Reappraisal of Tellez (2022) - Land Opportunism and Displacement in Civil Wars

46673

Mon/19/May

1 Introduction

The displacement of people from their homes is an ever-present consequence of war, as demonstrated by the tragic ongoing conflicts in Palestine, Sudan, and Ukraine: which have led to the forced displacement of many families over the course of the conflict. The resulting humanitarian crises warrant a focus on identifying the drivers of conflict-led displacement, where identifying the causal mechanism that gives rise to displacement may shed light on how these humanitarian crises are likely to unfold. Tellez (2022) proposes to study the effect of opportunism as an underlying motivation for civilian displacement during a conflict, leveraging the introduction of palm plantations during the Colombian civil war as an indication of the potential for opportunistic displacement. They argue that the expansion of the African palm oil industry in the 1990s led to an increase in the demand for land, resulting in the opportunistic acquisition of land via the forced displacement of civilians with the help of armed militant groups. To this end, they implement a difference-in-difference design at the municipal- year level utilising a panel dataset that includes an indicator variable for the presence of palm oil plantations and the displacement rate in a given municipality during a given year.

They conclude that the years in which municipalities begin and continue the expansion of local palm oil industries record higher rates of civilian displacement compared to before they adopted the industry. They go on to model and conclude that this increased displacement is more pronounced in years where palm-oil production is higher, and when a municipality has a historical record of paramilitary presence. In addition, they show that this relationship does not exist in municipalities with historical left-wing guerrilla presence, observing that opportunistic displacement is therefore reliant on the elite- capture of the state, and not on violence alone.

While the author uses both municipal-level data and a household-level survey to substantiate their claims, the difference-in-difference study is of particular interest here as it requires a number of underlying assumptions to be true for its causal conclusions to hold water. I subject the author's research design to a battery of tests to investigate the validity of the conclusions they make, first reproducing select yet important parts of their analysis, and then providing evidence that the research design and analysis conducted by Tellez does not satisfy the necessary conditions to draw a clear causal relationship between palm oil production and opportunistic displacement.

2 Research-Design and Background

The author uses a two-way fixed effects model (TWFE) to implement their diff-in- diff design, regressing the inverse-sine-transformed displacement rate per thousand residents on an indicator dummy variable recording the presence of a palm plantation in the municipality. As previously stated, the study is conducted at the municipality-year level. Further, they control for the number of left-wing guerrilla attacks and the presence of coca cultivation in the municipality in a given year, suggesting that guerrilla group behaviour and changes to the drug trade are likely to affect the costs of palm oil production and thereby palm oil adoption within a municipality. These variables may affect displacement confounding the results: where municipalities with a higher guerrilla presence may have higher levels of conflict, resulting in a higher rate of forced displacement: and the presence of the drug trade in a municipality may induce opportunistic displacement due to coca cultivation.

$$dispRate_{it} = \alpha_i + \omega_t + \beta\, palmOil_{it} + \phi\, X_{it} + \epsilon_{it}$$

The adoption of palm oil within a municipality acts as the treatment assignment where the treatment of a municipality is conditioned on coca cultivation, guerrilla presence, and the fixed effects are assumed to be as-if random resulting in a potential displacement rate that is independent of treatment. A further set of assumptions is required for the author's causal mechanism to hold, given that a TWFE model is applied to a dataset with staggered treatment timing. First, there should be no interference between municipalities, where in the case of the current research design, the treatment of any municipality should not spill over to another municipality. This assumption can be violated when palm oil adoption in a municipality causes palm oil adoption in its neighbouring municipalities, resulting in a spillover effect. Second, we require the conditional parallel trends assumption to hold, where the trend of the potential displacement rate for the treated municipalities if they were untreated should remain in parallel with the untreated municipalities' trend, conditional on the other covariates. Third, opportunists within municipalities must not anticipate the adoption of palm oil resulting in an early increase in the displacement rate, termed the no-anticipation assumption. Lastly, we require a homogeneous treatment effect over time.

Once these assumptions are satisfied, the β parameter identifies the TWFE treatment effect estimand, allowing the author to conclude that palm oil adoption results in an increase in the displacement rate driven by opportunism, given that their transfer mechanism is justified. However, can we be sure these assumptions are satisfied? While the author uses a Sun & Abraham and synthetic control study to provide further evidence in favour of their conclusions, a more thorough set of tests are required to validate the causal conclusions made. Additionally, a static TWFE model is most appropriate when there are no staggered treatment timings with heterogeneous treatment effects. Therefore, I propose a Callaway & Sant'Anna model which I implement and compare against the author's model choice to account for the characteristics of the research design.

3 Data

I download the raw municipality dataset from the author's online appendix repository, including any code used to replicate the results in R. The attached muni.rds file is briefly cleaned by reformatting some variables to make future exploratory and replicative analysis more convenient. I use the code provided by the author, making minor changes where necessary to replicate the analysis. Additionally, I access the Marco geoestadístico nacional MGN2005 shapefile datasets available on the Colombian National Administrative Department of Statistics website, providing me with fine-grained geospatial information on the municipalities with identification codes in line with the author's data.

The municipality data includes forced displacement counts provided by the Colombian Victim's Unit, the palm oil indicator variable and palm oil production values collected from the National Federation of Palm Oil Growers of Colombia. Alongside these variables, the author provides indicator functions that measure the historical presence of FARC (paramilitary) and AUC (guerrilla) groups used as controls in the study.

4 Replication of The Original Results

The results of the municipal-level analysis are replicated in Figure 1A, 2 and Table 1 below. As Tellez discusses, Figure 1A suggests that the displacement rate is approximately similar between treated and control municipalities at the beginning of the 1990s. The rate subsequently diverges from the 2000s onward, indicating that the treatment effect may begin to take effect further into treatment. While the author makes an argument based on changes in the displacement rate, they proceed to conduct their diff-in-diff analysis using the inverse-sine displacement rate. The same graph as 1A using the transformed rate is depicted in Figure 1B. First, the rate is distinctly different between both groups from the onset of the study. Second, the divergence in the rate between the two groups is not as pronounced after the transformation. These observations dampen the conclusion that Tellez makes where they state that "... Figure 1 below foreshadows some of the results of the analysis."

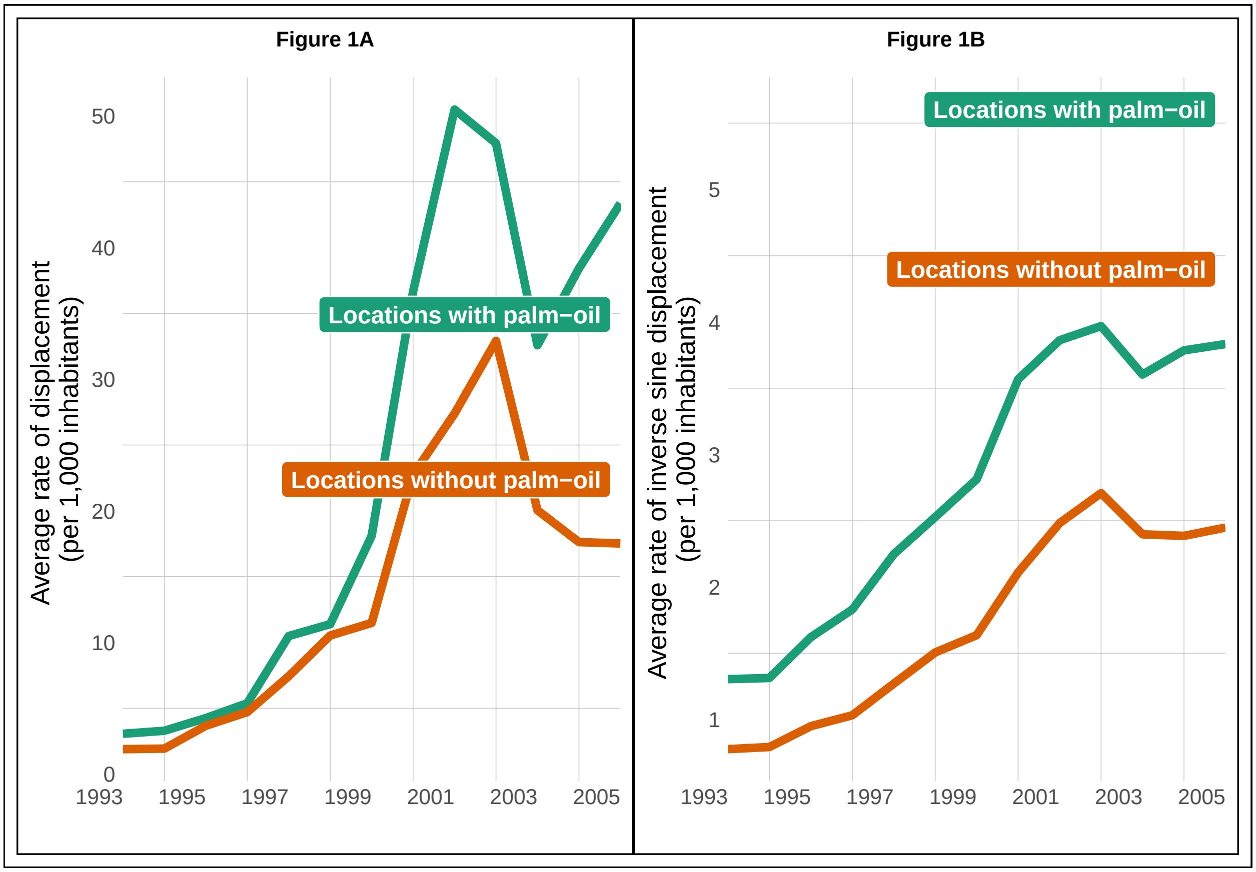

Figure 1: Displacement Rate for treated and control municipalities over time.

The author goes on to construct four models, the results of which are depicted in Table 1 below. The results accurately depict a TWFE generalised diff-in-diff design, modelling the effect of palm oil adoption on the inverse-sine transformed displacement rate. It is important to note that models 1, 2, and 3 only vary in terms of a single coefficient that interacts with the treatment variable of interest with the plantation treatment indicator. Given the model specification and underlying assumptions are accurate, the treatment effect under the study design is positive, indicating that palm-oil adoption results in an increase in the forced displacement rate. Additionally, models 2 and 3 suggest that the increase in the rate are driven both by increased production of palm-oil, and the presence of paramilitary groups. However, in both these models, the treatment effect coefficient flips sign, indicating that the baseline displacement rate reduces with the adoption of a plantation, increasing only after a certain level of palm oil production or para-military presence is reached. Model 4 confirms the author's conclusion that the presence of guerrilla groups is not a significant determinant of displacement. Further, the marginal effect of palm oil production and the presence of paramilitary groups are reproduced in

Figure 2 below.

Table 1: Effect of palm-oil growth on displacement. Models include municipal and year fixed effects and controls for time-varying presence of coca and FARC attacks.

	Dependent variable:			
	Displacement rate (inverse-sine transformation)			
	(1)	(2)	(3)	(4)
Palm-oil plantation	0.382***	−2.056***	−1.213***	0.692
	(0.120)	(0.642)	(0.023)	(0.548)
Plantation X Natl Prod (log)		0.248***		
		(0.063)		
Plantation X AUC presence (dummy)			1.614***	
			(0.120)	
Plantation X FARC presence (dummy)				−0.327
				(0.559)
Observations	14,192	14,192	14,192	14,208
Note:	*p<0.1; **p<0.05; ***p<0.01			

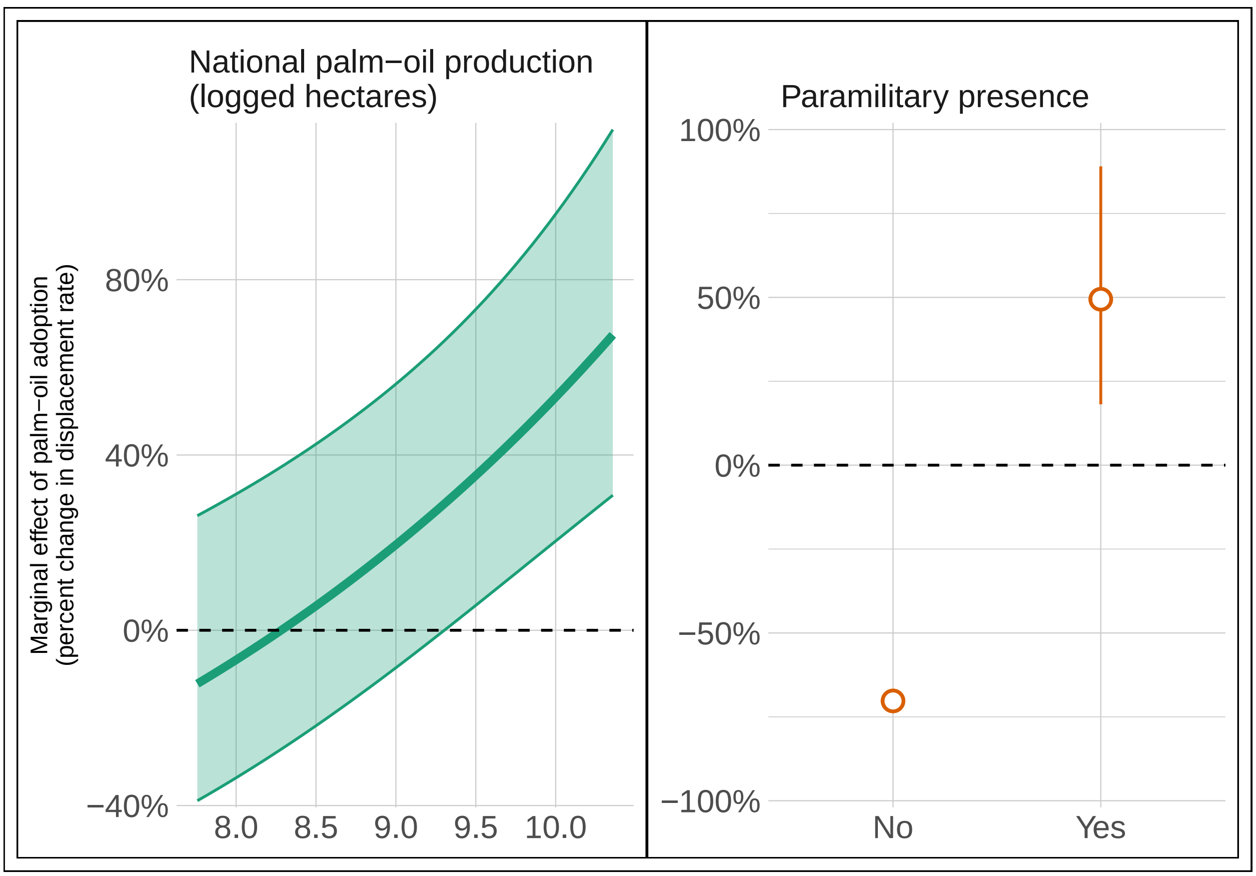

Figure 2: Marginal effect of palm oil production and para-military presence.

5 Alternative Estimation Using Callaway & Sant'Anna

I estimate the group-time ATT according to the Callaway & Sant'Anna study design to account for the staggered treatment timing inherent in the data. I utilise a doubly-robust estimation procedure with 1000 bootstrap samples. The design has the added benefit of loosening the homogeneous treatment effect assumption required by a TWFE design. The group-time ATTs with the same group-time differences are averaged to compute the relative time ATT presented in Figure 3. Further, the simple average and weighted average ATT are presented in Table 2.

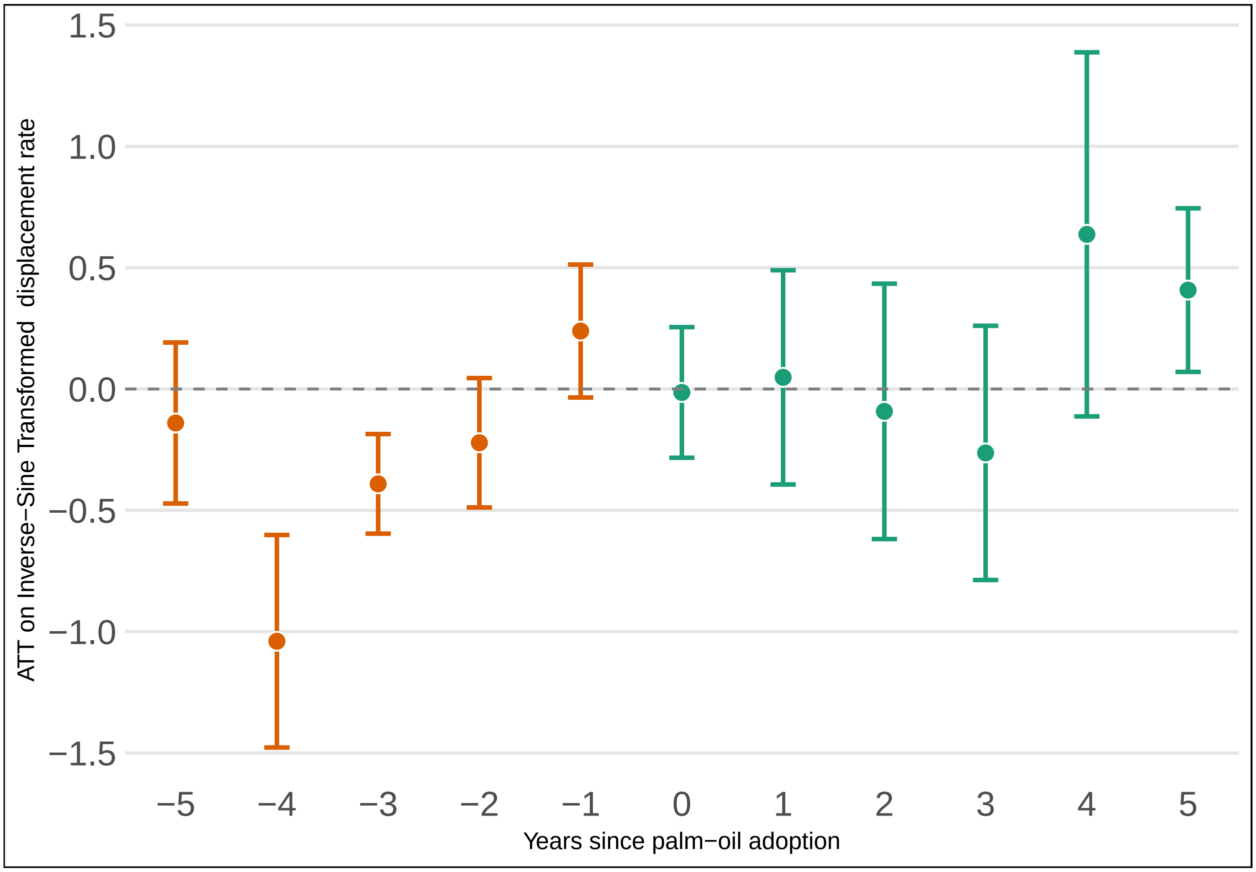

Figure 3: Relative-Time ATT based on the Callaway & Sant'Anna model.

While the β coefficient of the TWFE model presented a significantly positive relationship between palm oil adoption and displacement, both the simple and weighted average ATT under the Callaway & Sant'Anna model indicate that there may be no overall effect, disputing the author's claims. The relative-time ATTs plotted in Figure 2 provide a more interesting picture, hinting at potential assumption violations that will require further tests to confirm. First, the post-treatment ATT remains around 0 for the first three years following treatment before rising to approximately 50% on average in the fourth and fifth post-treatment years. This suggests that the treatment effect may begin to take effect later in treatment, similar to the author's conclusion based on their plots in Figure 1 and appendix Figure A4. Second, the dip in the pre-treatment ATT at the third and fourth years indicates that the inverse-sine displacement rate of soon-to-be treated municipalities defer from the control group municipalities, suggesting a potential violation of the parallel trends assumption. I test for these assumption violations next, as their results may bring the authors' design, and thereby their conclusions, into question.

Table 2: ATT estimates: simple vs. weighted average

Measure	ATT	SE	CI low	CI high
Simple avg (equal-wt across g,t)	-0.0698	0.361	-0.777	0.638
Weighted avg (wt by group size)	0.0519	0.186	-0.313	0.417

6 Diagnostic and Falsification Tests

I leverage four diagnostic and falsification tests to identify any potential violations of the key assumptions made in the two models above. First, the Goodman-Bacon decomposition is used to identify the determinants of the treatment effect estimated by the TWFE model. Once identified, we can reason as to how much of the effect results from comparing treated-vs-untreated municipalities. Second, a parallel trends test on the original TWFE model specification as well as a Sun and Abraham (2020) specification are utilised to provide multiple comparative viewpoints as to whether the parallel trends assumption is likely to be violated. Third, I test the no-interference assumption under SUTVA by testing for possible spillover effects from neighbouring treated municipalities: using geospatial data to identify neighbouring municipalities. Finally, I perform a test for no anticipation, using placebo treatment years in the past to test for any significant anticipatory ATT.

6.1 Goodman-Bacon Decomposition

The Goodman-Bacon decomposition indicates that most of the identifying variation in the TWFE estimate comes from comparing municipalities that receive treatment with municipalities that are never treated, resulting in a positive treatment effect. Further, it implies that the bias from already-treated controls is small. Given that the TWFE estimate is an amalgamation of different 2x2 comparisons, the decomposition results reflect positively on the interpretability of the estimate as a comparison of treated municipalities vs untreated control municipalities.

Table 3: Goodman-Bacon decomposition of the TWFE estimate

Comparison	Weight	Average Estimate
Both Treated	0.00958	0.10943
Later vs Always Treated	0.04427	0.09587
Treated vs Untreated	0.94615	0.43840

6.2 Parallel-Trends Test

The parallel trends assumption is tested using the relative-time ATTs from three different designs. Specifically, the Callaway and Sant'Anna specification in Figure 3 above and a dynamic TWFE, and Sun & Abraham specification, the results of which are depicted in Figure 4 below. Comparing the pre-treatment ATTs reveal a shortcoming in the application of a TWFE model to a study with staggered treatment timing. The dynamic TWFE plot depicts a clear negative pre-treatment effect likely resulting from bias' given comparisons between "to be treated" and treated municipalities: comparisons that are dropped in the other designs resulting in next to no pre-treatment effect. Therefore, the parallel trends assumption is likely to hold given the pre-treatment effects in the Callaway and Sun designs, corroborating Tellez's conclusions. However, I suggest some caution when interpreting these results given the negative pre-treatment effect observed in the Callaway & Sant'Ana specification.

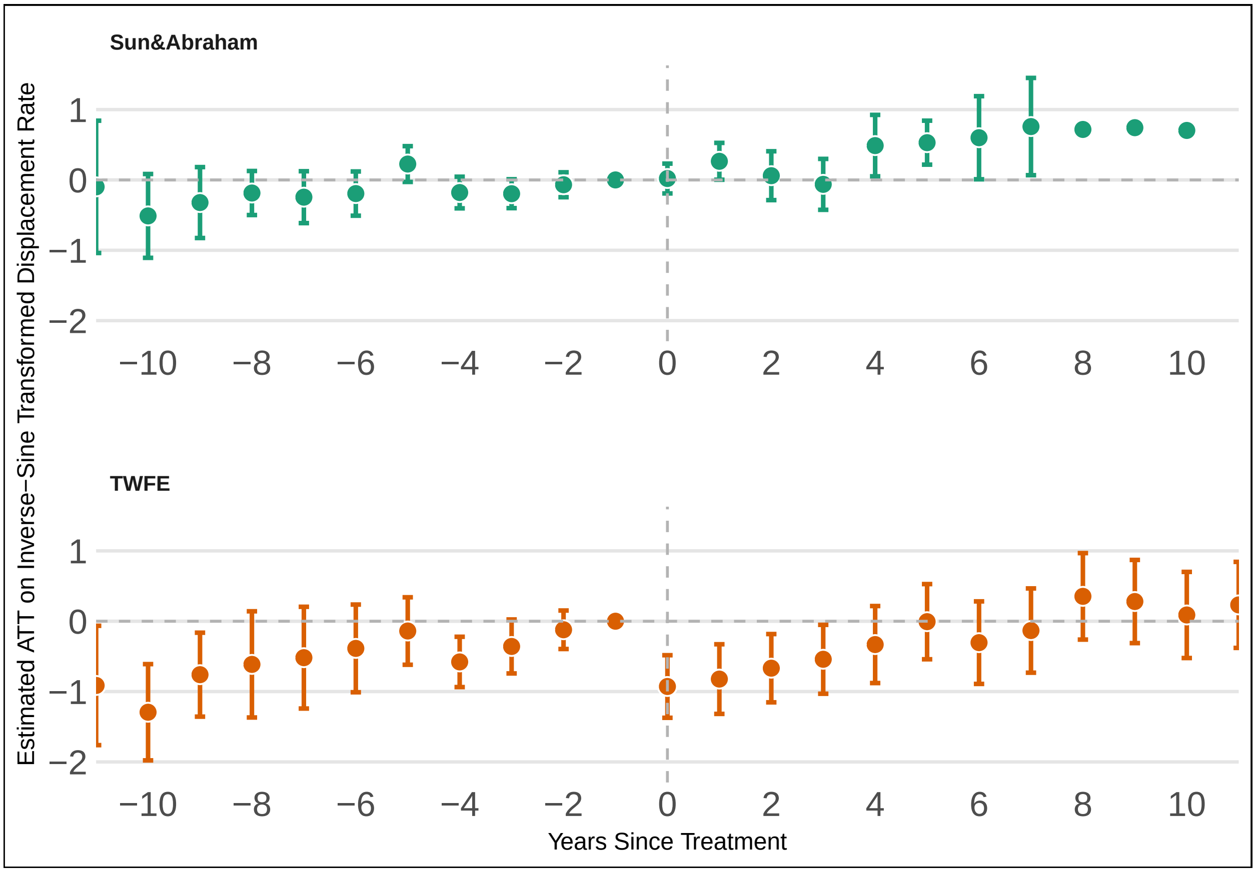

Figure 4: Parallel trends test using a dynamic TWFE design and Sun and Abraham's design

6.3 Spillover (No-Interference) Test

To conduct a spillover hypothesis test, I first use geospatial data obtained from the Colombian National Administrative Department of Statistics to identify neighboring municipalities, by selecting a municipality as a neighbor if the distance between the centroid of two municipalities is less than or equal to 50 km. Once all neighbours are determined, I create a variable that records the proportion of treated neighbors in the previous year for each municipality-year record in the dataset. Given that the "did" package was used to implement the Callaway & Sant'Anna design does not currently implement a method to interact a spillover variable, I interact the spillover variable with each relative-time indicator in a dynamic TWFE model to estimate the spillover coefficients. Finally, a Wald hypothesis test is applied to the joint pre-treatment spillover coefficients to determine if a spillover effect is likely, the results of which are displayed in Table 4 below. A p-value below 0.01 suggests that there is strong evidence to reject the hypothesis that there is no spillover effect. This should lead us to question if the no-interference assumption is likely to be satisfied, in this study design.

Table 4: Wald test for the joint nullity of the pre-treatment spillover coefficients

Hypothesis	Test Statistic	P-value	DF (num.)	DF (den.)
H_0: $\beta_{relative\_time=-10:spillover} = \dots = \beta_{relative\_time=-2:spillover} = 0$	2.789	0.003	9	13012

6.4 No-Anticipation Placebo Test

Finally, I subtract 2 years and 3 years from the treatment year variables, dropping any treatment years that fall below the minimum year of the study to create a placebo treatment indicator. This placebo is used as the treatment variable in two Callaway & Sant'Anna models, the results of which are depicted in Figures 5A and 5B, respectively. The post-treatment ATTs in the 2-year model hover close to or just below zero, which suggests that the no-anticipation assumption is likely to hold. However, the 3-year model identifies a negative ATT across all post-treatment years. While this may suggest a violation of the no-anticipation assumption; it may be a potential artefact of the negative pre-treatment ATT observed in the parallel trends test. Altogether, some caution is advised in the interpretation of all model coefficients, given the anomalous observations in both tests.

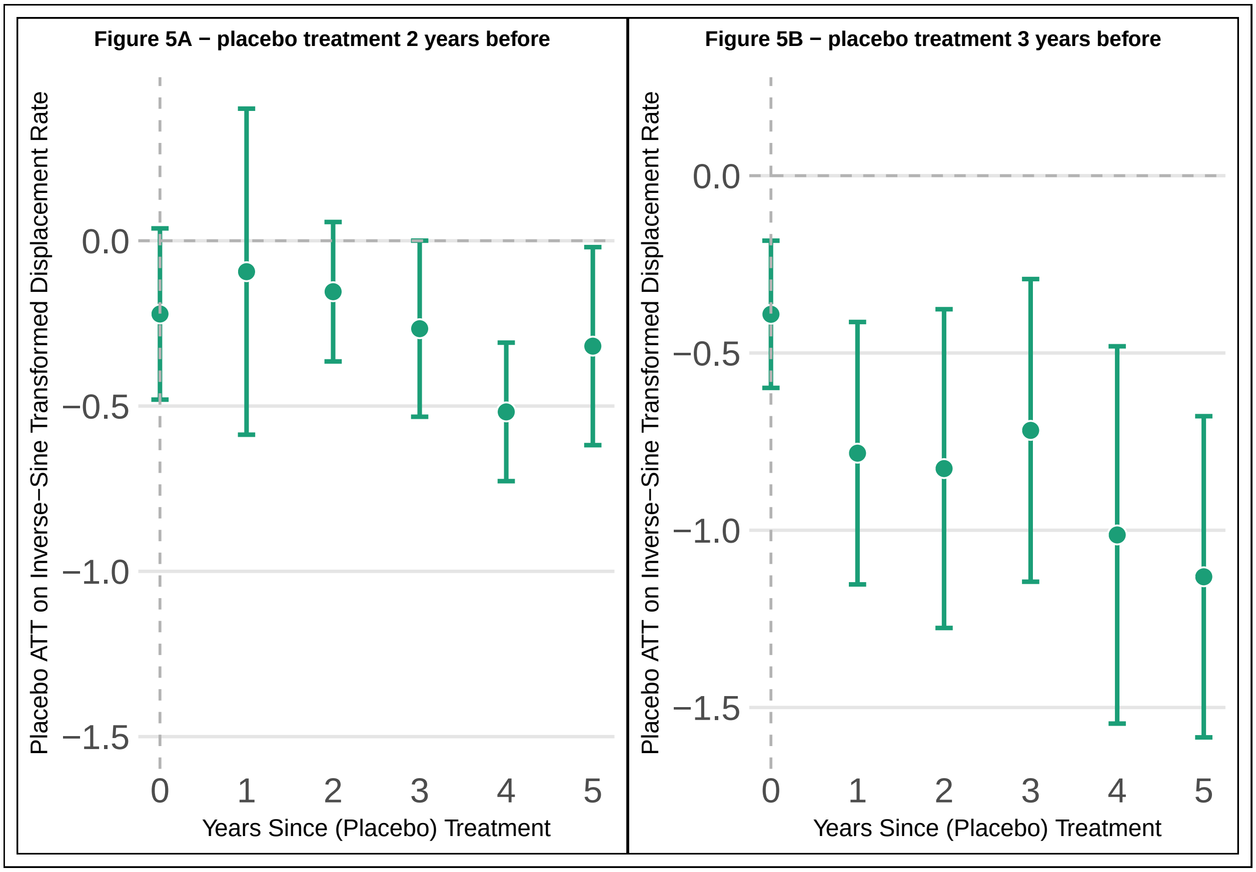

Figure 5: Callaway & Sant'Anna placebo (no-anticipation) test.

7 Conclusion

While a TWFE model does not always result in a convenient interpretation of the ATT due to the different components that make up the estimand given a staggered treatment timing, the Goodman-Bacon decomposition does provide some solace in that the comparison being made is between the treated and the untreated resulting in a believable Average Treatment Effect that is not exposed to any negatively weighted components. However, the ability for the specification to identify this ATT depends on a series of strict assumptions. The tests conducted provide evidence to reject the no-interference assumption and cast some doubt on the validity of the parallel trends and no-anticipation assumption: although the jury is not yet out on this front. Therefore, I suggest some caution when interpreting the author's central claim, that the adoption of palm oil within a municipality results in an increase in forced displacement driven by an opportunistic elite-state interaction.

I provide an alternative model (Callaway & Sant'Anna), alongside the generalised TWFE model and the Sun and Abraham model included in the author's online appendix, that make valid comparisons between treated and untreated municipalities providing further support in favour of the author's claim that the ATT is significant and positive at some post-treatment years. However, it is important that future work include additional controls that may improve the validity of making a conditional parallel trends assumption. Alternatively, the parallel trends assumption may hold when using the raw displacement rate or log displacement rate, given that the parallel trends assumption is sensitive to the functional form of the response variable. Additionally, I suggest purging the spillover effect before model estimation which may result in a more believable group-time ATT in the case of the Callaway & Sant'Anna model. Modern estimation techniques do result in variable point estimates due to an issue of low power. Therefore, I recommend revisiting the study design given the mounting evidence in favour of several violations of the causal assumptions.

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1 Code appendix

```r
# set global options
knitr::opts_chunk$set(
  echo=FALSE,
  warning=FALSE,
  message=FALSE,
  linewidth=60,
  fig.pos = "H",
  fig.align = "center"
  )

# library import:
source(file = "../code/package_manager.R")
update_geom_defaults("text", list(family = "sans"))

# other options:
options(scipen=999)

# run analysis scripts
source(file = "../code/analysis/replication-analysis.R")
source(file = "../code/analysis/callaway-analysis.R")
source(file = "../code/analysis/assumption-tests.R")
f1 <- f1 + labs(title = "Figure 1A")
f2 <- f2 + labs(title = "Figure 1B")

shared_theme <- theme(
  plot.title.position = "plot",
  plot.title          = element_text(size = 8, hjust = 0.5),
  plot.margin         = margin(10, 5, 5, 5)
)

combo <- (f1 + f2) +
  plot_layout(ncol = 2, widths = c(1,1)) &
  shared_theme &
  theme(
    plot.background = element_rect(
      colour = "black",
      size   = 0.5,
      fill   = NA
    ),
    plot.margin = margin(5,5,5,5)
  )

combo
p1 + p2 +
  plot_layout(ncol = 2, widths = c(1,1)) &
  theme(
    plot.background = element_rect(
      colour = "black",
      size   = 0.5,
      fill   = NA
    ),
```

```r
    plot.margin = margin(5,5,5,5)
  )
csa_plot +
  theme(
    plot.background = element_rect(
      colour = "black",
      size   = 0.5,
      fill   = NA
    ),
    plot.margin = margin(5,5,5,5)
  )
df_table <- tibble::tribble(
  ~Measure,                                 ~ATT,     ~SE,    ~`CI low`,  ~`CI high`,
  "Simple avg (equal-wt across g,t)",      -0.0698,  0.361,   -0.777,    0.638,
  "Weighted avg (wt by group size)",       0.0519,  0.186,   -0.313,    0.417
)

df_table %>%
  kable(
    format    = "latex",
    booktabs  = TRUE,
    caption   = "ATT estimates: simple vs. weighted average",
    label     = "tab-att"
  ) %>%
  kable_styling(latex_options = c("hold_position"))
library(knitr)

bacon_table <- data.frame(
  Comparison      = c("Both Treated",
                      "Later vs Always Treated",
                      "Treated vs Untreated"),
  Weight          = c(0.00958, 0.04427, 0.94615),
  Avg_Estimate    = c(0.10943, 0.09587, 0.43840)
)

bacon_table %>%
  kable(
    format    = "latex",
    booktabs  = TRUE,
    caption   = "Goodman-Bacon decomposition of the TWFE estimate",
    col.names = c("Comparison", "Weight", "Average Estimate"),
    digits    = c(NA, 5, 5)
    ) %>%
  kable_styling(latex_options = c("hold_position"))
ptrend_plot +
  theme(
    plot.background = element_rect(
      colour = "black",
      size   = 0.5,
      fill   = NA
    ),
    plot.margin = margin(5,5,5,5)
  )
```

```r
stat  <- wald_res$stat
pval  <- wald_res$p
df1   <- wald_res$df1
df2   <- wald_res$df2

hyp <- "$H_0$: $\\beta_{relative\\_time=-10:spillover} = \\dots$ \\\\ $=
\\beta_{relative\\_time=-2:spillover} = 0$"

test_tbl <- data.frame(
  Hypothesis = hyp,
  `Test Statistic`= stat,
  `P-value` = pval,
  `DF (num.)` = df1,
  `DF (den.)` = df2,
  check.names = FALSE,
  stringsAsFactors = FALSE
)

test_tbl %>% kable(
  format = "latex",
  booktabs = TRUE,
  caption = "Wald test for the joint nullity of the pre-treatment spillover coefficients",
  escape = FALSE,
  digits = c(3)
) %>%
    kable_styling(latex_options = c("hold_position"))
placebo_plot_1  <- placebo_plot_1 +
  labs(title = "Figure 5A - placebo treatment 2 years before")
placebo_plot_2  <- placebo_plot_2 +
  labs(title = "Figure 5B - placebo treatment 3 years before")

shared_theme <- theme(
  plot.title.position = "plot",
  plot.title = element_text(size = 8, hjust = 0.5),
  plot.margin = margin(10, 5, 5, 5)
)

placebo_plot_1 + placebo_plot_2 +
  plot_layout(ncol = 2, widths = c(1,1)) &
  shared_theme &
  theme(
    plot.background = element_rect(
      colour = "black",
      size = 0.5,
      fill = NA
    ),
    plot.margin = margin(5,5,5,5)
  )
```