Central America.

[1] Avelino et al. (2015) reports that before the 2012 epidemic, it was rare to observe high-intensity CLR infection above 1100 meters. However, due to increasing temperatures, the CLR started to cause equivalent damages in a 400-1400 meters altitude range in the Guatemalan landscape, generating yields losses up to 1800 meters.

In addition, weather-related factors interact in complex ways with other environmental characteristics such as altitude or shade to explain local variations in CLR intensity (Liebig et al., 2019). The protecting or aggravating effect of shade trees is controversial: Liebig et al. (2019) observe a lower CLR intensity in high shade plots but only for farms in higher altitudes, while Avelino et al. (2020) find that shade reduces the washing capacity of rain, thus increasing the propagation of CLR. By contrast, Castillo et al. (2020) mention that shade could have a protective effect by lowering the level of physiological stress of coffee plants, and Avelino and Anzueto (2020) advocate shade management as one of the three pillars of strategies aimed at limiting the risk of resistance breakdown of hybrids.

Finally, economic factors play an important role in the 2012 CLR outbreak, since plants' vulnerability to diseases depends also partly on farmers' management capacity and resources. The pre-CLR years coincide with low international coffee prices and increasing input costs in Latin America and the Caribbean (Avelino et al., 2015). In the case of Nicaragua, Villarreyna et al. (2020) find that farmers, anticipating low or no profit reduced their production costs by reducing the level of inputs such as fertilisers and fungicides or labor intensive activities like pruning and monitoring. Furthermore, the low profitability of the coffee sector delayed the replacement of old coffee trees, more vulnerable to CLR (Avelino et al., 2015).

2.3 The PROCAFE program

The Mexican Ministry of Agriculture first responded to the CLR crisis in 2013 by promoting the use of new fungicides to contain the disease. However, this new fungicide proved poorly efficient and was soon abandoned (Renard Hubert and Larroa Torres, 2017).

The PROCAFE program launched in 2014 illustrated a change of direction in the government response to the CLR crisis. All coffee producers, either affected by CLR or not, were eligible for the program and we indeed observe in our data that virtually all coffee-producing municipalities received PROCAFE transfers. PROCAFE promoted the replacement of traditional coffee varieties by CLR-resistant hybrids as a means to combat CLR. Although the program was readjusted several times from 2014 to 2017, its main line remained unchanged. The program comprises of several packages with different beneficiaries (individual farmers, cooperatives, or hybrid producers). In the first two years of the program, direct transfers were made to individuals farmers, while after 2015, most funds were paid out to cooperatives. In addition, PROCAFE subsidized hybrid plant producers (nurseries).

The development of CLR-resistant cultivars dates back to the 1960s. CLR-resistant hybrids available on the market in the 2010s are derived from the Catimor variety that is a cross of Timor hybrid (itself a cross of Robusta (*Coffea canephora*) and Arabica) and the Caturra Arabica coffee variety. Robusta coffee plants are naturally resistant to CLR. One key feature of CLR-resistant hybrids, similar in that to Robusta, is that they tolerate well full-sun cultivation, as opposed to Arabica varieties that are shade adapted. Concerns about the lower cup quality and poor productivity of CLR-resistant hybrids are mentioned in the literature (Renard Hubert and Larroa Torres, 2017). The demand for CLR-resistant hybrids increased sharply after the 2012 outbreak and their being promoted by public-private agencies (Valencia et al., 2018; Henderson, 2020; Libert Amico et al., 2020).

The replacement of traditional Arabica by hybrids as a relevant strategy to fight CLR is questioned by phytopathologists, since the fungus responsible for the CLR has a high adaptation potential and has already broken down the resistance of deemed CLR-resistant hybrid varieties (Avelino and Anzueto, 2020).

2.4 Measuring CLR spread

For lack of epidemiologic information, we infer the dissemination of CLR from observed variations in coffee production in a similar vein as Banerjee et al. (2010) who use wine production data to proxy for the dissemination of phylloxera in French vineyards. We gather agricultural production statistics from SIAP (Servicio de Información Agroalimentaria y Pesquera), a sub-government unit connected to the Agriculture Ministry of Mexico. SIAP data contain municipality level information on agricultural production, and planted and harvested areas (in hectares) for 307 products, including coffee, over 2003-2018.[2] We focus our analysis on the six largest coffee-producing states from Southern Mexico (Chiapas, Veracruz de Ignacio de la Llave, Oaxaca, Puebla, Guerrero, and Hidalgo), that represented more than 94% of Mexican coffee production in 2011.

More specifically, we use coffee production data series available at municipality level to detect abnormal drops in production that signal a local outbreak of CLR. We restrict the pool of municipalities potentially affected by CLR to those where sown coffee area represents at least 5% of agricultural area.[3] In Mexico, although already present since the 1980s, CLR started to spread massively during the 2012-2013 coffee season and caused significant production losses (Avelino et al., 2015; Avelino and Anzueto, 2020). The coffee harvest period in Mexico goes from August to May depending on regional characteristics. In what follows, for simplification purpose, year 2012 will refer to coffee harvest season 2012-2013, and so on. In order to identify affected municipalities, we compare production in 2012 and after to pre-CLR production level, accounting for the natural variability in coffee production that cannot be attributed to CLR. Municipality i is defined as affected by CLR in year t if there is a reduction of coffee production greater or equal to one z-score in both year t and year $t+1$.[4] Production z-scores are computed using the mean of municipality level coffee production in the pre-CLR period (2005-2011) and standard deviation over 2005-2018. Conditioning the definition of affected municipalities on two years of production reduction limits the probability to capture temporary shocks other than CLR, and is consistent with the documented impact of CLR on production, with secondary losses in years following the outbreak due to weakened plants (Cerda et al., 2017; Avelino and Anzueto, 2020).

Note however that CLR is perfectly observable to coffee farmers, due to the characteristic rusty spots that appear on affected leaves, which justifies that we date the beginning of the local outbreak to t and not $t+1$. Evidence suggests that after the 2012 outbreak, once established in a specific area, the disease remains. As a consequence, municipalities defined as affected in year t are considered affected until the end of the observation period, i.e. 2018. Our treatment variable is thus a dummy equal to one from the year municipality i is first severely affected by CLR. Note that we obtain very similar findings when using yields instead of production. Yields are constructed as production divided by coffee planted area. Given that the two series are very similar, we choose to constructed our CLR measure based on production in our main specification to avoid multiplying potential misreporting errors.

We acknowledge that using a statistical method to detect CLR affected areas may introduce noise in our treatment variable, and that it should ideally be corroborated by field reports indicating the local prevalence of CLR. However, such data are not available for the whole area and time period under study.

[2] Due to misreporting errors detected for year 2004, we choose to limit our analysis to 2005-2020, however our results are robust to the inclusion of 2003 and 2004 in the pre-epidemic period.

[3] This threshold being arbitrarily set to avoid capturing anecdotal or very isolated coffee zones, we test the robustness of our results to an alternative threshold set at 1%. All results are unchanged (see Table 16 in the Appendix).

[4] In alternative specifications, we choose an alternative cutoff point (1.5 z-score) and obtain consistent results (see Table 17 in the Appendix and Section 5.3.3 for further discussion).

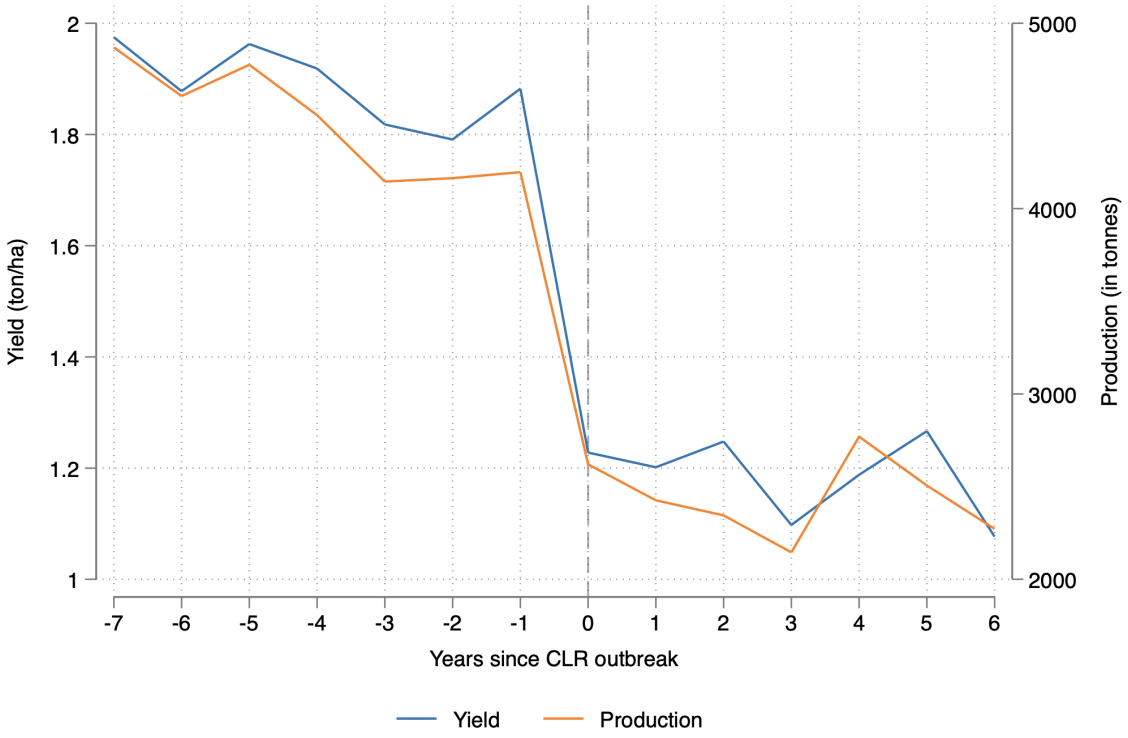
One particular concern raised by the indirect method that we use to detect CLR is that we may wrongly interpret as CLR outbreaks mere decreases in production that would be due to other causes (bad weather conditions, other adverse income shocks, etc.). In order to check the validity of our measure of CLR, we focus on the 2005-2010 period, i.e. prior to CLR massive epidemic outbreak in Mexico, and construct municipality-level placebo outbreaks. Applying the same rule as exposed above (i.e. a reduction of coffee production greater or equal to one z-score in both year t and year $t+1$), no municipality appears as treated. This finding suggests that our method truly detects CLR and does not capture the impact of other shocks.

Another concern is that we may fail to detect areas with low CLR intensity. We discuss this point below, when comparing treated municipalities to non-treated coffee municipalities, and show that our results are robust to choosing a less restrictive threshold in the definition of our CLR indicator (see Section 6 and Appendix Table 18.

Figure 1 plots the average evolution of coffee production and yields in municipalities affected by the CLR depending on the time since CLR is detected in the municipality (based on the methodology exposed above). We observe a sharp decline in both series in the first year of the epidemic that amounts to about 35% for production.[5] As an illustration of the persistence of the disease once installed, production and yields remained low until the end of the observation period. Consistent with this graph, Figure 12, in the Appendix, shows that the normalized production and yields follow the same pattern.

[5]This figure is consistent with production losses reported by Avelino et al. (2015) for Colombia (31%) affected in 2008-2011 by the same epidemic.

Figure 1: Evolution of average coffee yield and production in eventually treated group by CLR start year



Note: The eventually treated group consists of 243 municipalities affected by CLR between 2012-2018.

To further validate our measure of CLR, we estimate the following equation:

$$Y_{it} = \beta_0 CLR_{it} + \delta_i + \phi_t + \psi_{st} + \epsilon_{it} \tag{1}$$

where Y_{it} represents the inverse hyperbolic sine transformation of coffee production (in tonnes of green beans), coffee planted area (in hectares), and coffee yields (in tonnes per hectare) for year t. CLR_{it} is a binary variable, the construction of which is described above. CLR_{it} is equal to one from year t to the end of the period if municipality i is first affected by CLR in t ($t \geq 2012$). δ_i, ϕ_t, and ψ_{st} are municipality, year, and state-year fixed-effects respectively. We estimate equation 1 with OLS. Results are reported in Table 1 for two different samples: first on the sample that includes all municipalities from the six major coffee producing states (panel A), then for the subsample of 351 municipalities where coffee planted area represents at least 5% of total agricultural area (panel B). We find that CLR is associated with a 53% decrease in coffee production (column 1, panel A) in the total sample and a 56% decrease in coffee municipalities (column 1, panel B), a 31% decrease in yields (column 3) and a 18% decrease in coffee planted area (column 2).[6] Columns 4 to 7 additionally report regression results for

[6]Dependent variables are inverse hyperbolic sine transformation of raw variables. To interpret coefficients on the CLR dummy as the percentage change in the dependent variable due to a discrete change in the CLR dummy we need to apply to following formula $100(exp(\hat{\beta}) - 1)$ (Bellemare and Wichman,

production and agricultural area for seven major perennial crops other than coffee and four major annual crops.[7] Columns 8 and 9 report results for total agricultural production and area excluding coffee and pastures, the latter being separately analyzed in column 10. Results from columns 4 to 10 suggest that CLR-induced coffee production losses were not offset by concurrent increases in the production of other crops.

2020).

[7]Those seven major perennial crops and four annual crops represent 63% of total agricultural production (excluding coffee) and 83% of agricultural area in municipalities from the total sample

Table 1: CLR impact on coffee and other agricultural variables - Period: 2005-2018

	Coffee			Perennial crops		Annual crops		All crops		Pastures
	Ihs(Prod.)	Ihs(Area)	Ihs(Yield)	Ihs(Prod.)	Ihs(Area)	Ihs(Prod.)	Ihs(Area)	Ihs(Prod.)	Ihs(Area)	Ihs(Area)
Panel A: Total sample										
CLR dummy	-0.753***	-0.200***	-0.372***	-0.057	-0.042	-0.124***	-0.040	-0.078*	-0.040	0.043
	(0.034)	(0.030)	(0.016)	(0.075)	(0.050)	(0.028)	(0.022)	(0.033)	(0.023)	(0.031)
Observations	17,948	17,948	17,948	17,948	17,948	17,948	17,948	17,948	17,948	17,948
Municipalities	1,282	1,282	1,282	1,282	1,282	1,282	1,282	1,282	1,282	1,282
$R^2(within)$	0.095	0.022	0.215	0.019	0.023	0.085	0.031	0.071	0.033	0.038
Panel B: Sample restricted to coffee municipalities										
CLR dummy	-0.823***	-0.346***	-0.305***	-0.048	-0.003	-0.069	-0.091**	-0.070	-0.078*	-0.001
	(0.054)	(0.050)	(0.020)	(0.096)	(0.064)	(0.035)	(0.031)	(0.041)	(0.032)	(0.019)
Observations	4,914	4,914	4,914	4,914	4,914	4,914	4,914	4,914	4,914	4,914
Municipalities	351	351	351	351	351	351	351	351	351	351
$R^2(within)$	0.201	0.070	0.387	0.042	0.049	0.111	0.071	0.086	0.071	0.054

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018. Perennial crops are sugar cane, orange, banana, lemon, mango, palm oil, and cacao in descending order. Annual crops are corn, sorghum, beans, and wheat in descending order.
Data sources: Agricultural data from SIAP/SAGARPA.

3 Data and descriptive statistics

3.1 Deforestation data

We measure deforestation using satellite-derived data from the Global Forest Change (GFC) project (Hansen et al., 2013). Data are available at a 30 × 30 meters resolution at the equator. For each pixel we know the tree cover in percentage in 2000 and, for each year starting from 2001, whether the pixel has been totally deforested. Trees in the GFC data correspond to any vegetation taller than five meters.[8] Therefore crops such as bananas and oil palm trees are defined as trees. Note that cultivated coffee plants do not exceed five meters. As a consequence, open-sun coffee fields will not be detected as forest. By contrast, agroforestry systems where coffee is cultivated under the shade of taller trees are defined as forest in the GFC data. Therefore, the complete removal of shade trees in agroforest would be detected as deforestation. In order to exclude low shade cultivation systems from our forest definition, we choose to focus on medium and high forest density and count the deforestation that occurred in pixels with at least 30% of tree cover in 2000 when calculating deforestation per municipality.[9]

The GFC dataset has been frequently used in the literature to produce different measures of deforestation. Raw deforestation (in hectares) is obtained by calculating deforested area from the number of deforested pixels within given boundaries - municipalities in our setting. However, authors commonly use a functional transformation of the variable, or divide deforested area by tree cover area at origin due to the skewness of the raw deforestation variable (Abman and Carney, 2020; Desbureaux and Damania, 2018; Heß et al., 2021). Other studies choose to focus on normalised deforestation variables (Assunção et al., 2020). Since they all are equally relevant and provide complementary information, we choose to use four municipality-level alternative measures of deforestation: raw deforestation (in hectares), the inverse hyperbolic sine transformation of raw deforestation, normalised deforestation defined as a z-score, and deforested area out of total forest area in 2000.

One limitation of the GFC data is that it does do not detect the partial deforestation of a pixel. In order to be able to assess the impact of CLR at a finer scale, we use the Global Forest Cover Change (GFCC) dataset (Townshend, 2016). Similar to the GFC data in terms of spatial resolution and tree definition, the GFCC data provide information on the percentage of tree cover of a pixel every five years (in 2000, 2005, 2010, and 2015). We use GFCC to compute tree cover at the municipality level by aggregation of pixel-level information. In this second approach, we do not exclude pixel below a specific tree cover threshold as we want to capture total tree cover dynamics.

Finally, we complement our analysis by using EC JRC data on forest degradation (Vancutsem et al., 2021).[10] This dataset specifically documents forest degradation in tropical moist forests using satellite imagery and provides high-resolution (pixel size of 30 × 30 meters) annual data. Compared to GFC data, forest degradation data are able to capture short-term disturbances and reflect the evolution of forest cover more accurately than GFC in the case of tropical moist forests. Additional results on tree cover change based on GFCC data and forest degradation are reported in Section 5.3 Table 3.

[8] https://glad.earthengine.app/view/global-forest-change

[9] We show in Table 19 that our results are robust to including pixels with different shares of tree cover - ranging from 10% to 90%.

[10] Forest degradation is defined as "a disturbance in the tree cover canopy that is visible from space over a short time period (less than 2.5 years), leading to a loss of biodiversity and/or carbon storage" (Vancutsem et al., 2021).

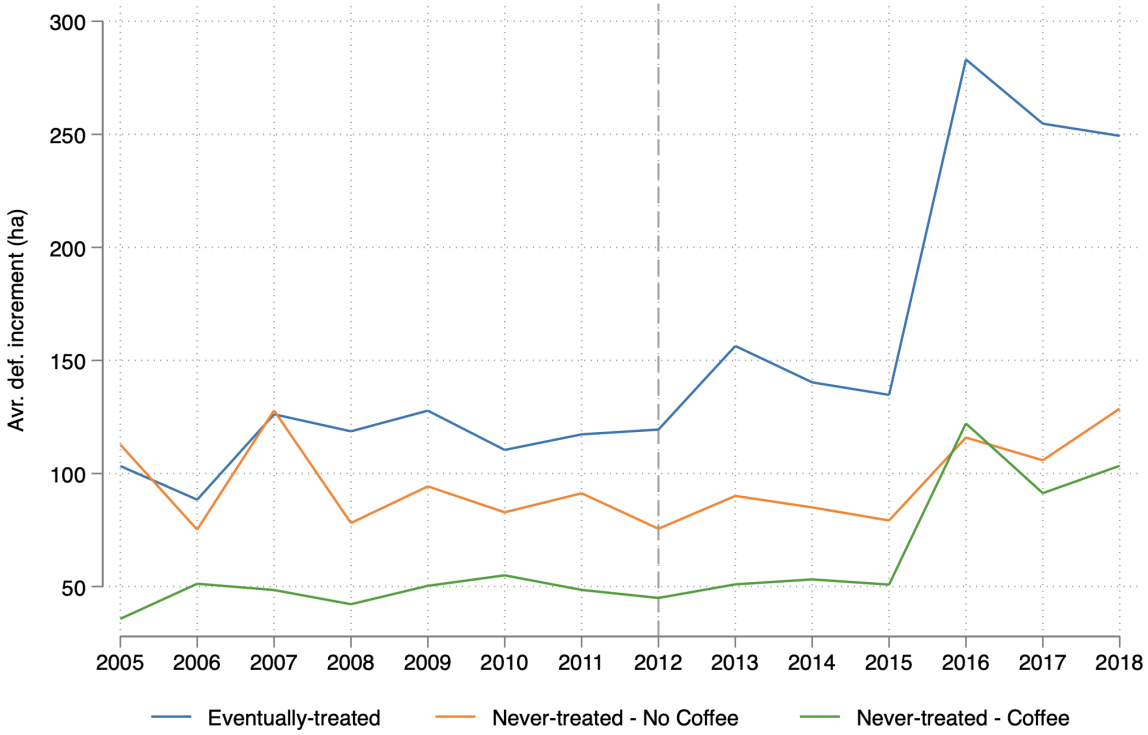
3.2 Sample description

In the subsequent analysis we exploit the propagation of CLR across Mexican municipalities over time to estimate its impact on deforestation in a staggered difference in differences design. Our estimation sample consists of 778 municipalities from the top six coffee producing states with at least 30% of forest cover in 2000. This threshold is arbitrary but we further check that our main results are robust to different sample definitions, i.e. to including municipalities with a share of forest cover varying from 10 to 50% (see Table 20 in the Appendix). Among those 778 municipalities, 243 are coffee growing municipalities (i.e. coffee area represents at least 5% of municipality agricultural area) that are eventually affected by CLR between 2012 and 2018, 427 are municipalities where coffee production is null or marginal (less than 5% of municipality agricultural area) and that we consider as being unaffected by CLR, and 108 are coffee growing municipalities (more than 5% of municipality agricultural area) that were not affected by CLR over the observation period. Note that within this group, some municipalities may indeed be affected by CLR but undetected by our statistical method used to retrace ex-post the spread of the disease. We discuss potential biases introduced in our results by this group of potentially affected municipalities in Section 5.3.3 and provide additional robustness checks.

Appendix Table 12 compares eventually treated and control municipalities over the pre-epidemic period (2005-2011). Municipalities affected by CLR have on average a greater initial forest cover, receive lower amounts of PROCAMPO, and are affected by a larger number of drought shocks. In terms of past deforestation averaged over 2005-2011, the picture is less clear since different indicators yield opposite results.

Figure 2 represents deforestation trends for municipalities eventually affected by CLR over the 2012-2018 period (blue line), and control municipalities broken into two sub-groups (municipalities without significant coffee production - orange line - and coffee municipalities for which we did not detect any CLR outbreak over 2012-2018 - green line). Descriptive analysis suggests that deforestation trends in treated and control municipalities were very similar before the CLR epidemic first outburst in Mexico in 2012 although the level of deforestation seems higher in treated municipalities. Notably, deforestation steeply increases in the treated group in 2013 and again in 2016, widening the gap between treated and control municipalities. Note however that deforestation also increases in 2016 in coffee municipalities that were not affected by CLR. This may suggest that either CLR is present in those municipalities but its incidence is below our detection levels, or that factors other than CLR and common to all coffee municipalities influence deforestation at the end of the period. We further explore these two possibilities in Section 6.3.

Figure 2: Deforestation in eventually-treated and control groups, 2005-2018



Note: Control group includes both non-coffee municipalities and coffee municipalities not affected by CLR. This graph presents separately these two sub-groups. The eventually-treated group includes municipalities that experienced an outbreak of CLR between 2012 and 2018.

Appendix Figure 13 compares total deforestation in out of sample Mexican municipalities to deforestation in control and treated municipalities. Note that as specified above deforestation is defined based on deforested pixels with at least 30% of tree cover in 2000. Yearly deforestation in out-of sample municipalities is about 125,000 hectares over the whole period, and deforestation in our sample (control plus treated) represents roughly the same area than in all other Mexican municipalities at the end of the period. This may seem disproportionate, but obviously, given the specific soil and weather conditions suited to coffee cultivation, our sample comprises areas with a higher density of forests than other parts of the country.

Our main estimation strategy exploits the unpredictable spread of the CLR epidemic from 2012 to 2018. One major difference with the propagation of phylloxera in France documented by Banerjee et al. (2010) is that phylloxera is an insect that spread from southern regions to the rest of the country, while CLR was already present in Latin America as early as in the 1970s[11], but its evolution was contained and its consequences mostly unnoticed before the 2012-2013 outbreak.[12] The immediate causes of the massive epidemic that reached Mexico in 2012-2013 are thoroughly discussed in Avelino et al. (2015)

[11]It was first detected in Nicaragua in 1976 (Schuppener et al., 1977).

[12]Avelino et al. (2015) explain that chemicals and high altitude contributed to limit the intensity of the disease before the recent outbreak. Production losses occurring due to previous CLR epidemics could be confounded with the natural alternation of good and bad harvests, due to the biennial production pattern of coffee trees.

and mentioned in Section 2.2 above. The fact that the fungus was already dormant throughout all coffee areas in Southern Mexico explains the erratic geographical pattern of local outbreaks of CLR from 2012 onwards. The geographic spread of the disease is illustrated on a map in Figure 14, in the Appendix.

3.3 Additional data sources and variables

We use additional municipality-level information to control for time-varying characteristics of municipalities that may be correlated with deforestation. First, local economic development, urbanization and demographic trends are likely to affect deforestation. We use nighttime lights data series from Li et al. (2020) as a proxy for municipality-year level economic activity (Henderson et al., 2012; Bruederle and Hodler, 2018) for lack of yearly information on municipality-level GDP or population. Nighttime light data capture the radiance of city lights at night with a spatial resolution of 30 arc second (which is approximately equal to 0.86 square km (86 hectares) at the equator). We construct a municipality-level measure of nighttime lights by aggregating relevant pixels and use the inverse hyperbolic sine transformation of municipality-level nighttime light intensity to take into account zero values.

Second, weather shocks are expected to directly impact agricultural prospects and may consequently also affect deforestation. We use satellite-derived yearly precipitation data from the CHIRPS project (Funk et al., 2015), available at a spatial resolution of 0.05 degrees. We calculate yearly precipitation for each municipality from 1981 to 2000. We then normalise precipitations by calculating deviations to municipality-level average precipitations over 1981-2012 divided by the municipality-level standard deviation of precipitations over the same period. To account for the impact of weather shocks on land use decisions and deforestation, we compute for each municipality the cumulative number of drought shocks (defined as the number of years characterized by normalized precipitations below -1).

Third, we use data on agricultural subsidies provided by the Mexican government through the PROCAMPO program (renamed PROAGRO Productive in 2014). PROCAMPO is the largest Mexican cash transfer program related to agriculture and was launched in 1994 to compensate possible negative impacts of the North American Free Trade Agreement (NAFTA) on agricultural producers (Sadoulet et al., 2001). Funds are allocated to plots conditional on their being sown prior to August 1993 to one of a close list of nine crops.[13] Therefore the program does not cover all actually cultivated lands: in 2009, only 62% of agricultural areas in Mexico was eligible to the program (Gonzalez et al., 2017). Data on PROCAMPO/PROAGRO come from the Mexican Ministry of Agriculture (SADER, formerly SAGARPA). We adjust raw amounts to account for inflation and divide them by total agricultural area in each municipality. Although we do not expect a priori any direct effect of PROCAMPO/PROAGRO subsidies on deforestation, funds received by farmers may be used to extend agricultural land or, conversely, to intensify existing agricultural areas (Klepeis and Vance, 2003; Vance and Geoghegan, 2002).

Finally, we use data on the PROCAFE program coming from the Mexican Ministry of Agriculture (SADER, formerly SAGARPA). The data contain information on transfers made to either individual beneficiaries or cooperatives from the launch of the program in 2014 to 2017. For years 2014, 2015, and 2016, the municipality of each beneficiary is provided in the dataset, whereas for 2017 we only know the state of beneficiaries. We use PROCAFE amounts per coffee sown area as an additional municipality-level control in an alternative specification (see Appendix Table 21).

[13] Eligible crops are: corn, beans, rice, wheat, sorghum, barley, soybeans, cotton, and safflower.

4 Empirical Strategy

4.1 Impact of CLR on deforestation

In order to estimate the causal impact of CLR on deforestation, we first want to assess whether deforestation increased (or decreased) in municipalities affected by CLR compared to non-affected municipalities.

We first estimate the following base equation:

$$Y_{it} = \beta CLR_{it} + X'_{it}\gamma + \delta_i + \phi_t + \psi_{st} + \epsilon_{it} \tag{2}$$

where Y_{it} represents deforestation in municipality i and year t. We use four alternative measures of deforestation: raw deforestation in hectares, deforestation as a share of municipality-level forest area in 2000, the inverse hyperbolic sine transformation of raw deforestation,[14] and normalised deforestation, computed as a z-score.[15] As described above in Section 2.4, CLR_{it} is a binary variable equal to 1 in municipality i if an outbreak of CLR has been detected in year $\tau \leq t$.[16] X_{it} is a set of municipality level time-varying controls including the inverse hyperbolic sine transformation of the nighttime lights indicator provided (Li et al., 2020) that proxies for growth and urbanization trends, the cumulative number of drought shock in municipality i up to year t, and the inflation-adjusted amount of agricultural subsidies received per hectare of agricultural area. Amounts directly received by coffee producers to compensate production losses due to CLR (PROCAFE program) are not included in our main estimations since they are likely to be endogenously determined by CLR. We however re-estimate our main equation adding the municipality level lagged inflation-adjusted amount of PROCAFE per coffee planted hectare and find very similar results (see Table 2 in the Appendix).[17] δ_i are municipality fixed effects that control for time invariant characteristics of municipalities that may be correlated with deforestation, ϕ_t are year fixed-effects that capture time shocks common to all municipalities, and ψ_{ts} are state-year fixed effects that control for state-specific time trends. ϵ_{it} is the error term. Standard errors are clustered at the municipality level to allow for correlation of errors over time within municipalities.In this regression, the estimated β parameter represents the average yearly impact of CLR on deforestation during the whole period of exposure to the disease.

Second, we estimate the dynamic effects of CLR on deforestation. We run a regression with an

[14] Our dependent variable is characterized by a small proportion of zero values (707 out of 10892 observations, approximately 6.5% of the total). Aihounton and Henningsen (2021) caution against using the IHS transformation when more than 50% of observations are equal to zero while Bellemare and Wichman (2020) advise against IHS transformation and suggest using alternative models (Tobit or negative binomial for example) that account for selection into non-zero values when the share of zero-valued observations exceeds one-third of all observations.

[15] Deforestation z-score for municipality i and year t is raw deforestation in municipality i and year t minus yearly average deforestation in municipality i over the whole observation period, divided by the standard deviation of deforestation in i over the whole period. One further complexity of the IHS transformation is that coefficients are sensitive to the choice of measurement unit. We apply the criteria suggested by Aihounton and Henningsen (2021) based on the R^2 and the test statistic of the Ramsey Regression Equation Specification Error Test that validate the use of hectares as our measurement unit of deforestation.

[16] Banerjee et al. (2010) use in their main specification a measure of the intensity of the disease defined as the production loss in affected municipalities, compared to the pre-phylloxera period. We replicate our estimation with this continuous measure and find consistent results (see Appendix Table 22).

[17] Note that the estimation period is different since our PROCAFE data do not extend beyond 2016.

event-study design and estimate the following equation:

$$Y_{it} = \beta_{-6} CLR_{i,\tau \leq -6} + \sum_{\tau=-5}^{\tau \leq 6} \beta_\tau CLR_{i\tau} + X'_{it}\gamma + \delta_i + \phi_t + \psi_{st} + \epsilon_{it} \quad (3)$$

where Y_{it} represents deforestation in municipality i and year t, $CLR_{i\tau}$ is the same binary variable for CLR as in the previous equation which equals one for any period τ contemporaneous or subsequent to the first outbreak of CLR in municipality i. τ indicates the relative year to CLR outbreak, which varies from -13 to 6.[18] The omitted period is $\tau = -1$. X_{it} represents the same set of time varying controls as in equation 2. δ_i, ϕ_t, and ψ_{st} are respectively municipality, year, and state-year fixed effects. ϵ_{it} is the error term and standard errors are clustered at the municipality level. The β_τ coefficients of interest represent the average change in deforestation between time τ and the previous year relative to the change in deforestation over the same time period for unaffected municipalities. β_{-6} to β_{-2} represent non parametric deforestation trends prior to the CLR outbreak.

Our setting differs from the canonical DID model developed for two time periods and two groups (treatment and control), and we need to take into account the staggered nature of exposure to CLR which is described in Section 2.4 and is illustrated in Map 14 in the Appendix. We observe municipalities over 14 time periods (i.e. years), and we have substantial variation in treatment timing, since the first municipalities to be hit by CLR were affected in 2012, and the last ones in 2018. Table 11 in Appendix reports the number of observation in each treatment group (depending on the year of the CLR outbreak). The implicit assumption of constant treatment effect between groups and over time in two-way fixed-effects estimators is unlikely to hold in this setting, and two-way fixed-effects estimation may be biased (see Roth et al. (2022) and De Chaisemartin and D'Haultfoeuille (2022) for a review). The latest contributions in the DID literature point out the pitfalls in two-way fixed-effects estimators when the treatment is staggered and/or when the treatment effect is heterogeneous (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Gardner, 2021; Sun and Abraham, 2021; Borusyak et al., 2021; Athey and Imbens, 2022). To account for potential heterogeneous treatment issues in our setting, we use the estimators developed by De Chaisemartin and d'Haultfoeuille (2020) and Callaway and Sant'Anna (2021) as alternatives to the two-way-fixed-effects estimator.

4.2 Identification issues

The identification of a causal effect in a DID setup relies on two key assumptions: the existence of parallel trends for the outcome variable between treated and control observations, and the absence of anticipation of the treatment. Adapted to our setting, the first assumption implies that deforestation trends would have been similar in municipalities affected by CLR and those that were not affected if the epidemic had not broken out. The second assumption means that not-yet-affected municipalities did not anticipate the propagation of the disease.

We discuss in this section the limits of those two assumptions in our setting and potential estimation biases that may result. First, the parallel trends assumption cannot be tested directly for lack of counterfactual data, but it is more credible if treated and control units are as similar as possible in terms of observable characteristics before the treatment. In our main analysis we only condition the inclusion of municipalities in the control sample on a minimum of 30% of forest cover in 2000. As shown above

[18] Due to the limited number of observations, time periods from -13 to -6 are grouped in a single category.

in Table 12, treated and control municipalities meaningfully differ over the pre-treatment period (2005-2011) as regards some of their observable characteristics. Even though graphical evidence presented by Figures 3 to 6 suggest that pre-treatment deforestation trends are parallel in the eventually treated and control groups, differences in observed pre-treatment characteristics may cast doubt on their counterfactual parallel time path in the absence of CLR. We implement two robustness tests to manage this issue: first, we use the synthetic control approach adapted to staggered treatment developed by Ben-Michael et al. (2021), second, we use a propensity score matching approach. Results are reported in Section 5.3.1 and 5.3.2 and are consistent with our main results. However, traditional tests of parallel trends are criticized in the recent literature (see Sun and Abraham (2021) or Roth (2019)) for their lack of power and failure to detect even large violations in the assumption of parallel pre-treatment trends. We follow the recommendations of Roth (2019) and Rambachan and Roth (2022) and provide a sensitivity analysis of our main results to violations of the parallel trend assumptions (see Appendix C).

The second assumption implies that the propagation of CLR was not anticipated. Again, the assumption cannot be tested directly. According to phytopathologists, the initial outbreak of 2012 was highly unexpected (Avelino et al., 2015), however, it is possible that in the subsequent years agents living in municipalities where we do not detect the presence of CLR adapt their behavior in anticipation and deforest more. We propose in Section 6.3.2 an indirect test of this anticipation effect based on the assumption that anticipation effects or learning effects may be larger in municipalities that are not yet affected by the disease and are neighbours of a municipality that was affected in the first two years of the epidemic. Results reported in Table 10 suggest that deforestation is similar in late treated municipalities, whether or not one of their neighbours was affected by the disease in 2012 or 2013. Although we cannot rule out the possibility that the propagation of CLR was anticipated in the years following the initial unexpected outbreak, two remarks limit the scope of the problem. First, if CLR-free municipalities anticipate the treatment, this implies that deforestation will increase also in control municipalities, and that our estimates will be downward biased. Our results will thus tend to under-estimate the impact of CLR rather than the opposite. Second, CLR is a disease that affects only coffee, so that non-coffee municipalities included in the control sample cannot be treated. Reassuringly, we find very similar results when restricting our control group to non-coffee municipalities (see Appendix Table 15 and Section 5.3.3).

We explore further the dynamics of CLR propagation by focusing on the subsample of coffee municipalities. We run a cross-sectional regression using our CLR outbreak indicator as an outcome variable (equal to one for municipalities affected at any time by CLR over 2012-2018) on a number of municipality level indicators such as area, tree cover at the beginning of the period, elevation[19], population, economic activity proxied by nighttime lights, rainfall (averaged over 2012-2018), and a coffee suitability index from the FAO/GAEZ database (version 4)[20] (Fischer et al., 2021) for the period 1981-2010. To match agricultural conditions from Southern Mexico, we select index values for low-input and rain-fed conditions. Results are reported in Appendix Table 7. We find that municipalities with a larger tree cover in 2000 are more likely to be affected by CLR. This is not surprising, since those municipalities are more likely to host rustic shade coffee farms planted with CLR-sensitive Arabica coffee. Second, municipalities with a larger population and/or economic activity are also more likely to be affected. We control for nighttime lights in our main specification, and we control for time invariant community characteristics through municipality fixed-effects. Elevation or agro-climatic suitability have no significant effect on the probability to be affected by CLR. However, we may expect local conditions such as elevation or

[19]We calculate median elevation for each municipality using the NASA JPL (2020) dataset.

[20]https://gaez.fao.org/pages/theme-details-theme-4

coffee suitability to play a different impact on CLR propagation and deforestation over time. We explore further this issue in Section 5.3.3.

5 Results

5.1 CLR and deforestation

Estimation results of equation 2 are presented in Table 2. The coefficient on the CLR binary variable is positive and significant in all specifications. The average yearly increase in deforestation in CLR affected municipalities is 37 hectares (column 1), which represents roughly 15% of the average yearly deforestation in 2016-2018 observed in municipalities included in the treatment group (see Appendix Figure 13). According to column (2), in CLR affected municipalities, annual deforestation as a share of the initial stock of forest is 0.10 percentage point higher. Results reported in column (3) indicate that deforestation increased by about 32%.[21] Finally, column (4) suggests that deforestation z-score is 0.35 points larger in municipalities affected by the disease than in control municipalities.

Table 2: TWFE - CLR impact on deforestation - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	37.014**	0.103***	0.280***	0.352***
	(14.887)	(0.027)	(0.051)	(0.059)
Ihs(Nighttime lights)	32.775**	0.057**	0.101**	0.133***
	(13.806)	(0.023)	(0.040)	(0.047)
Agri. subventions	0.184	-0.001	0.020	0.043*
	(1.806)	(0.005)	(0.019)	(0.024)
Past drought shocks	49.992***	0.067***	0.078***	0.125***
	(13.434)	(0.016)	(0.021)	(0.025)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Mean Y	108.570	0.354	3.419	-0.000
$R^2(within)$	0.104	0.128	0.166	0.174

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Estimation results shown in Table 2 report estimates of the average yearly impact of CLR on deforestation in affected municipalities over the whole treatment period. This analysis needs to be supplemented by an event-study to illuminate the dynamic effects of the disease. Figures 3 to 6 report the results of an event-study analysis with three different estimators: the two-way fixed-effects estimator, and the robust estimators developed by De Chaisemartin and d'Haultfoeuille (2020) and Callaway and

[21] Since the dependent variable in column 3 is the inverse hyperbolic sine transformation of the raw deforestation variable, the percentage change in the dependent variable due to a discrete change in the CLR dummy is approximated by $100(exp(0.280) - 1) = 32,313$ (Bellemare and Wichman, 2020).

Sant'Anna (2021). First, estimated coefficients for pre-treatment years are not significantly different from zero in all specifications, whatever the estimator used. This finding suggests that there is no difference in pre-CLR trends in municipalities affected by CLR and control municipalities. However the power of such test is questioned in the recent DID literature (Sun and Abraham, 2021; Roth, 2019; Rambachan and Roth, 2022). We provide additional sensitivity tests with regard to the parallel pre-trends assumption in Appendix C.

Second, we find very similar estimated coefficients and confidence intervals with the three estimators, which suggests that our baseline two-way fixed-effects results are not subject to large biases due to heterogeneous treatment effects issues.

Third, we observe a similar inverse U-shape pattern for three of our four deforestation variables (3 to 6): when the dependent variable is deforestation out of initial forest area, the inverse hyperbolic sine transformation of raw deforestation or deforestation z-score, we find that the estimated coefficient on the CLR binary variable gradually increases in the first post-treatment period, and then decreases while remaining positive and significant up to five years after the initial outbreak. Results are not significant when the dependent variable is raw deforestation in hectares due to large standard errors. The dynamic analysis suggests that CLR-induced deforestation is not an immediate response: the impact of CLR on deforestation appears to be the highest three to four years after the local outbreak of the epidemic.

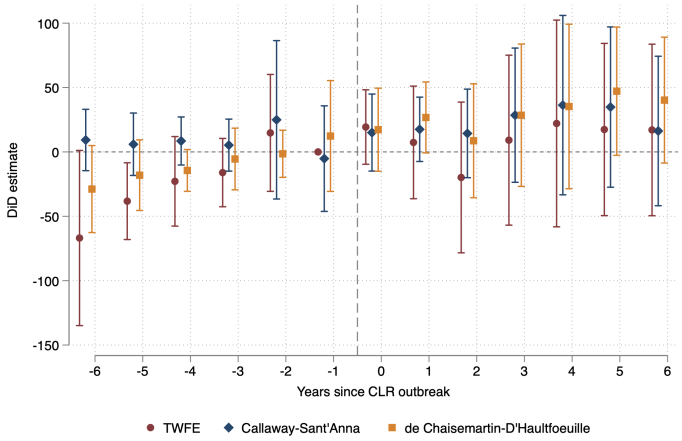


Figure 3: Raw deforestation

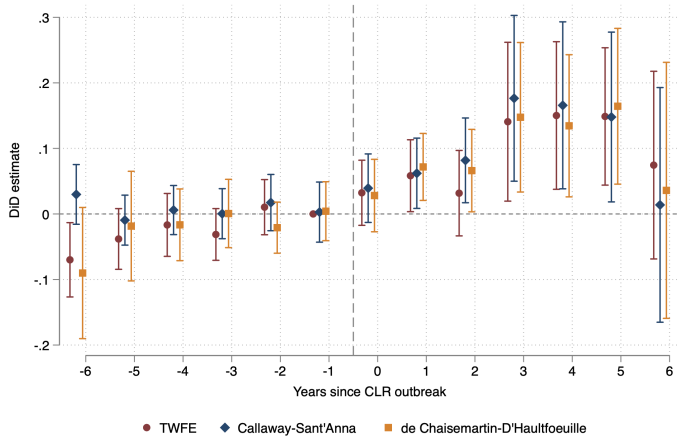


Figure 4: Deforestation part (%)

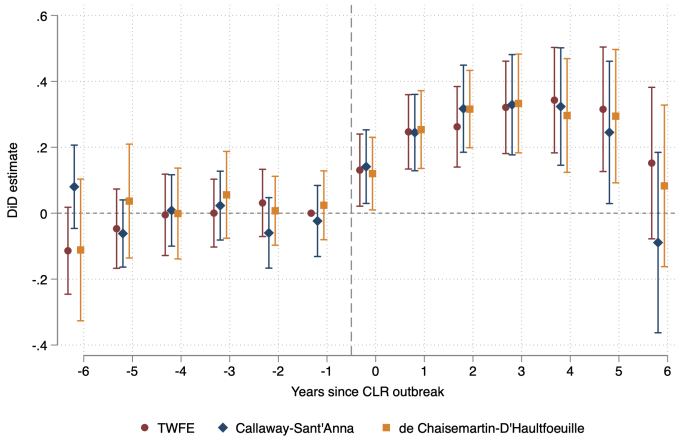


Figure 5: IHS deforestation

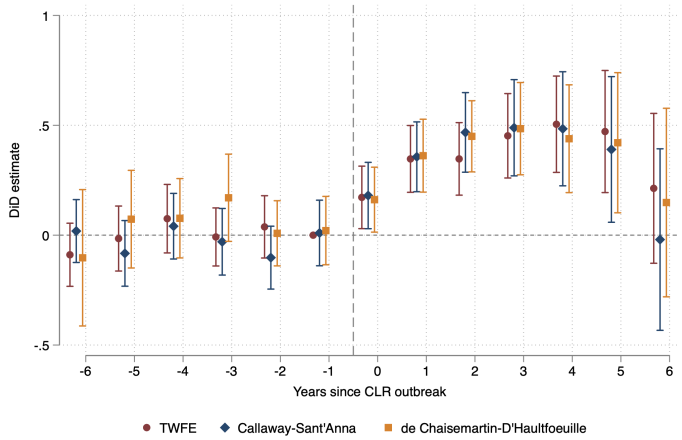


Figure 6: Normalised deforestation

Note: The TWFE estimators corresponds to equation 3. For the Callaway and Sant'Anna (2021) method, we use user-written Stata command *csdid* (Rios-Avila et al., 2022) with *drimp* option which is the 'Improved doubly robust DiD estimator based on inverse probability of tilting and weighted least squares' from Sant'Anna and Zhao (2020). We also use multiplicative wildbootstrap procedure (999 repetitions using *mammen* approach) for standard errors. For De Chaisemartin and D'Haultfoeuille (2022) method, we employ user-written Stata command *did_multiplegt* with *robust_dynamic* and *longdiff_placebo*. For all settings, we use both not-yet and never treated observations as control municipalities.

5.2 CLR, tree cover and forest degradation

We complement our analysis with an exploration of the impact of CLR on alternative measures of canopy and forest cover. Table 3 replaces our four baseline measures of deforestation generated from GFC by the percentage of tree cover obtained from GFCC data, available on a 5-year basis (Townshend, 2016) (col. (1) and (2)), and four measures of forest degradation (col. (3) to (6)). Forest degradation indicators are calculated from the EC JRC dataset (Vancutsem et al., 2021), which is available on a yearly basis. Forest degradation differs from deforestation in that it captures short-term and/or partial disturbances in tropical moist forests. Note that degraded forests in the EC JRC product are still classified as forests.

In column (1), we use GFCC data for 2000, 2005, 2010, and 2015 and do not control for agricultural subventions (not available in 2000). In column (2), we use the full set of controls and limit the estimation period to 2005, 2010, and 2015. In both cases, we observe a decrease in tree cover by 1.7 to 1.9 percentage points, which represents a 5% decrease with respect to median tree cover in 2000 (which is 38% in our sample). Columns (3) to (6) replicate our main results with the same four indicators applied to forest degradation instead of deforestation. We find that, in municipalities affected by the disease, 75 additional hectares or 5% of tropical moist forest cover (col. (5)) are degraded each year (col. (3)). These

Table 3: TWFE - CLR impact on tree cover and forest degradation)

	% tree cover		Forest degradation (2005-2018)			
	(1) (2000-2015)	(2) (2005-2015)	(3) Level (ha)	(4) Part (%)	(5) IHS transformed	(6) Normalised
CLR dummy	-1.746***	-1.915***	75.716**	0.042	0.052***	0.280***
	(0.281)	(0.272)	(33.733)	(0.093)	(0.009)	(0.082)
Ihs(Nighttime lights)	-0.203	-0.588***	-100.244***	0.068	0.020***	0.156**
	(0.205)	(0.216)	(31.695)	(0.061)	(0.008)	(0.064)
Past drought shocks	-0.253**	-0.478***	-101.795***	-0.253***	-0.027***	-0.279***
	(0.106)	(0.128)	(25.388)	(0.040)	(0.005)	(0.036)
Agri. subventions		-0.029	5.796	-0.059	-0.001	-0.041
		(0.036)	(10.217)	(0.042)	(0.003)	(0.037)
Observations	3,112	2,334	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778	778	778
Eventually treated	180	180	243	243	243	243
Mean Y	38.227	38.784	2,234.666	10.464	7.071	0.000
$R^2(within)$	0.492	0.534	0.148	0.349	0.318	0.344

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years for 2000, 2005, 2010 and 2015 for tree cover (col. (1) and (2), source: GFCC data (Townshend, 2016)) and from 2005 to 2018 for forest degradation (source: EC JRC (Vancutsem et al., 2021)).
Additional data sources: agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

findings suggest that, in addition to total deforestation measured by GFC data, CLR also contributed to significantly decrease overall tree cover and increase forest degradation.

5.3 Robustness tests

5.3.1 Synthetic control method

Although we find no evidence of differential deforestation trends in our group of treated and control municipalities prior to the CLR epidemic, non-experimental data raise concerns about the comparability

of treated and control units. To further test the robustness of our results, we replicate our event-study analysis with a synthetic control method adapted to empirical designs with staggered treatment (Ben-Michael et al., 2021). The synthetic control method estimates a counterfactual untreated outcome using a weighted average of control units, with weights set so as to minimize pre-trends differences between treated observations and this synthetic control.

Results of the event-study with synthetic control presented in Figures 7a to 7d are similar to the results obtained with the two-way fixed-effects and robust DID estimators displayed in Figures 3 to 6. Again, the effect of CLR presents an inverse-U-shaped pattern. Consistent with our previous results, we find that the impact of CLR on deforestation is the largest four to five years after the local epidemic outbreak.

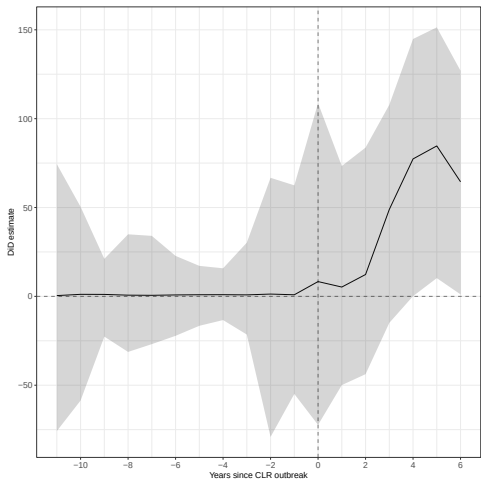
5.3.2 Propensity score matching

In a closely related analysis, we conduct an additional robustness test by applying the kernel-based propensity score matching (PSM) method (Heckman et al., 1997, 1998; Blundell and Dias, 2009). The kernel method matches a treated unit with the control unit(s) ranging in a specific bandwidth and assigns positive weights to these units depending on the selected kernel function. The distance between units is based on propensity scores constructed through the pre-treatment variables (Blundell and Dias, 2009). To be able to apply the method, we modify our data to have classical DID setup with two time periods (pre- and post-treatment) and two groups (treated and control). We thus construct two 7 years periods (2005-2011 and 2012-2018), and modify our outcome variables so that they equal to total deforestation that occurred in each period. The treatment variable is now equal to one for all municipalities that were affected by CLR any year from 2012 to 2018 regardless of the number of years they remained treated. Time-varying covariates (nighttime lights, agricultural subventions, and past drought shocks) are averaged over each of the 7-year periods. We use the Epanechnikov kernel function which puts more weight on control units closest to matched treated observations. We specify bandwidth with an automatic selector based on cross-validation with respect to the mean of the propensity score (Jann, 2017).

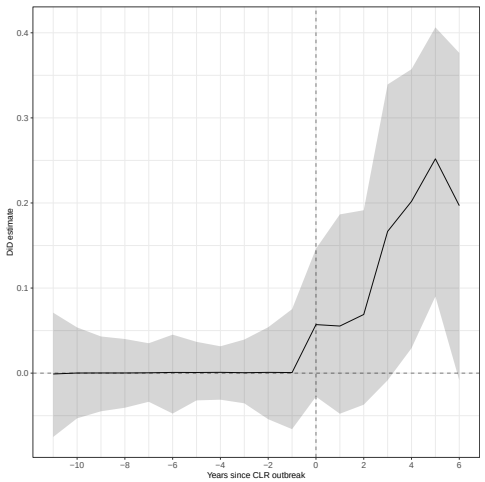
Results are shown in Table 4. In columns (1) to (3), as a basis for comparison, we report two-way fixed-effects estimates on two aggregate periods with a single treatment group. Columns (4) to (6) report matching results with the lowest and highest 1% of observation trimmed while in matching column 2, we trim the lowest and highest 5% of the observations according to their propensity scores. Overall, consistent with our main findings, results reported in Table 4 show that deforestation increased more in treated municipalities. The effect size increases in matched sample.

Figure 7: Difference-in-differences with augmented synthetic control adapted to staggered design

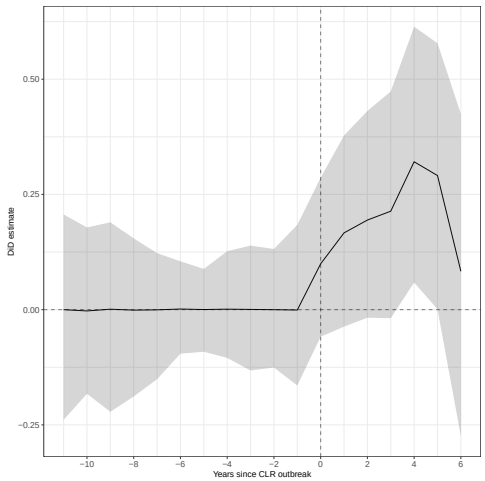
(a) Raw deforestation (ha)



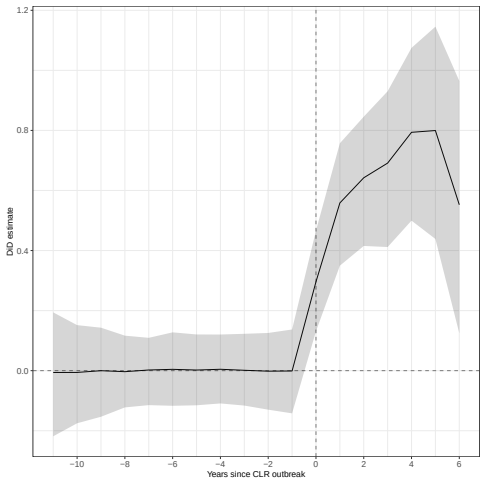
(b) Def. part (%)



(c) IHS deforestation



(d) Normalised def.



Note: We use *multisynth* function from *augsynth* package for R. Standard errors are bootstrapped. Included controls are the same as those included in the baseline equation. The v values are 0.39, 0.2, 0.09, and 0.14 respectively for raw deforestation, deforestation part, IHS deforestation and normalised deforestation. The intercept shift is included.

Table 4: Kernel-based propensity score matching - Period: 2005-2011 and 2012-2018

	TWFE			Kernel-based PS matching - (1)			Kernel-based PS matching - (2)		
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) Level (ha)	(5) Def. part (%)	(6) IHS def.	(7) Level (ha)	(8) Def. part (%)	(9) IHS def.
CLR	372.840***	0.917***	0.307***	870.322***	1.262***	0.352**	793.944***	1.047**	0.328**
	(125.879)	(0.181)	(0.066)	(288.946)	(0.415)	(0.147)	(293.507)	(0.414)	(0.153)
Observations	1,340	1,340	1,340	1,250	1,250	1,250	964	964	964
Control units	427	427	427	384	384	384	260	260	260
Treated units	243	243	243	241	241	241	222	222	222
Mean Y	814.132	2.471	5.411	1,660.218	3.401	5.917	1,545.984	3.234	5.858
Bootstrapped $p-val.$	0.000	0.000	0.000	0.004	0.008	0.000	0.000	0.022	0.020

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors are in parentheses. P-values from wild bootstrap with mammen methods are in below table. // Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015). Weights are calculated with the user-written Stata command *kmatch*

5.3.3 Additional robustness tests

As explained in section 4.2, the propagation of CLR may be correlated with characteristics of municipalities that could also affect local deforestation. We control for time-invariant observed and unobserved characteristics of municipalities with municipality fixed-effects in our main specification but do not account for potential time-varying effect of local characteristics such as elevation or agro-climatic suitability for coffee that would result in more or less vulnerability to CLR. As a robustness check, we re-estimate our initial model augmented with IHS transformed measures of population in 2005, tree cover in 2000, median elevation, and coffee suitability interacted with year fixed effects. Results are reported in Appendix Table 14. Estimated coefficients on the CLR dummy are slightly smaller than in our main specification but remain significant at the 1% level (except in col. 1 with raw deforestation measured in level (ha)).

Appendix Table 15 presents results based on alternative definitions of treated and control groups. First, in columns (1) to (4), we restrict the analysis to municipalities from the three Mexican states that are top coffee producers (Chiapas, Oaxaca, and Veracruz). Second, as mentioned in Section 2.4, the statistical approach that we use to detect CLR may lead us to misclassify coffee municipalities with low intensity of the disease as non-affected, which may bias our estimates. We address this issue by excluding never-treated coffee municipalities from the control group (columns (5) to (8)). In both cases sample size is mechanically reduced but results are very similar to our main estimates. The magnitude of the estimated effects is larger for the IHS transformed and z-score deforestation variable on the two restricted samples, which could suggest that including in the sample municipalities where coffee production is relatively marginal or including in the group of control potentially affected municipalities could slightly downward bias our main results.

In Appendix Table 16, we change the threshold used to define coffee municipalities: in our preferred sample definition we include in the pool of coffee municipalities (that may either be treated or not) only those where coffee area represents at least 5% of municipality agricultural area. Reducing this threshold to 1% does not change our results.

In Appendix Table 17, we vary the condition on reduction of coffee production used to identify local CLR outbreaks. While our preferred specification identifies a CLR outbreak when coffee production falls 1 standard deviation below 2005-2011 municipality average for two consecutive years, we here impose a more restrictive condition using a 1.5 standard deviation threshold. The number of treated municipalities decreases accordingly from 243 to 178, but with the exception of the coefficient on raw deforestation (column (1)) which is no longer significant, all other coefficients are similar in sign, significance, and magnitude to our main estimates. Conversely, Appendix Table 18 tests the robustness of our results when using a less restrictive threshold for CLR definition. Indeed, as discussed above, a potential threat to identification is that the fact that we observe non-affected coffee municipalities could result from our failure to detect low intensity epidemic outbreaks. We thus set a less restrictive threshold at 0.5 standard deviation. With this threshold, the number of municipalities increases by 17% (from 243 to 285 eventually affected municipalities). Point estimates are slightly smaller but remain significantly different from zero.

We vary conditions on the pixel-level share of tree cover in 2000 to calculate deforestation in Appendix Table 19, and on the municipality-level forest cover threshold that determines the inclusion of municipalities in our sample in Appendix Table 20. Both are set at 30% in our main specification, and Table 19 and Table 20 suggest that our results are insensitive to alternative threshold choices.

Results are also similar when we include lagged municipality-level PROCAFE amounts received over 2014-2016 (see Appendix Table 21). Note that since we have municipality-level PROCAFE data only

until 2016, our estimation period is in this case restricted to 2005-2017.

Another potential concern with our main specification is that all municipalities contribute in the same way to the estimation regardless of their area. Yet, there is considerable heterogeneity in municipality area, as shown in Figure 14. In Appendix Table 23, we report estimation results with each municipality being weighted by its area in hectares. Although the coefficient on the CLR dummy is no longer significant for the raw deforestation variable (column (1)), results are overall very similar to our main estimates.

Finally, although the propagation of the disease does not follow obvious spatial patterns (see Figure 14), we replicate our main results accounting for potential spatial correlation in the data by using Conley standard errors. As shown by Appendix Table 25, the statistical significance of our results is unaffected by this correction.

6 Heterogeneity analysis and mechanisms

6.1 Deforestation in cropland

As shown in Table 1 (in Section 2.4), CLR is not associated with an increase in total agricultural area, nor in area devoted to the top permanent and annual crops cultivated in those six states of Southern Mexico. If deforestation due to CLR were a response of farmers trying to compensate coffee production losses by increasing agricultural area, we would expect to find a positive impact of CLR on agricultural area. Results from Table 1 thus suggest that CLR-induced deforestation is due to other motives than agricultural expansion.

To further explore this issue, we use land use maps provided by INEGI[22] constructed based on a combination of field observation made during April-June 2012 and satellite images from 2011. We select non-irrigated agricultural zones with either perennial crops or a combination of annual and perennial crops. These categories should in theory include coffee plantations, either in agroforestry or open-sun systems. We merge land use data with deforestation data and construct the same four indicators of deforestation, restricted here to agricultural areas. Indeed, forest and agricultural areas may overlap in the case of perennial crops taller than five meters, or in agroforestry systems: such zones that are considered as agricultural areas in the INEGI classification will appear as forests in the GFC data. We then re-estimate our baseline model to analyse the impact of CLR on deforestation in those areas. Results reported in Table 5 show that CLR increased deforestation in areas defined as agricultural land allocated to permanent crops. These findings suggest that at least part of estimated CLR-induced deforestation occurred in areas planted with permanent crops. Since we find no otherwise significant change in area or production of permanent crops other than coffee (see Table 1), and since coffee is by far the main crop cultivated in agroforestry systems in Mexico (Manson et al., 2017), our findings thus suggest that deforestation caused by CLR occurred at least in part in coffee agroforestry systems.

6.2 Heterogeneity analysis

For lack of data on the type of coffee landscape, we use data on yields to construct a proxy for predominant coffee agroforestry systems. Rustic shade coffee is characterized by a lower plant density, and thus lower yields per hectare than intensive monoculture (Vaast et al., 2006; Jezeer et al., 2017). We construct

[22] https://www.inegi.org.mx/temas/usosuelo/

Table 5: TWFE - CLR impact on deforestation in cropland - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) Normalised
CLR dummy	7.345***	0.027***	0.214***	0.245***
	(2.480)	(0.007)	(0.041)	(0.048)
Ihs(Nighttime lights)	0.988	0.003	0.008	0.020
	(1.088)	(0.003)	(0.022)	(0.026)
Agri. subventions	0.014	-0.000	-0.009	-0.012
	(0.166)	(0.001)	(0.008)	(0.009)
Past drought shocks	3.155**	0.008**	-0.008	0.017
	(1.523)	(0.003)	(0.017)	(0.019)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Mean Y	9.843	0.045	1.029	0.000
$R^2(within)$	0.074	0.083	0.120	0.108

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

a $LowYield$ dummy variable equal to one for municipalities with coffee yields in the bottom quartile of the distribution (computed over 2005-2011 for municipalities where coffee represents at least 5% of municipality agricultural area). We then interact our measure for CLR with the $LowYield$ binary variable and add this interaction term to our main equation. Estimation results are reported in Table 6. For two of our deforestation measures, the coefficient on the interaction term is positive and significant (col. (3) and (4)), which suggests that CLR drove up deforestation more in municipalities with low yields. According to the results shown in column (3), deforestation increases by 25% in municipalities with yields in the top three quartiles, while deforestation jumped by 61% in municipalities with coffee yields in the bottom quartile. These result suggest that CLR pushed deforestation higher in areas where traditional shade coffee was still predominant.

To further validate this interpretation, we estimate our regressions separately for the three states that are the largest Mexican coffee producers. Appendix Table 24 displays estimation results for Chiapas, Oaxaca, and Veracruz. We find positive and significant effects of CLR on deforestation in Oaxaca and to a lesser extent in Chiapas, and no impact of CLR on deforestation in Veracruz. These findings can be related to the transformation of coffee landscape induced by the government-supported institute INMECAFE in the 1970s and 1980s that promoted the transition to lower density shade systems or open-sun cultivation (Nestel, 1995).[23] Data on coffee yield evolutions from 1970 to 1982 (Nestel, 1995) and qualitative evidence (Potvin et al., 2005) suggest that the resulting intensification was larger in the coastal state of Veracruz, and lower in more remote areas of Oaxaca. Rustic coffee systems represented a larger part of coffee area in the latter state in the late 1990s (Moguel and Toledo, 1999).

[23]The INMECAFE disappeared in 1990.

Table 6: TWFE - CLR impact on deforestation in municipalities with coffee yields in the bottom quartile - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	39.455**	0.101***	0.227***	0.283***
	(16.995)	(0.030)	(0.056)	(0.066)
CLRxLowYield	-11.632	0.009	0.253***	0.330***
	(39.061)	(0.061)	(0.095)	(0.116)
Ihs(Nighttime lights)	32.633**	0.057**	0.104**	0.138***
	(13.852)	(0.023)	(0.040)	(0.047)
Agri. subventions	0.262	-0.002	0.019	0.041*
	(1.805)	(0.005)	(0.019)	(0.024)
Past drought shocks	50.144***	0.067***	0.075***	0.121***
	(13.419)	(0.016)	(0.021)	(0.025)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Mean Y	108.570	0.354	3.419	-0.000
$R^2(within)$	0.104	0.128	0.167	0.175

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

6.3 CLR or PROCAFE?

The previous sections show that CLR increased deforestation, and strongly suggest that at least part of CLR-induced deforestation took place in coffee agroforestry systems. These findings invite us to reconsider the effect of CLR alone and question the concurrent role of the PROCAFE program. Indeed, CLR induced a policy response that in itself may have altered farmers' incentives. As stated above, the Mexican government responded in 2014 to the crisis of the coffee sector caused by CLR with PROCAFE, a massive program that promoted and subsidized CLR-resistant hybrid plants to replace traditional Arabica plants that were sensitive to the disease. Hybrids share with Robusta cultivars a number of characteristics, including resistance to CLR and adaptation to open-sun cultivation. This latter feature may explain part of deforestation that occurred following the CLR outbreak. In the remainder of this section, we try to disentangle the impacts of CLR and PROCAFE on deforestation. Since we cannot directly investigate the impact of PROCAFE on deforestation, due to obvious endogeneity concerns regarding PROCAFE, we exploit the different timing of CLR outbreaks and the launch of the program.

6.3.1 Interactions between CLR and PROCAFE

Launched in 2014 as a response to CLR, the PROCAFE program initially directly transferred cash to individual coffee producers. We first investigate whether PROCAFE funds were targeted to CLR affected municipalities. We estimate a cross-sectional regression on the subsample of coffee producing municipalites to explore the correlation between being affected by CLR and PROCAFE amounts (per

coffee planted area) received in 2014 and 2015.[24] Results are reported in Table 7. In columns (1), (3), and (5), the CLR variable is a dummy equal to one for municipalities first affected by CLR in 2012 or 2013, and the dependent variable refers to PROCAFE amounts received in 2014. In columns (2), (4), and (6), the CLR variable is a dummy equal to one for municipalities first affected by CLR in 2012, 2013 or 2014, and the dependent variable refers to PROCAFE amounts received in 2015. We find that municipalities with an epidemic outbreak in 2012 and 2013 tend to receive less PROCAFE funds per hectare in 2014. When broadening the scope to municipalities affected up to 2014, we find no correlation with PROCAFE amounts received in 2015 : municipalities first affected by CLR in 2012, 2013 or 2014 did not receive more PROCAFE amounts per coffee planted area than municipalities that were not affected. This finding is consistent with the orientation of the program, aimed at promoting CLR-resistant plants even in non-affected areas in anticipation of a predictable epidemic outbreak.

Table 7: CLR relation with PROCAFE per ha (coffee producing municipalities)

	OLS (Raw PROCAFE)		OLS (IHS PROCAFE)		PPML (Raw PROCAFE)	
	(1) 2014	(2) 2015	(3) 2014	(4) 2015	(5) 2014	(6) 2015
CLR	-192.544***	-71.890	-0.792***	-0.210	-0.443***	-0.150
	(61.839)	(72.571)	(0.267)	(0.228)	(0.159)	(0.110)
Ihs(NTL)	80.285	293.084***	0.259	0.362	0.161	0.406***
	(70.043)	(108.706)	(0.348)	(0.340)	(0.139)	(0.129)
Agri. subventions	26.106	267.146*	-0.556	-0.141	0.043	0.381**
	(74.706)	(148.797)	(0.449)	(0.382)	(0.143)	(0.176)
Past drought shocks	19.299	32.795	0.070	0.122**	0.040	0.052
	(17.106)	(26.299)	(0.066)	(0.055)	(0.033)	(0.037)
Observations	351	351	351	351	351	351
Treated units	91	127	91	127	91	127
Mean Y	500.910	690.588	5.900	6.320	500.910	690.588
R^2	0.045	0.148	0.140	0.118	0.088	0.198

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include state fixed effects. Units of observation are municipalities. We present adjusted R^2 for OLS and pseudo R^2 for PPML.
Data sources: PROCAFE data come from SAGARPA (Secretariat of Agriculture and Rural Development). Agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015). Dependent variable is a binary variable indicating the eventually treated municipalities. CLR variable is equal to 1 if municipality is treated in 2012 or 2013 for column 1, 3 and 5 and for columns 2, 4 and 6 the CLR variable is equal to 1 if municipality is treated in 2012, 2013 or 2014.

A second related issue is whether PROCAFE payments were associated with a lower vulnerability to CLR in the following years for municipalities that had not been affected yet. We investigate this issue in a cross-sectional regression on the subsample of coffee municipalities that had not been affected by CLR prior to 2016. The dependent variable is a binary measure for CLR if municipalities were affected in 2016 or later. Results reported in Table 26 suggest a negative correlation between PROCAFE amounts (per coffee planted hectare) received in 2014 and 2015 and the probability to be affected by CLR over 2016-2018, but the coefficients are not significant at conventional levels in two of our specifications and significant only at the 10% level (col. 1) when we use raw PROCAFE amounts.

These results suggest that PROCAFE payments in 2014 and 2015 were not specifically directed to CLR-impacted areas and had little impact on the probability to suffer from an epidemic outbreak in the later period for municipalities that had resisted so far. This latter point is important. If we had found evidence of a protective effect of PROCAFE, i.e. that areas receiving more PROCAFE funds were

[24]We do not include PROCAFE transfers for later years since from 2016 PROCAFE funds were mainly directed to cooperatives (see Appendix Figure 15) that operate over multiple municipalities. The georeferencing of PROCAFE funds is thus less precise from 2016.

significantly less likely to be affected by CLR in later years, using the same definition for our treatment variable before and after the launch of PROCAFE would lead us to miss municipalities that received more PROCAFE and for which the CLR epidemic entailed lower damages on production: those municipalities would have fallen below our detection threshold. Reassuringly, results from Table 26 that PROCAFE is unlikely to interact with our definition of treated municipalities.

6.3.2 Sub-periods comparison

We first add to our baseline equation an interaction term between the CLR binary variable and a post-2014 dummy to test whether CLR has a larger effect on deforestation after PROCAFE is launched. Results are reported in Table 8. We find that the coefficient on the CLR × Post-2014 variable is positive in all four specifications and significant in columns (3) and (4), suggesting that CLR has a stronger effect on deforestation after 2014. This result may point to the joint responsibility of the PROCAFE program, but it may also be explained by other mechanisms. In particular, while the disease was not well known to coffee producers in the first year of the epidemic, awareness of its long-lived consequences rose gradually in the subsequent years.

Table 8: TWFE - Impact of CLR before and after 2014 - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	20.771**	0.078***	0.169**	0.199**
	(10.054)	(0.028)	(0.066)	(0.089)
CLR × Post 2014	18.812	0.030	0.128*	0.178*
	(11.950)	(0.031)	(0.068)	(0.095)
Ihs(Nighttime lights)	32.609**	0.056**	0.099**	0.132***
	(13.834)	(0.023)	(0.040)	(0.047)
Agri. subventions	0.178	-0.002	0.020	0.043*
	(1.806)	(0.005)	(0.019)	(0.024)
Past drought shocks	49.978***	0.067***	0.078***	0.125***
	(13.433)	(0.016)	(0.021)	(0.025)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Mean Y	108.570	0.354	3.419	-0.000
$R^2(within)$	0.104	0.128	0.166	0.174
Sum CLR and CLR × Post 2014 coefficients	39.582	0.107	0.297	0.376
Sum CLR and CLR × Post 2014 P-val.	0.014	0.000	0.000	0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

In a complementary analysis, we compare our baseline results over the whole observation period (2005-2018) to estimation results over the period before the PROCAFE program (2005-2013). Results are presented in Table 9 (Panel A). Estimates reported in columns 5 to 8 over the period 2005 to 2013 (included) show that CLR has a positive and significant impact on deforestation already in the first two years of the epidemic (that started in 2012). The comparison of columns 5 to 8 to the first four columns of Table 9 that reproduce our baseline results presented in Table 2 reveals that the magnitude of the effect is lower over 2005-2013 than over the whole period. This finding is fully consistent with the

dynamic pattern of CLR effects illustrated by Figures 3 to 6 showing that the impact of CLR increases up to five years after the initial outbreak. The restriction of the estimation period to 2005-2013 means that we observe at most two post-treatment periods (2012 and 2013, for municipalities first affected in 2012), which explains that estimated coefficients are smaller. However, an important result here, consistent with results shown in Table 8, is the fact that CLR has a positive and significant impact on deforestation, even before PROCAFE is launched. Over 2005-2013, we are quite confident that the effect that we estimate is that of CLR alone.

By contrast, results over the whole period may reflect a combination of the impact of CLR with that of PROCAFE, launched in 2014. In order to try to disentangle CLR from PROCAFE, we vary the composition of the control group and focus on coffee municipalities only. Control municipalities thus include not-yet-treated and never affected coffee municipalities. The idea is that whereas CLR is expected to affect only municipalities that experienced a local outbreak of the disease, PROCAFE promoted from 2014 the replacement of traditional coffee plants by hybrids on a large scale as a preventive strategy in anticipation of an expansion of the disease. This implies that only CLR-affected municipalities can be considered as treated if we investigate the impact of the disease, while all coffee municipalities are virtually affected if PROCAFE is the treatment. We then expect to find no different deforestation trends in CLR-affected and CLR-free coffee municipalities if deforestation is mainly due to PROCAFE rather than CLR alone. A first intuition of this is provided by Figure 2, shown in Section 3.2. Indeed, as discussed above, descriptive evidence suggest that CLR-free coffee municipalities experience a jump in deforestation in 2016 similar, although smaller in magnitude, to that observed in CLR-affected municipalities. Note although PROCAFE was launched in 2014, hybrids became commonly available only in 2015-2016.

Estimation results on coffee municipalities only are reported in Table 9, Panel B. Columns 1 to 4 display estimation results over the whole period (2005-2018). We find that on this restricted sample, point estimates for the impact of CLR on deforestation are very small and never significantly different from zero. One may wonder whether this finding could also be interpreted as a failure on our part to identify, among coffee municipalities, those that are actually affected by CLR. However, as shown in columns 5 to 8 of Table 9, Panel B, we find that when restricting the estimation period to 2005-2013 the coefficient on the CLR dummy is positive and significant for three of our four deforestation variables. These findings suggest that CLR-affected municipalities deforest more than unaffected coffee municipalities in the first two years of the epidemic, but this is no longer the case over the whole period. Taken together, the results reported in Table 9 thus strongly suggest that CLR explains deforestation prior to 2014, but that over the whole period other factors common to all coffee municipalities, either affected by CLR or not, contribute to explaining deforestation. Although determinants of deforestation common to all coffee municipalities after 2014 may not solely be caused by PROCAFE, our findings suggest that PROCAFE contributed to deforestation in coffee municipalities. Among confounding factors common to all coffee municipalities that may cause an increase of deforestation is coffee price. Indeed, a negative shock on coffee prices may affect decisions of coffee farmer, and for example lead them to intensify coffee production in order to increase coffee yields. Coffee price series for "Other Milds" that include Mexican coffee made available by the International Coffee Organization[25] suggest that after a drop in 2013, coffee prices tend to rebound in 2014, suggesting that price variations are unlikely to explain our results.

To further investigate the possible impact of PROCAFE, we explore the dynamic effects of CLR in two different groups of treatment: we separate event-study analyses for municipalities affected by CLR in 2012 and 2013, before PROCAFE was launched, and municipalities affected after 2014. Figures

[25] https://www.ico.org/new_historical.asp

Table 9: TWFE - CLR impact on deforestation - Different control groups and time periods

	2005-2018				2005-2013 (before PROCAFE)			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.	(5) Level (ha)	(6) Def. part (%)	(7) IHS def.	(8) ZS Def.
Panel A: Total sample								
CLR	37.014*	0.103***	0.280***	0.352***	25.804*	0.110***	0.173*	0.201*
	(14.887)	(0.027)	(0.051)	(0.059)	(12.749)	(0.033)	(0.074)	(0.096)
Observations	10,892	10,892	10,892	10,892	7,002	7,002	7,002	7,002
Municipalities	778	778	778	778	778	778	778	778
Eventually treated	243	243	243	243	91	91	91	91
$R^2(within)$	0.104	0.128	0.166	0.174	0.043	0.049	0.108	0.094
Panel B: Only coffee producers								
CLR	13.635	-0.002	-0.059	-0.019	18.959	0.101**	0.156*	0.275**
	(22.825)	(0.034)	(0.057)	(0.067)	(14.150)	(0.034)	(0.077)	(0.099)
Observations	4,914	4,914	4,914	4,914	3,159	3,159	3,159	3,159
Municipalities	351	351	351	351	351	351	351	351
Eventually treated	243	243	243	243	91	91	91	91
$R^2(within)$	0.166	0.287	0.309	0.330	0.083	0.133	0.161	0.168

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018 in columns 1-4 and 2005-2013 in columns 5-8.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

8 to 11 display estimated coefficients and confidence intervals for the two groups. The comparison of the two groups reveal different time patterns: although confidence intervals overlap in most cases, the figures suggest that for municipalities affected by the epidemic in 2012 or 2013 the effect of CLR on deforestation became significantly different from zero only 3 years after the initial outbreak. By contrast, in municipalities affected after 2014 CLR tends to have a positive and significant effect on deforestation as early as the year following the outbreak (Figures 10 and 11). These findings are consistent with the results from the event-study analysis over the whole sample reported in Figures 3 to 6 and suggest that CLR increased deforestation especially after 2015, which coincides with the full effectiveness of the PROCAFE program.

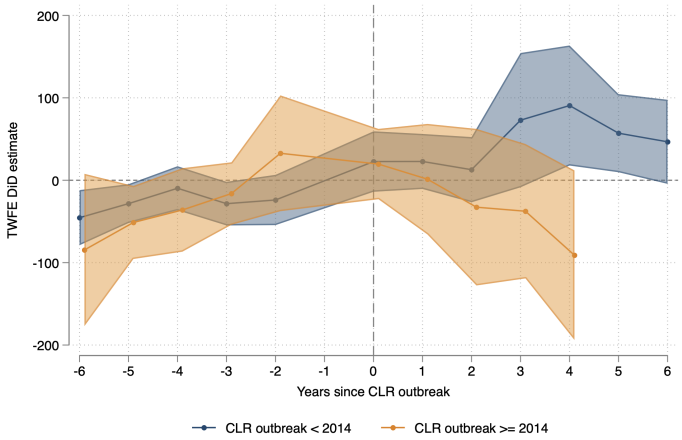


Figure 8: Raw deforestation

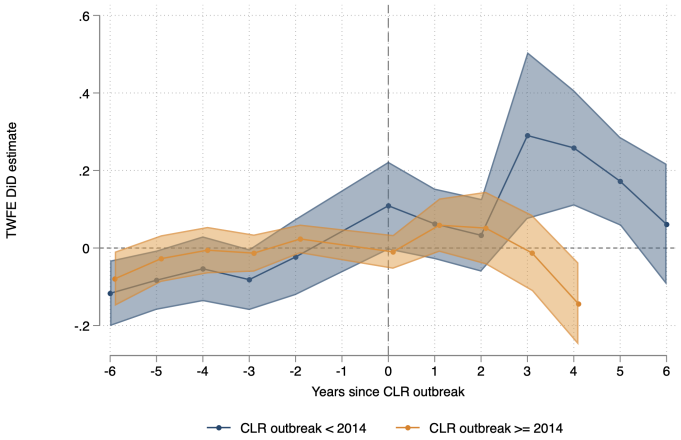


Figure 9: Deforestation part (%)

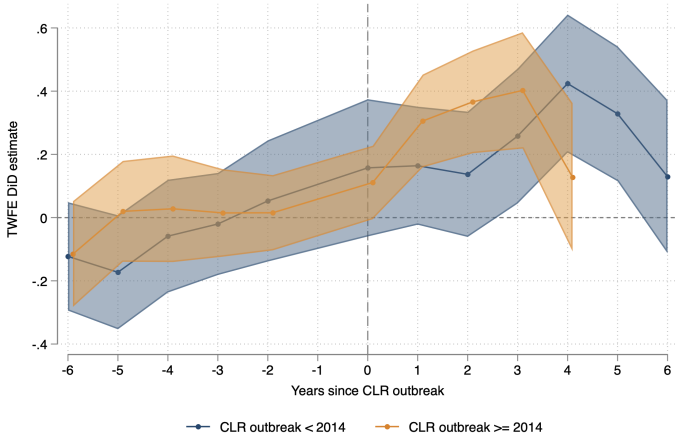


Figure 10: IHS deforestation

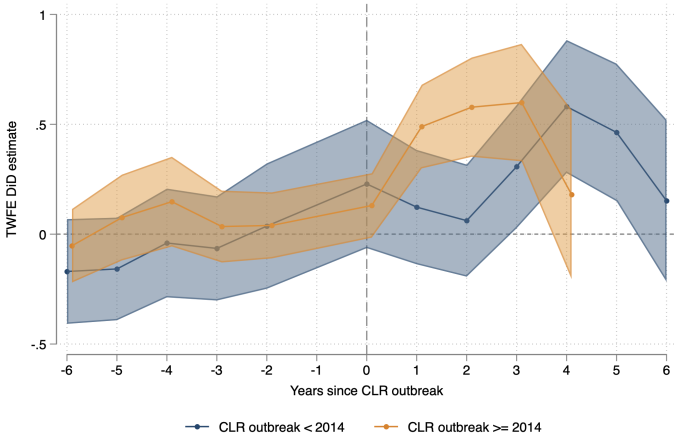


Figure 11: Normalised deforestation

Note:

6.3.3 Discussion: CLR intensity and learning effects

Our interpretation of sub-period differences in the impact of CLR implicitly relies on the assumption that our CLR variable is actually measuring the same reality over the whole period. One particular concern is thus that our measure or CLR could capture different intensities of the disease at the beginning and at the end of the period. This could be the case in particular if PROCAFE payments had a protective effect (which they do not seem to have, as discussed above), or if the intensity of the disease increased over time due to a larger quantity of inoculum. In this case, we would attribute to PROCAFE changes in impact of CLR on deforestation over time that may be due to different reactions to different treatment intensities. We report in Appendix Table 27 for each treatment year the median and mean production used to detect CLR (averaged over t and $t+1$ as explained in Section 2.4), compared to pre-CLR production levels (over 2005-2011), and the mean and median z-scores for production.[26] Reassuringly we find no specific time pattern nor difference in the mean and median z-score in the groups of early affected municipalities compared to the late affected ones.

Table 10: TWFE - CLR impact after 2014 in municipalities neighbor to already treated municipalities - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	24.007*	0.102***	0.179***	0.222**
	(13.207)	(0.031)	(0.069)	(0.092)
CLRxPost2014	22.756	0.059*	0.141**	0.206**
	(15.213)	(0.035)	(0.067)	(0.096)
CLRxPost2014xNeighbor	-17.139	-0.127**	-0.054	-0.124
	(33.323)	(0.052)	(0.092)	(0.108)
Ihs(Nighttime lights)	32.848**	0.058**	0.100**	0.134***
	(13.687)	(0.023)	(0.040)	(0.047)
Agri. subventions	0.096	-0.002	0.020	0.042*
	(1.800)	(0.006)	(0.019)	(0.024)
Past drought shocks	49.973***	0.067***	0.078***	0.125***
	(13.423)	(0.016)	(0.021)	(0.025)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Mean Y	108.570	0.354	3.419	-0.000
$R^2(within)$	0.104	0.130	0.166	0.174

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

It is also possible that the different time patterns for municipalities infected late versus early are due to a better knowledge of the disease and its characteristics. Learning effects may thus explain that producers in municipalities affected late respond sooner to the disease than those affected at the beginning of the epidemic who may be more likely to wait and see. To test this, we estimate an augmented version

[26] Remember that a municipality is defined as affected by CLR if the coffee production z-score falls below -1 for two consecutive years (t and $t+1$).

of our baseline equation including interactions between the CLR binary indicator, the post-2014 period, and a dummy equal to one for municipalities affected after 2014 and neighbors to a municipality affected by CLR in 2012 or 2013. The variant of equation 2 that we estimate in this section formally writes:

$$\begin{aligned} Y_{it} &= \beta_{CLR} CLR_{it} + \beta_{Post} CLR_{it} \times Post2014 + \beta_{PostN} CLR_{it} \times Post2014 \times Neighbor \\ &\quad + X'_{it}\gamma + \delta_i + \phi_t + \psi_{st} + \epsilon_{it} \end{aligned} \tag{4}$$

where Y_{it} represents deforestation in municipality i and year t, $X'_{it}, \delta_i, \phi_t, \psi_{st}$ are same as in 2. $Post2014$ is a binary variable equal to one for year 2014 and beyond. $Neighbor$ equals one for municipalities that are neighbors to at least one municipality affected by CLR in 2012 or 2013. We here assume that learning effects, if any, should be stronger in municipalities that are not yet affected by the disease but are neighbors to at least one municipality already affected. Under the assumption that learning effects are at least partially channelled by neighbor effects, if the larger impact of CLR on deforestation observed after 2014 is due to learning effects we expect to find more deforestation in late affected municipalities neighbor to an already affected municipality than in late affected municipalities surrounded by CLR-free municipalities, which means that we expect the β_{PostN} coefficient to be positive and significant.

Results are reported in Table 10. Consistent with results shown in Table 8, we find that CLR has a stronger impact on deforestation after 2014 in two or our four specifications (columns (3) and (4)), but the coefficient on the triple interaction between CLR, the $Post2014$ dummy and the $Neighbor$ dummy is always negative and not significant except in column (2). Overall, these results suggest that learning effect transiting through neighbors are unlikely to explain the larger impact of CLR after 2014.

7 Conclusion

We analyze in this article the impact of the massive outbreak of coffee leaf rust (CLR) that hit Mexico from 2012 on deforestation. We find that CLR increased deforestation in Mexico, but we find no evidence of any significant change in agricultural areas. Further exploration suggests that deforestation increased in particular in areas where there agriculture and forest overlap, that is in agroforestry systems. We find heterogeneous effects of CLR, deforestation increasing more in municipalities with low coffee yields, that signal the predominance of agroforestry cultivation systems, and in states with a still high share of shade coffee, and in particular in Oaxaca. The Mexican government responded in 2014 to the spread of the CLR with the PROCAFE program providing incentives to coffee farmers to adopt new varieties resistant to the fungal disease. Those varieties differ from traditional ones with regard their cultivation needs, and especially their tolerance to sun exposure. PROCAFE may have thus contributed to increase deforestation in coffee shade cultivation systems. We exploit the late implementation of the program and the comparison between coffee and non-coffee municipalities to try to disentangle the impact of CLR from that of PROCAFE. Consistent with qualitative or field evidence (Ruiz-de Oña et al., 2019; Valencia et al., 2018), our findings suggest a drift from agroforestry practices and shade coffee production towards monoculture plantations through the combined effect of a massive outbreak of a persistent fungal disease and a short-term government response. While we are not able to measure the counterfactual deforestation that would have resulted from the disease alone, our results suggest that the PROCAFE program contributed to magnify the impact of CLR on deforestation and forest degradation by promoting CLR-resistant hybrid coffee varieties. A rough calculation based on our main estimation results suggests

that CLR and PROCAFE combined directly caused the deforestation of 42,000 hectares over 2012-2018, which represents 2.7% of total deforestation in Mexico over the same period. Our findings emphasize the particular vulnerability of agroforests to a negative and persistent agricultural shock, with both global and local irreversible consequences in terms of biodiversity loss and ecosystem services, and reduced resilience of households to future shocks. This study emphasizes the need to better account for long-term consequences and environmental spillovers of agricultural programs, which involves the anticipation of future crises such as the CLR epidemic whose frequency and severity is expected to increase due to climate change.

References

Abman, R. and Carney, C. (2020). Agricultural productivity and deforestation: Evidence from input subsidies and ethnic favoritism in Malawi. *Journal of Environmental Economics and Management*, 103:102342.

Aihounton, G. B. and Henningsen, A. (2021). Units of measurement and the inverse hyperbolic sine transformation. *The Econometrics Journal*, 24(2):334–351.

Alix-Garcia, J., McIntosh, C., Sims, K. R., and Welch, J. R. (2013). The ecological footprint of poverty alleviation: evidence from Mexico's Oportunidades program. *Review of Economics and Statistics*, 95(2):417–435.

Alix-Garcia, J. M., Shapiro, E. N., and Sims, K. R. (2012). Forest conservation and slippage: Evidence from Mexico's national payments for ecosystem services program. *Land Economics*, 88(4):613–638.

Alix-Garcia, J. M., Sims, K. R., and Yañez-Pagans, P. (2015). Only one tree from each seed? Environmental effectiveness and poverty alleviation in Mexico's payments for ecosystem services program. *American Economic Journal: Economic Policy*, 7(4):1–40.

Assunção, J., Gandour, C., Rocha, R., and Rocha, R. (2020). The Effect of Rural Credit on Deforestation: Evidence from the Brazilian Amazon. *The Economic Journal*, 130(626):290–330.

Athey, S. and Imbens, G. W. (2022). Design-based analysis in Difference-In-Differences settings with staggered adoption. *Journal of Econometrics*, 226(1):62–79. Annals Issue in Honor of Gary Chamberlain.

Avelino, J. and Anzueto, F. (2020). Coffee rust epidemics in Central America: Chronicle of a resistance breakdown following the great epidemics of 2012 and 2013. *Emerging Plant Diseases and Global Food Security, JB Ristaino, A. Records, Eds.(The American Phytopathological Society, 2020)*, pages 185–198.

Avelino, J., Cristancho, M., Georgiou, S., Imbach, P., Aguilar, L., Bornemann, G., Läderach, P., Anzueto, F., Hruska, A. J., and Morales, C. (2015). The coffee rust crises in Colombia and Central America (2008–2013): impacts, plausible causes and proposed solutions. *Food Security*, 7(2):303–321.

Avelino, J., Vilchez, S., Segura-Escobar, M. B., Brenes-Loaiza, M. A., Virginio Filho, E. d. M., and Casanoves, F. (2020). Shade tree Chloroleucon eurycyclum promotes coffee leaf rust by reducing uredospore wash-off by rain. *Crop Protection*, 129:105038.

Banerjee, A., Duflo, E., Postel-Vinay, G., and Watts, T. (2010). Long-run health impacts of income shocks: Wine and phylloxera in nineteenth-century France. *The Review of Economics and Statistics*, 92(4):714–728.

Baragwanath, K. and Bayi, E. (2020). Collective property rights reduce deforestation in the Brazilian Amazon. *Proceedings of the National Academy of Sciences*, 117(34):20495–20502.

Bellemare, M. F. and Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1):50–61.

Ben-Michael, E., Feller, A., and Rothstein, J. (2021). Synthetic controls with staggered adoption. Technical report, National Bureau of Economic Research.

Blackman, A., Goff, L., and Planter, M. R. (2018). Does eco-certification stem tropical deforestation? Forest Stewardship Council certification in Mexico. *Journal of Environmental Economics and Management*, 89:306–333.

Blackman, A. and Villalobos, L. (2021). Use forests or lose them? Regulated timber extraction and tree cover loss in Mexico. *Journal of the Association of Environmental and Resource Economists*, 8(1):125–163.

Blundell, R. and Dias, M. C. (2009). Alternative Approaches to Evaluation in Empirical Microeconomics. *Journal of Human Resources*, 44(3):565–640.

Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation.

Bradshaw, C. J., Sodhi, N. S., and Brook, B. W. (2009). Tropical turmoil: a biodiversity tragedy in progress. *Frontiers in Ecology and the Environment*, 7(2):79–87.

Brondizio, E. S., Settele, J., Díaz, S., and Ngo, H. T. (2019). Global assessment report on biodiversity and ecosystem services of the intergovernmental science-policy platform on biodiversity and ecosystem services.

Bruederle, A. and Hodler, R. (2018). Nighttime lights as a proxy for human development at the local level. *PloS One*, 13(9):e0202231.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230. Themed Issue: Treatment Effect 1.

Castillo, N. E. T., Melchor-Martínez, E. M., Sierra, J. S. O., Ramirez-Mendoza, R. A., Parra-Saldívar, R., and Iqbal, H. M. (2020). Impact of climate change and early development of coffee rust–An overview of control strategies to preserve organic cultivars in Mexico. *Science of the Total Environment*, 738:140225.

Cerda, R., Avelino, J., Gary, C., Tixier, P., Lechevallier, E., and Allinne, C. (2017). Primary and secondary yield losses caused by pests and diseases: Assessment and modeling in coffee. *PloS One*, 12(1):e0169133.

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1):1–45.

Davidson, S. (2004). Shade coffee agro-ecosystems in Mexico: A synopsis of the environmental services and socio-economic considerations. *Journal of Sustainable Forestry*, 21(1):81–95.

De Beenhouwer, M., Aerts, R., and Honnay, O. (2013). A global meta-analysis of the biodiversity and ecosystem service benefits of coffee and cacao agroforestry. *Agriculture, Ecosystems & Environment*, 175:1–7.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

De Chaisemartin, C. and D'Haultfoeuille, X. (2022). Difference-in-differences estimators of intertemporal treatment effects. Working Paper 29873, National Bureau of Economic Research.

Desbureaux, S. and Damania, R. (2018). Rain, forests and farmers: Evidence of drought induced deforestation in Madagascar and its consequences for biodiversity conservation. *Biological Conservation*, 221:357–364.

Fetzer, T. R. (2014). Can Workfare Programs Moderate Violence? Evidence from India. *London School of Economics (LSE) Working Paper*, 53.

Fischer, G., Nachtergaele, F. O., van Velthuizen, H., Chiozza, F., Francheschini, G., Henry, M., Muchoney, D., and Tramberend, S. (2021). Global agro-ecological zones (GAEZ V4) - Model Documentation. *FAO & IIASA*.

Foster, A. D. and Rosenzweig, M. R. (2003). Economic growth and the rise of forests. *The Quarterly Journal of Economics*, 118(2):601–637.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., et al. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data*, 2(1):1–21.

Gardner, J. (2021). Two-stage difference-in-differences.

Gonzalez, A. M., Plakias, Z., and Partridge, M. (2017). The Mexican PROCAMPO Farmland Subsidy and Its Effectiveness as a Rural Anti-Poverty Program.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277. Themed Issue: Treatment Effect 1.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., et al. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, 342(6160):850–853.

Harvey, C. A., Pritts, A. A., Zwetsloot, M. J., Jansen, K., Pulleman, M. M., Armbrecht, I., Avelino, J., Barrera, J. F., Bunn, C., García, J. H., Isaza, C., Munoz-Ucros, J., Pérez-Alemán, C. J., Rahn, E., Robiglio, V., Somarriba, E., and Valencia, V. (2021). Transformation of coffee-growing landscapes across Latin America. A review. *Agronomy for Sustainable Development*, 41(5):62.

Heß, S., Jaimovich, D., and Schündeln, M. (2021). Environmental effects of development programs: Experimental evidence from West African dryland forests. *Journal of Development Economics*, 153:102737.

Heckman, J. J., Ichimura, H., and Todd, P. (1998). Matching As An Econometric Evaluation Estimator. *The Review of Economic Studies*, 65(2):261–294.

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies*, 64(4):605–654.

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028.

Henderson, T. P. (2020). Elite-led development and Mexico's independent coffee organisations in the wake of the rust epidemic. *Third World Quarterly*, 41(6):1012–1029.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences*, 107(35):15367–15372.

Hu, X., Huang, B., Verones, F., Cavalett, O., and Cherubini, F. (2021). Overview of recent land-cover changes in biodiversity hotspots. *Frontiers in Ecology and the Environment*, 19(2):91–97.

International Coffee Organization (2020). ICO 2020 Report - The value of coffee. *International Coffee Organization*.

Jann, B. (2017). KMATCH: Stata module for multivariate-distance and propensity-score matching.

Jayachandran, S. (2013). Liquidity constraints and deforestation: The limitations of payments for ecosystem services. *American Economic Review*, 103(3):309–13.

Jezeer, R. E., Verweij, P. A., Santos, M. J., and Boot, R. G. (2017). Shaded coffee and cocoa–double dividend for biodiversity and small-scale farmers. *Ecological Economics*, 140:136–145.

Jha, S., Bacon, C. M., Philpott, S. M., Ernesto Mendez, V., Läderach, P., and Rice, R. A. (2014). Shade coffee: update on a disappearing refuge for biodiversity. *BioScience*, 64(5):416–428.

Kissinger, G., Herold, M., and De Sy, V. (2012). Drivers of deforestation and forest degradation: a synthesis report for REDD+ policymakers. Technical report, Citeseer.

Klepeis, P. and Vance, C. (2003). Neoliberal policy and deforestation in southeastern Mexico: An assessment of the PROCAMPO program. *Economic Geography*, 79(3):221–240.

Koch, N., Ermgassen, E. K., Wehkamp, J., Oliveira Filho, F. J., and Schwerhoff, G. (2019). Agricultural Productivity and Forest Conservation: Evidence from the Brazilian Amazon. *American Journal of Agricultural Economics*, 101(3):919–940.

Lasso, E., Corrales, D. C., Avelino, J., de Melo Virginio Filho, E., and Corrales, J. C. (2020). Discovering weather periods and crop properties favorable for coffee rust incidence from feature selection approaches. *Computers and Electronics in Agriculture*, 176:105640.

Li, X., Zhou, Y., Zhao, M., and Zhao, X. (2020). A harmonized global nighttime light dataset 1992–2018. *Scientific data*, 7(1):1–9.

Libert Amico, A., Ituarte-Lima, C., and Elmqvist, T. (2020). Learning from social–ecological crisis for legal resilience building: multi-scale dynamics in the coffee rust epidemic. *Sustainability Science*, 15(2):485–501.

Libois, F., Baland, J.-M., Delbart, N., Pattanayak, S., et al. (2021). Community forest management: The story behind a success story in Nepal. Technical report, University of Namur, Development Finance and Public Policies.

Liebig, T., Ribeyre, F., Läderach, P., Poehling, H.-M., Van Asten, P., and Avelino, J. (2019). Interactive effects of altitude, microclimate and shading system on coffee leaf rust. *Journal of Plant Interactions*, 14(1):407–415.

Lipscomb, M. and Prabakaran, N. (2020). Property rights and deforestation: Evidence from the Terra Legal land reform in the Brazilian Amazon. *World Development*, 129:104854.

Manson, R., Binnqüist, C. L., and NegrerosCastillo, P. (2017). Expanding the North American perspective—Mexico. In *Agroforestry: enhancing resiliency in US agricultural landscapes under changing conditions*. Gen. Tech. Report WO-96. Washington, DC: US Department of Agriculture, Forest Service.

Merle, I., Tixier, P., de Melo Virginio Filho, E., Cilas, C., and Avelino, J. (2020). Forecast models of coffee leaf rust symptoms and signs based on identified microclimatic combinations in coffee-based agroforestry systems in Costa Rica. *Crop Protection*, 130:105046.

Moguel, P. and Toledo, V. M. (1999). Biodiversity conservation in traditional coffee systems of Mexico. *Conservation biology*, 13(1):11–21.

NASA JPL (2020). NASADEM Merged DEM Global 1 arc second V001 [Data set]. *NASA EOSDIS Land Processes DAAC*.

Nestel, D. (1995). Coffee in Mexico: international market, agricultural landscape and ecology. *Ecological Economics*, 15(2):165–178.

Noack, F., Riekhof, M.-C., and Di Falco, S. (2019). Droughts, Biodiversity, and Rural Incomes in the Tropics. *Journal of the Association of Environmental and Resource Economists*, 6(4):823–852.

Potvin, C., Owen, C. T., Melzi, S., and Beaucage, P. (2005). Biodiversity and modernization in four coffee-producing villages of Mexico. *Ecology and Society*, 10(1).

Rambachan, A. and Roth, J. (2022). A more credible approach to parallel trends. Technical report, Working Paper.

Renard Hubert, M.-C. and Larroa Torres, R. M. (2017). Política pública y sustentabilidad de los territorios cafetaleros en tiempos de roya: Chiapas y Veracruz. *Estudios Latinoamericanos*, (40):95.

Rhiney, K., Guido, Z., Knudson, C., Avelino, J., Bacon, C. M., Leclerc, G., Aime, M. C., and Bebber, D. P. (2021). Epidemics and the future of coffee production. *Proceedings of the National Academy of Sciences*, 118(27).

Rios-Avila, F., Sant'Anna, P., and Callaway, B. (2022). CSDID: Stata module for the estimation of Difference-in-Difference models with multiple time periods.

Rodriguez-Solorzano, C. (2014). Unintended outcomes of farmers' adaptation to climate variability: deforestation and conservation in Calakmul and Maya biosphere reserves. *Ecology and Society*, 19(2).

Roth, J. (2019). Pre-test with caution: Event-study estimates after testing for parallel trends. *Department of Economics, Harvard University, Unpublished manuscript*.

Roth, J., Sant'Anna, P. H., Bilinski, A., and Poe, J. (2022). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *arXiv preprint arXiv:2201.01194*.

Ruiz-de Oña, C., Rivera-Castañeda, P., and Merlín-Uribe, Y. (2019). Coffee, migration and climatic changes: challenging adaptation dichotomic narratives in a transborder region. *Social sciences*, 8(12):323.

Sadoulet, E., de Janvry, A., and Davis, B. (2001). Cash transfer programs with income multipliers: PROCAMPO in Mexico. *World Development*, 29(6):1043–1056.

Sant'Anna, P. H. and Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics*, 219(1):101–122.

Schuppener, H., Harr, J., Sequeira, F., Gonzales, A., et al. (1977). First occurrence of the coffee leaf rust hemileia vastatrix in nicaragua, 1976, and its control. *Café Cacao Thé*, 21(3):197–202.

Somarriba, E. and López-Sampson, A. (2018). Coffee and cocoa agroforestry systems: pathways to deforestation, reforestation, and tree cover change. *PROFOR, CATIE*.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199. Themed Issue: Treatment Effect 1.

Toledo, V. M. and Moguel, P. (2012). Coffee and sustainability: the multiple values of traditional shaded coffee. *Journal of Sustainable Agriculture*, 36(3):353–377.

Townshend, J. (2016). Global Forest Cover Change (GFCC) tree cover multi-year global 30 m V003.

Vaast, P., Bertrand, B., Perriot, J.-J., Guyot, B., and Genard, M. (2006). Fruit thinning and shade improve bean characteristics and beverage quality of coffee (coffea arabica l.) under optimal conditions. *Journal of the Science of Food and Agriculture*, 86(2):197–204.

Valencia, V., García-Barrios, L., Sterling, E. J., West, P., Meza-Jiménez, A., and Naeem, S. (2018). Smallholder response to environmental change: Impacts of coffee leaf rust in a forest frontier in Mexico. *Land Use Policy*, 79:463–474.

Vance, C. and Geoghegan, J. (2002). Temporal and spatial modelling of tropical deforestation: a survival analysis linking satellite and household survey data. *Agricultural Economics*, 27(3):317–332.

Vancutsem, C., Achard, F., Pekel, J.-F., Vieilledent, G., Carboni, S., Simonetti, D., Gallego, J., Aragao, L. E., and Nasi, R. (2021). Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. *Science Advances*, 7(10):eabe1603.

Villarreyna, R., Barrios, M., Vílchez, S., Cerda, R., Vignola, R., and Avelino, J. (2020). Economic constraints as drivers of coffee rust epidemics in Nicaragua. *Crop Protection*, 127:104980.

Zaveri, E., Russ, J., and Damania, R. (2020). Rainfall anomalies are a significant driver of cropland expansion. *Proceedings of the National Academy of Sciences*, 117(19):10225–10233.

Appendix

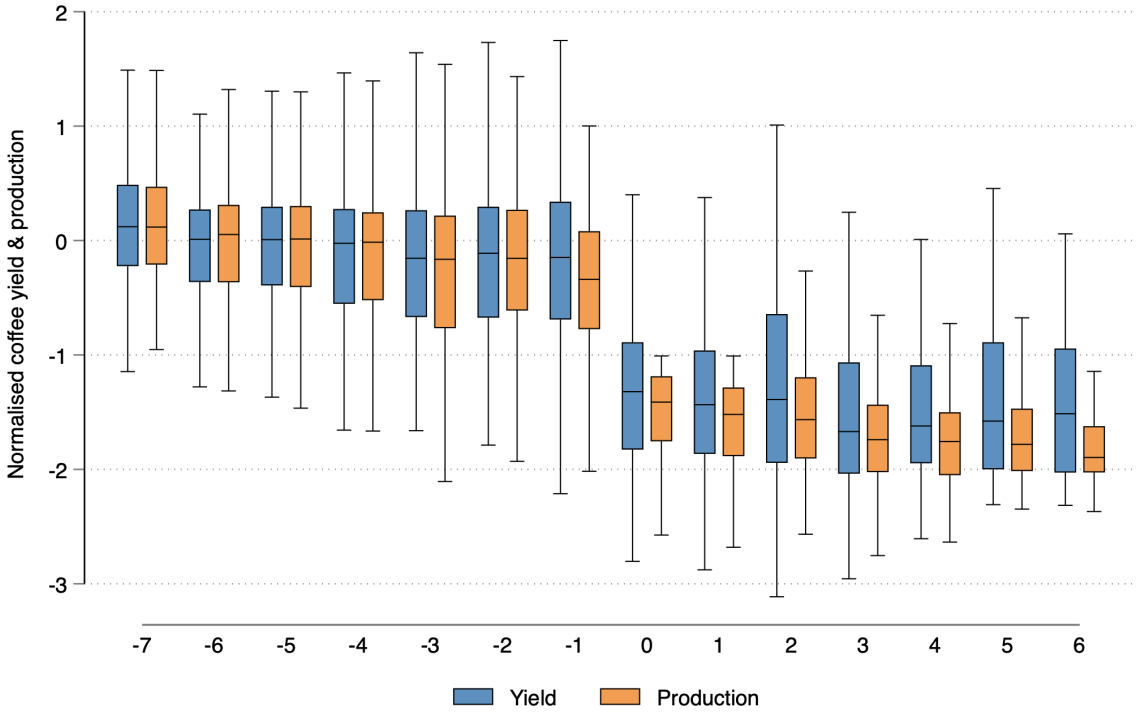
Appendix A: Agriculture data, CLR variable and PROCAFE

Table 11: Sample composition

	Observation number	Group share	Treatment coverage
Non coffee municipalities	427	0.55	.
Never treated coffee municipalities	108	0.14	.
Treated since 2012	48	0.06	0.50
Treated since 2013	43	0.06	0.43
Treated since 2014	36	0.05	0.36
Treated since 2015	53	0.07	0.29
Treated since 2016	44	0.06	0.21
Treated since 2017	15	0.02	0.14
Treated since 2018	4	0.01	0.07

Notes: The table reports the number and share of municipalities first affected by CLR for each year since 2012, and the treatment coverage which represents the percentage of time periods (years) each group is considered treated over the whole estimation period (2005-2018).

Figure 12: Evolution of normalised coffee yield & production of eventually treated group by CLR start year



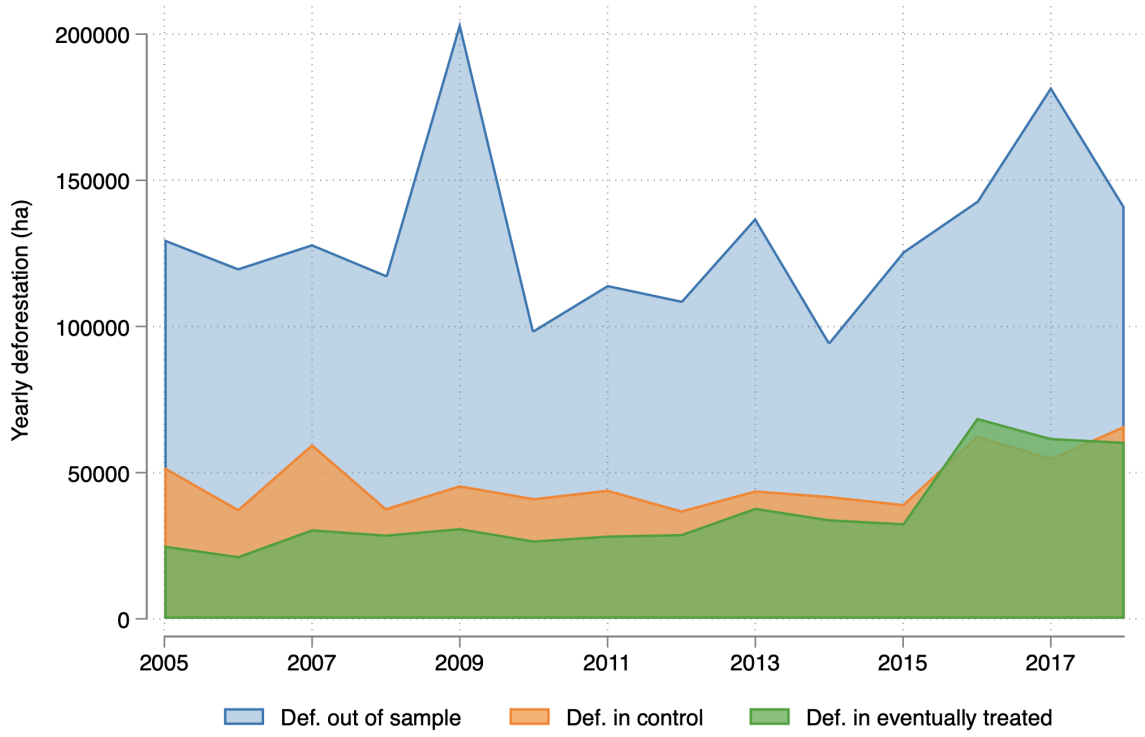
Note: Outliers are excluded. The variables are normalised by using the pre-CLR average (2005-2011) and standard deviation for 2005-2018.

Table 12: Summary statistics - Comparison of eventually treated to control municipalities - Yearly averages over 2005-2011 unless specified otherwise

Variable	(1) Even. treated Mean/SE	(2) Control Mean/SE	T-test Difference (1)-(2)
Deforestation (ha)	113.157	85.076	28.080
	(24.338)	(11.974)	
Def. part (%)	0.283	0.323	-0.040*
	(0.017)	(0.015)	
Ihs(Deforestation)	3.909	3.268	0.641***
	(0.105)	(0.094)	
Tree cover % in 2000	79.754	58.591	21.163***
	(0.844)	(0.682)	
Coffee area (ha)	2447.318	265.944	2181.374***
	(221.719)	(36.684)	
Coffee production (tonnes)	4609.863	480.256	4129.608***
	(473.891)	(67.814)	
Nighttime light (raw)	4.456	4.397	0.059
	(0.443)	(0.233)	
Agri. subventions	0.608	0.842	-0.234***
	(0.030)	(0.027)	
Past drought shocks	4.309	3.989	0.320***
	(0.104)	(0.051)	
Municipality area (ha)	36572.840	31710.467	4862.372
	(5530.199)	(2004.904)	
N	243	535	

Notes: Coffee production unit is green beans. Column (3) reports t-tests for the differences in the means across groups. Standard errors are bootstrapped. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 13: Total deforestation in Mexico, 2005-2018



Note: Out of sample group includes all Mexican municipalities that are not included in our sample. Eventually treated and control groups are the same as above.

Figure 14: CLR spread in Mexico (2012-2018): treated and control municipalities

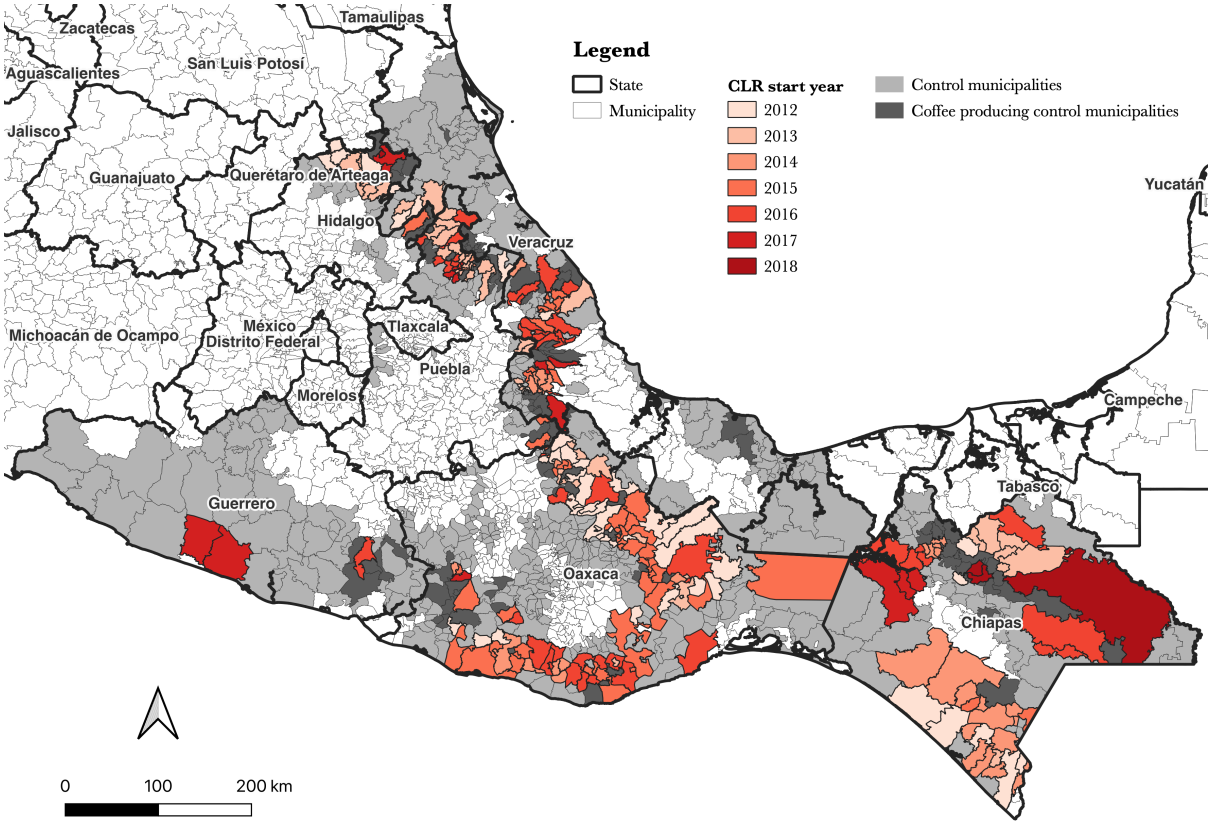
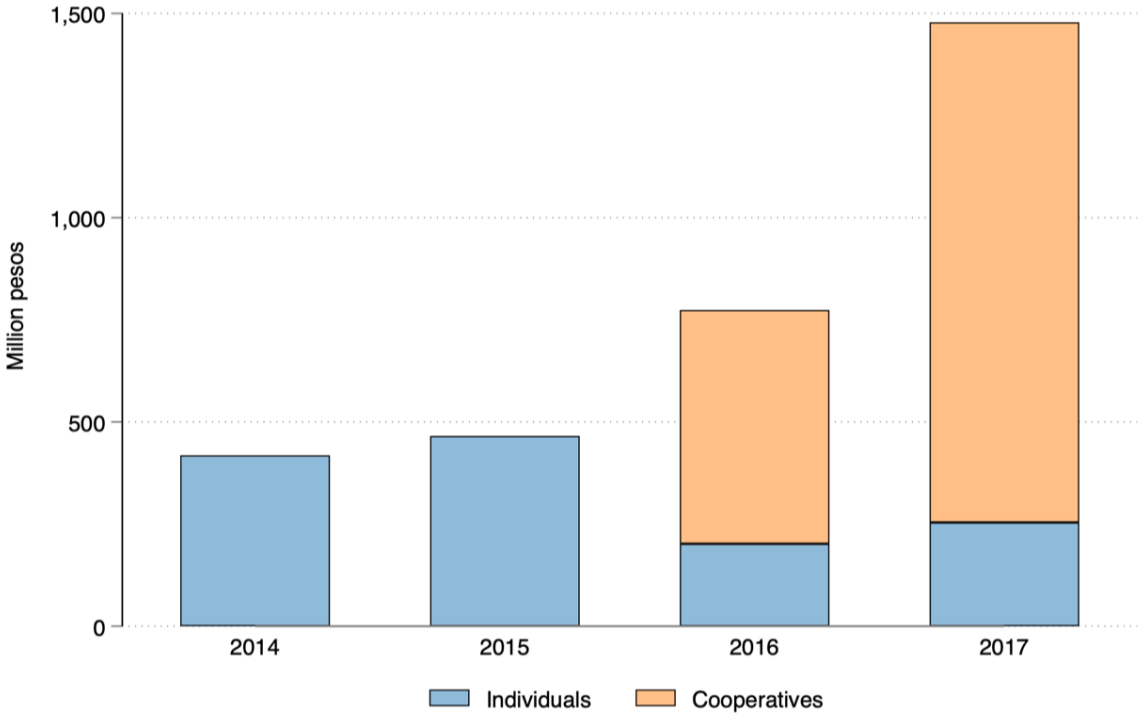


Table 13: Differences between treatment and control group (cross-section OLS - Sample: Coffee producing municipalities)

	Treated probability (Eventually treated)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10) All together
Ihs(Area)	0.075***									-0.184
	(0.020)									(0.182)
Ihs(Tree cover in 2000)		0.082***								0.349*
		(0.021)								(0.178)
Ihs(Tree cover % in 2000)			0.078							
			(0.136)							
Ihs(Elevation)				-0.003						0.016
				(0.027)						(0.038)
Ihs(Population)					0.075***					-0.053
					(0.024)					(0.057)
Ihs(Pop. density in 2010)						-0.036				
						(0.031)				
Ihs(NTL)							0.002			0.150**
							(0.037)			(0.065)
Ihs(Precipitation)								-0.074		-0.055
								(0.089)		(0.107)
Ihs(Coffee suitability)									0.047	-0.009
									(0.036)	(0.046)
Observations	351	351	351	351	351	351	351	351	351	351
Treated units	243	243	243	243	243	243	243	243	243	243
Mean Y	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692	0.692
$R^2(within)$	0.043	0.047	0.011	0.010	0.035	0.013	0.010	0.012	0.014	0.054

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include state fixed effects. Units of observation are municipalities. Tree cover is from 2000. Population, nighttime light, precipitation data from 2010.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015), population from 2010 Mexican census, coffee suitability from FAO/GAEZ (Fischer et al., 2021), elevation data from NASA (NASA JPL, 2020). Dependent variable is a binary variable indicating the eventually treated municipalities.

Figure 15: PROCAFE amounts by year (2014-2017)



Appendix B: Robustness tables

Table 14: TWFE - CLR impact on deforestation - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	15.602	0.092***	0.249***	0.294***
	(18.831)	(0.027)	(0.051)	(0.057)
Ihs(Nighttime lights)	7.589	0.040*	0.066	0.035
	(10.168)	(0.023)	(0.049)	(0.054)
Agri. subventions	1.930	-0.002	0.018	0.042*
	(2.449)	(0.005)	(0.019)	(0.024)
Past drought shocks	40.073***	0.076***	0.090***	0.131***
	(11.192)	(0.016)	(0.023)	(0.025)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Mean Y				
$R^2(within)$	0.153	0.147	0.194	0.207

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018. We interact 2005 population, tree cover in 2000, median elevation and coffee suitability index variables (all inverse hyperbolic sine transformed) with year FEs.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015), population from 2005 Mexican intermediate census, coffee suitability from FAO/GAEZ (Fischer et al., 2021), median elevation data from NASA (NASA JPL, 2020).

Table 15: TWFE - CLR impact on deforestation - Alternative sample definitions - Period: 2005-2018

	3 states				Coffee producers excluded			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.	(5) Level (ha)	(6) Def. part (%)	(7) IHS def.	(8) ZS Def.
CLR dummy	37.097***	0.109***	0.394***	0.510***	29.677*	0.124***	0.367***	0.447***
	(9.032)	(0.030)	(0.067)	(0.077)	(17.757)	(0.027)	(0.052)	(0.060)
Ihs(Nighttime lights)	10.097*	0.052**	0.106**	0.144***	35.015**	0.057**	0.104**	0.152***
	(5.538)	(0.025)	(0.047)	(0.054)	(15.392)	(0.023)	(0.041)	(0.047)
Agri. subventions	-1.863	-0.006	0.012	0.031	1.383	-0.001	0.016	0.039
	(1.572)	(0.007)	(0.021)	(0.027)	(2.309)	(0.005)	(0.020)	(0.024)
Past drought shocks	8.201	0.019	0.079***	0.085**	57.308***	0.069***	0.078***	0.130***
	(7.073)	(0.016)	(0.029)	(0.035)	(16.720)	(0.018)	(0.022)	(0.027)
Observations	7,084	7,084	7,084	7,084	9,380	9,380	9,380	9,380
Municipalities	506	506	506	506	670	670	670	670
Eventually treated	146	146	146	146	243	243	243	243
Mean Y	77.192	0.338	3.064	-0.000	116.305	0.353	3.415	-0.000
$R^2(within)$	0.052	0.087	0.133	0.135	0.110	0.122	0.160	0.165

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 16: TWFE - CLR impact on deforestation (sample with 1% as coffee producer threshold) - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	43.013***	0.101***	0.270***	0.335***
	(14.223)	(0.026)	(0.049)	(0.056)
Ihs(Nighttime lights)	32.984**	0.058**	0.103**	0.137***
	(13.747)	(0.023)	(0.040)	(0.046)
Agri. subventions	0.191	-0.001	0.021	0.044*
	(1.780)	(0.005)	(0.019)	(0.024)
Past drought shocks	49.764***	0.067***	0.078***	0.124***
	(13.392)	(0.016)	(0.021)	(0.025)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Eventually treated	268	268	268	268
Mean Y	108.570	0.354	3.419	-0.000
$R^2(within)$	0.104	0.128	0.166	0.173

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 17: TWFE - CLR impact on deforestation with $CLR_t = 1$ if production z-score < -1.5 in t and $t+1$ - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy ($< -1.5 zscore$ in t and $t+1$)	26.179	0.119***	0.339***	0.396***
	(16.702)	(0.034)	(0.060)	(0.072)
Ihs(Nighttime lights)	33.433**	0.057**	0.102**	0.136***
	(13.784)	(0.023)	(0.040)	(0.047)
Agri. subventions	0.691	-0.001	0.023	0.046*
	(1.843)	(0.005)	(0.019)	(0.024)
Past drought shocks	50.452***	0.068***	0.081***	0.129***
	(13.477)	(0.016)	(0.021)	(0.026)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Eventually treated	178	178	178	178
Mean Y	108.570	0.354	3.419	-0.000
$R^2(within)$	0.102	0.128	0.166	0.173

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 18: TWFE - CLR impact on deforestation with $CLR = 1$ if production z-score < -0.5 in t and $t+1$ - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	26.737**	0.090***	0.266***	0.314***
	(13.065)	(0.024)	(0.048)	(0.054)
Ihs(Nighttime lights)	33.007**	0.057**	0.100**	0.133***
	(13.858)	(0.023)	(0.040)	(0.047)
Agri. subventions	0.229	-0.002	0.019	0.042*
	(1.814)	(0.005)	(0.019)	(0.024)
Past drought shocks	50.055***	0.067***	0.078***	0.124***
	(13.480)	(0.016)	(0.021)	(0.025)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Eventually treated	285	285	285	285
Mean Y	108.570	0.354	3.419	-0.000
$R^2(within)$	0.103	0.127	0.166	0.173

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 19: TWFE - CLR impact on deforestation with varying conditions on initial forest cover in the definition of deforested pixels - Period: 2005-2018

	Pixel 10%		Pixel 30%		Pixel 50%		Pixel 70%		Pixel 90%	
	(1) Level (ha)	(2) IHS def.	(3) Level (ha)	(4) IHS def.	(5) Level (ha)	(6) IHS def.	(7) Level (ha)	(8) IHS def.	(9) Level (ha)	(10) IHS def.
CLR dummy	36.892**	0.272***	37.014**	0.280***	35.516**	0.272***	33.033**	0.256***	22.532***	0.125**
	(15.150)	(0.050)	(14.887)	(0.051)	(14.477)	(0.051)	(13.410)	(0.052)	(8.389)	(0.051)
Ihs(Nighttime lights)	33.887**	0.100**	32.775**	0.101**	31.523**	0.093**	26.348**	0.074*	3.098	-0.007
	(13.976)	(0.041)	(13.806)	(0.040)	(13.402)	(0.040)	(12.142)	(0.040)	(8.218)	(0.043)
Agri. subventions	0.114	0.021	0.184	0.020	-0.045	0.018	-0.386	0.015	-1.586	-0.006
	(1.826)	(0.019)	(1.806)	(0.019)	(1.716)	(0.020)	(1.550)	(0.020)	(1.439)	(0.024)
Past drought shocks	51.874***	0.086***	49.992***	0.078***	48.222***	0.069***	43.200***	0.056***	18.800***	0.066***
	(13.668)	(0.021)	(13.434)	(0.021)	(13.122)	(0.021)	(12.197)	(0.021)	(7.049)	(0.023)
Observations	10,892	10,892	10,892	10,892	10,892	10,892	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778	778	778	778	778	778	778
Mean Y	111.774	3.457	108.570	3.419	101.507	3.307	86.025	3.074	55.136	2.503
$R^2(within)$	0.107	0.174	0.104	0.166	0.102	0.159	0.100	0.150	0.065	0.118

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015). Column headings indicate the type of pixels that are retained to compute deforestation. In columns (1) and (2), only pixels with at least 10% of forest cover in 2000 are retained to compute municipality level deforestation variables. In columns (3) and (4), only pixels with at least 20% of forest cover in 2000 are retained, and so on.

Table 20: TWFE - CLR impact on deforestation with alternative municipality-level forest cover thresholds to define treated and control samples - Period: 2005-2018

	Forest cover 10%		Forest cover 20%		Forest cover 30%		Forest cover 40%		Forest cover 50%	
	(1) Level (ha)	(2) IHS def.	(3) Level (ha)	(4) IHS def.	(5) Level (ha)	(6) IHS def.	(7) Level (ha)	(8) IHS def.	(9) Level (ha)	(10) IHS def.
CLR dummy	41.069***	0.361***	39.044***	0.323***	37.014**	0.280***	33.213**	0.240***	26.887	0.196***
	(13.544)	(0.048)	(14.138)	(0.049)	(14.887)	(0.051)	(15.671)	(0.052)	(17.334)	(0.054)
Ihs(Nighttime lights)	24.364**	0.068**	27.826**	0.077**	32.775**	0.101**	40.883***	0.130***	46.189**	0.127***
	(10.124)	(0.032)	(11.658)	(0.036)	(13.806)	(0.040)	(15.731)	(0.044)	(18.531)	(0.048)
Agri. subventions	1.485	0.024	1.396	0.024	0.184	0.020	-2.127	0.027	-9.964	-0.045
	(1.774)	(0.017)	(1.929)	(0.018)	(1.806)	(0.019)	(4.050)	(0.044)	(9.631)	(0.049)
Past drought shocks	42.584***	0.084***	45.756***	0.089***	49.992***	0.078***	56.230***	0.085***	63.222***	0.089***
	(11.482)	(0.020)	(12.229)	(0.021)	(13.434)	(0.021)	(14.853)	(0.022)	(16.409)	(0.023)
Observations	15,176	15,176	12,852	12,852	10,892	10,892	9,324	9,324	7,882	7,882
Municipalities	1,084	1,084	918	918	778	778	666	666	563	563
Eventually treated	243	243	243	243	243	243	243	243	237	237
Mean Y	83.002	2.837	95.822	3.160	108.570	3.419	117.959	3.565	122.105	3.616
$R^2(within)$	0.092	0.128	0.098	0.148	0.104	0.166	0.113	0.194	0.125	0.228

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 21: TWFE - CLR impact on deforestation, controlling for lagged inflation-adjusted PROCAFE amounts per coffee planted hectare - Period: 2005-2017

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	27.728	0.112***	0.279***	0.348***
	(18.633)	(0.028)	(0.052)	(0.060)
Ihs(Nighttime lights)	27.061**	0.048**	0.076*	0.114**
	(13.224)	(0.020)	(0.040)	(0.045)
Agri. subventions	1.026	0.003	0.027	0.052**
	(2.091)	(0.004)	(0.019)	(0.025)
Past drought shocks	47.619***	0.063***	0.094***	0.140***
	(13.808)	(0.018)	(0.023)	(0.027)
Lagged PROCAFE	-2.526	-0.004**	0.001	-0.007
	(1.556)	(0.002)	(0.005)	(0.006)
Observations	10,114	10,114	10,114	10,114
Municipalities	778	778	778	778
Mean Y	104.394	0.338	3.375	-0.060
$R^2(within)$	0.093	0.118	0.135	0.141

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 22: TWFE - CLR impact on deforestation by production loss - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLRxPL	0.512**	0.002***	0.005***	0.006***
	(0.255)	(0.000)	(0.001)	(0.001)
Ihs(Nighttime lights)	33.248**	0.058**	0.103**	0.136***
	(13.834)	(0.023)	(0.041)	(0.047)
Agri. subventions	0.340	-0.001	0.020	0.043*
	(1.836)	(0.005)	(0.019)	(0.024)
Past drought shocks	49.863***	0.067***	0.076***	0.122***
	(13.510)	(0.016)	(0.021)	(0.026)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Mean Y	108.570	0.354	3.419	-0.000
Median PL	50.726	50.726	50.726	50.726
$R^2(within)$	0.103	0.127	0.165	0.173

† $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 23: TWFE - CLR impact on deforestation (weighted by municipality area) - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	-37.352	0.125**	0.206**	0.301**
	(162.126)	(0.051)	(0.080)	(0.126)
Ihs(Nighttime lights)	172.148	0.021	0.079	0.124
	(134.732)	(0.038)	(0.063)	(0.093)
Agri. subventions	43.709	0.017	0.046*	0.075*
	(43.064)	(0.015)	(0.027)	(0.041)
Past drought shocks	191.725***	0.081***	0.058**	0.127***
	(68.331)	(0.023)	(0.026)	(0.039)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778
Mean Y	610.202	0.505	5.402	0.000
$R^2(within)$	0.279	0.221	0.250	0.258

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. Observations are weighted by municipality area (ha). All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Appendix C: Sensitivity analysis

We here apply the method developed by Rambachan and Roth (2022) to assess the sensitivity of the significance of our results to violations of the parallel trend assumption. We use results by Zaveri et al. (2020) to interpret our graphs. They find that in developing countries one additional year with dry anomalies within the past 10 years decreases forested areas by 0.1%. If we focus on the effect of CLR one year after the shock for the inverse hyperbolic sine transformation of raw deforestation (Figure 17), the confidence interval increases with the value of M and includes zero for a value of M above 0.03. This means that our estimated coefficient remains significantly positive as long as the slope of the differential trend between CLR-affected and control municipalities does not change from one period to the other by more than the equivalent of one third of the impact of a drought over the past ten years. Note that this equivalent in terms of drought shocks is used only as a reference point to assess the magnitude of the violation of the parallel trends that is allowed for our results to remain significant. We control in all specifications by past drought shocks so that those shocks are unlikely to generate different post-treatment trends. Moreover, estimates by (Zaveri et al., 2020) are obtained over all developing countries and thus, are not context specific.

Table 24: TWFE - CLR impact on deforestation - State by state - Period: 2005-2018

	Chiapas				Oaxaca				Veracruz			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) Normalised	(5) Level (ha)	(6) Def. part (%)	(7) IHS def.	(8) Normalised	(9) Level (ha)	(10) Def. part (%)	(11) IHS def.	(12) Normalised
CLR dummy	168.484**	0.265**	0.207*	0.170	42.650***	0.132***	0.472***	0.591***	7.445	-0.003	0.069	0.130
	(73.083)	(0.103)	(0.108)	(0.127)	(12.036)	(0.041)	(0.081)	(0.089)	(7.644)	(0.042)	(0.121)	(0.149)
Ihs(Nighttime lights)	136.239	-0.048	-0.223***	-0.197	16.553***	0.078***	0.152***	0.189***	-12.465	-0.050	-0.048	0.020
	(114.066)	(0.086)	(0.083)	(0.127)	(4.439)	(0.028)	(0.052)	(0.058)	(19.149)	(0.047)	(0.070)	(0.104)
Agri. subventions	4.279	0.132**	0.404***	0.513***	-2.834	-0.008	0.004	0.021	29.012	0.060	0.247**	0.313**
	(46.136)	(0.061)	(0.117)	(0.161)	(1.936)	(0.008)	(0.024)	(0.030)	(25.232)	(0.053)	(0.096)	(0.129)
Past drought shocks	165.248***	0.207***	0.099***	0.213***	12.017	0.032	0.112***	0.135***	-3.316	-0.024	-0.044	-0.097*
	(37.204)	(0.037)	(0.037)	(0.040)	(8.646)	(0.020)	(0.037)	(0.040)	(10.172)	(0.023)	(0.036)	(0.056)
Observations	1,442	1,442	1,442	1,442	4,732	4,732	4,732	4,732	2,352	2,352	2,352	2,352
Municipalities	103	103	103	103	338	338	338	338	168	168	168	168
Eventually treated	47	47	47	47	101	101	101	101	45	45	45	45
Mean Y	332.133	0.568	5.058	-0.000	56.112	0.272	2.782	-0.000	119.602	0.473	3.633	-0.000
$R^2(within)$	0.184	0.281	0.175	0.232	0.084	0.105	0.130	0.135	0.040	0.069	0.164	0.152

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 25: TWFE - CLR impact on deforestation (with Conley SEs) - Period: 2005-2018

	Deforestation			
	(1) Level (ha)	(2) Def. part (%)	(3) IHS def.	(4) ZS Def.
CLR dummy	37.014***	0.103***	0.280***	0.352***
	(11.888)	(0.031)	(0.066)	(0.104)
Ihs(Nighttime lights)	32.775**	0.057**	0.101*	0.133**
	(12.895)	(0.027)	(0.052)	(0.057)
Agri. subventions	0.184	-0.001	0.020	0.043**
	(1.625)	(0.006)	(0.014)	(0.017)
Past drought shocks	49.992***	0.067***	0.078***	0.125***
	(16.819)	(0.021)	(0.022)	(0.029)
Observations	10,892	10,892	10,892	10,892
Municipalities	778	778	778	778

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered using Conley (1999) error with spatial correlation kernal cutoff of 200 km and serial correlation kernal cutoff of 5 periods. We use *reg2hdfespatial* package (Fetzer, 2014) based on *ols_spatial_HAC* (Hsiang, 2010) command. All regressions include municipality, year, and, state-year fixed effects. Units of observation are municipality-years from 2005 to 2018.
Data sources: Deforestation data come from GFC (Hansen et al., 2013), agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015).

Table 26: PROCAFE distributed in 2014 and 2015 impact on treatment probabiltiy post-2015 (Sample: Coffee producing municipalities without those treated pre-2016)

	DV: Treatment probability post-2015	
	(1) Ihs(PROCAFE)	(2) Median dummy
PROCAFE per ha distributed in 2014 & 2015	-0.080	-0.106
	(0.060)	(0.079)
Ihs(NTL)	-0.194	-0.189
	(0.133)	(0.133)
Agri. subventions	0.179	0.172
	(0.152)	(0.152)
Past drought shocks	0.012	0.014
	(0.021)	(0.021)
Observations	171	171
Treated units	63	63
Mean Y	0.368	0.368
R^2	0.013	0.014

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses are clustered by municipality. All regressions include state fixed effects. Units of observation are municipalities. We present adjusted within R^2.
Data sources: PROCAFE data come from SAGARPA (Secretariat of Agriculture and Rural Development). Agricultural data from SIAP/SAGARPA, nighttime light data from Li et al. (2020), rainfall data from CHIRPS (Funk et al., 2015). Dependent variable is a binary variable equals to 1 if municipality is treated after 2015.

Table 27: Mean and median production (in tons) for treated municipalities by treatment timing groups and for pre-treatment period

	Obs. number	Mean prod. (2005-2011)	Median prod. (2005-2011)	Mean prod. (t,t+1)	Median prod. (t,t+1)	Mean z-score prod. (t,t+1)	Median z-score prod. (t,t+1)
Treated since 2012	48	4952.09	2542.05	2731.12	1223.93	-1.36	-1.31
Treated since 2013	43	5619.37	1840.45	3007.05	1149.50	-1.42	-1.38
Treated since 2014	36	6673.36	2500.00	3893.35	1175.00	-1.52	-1.49
Treated since 2015	53	2230.11	840.00	959.87	368.48	-1.72	-1.75
Treated since 2016	44	3531.52	1747.22	1803.66	1006.16	-1.63	-1.60
Treated since 2017	15	6606.38	2278.00	4453.11	794.94	-1.63	-1.40
Treated since 2018	4	6986.03	7753.09	5389.50	5876.08	-2.11	-2.02

Notes: The table lists the mean and median coffee production and ZS production by the treatment timing groups.

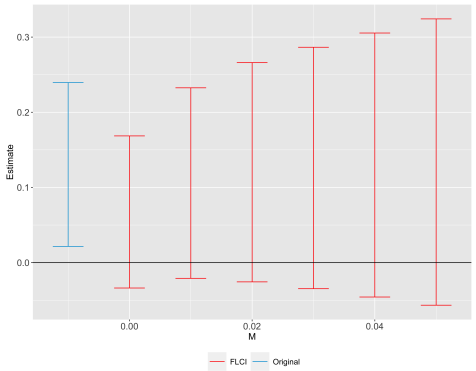


Figure 16: IHS def. - T0

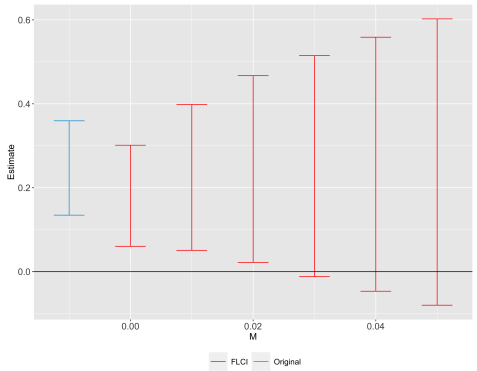


Figure 17: IHS def. - T1

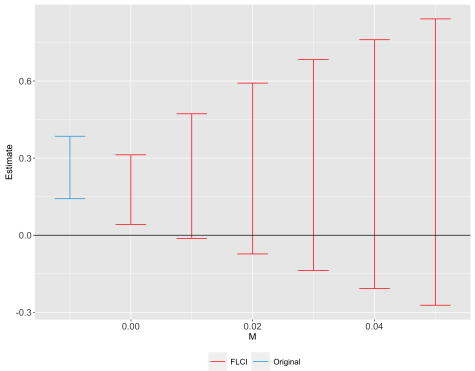


Figure 18: IHS def. - T2

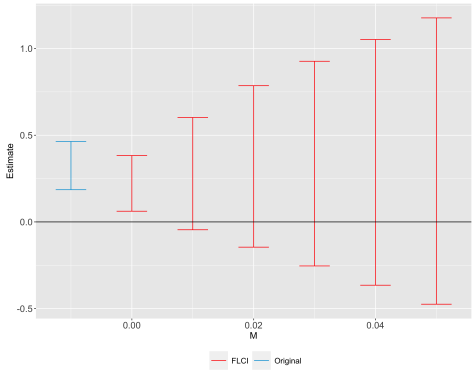


Figure 19: IHS def. - T3

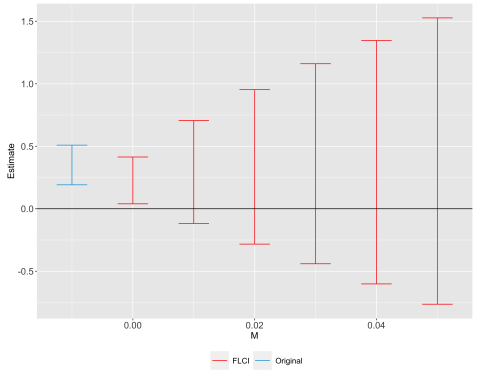


Figure 20: IHS def. - T4

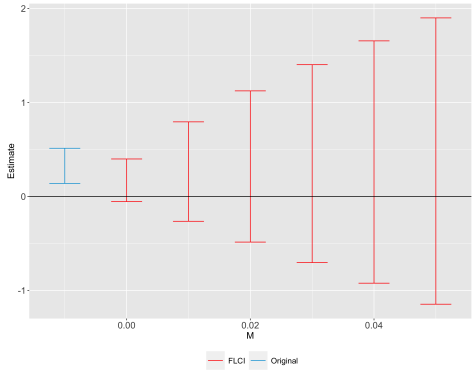


Figure 21: IHS def. - T5

Note: Point estimates and confidence intervals from baseline dynamic TWFE estimation are represented in blue. Confidence intervals robust to deviation in parallel trend are reported in red. Results are presented for the first 6 post-treatment years.

Sensitivity analysis - Baseline dynamic TWFE estimates for normalised deforestation

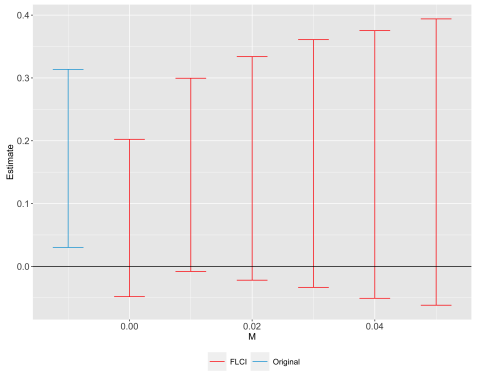


Figure 22: Normalised def. - T0

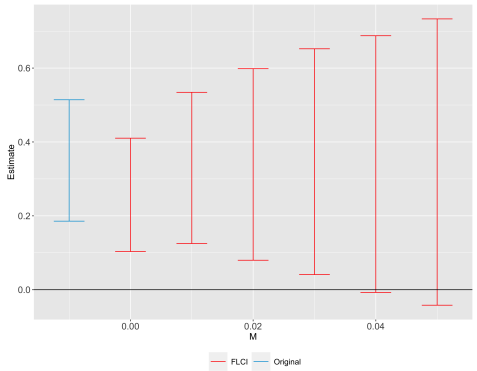


Figure 23: Normalised def. - T1

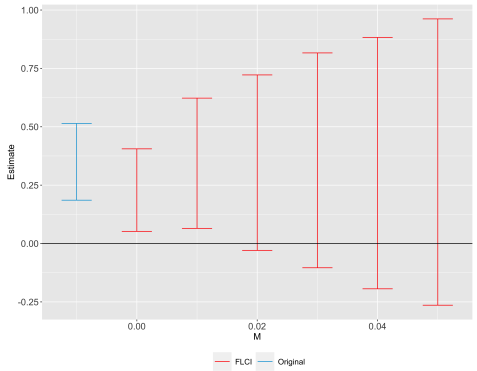


Figure 24: Normalised def. - T2

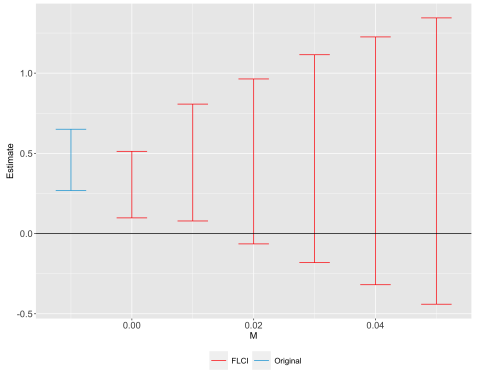


Figure 25: Normalised def. - T3

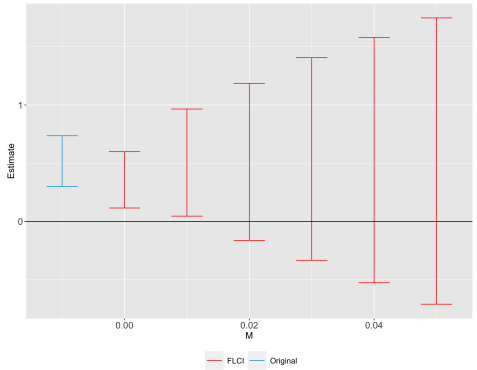


Figure 26: Normalised def. - T4

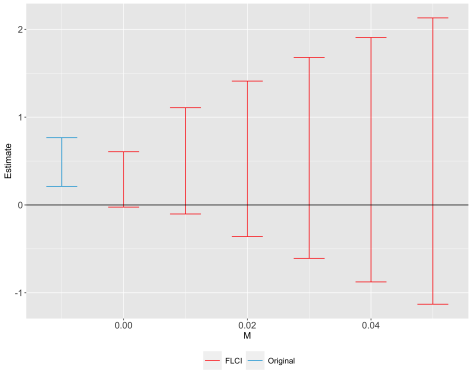


Figure 27: Normalised def. - T5

Note: Point estimates and confidence intervals from baseline dynamic TWFE estimation are represented in blue. Confidence intervals robust to deviation in parallel trend are reported in red. Results are presented for the first 6 post-treatment years.