Online Appendix:
The Effects of a Large-Scale Mental Health Reform: Evidence from Brazil

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A. Additional Figures and Tables

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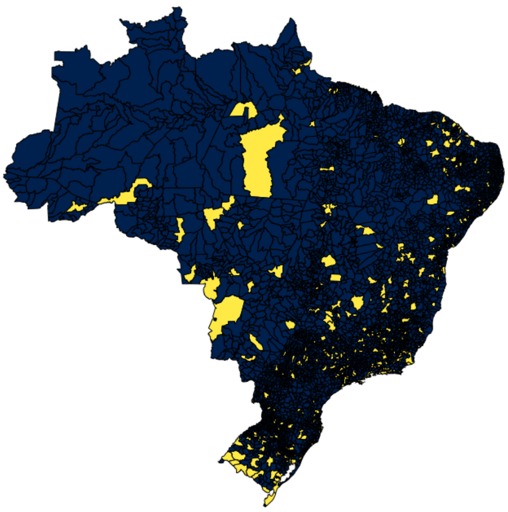
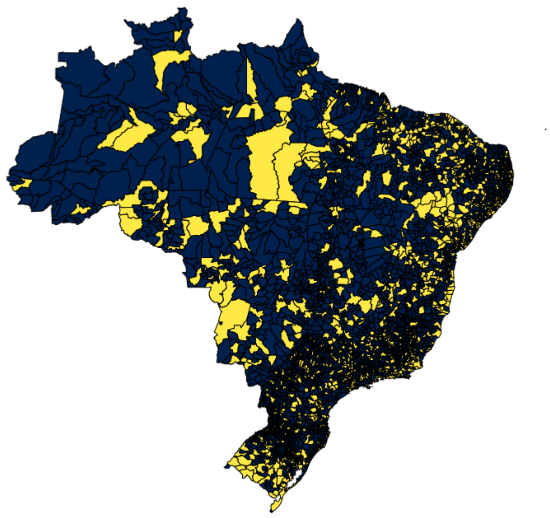
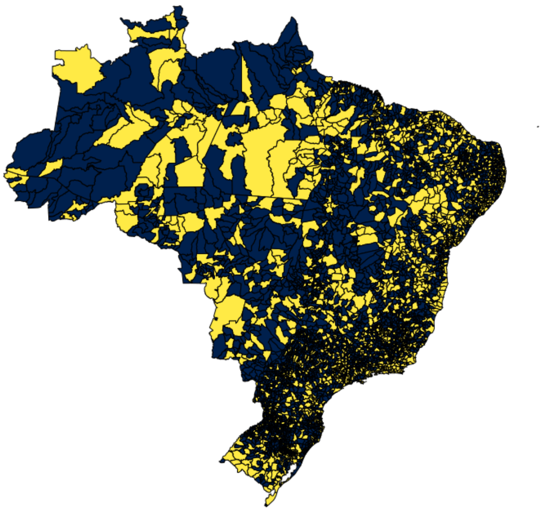


(a) 2003



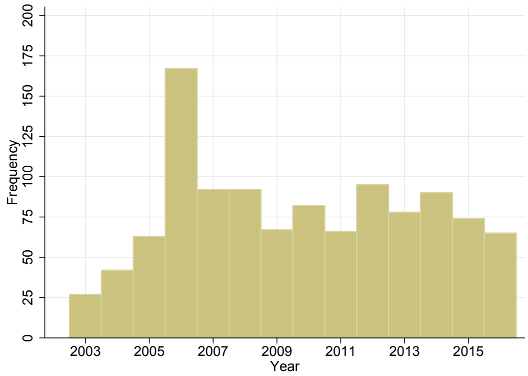
(b) 2010



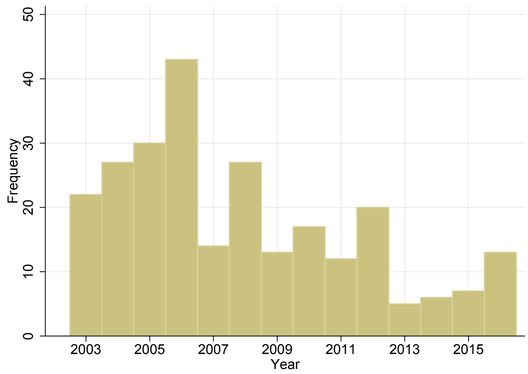
(c) 2016

Figure A1: Spatial allocation of CAPS in 2003, 2010, and 2016

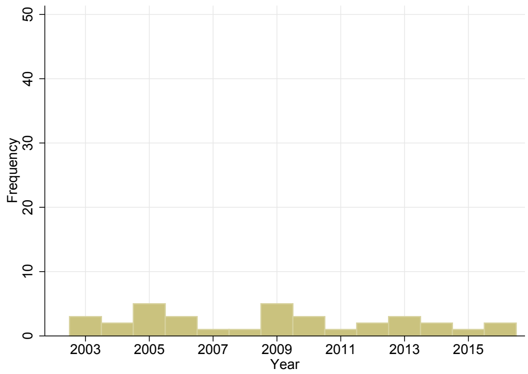
Notes: These maps plot the Brazilian municipalities with (yellow) and without (blue) a CAPS in 2003 (panel A), 2010 (panel B), and 2016 (panel C).



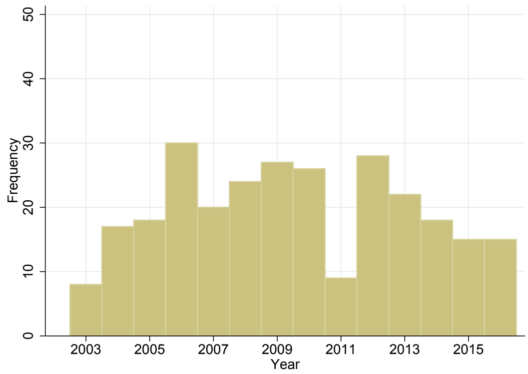
(a) CAPS I



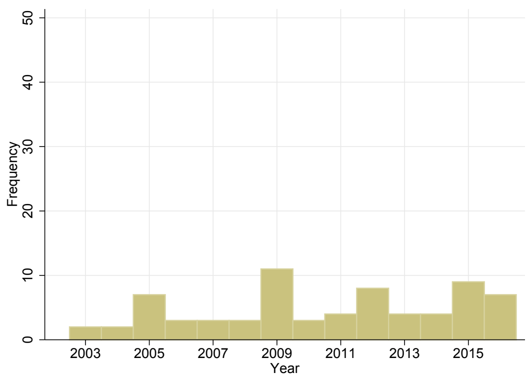
(b) CAPS II



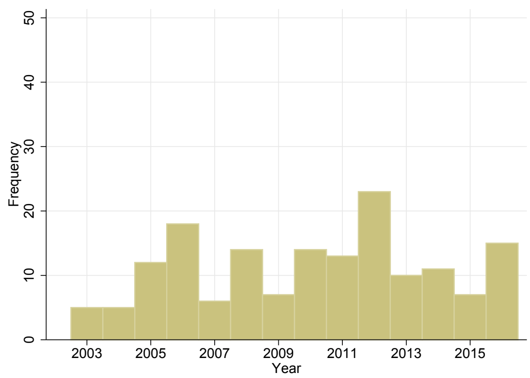
(c) CAPS III



(d) CAPS AD



(e) CAPS AD III



(f) CAPS Inf

Figure A2: Number of municipalities adopting CAPS (by CAPS' types) by year

Notes: These graphs plot the number of municipalities receiving a CAPS for the first time, by CAPS' type, from 2003 to 2016. Due to the discrepancy between the number of municipalities receiving a CAPS I and other types, panel (a) uses a different scale. We omit 2002 as we cannot distinguish municipalities that got a CAPS in 2002 from those that got earlier. This data show the first date of accreditation, or date of CAPS' opening for the vast majority.

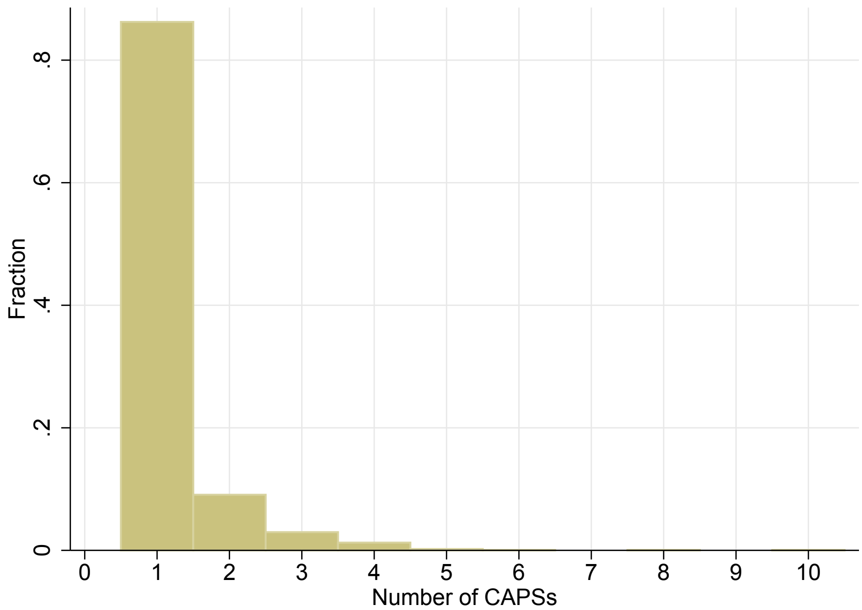
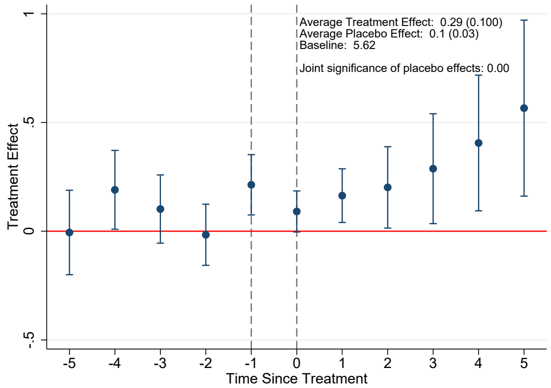
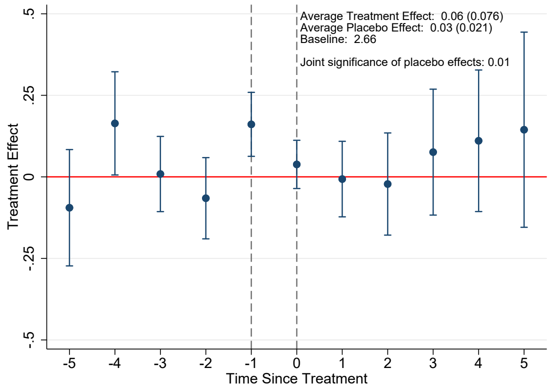


Figure A3: Fraction of treated municipalities by the number of adopted CAPS

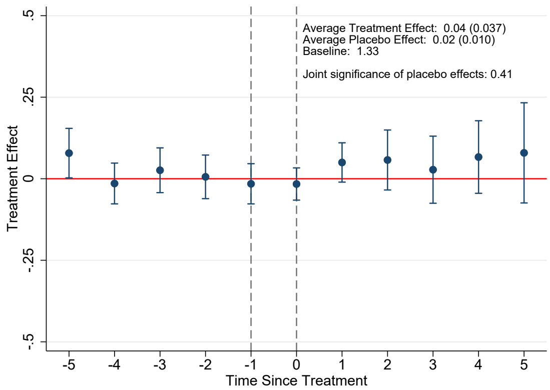
Notes: This graph plots the fraction of municipalities by the number of CAPS opened conditional on having gained a CAPS in 2003 or later.



(a) Overall supply of physicians



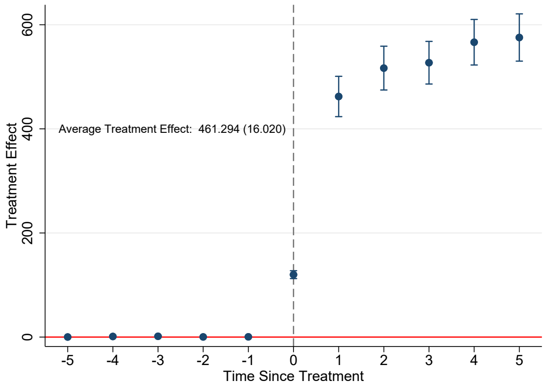
(b) General practitioners



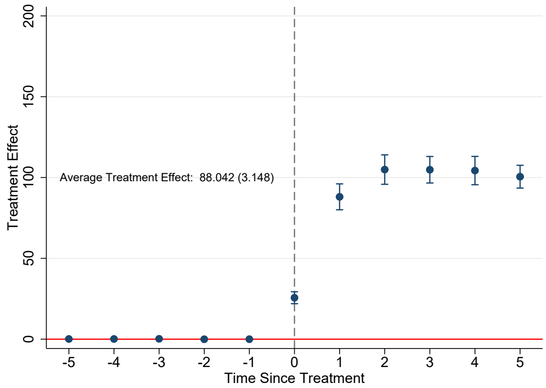
(c) Family doctors

Figure A4: The effects of CAPS on other health care practitioners: number of professionals per 10,000 people

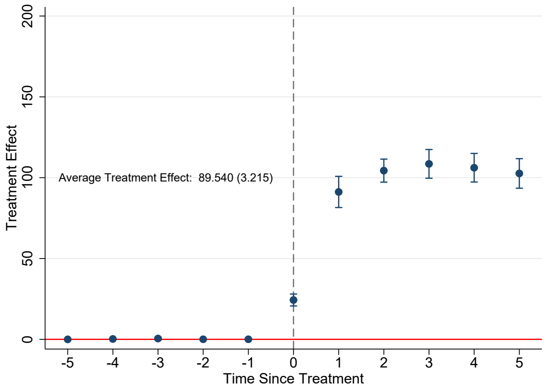
Notes: This figure plots 95% confidence-intervals computed with a municipality-level clustered bootstrap and dynamic and placebo DID estimators for the CAPS' effects on the number of selected types of health practitioners per 10,000 people. Placebo DID estimators estimate the CAPS' effects had the treatment occurred in a placebo, pre-treatment period. They use a varying baseline period –the one immediately before the placebo treatment date– so we do not normalize relative to a unique period. Controls include municipality GDP per capita, PBF spending per capita, a series of indicators for age-by-gender population bins, state×year fixed effects, and linear trends of pre-treatment characteristics. Pre-treatment municipality characteristics included are: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. The Average Treatment Effect computes a simple average of the instantaneous and dynamic effects. In parenthesis, standard errors computed with a municipality-level clustered boot-strap.



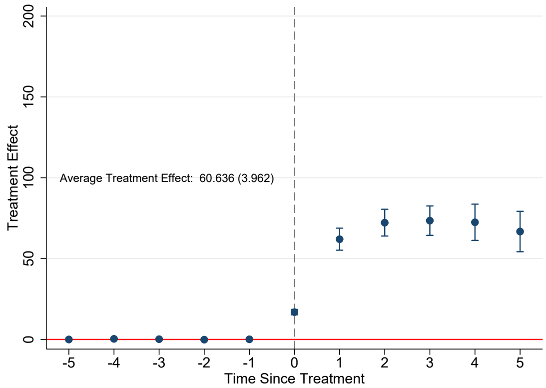
(a) Total Procedures



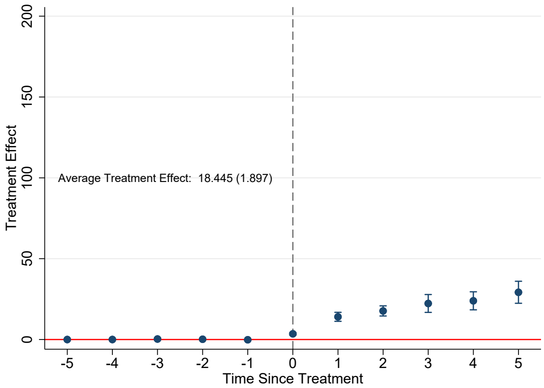
(b) Schizophrenia and Related Disorders



(c) Mood Disorders



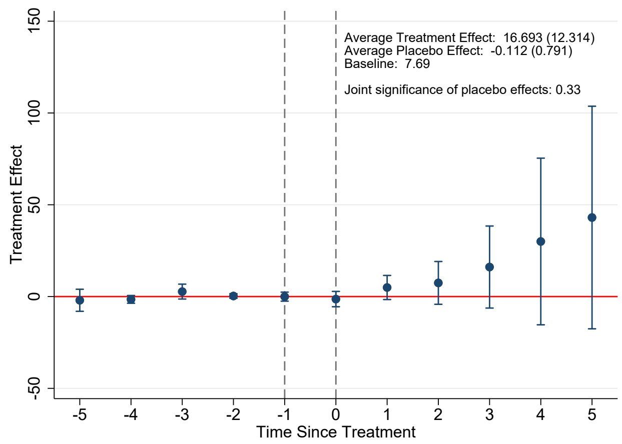
(d) Anxiety and Stress-Related Disorders



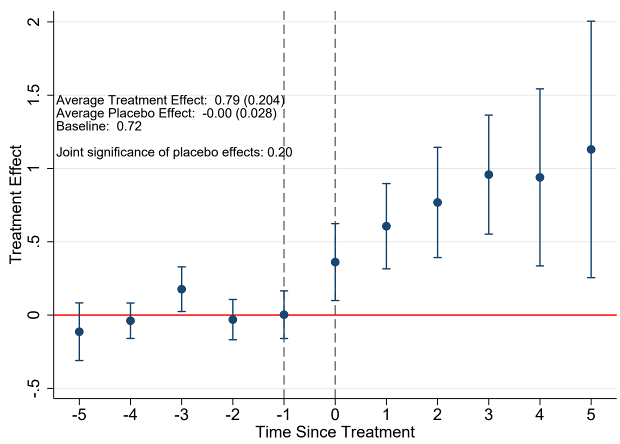
(e) Psychoactive Substance Abuse Disorders

Figure A5: The effects of CAPS on psychosocial care procedures: number of procedures per 10,000 people

Notes: This figure plots 95% confidence-intervals computed with a municipality-level clustered bootstrap and dynamic and placebo DID estimators for the CAPS' effects on the number of psychosocial care procedures per 10,000 people by cause. Placebo DID estimators estimate the CAPS' effects had the treatment occurred in a placebo, pre-treatment period. They use a varying baseline period –the one immediately before the placebo treatment date– so we do not normalize relative to a unique period. Controls include municipality GDP per capita, PBF spending per capita, a series of indicators for age-by-gender population bins, state×year fixed effects, and linear trends of pre-treatment characteristics. Pre-treatment municipality characteristics included are: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. The Average Treatment Effect computes a simple average of the instantaneous and dynamic effects. In parenthesis, standard errors computed with a municipality-level clustered boot-strap.



(a) Dispense of Antipsychotic Medications



(b) Occupational Therapies

Figure A6: Effects of CAPS on mental health outpatient procedures: number of procedures per 10,000 people

Notes: This figure plots 95% confidence-intervals computed with a municipality-level clustered bootstrap and dynamic and placebo DID estimators for the CAPS' effects on the number of number of prescribed antypsychotics and occupational therapies per 10,000 people. Placebo DID estimators estimate the CAPS' effects had the treatment occurred in a placebo, pre-treatment period. They use a varying baseline period –the one immediately before the placebo treatment date– so we do not normalize relative to a unique period. Controls include municipality GDP per capita, PBF spending per capita, a series of indicators for age-by-gender population bins, state×year fixed effects, and linear trends of pre-treatment characteristics. Pre-treatment municipality characteristics included are: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. The Average Treatment Effect computes a weighted average of the dynamic estimators, giving to each estimator a weight proportional to the number of switchers the estimator applies to, considering the specification with state-specific trends and controls. In parenthesis, standard errors computed with a municipality-level clustered boot-strap. Baseline indicates the sample mean values for the treated in the pre-CAPS period.

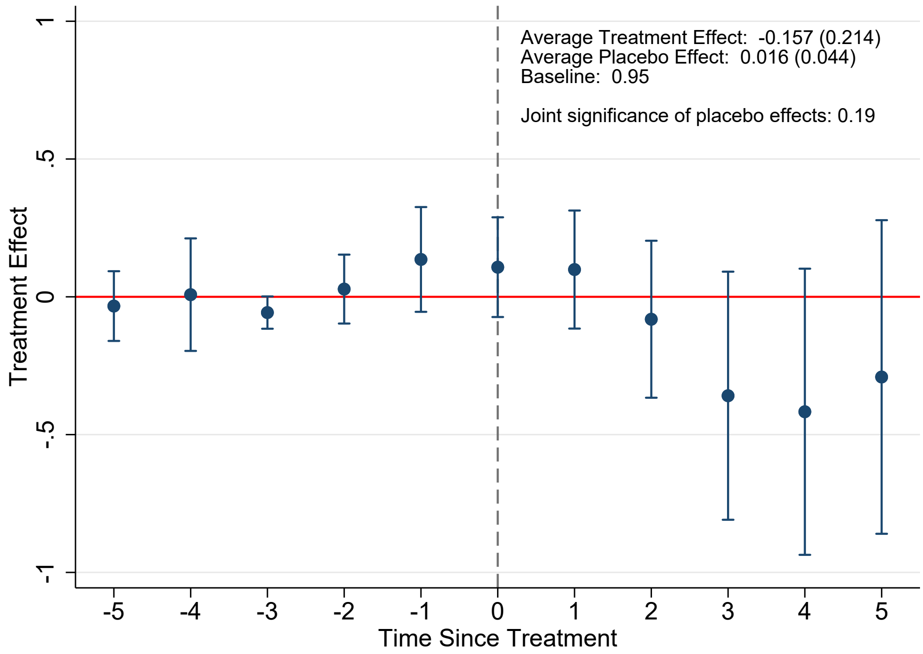


Figure A7: Effects of CAPS on psychiatric beds: number of beds per 10,000 people

Notes: This figure plots 95% confidence-intervals computed with a municipality-level clustered bootstrap and dynamic and placebo DID estimators for the CAPS' effects on the number of psychiatric beds per 10,000 people. Placebo DID estimators estimate the CAPS' effects had the treatment occurred in a placebo, pre-treatment period. They use a varying baseline period –the one immediately before the placebo treatment date– so we do not normalize relative to a unique period. Controls include municipality GDP per capita, PBF spending per capita, a series of indicators for age-by-gender population bins, state×year fixed effects, and linear trends of pre-treatment characteristics. Pre-treatment municipality characteristics included are: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. The Average Treatment Effect computes a weighted average of the dynamic estimators, giving to each estimator a weight proportional to the number of switchers the estimator applies to, considering the specification with state-specific trends and controls. In parenthesis, standard errors computed with a municipality-level clustered boot-strap. Baseline indicates the sample mean values for the treated in the pre-CAPS period.

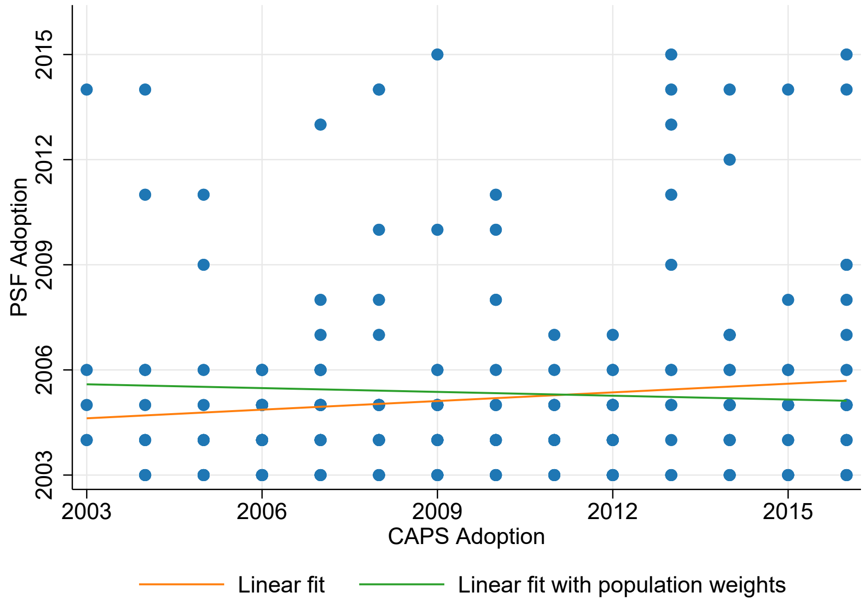
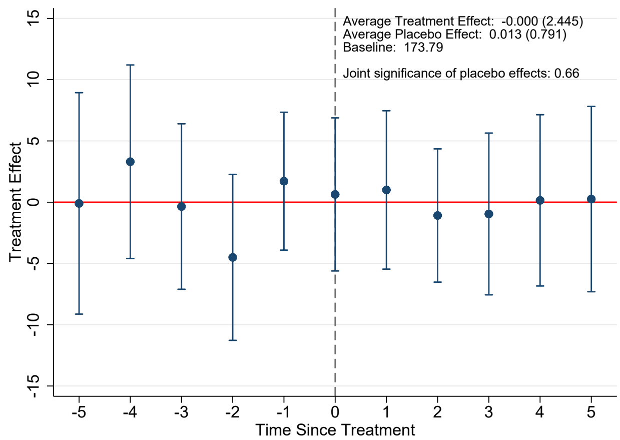
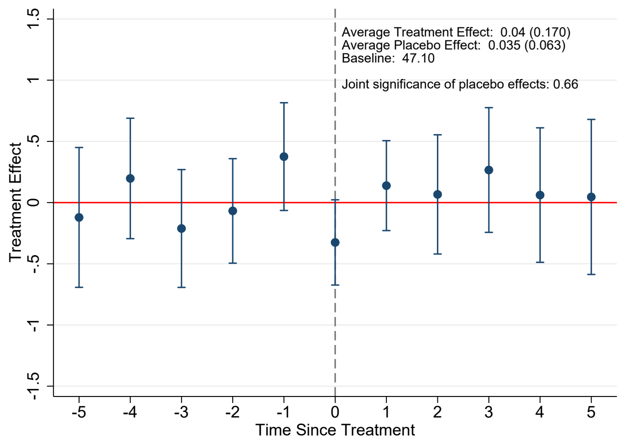


Figure A8: Correlation between Family Health Program (PSF) adoption and CAPS adoption

Notes: This graph plots the year of Family Health Program (PSF) against the year of CAPS adoption for all municipalities in our sample with both programs. The orange and green lines fit the data points linearly. The latter weights observations based on baseline population.



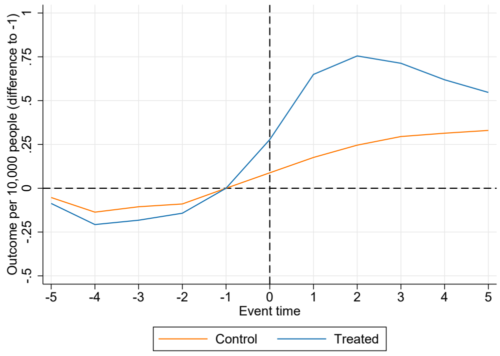
(a) Infant Mortality: deaths per 10,000 live births



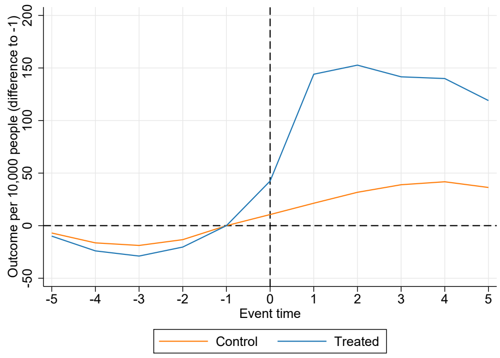
(b) All-cause Mortality: deaths per 10,000 people

Figure A9: Effects of CAPS on additional mortality outcomes

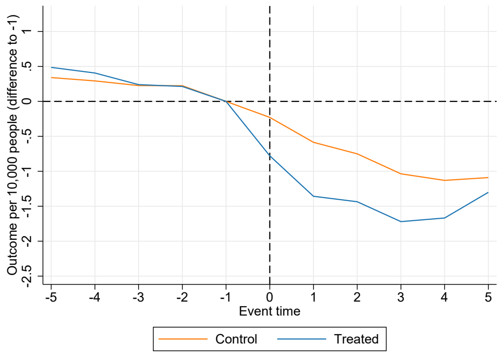
Notes: This figure plots 95% confidence-intervals computed with a municipality-level clustered bootstrap and dynamic and placebo DID estimators for the CAPS' effects on the number of infant deaths ($<$ 1 year old) per 10,000 live births and the overall number of deaths per 10,000 people. Placebo DID estimators estimate the CAPS' effects had the treatment occurred in a placebo, pre-treatment period. They use a varying baseline period –the one immediately before the placebo treatment date– so we do not normalize relative to a unique period. Controls include municipality GDP per capita, PBF spending per capita, a series of indicators for age-by-gender population bins, state$\times$year fixed effects, and linear trends of pre-treatment characteristics. Pre-treatment municipality characteristics included are: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. The Average Treatment Effect computes a weighted average of the dynamic estimators, giving to each estimator a weight proportional to the number of switchers the estimator applies to, considering the specification with state-specific trends and controls. In parenthesis, standard errors computed with a municipality-level clustered boot-strap. Baseline indicates the sample mean values for the treated in the pre-CAPS period.



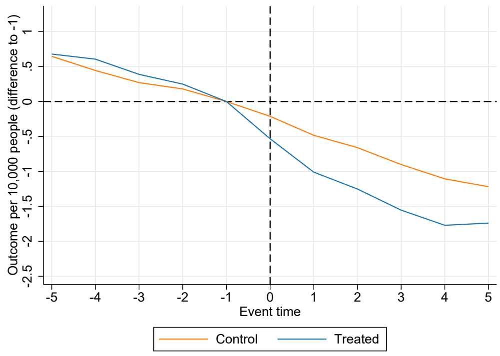
(a) Mental health practitioners: number of professionals per 10,000 people



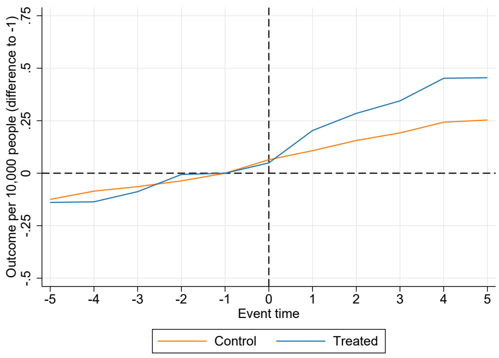
(b) Outpatient mental health care production: number of procedures per 10,000 people



(c) Hospitalizations due to mental and behavioral disorders: admissions per 10,000 people



(d) Hospitalizations due to schizophrenia: admissions per 10,000 people



(e) Homicides: deaths per 10,000 people

Figure A10: Trends of main outcomes for treated and control cities across event times

Notes: These figures aggregate data on our primary outcomes across the event times after we stack data for each treated cohort and its respective control group. We plot residualized (state×year fixed effects) time-series, evaluated relative to the event-time -1. When aggregating data, we follow **?** and use a weighted average based on the size of each treated cohort. We also follow the authors when choosing the control group, which includes the cities that will never be treated and those that will be eventually treated in more distant event-times. Panel (a) plots the rate of psychiatrists, psychologists, occupational therapists, and social worker per 10,000 people. Given the previous results suggesting that the supply of mental health practitioners increases one year before the treatment (Figure **??**), we define –for this outcome, in particular– the event-time 0 as the period immediately before the year CAPS starts functioning. Panel (b) plots the rate of outpatient procedures delivered by a mental health practitioner. Panel (c) plots the rate of hospital admissions due to mental and behavioral disorders (ICD-10, F00-F99). Panel (d) plots the rate of hospital admissions due to schizophrenia and related disorders (F20-F29). Panel (e) plots homicide rates (X85-Y09).

Table A1: Profile of people seeking treatment at CAPS and who report having a mental health illness in the 2019 National Health Survey

	CAPS	National Health Survey
Schizophrenia	28.36%	6.14%
Depression	12.63%	76.04%
Bipolar disorder	6.95%	10.03%
Anxiety and stress-related disorders	7.67%	-
Substance abuse disorders	22.76%	-

Note: This table shows the profile of people seeking treatment at CAPS and the profile of people who report having a mental illness in the 2019 National Health Survey. For the National Health Survey, we do not have anxiety/stress-related disorders (ICD-10 F40–F48) nor substance-abuse disorders (ICD-10 F10–F19) in a way that is comparable to the CAPS data.

Table A2: Descriptive Statistics—baseline year (2002, except where noted)

	All	Treated	Never Treated
Hospitalizations (per 10,000 people)			
Mental and behavioral disorders	14.90	13.90	14.90
Schizophrenia	6.59	6.46	6.55
Mood Disorders	1.70	1.50	1.73
Stress-related disorders	0.10	0.12	0.09
Psychoactive substance abuse	4.79	4.31	4.82
Mental retardation	0.22	0.21	0.20
Dementia	0.19	0.21	0.18
Others	1.29	1.10	1.33
Mortality (per 10,000 people)			
Suicide	0.56	0.45	0.60
Overdose	0.01	0.01	0.01
Alcoholic and chronic liver diseases	1.05	1.08	1.02
Mental and behavioral disorders	0.40	0.39	0.40
Homicide	1.29	1.70	1.06
Outpatient Care (per 10,000 people)			
By psychiatrists (2008)	30.85	45.44	28.47
By psychologists (2008)	77.58	67.05	79.29
By social workers (2008)	29.04	23.38	29.96
By occupational therapists (2008)	19.86	18.78	20.03
Antipsychotic drugs	0.77	0.55	0.16
Mental Health Facilities (per 10,000 people)			
Psychiatrists (2006)	0.21	0.30	0.14
Psychologists (2006)	0.86	0.65	0.89
Social workers (2006)	0.59	0.47	0.60
Occupational therapists (2006)	0.11	0.14	0.07

To be continued

Table A2 (continued)

	All	Treated	Never Treated
Psychiatric beds (2006)	0.85	1.57	0.28
Municipalities' Characteristics			
Number of municipalities	5180	1344	3836
Population	31011	43884	9437
Men	0.51	0.50	0.51
Age 10–19	0.23	0.24	0.23
Age 40–49	0.15	0.15	0.15
Age 70–79	0.04	0.04	0.05
PBF per capita	4.66	4.72	4.69
GDP per capita	2.82	2.83	2.77

Notes: All tabulations refer to the baseline year (2002), except where noted. Treated includes the cohorts of municipalities that implemented a CAPS for the first time in the period 2003-2016. Men, Age 10–19, Age 40–49, and Age 70–79 represent the fraction of the population that are men, and the fraction within each age bin (10-19, 40-49, and 70-79).

Table A3: Groups of Mortality and Morbidity Causes and Associated ICD-10 Codes

Group	ICD-10 Codes
Mental and behavioral disorders	**F00-F09**: Organic, including symptomatic, mental disorders **F10-F19**: Mental and behavioral disorders due to psychoactive substance abuse **F20-F29**: Schizophrenia, schizotypal and delusional disorders **F30-F39**: Mood disorders, including major depressive disorder and bipolar disorder **F40-F48**: Anxiety, dissociative, stress-related, and somatoform mental disorders **F50-F59**: Behavioral syndromes associated with physiological disturbances and physical factors **F60-F69**: Disorders of adult personality and behavior **F70-F79**: Mental retardation **F80-F89**: Disorders of psychological development **F90-F98**: Behavioral and emotional disorders with onset usually occuring in childhood and adolescence **F99**: Unspecified mental disorder
Homicide	**X85-Y09**: Assault, excluding injuries due to legal intervention and operations of war
Deaths of Despair	**X40-X45, Y10-Y15, Y45, Y47, Y49**: Alcoholic poisoning and overdose of prescription and illegal drugs **X60-X84**: Suicide **K70**: Alcoholic liver disease **K73, K74**: Unspecified chronic liver disease **F10-F19**: Mental and behavioral disorders due to psychoactive substance abuse

Table A4: Hazard estimation of probability of receiving a CAPS (marginal effects)

	(1)	(2)	(3)
A. Lagged variables (per 10,000 people)			
Δ_{-1}Hosp: Mental & Behavioral Disorders	0.00008		
	(0.00008)		
Δ_{-1}Deaths: Mental & Behavioral Disorders	-0.000013		
	(0.00061)		
Δ_{-1}Deaths of Despair	0.00008		
	(0.00032)		
Δ_{-1}Homicides	-0.00008		
	(0.00034)		
Δ_{-1}arcsinh(GDP per capita)	0.00149		
	(0.00457)		
Δ_{-2}Hosp: Mental & Behavioral Disorders		-0.00002	
		(0.00009)	
Δ_{-2}Deaths: Mental & Behavioral Disorders		0.00062	
		(0.00065)	
Δ_{-2}Deaths of Despair		-0.00028	
		(0.00034)	
Δ_{-2}Homicides		0.00036	
		(0.00036)	
Δ_{-2}arcsinh(GDP per capita)		0.00319	
		(0.00486)	
Δ_{-3}Hosp: Mental & Behavioral Disorders			-0.00009
			(0.00009)
Δ_{-3}Deaths: Mental & Behavioral Disorders			0.00000
			(0.00063)
Δ_{-3}Deaths of Despair			-0.00003
			(0.00034)
Δ_{-3}Homicides			0.00026
			(0.00036)
Δ_{-3}arcsinh(GDP per capita)			0.00604
			(0.00474)
B. Variables at baseline			

Table A4–*Continued*

	(1)	(2)	(3)
Theil Index (2000)	0.06134	0.06012	0.04952
	(0.00562)	(0.00602)	(0.00611)
Share Illiterate (2000)	-0.02865	-0.02497	-0.01717
	(0.01405)	(0.01479)	(0.01483)
Share Poor (2000)	-0.04439	-0.04626	-0.03486
	(0.00892)	(0.00941)	(0.00928)
Share Rural (2000)	-0.06110	-0.05962	-0.05738
	(0.00442)	(0.00465)	(0.00475)
Hosp: Mental & Behavioral Disorders (2003)	0.00005	0.00005	0.00002
	(0.00004)	(0.00005)	(0.00005)
Deaths: Mental & Behavioral Disorders (2003)	-0.00064	-0.0006	-0.00009
	(0.001)	(0.00106)	(0.00104)
Deaths of Despair (2003)	0.00057	0.0006	0.00073
	(0.00047)	(0.0005)	(0.00049)
Homicides (2003)	0.00242	0.00250	0.00205
	(0.00037)	(0.00040)	(0.00040)
arcsinh(GDP per capita) (2003)	-0.00041	-0.00094	0.00024
	(0.00139)	(0.00150)	(0.00149)
Observations	53,034	48,988	43,037
State FE	Yes	Yes	Yes
Time Polynomial Degree	5	5	5

Notes: Marginal effects of the hazard estimation of probability of receiving a CAPS. In this sample, covering the period from 2003 to 2016, units appear in the data until they receive a CAPS and, after that, they leave the sample. Each specification considers a different lagged difference of the main variables of interest and control for their baseline values, as well as the baseline values of other variables of interest as indicated in the table. A logit model is estimated and the reported marginal effects are taken at the average of each variable. Observations at the municipality level.

Table A5: Effects of CAPS on work hours by mental health providers (per 10,000 people)

	Work hours		Professionals		Ratio
	5-year effect	Baseline	5-year effect	Baseline	(1)/(3)
	(1)	(2)	(3)	(4)	
Psychiatrist	2.56	5.4	0.151	0.3	16.9
	(0.03)		(0.02)		
Psychologist	9.4	23.7	0.342	0.8	27.4
	(0.65)		(0.03)		
Therapist	3.04	4.4	0.104	0.17	29.2
	(0.27)		(0.01)		
Social worker	6.6	17.7	0.238	0.5	27.8
	(0.6)		(0.02)		

Note: This table reports the average effects of CAPS on the work hours of mental health practitioners working in the public system per 10,000 people. Standard errors in parenthesis are computed using a municipality-level clustered bootstrap. Controls include municipality GDP per capita, PBF spending per capita, a series of indicators for age-by-gender population bins, state$\times$year fixed effects, and linear trends of pre-treatment characteristics. Pre-treatment municipality characteristics included are: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. Columns 1 and 3 report the average effect after five years.

Table A6: Effects of CAPS on primary outcomes (all per 10,000 people) —controlling for Family Health Program (PSF) adoption

	Baseline specification (1)	PSF adoption (2)	PSF-year × time trend (3)
Mental health practitioners	0.835	0.835	0.830
	(0.053)	(0.046)	(0.046)
Outpatient procedures by MH practitioners	264.214	264.363	264.229
	(21.151)	(20.345)	(24.091)
Hospital admissions by MH disorders	-0.951	-0.953	-0.942
	(0.286)	(0.297)	(0.290)
MH hospital spendings	-0.157	-0.158	-0.157
	(0.038)	(0.036)	(0.038)
Deaths of despair	-0.022	-0.022	-0.019
	(0.034)	(0.034)	(0.033)
Homicides	0.149	0.149	0.146
	(0.042)	(0.044)	(0.042)

Note: This table reports the average effects of CAPS on our main outcomes (all per 10,000 people) controlling additionally for PSF adoption. Standard errors in parenthesis are computed using a municipality-level clustered bootstrap. Controls include municipality GDP per capita, PBF spending per capita, a series of indicators for age-by-gender population bins, state×year fixed effects, and linear trends of pre-treatment characteristics. Pre-treatment municipality characteristics included are: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. Column 1 reproduces the average effects with our main specification. Column 2 reports the average effects controlling for PSF adoption. Column 3 reports the same effects controlling for time trends based on PSF year of adoption.

Table A7: Effects of CAPS on primary outcomes (all per 10,000 people) —robustness checks

	Main specification	Without controls	Controlling for time-invariant covariates × time trend	Weighting by baseline population	Balanced panel	Extended event study
	(1)	(2)	(3)	(4)	(5)	(6)
Mental health practitioners	0.835	0.694	0.839	0.555	1.003	0.950
	(0.055)	(0.043)	(0.049)	(0.108)	(0.053)	(0.069)
Outpatient procedures by MH practitioners	264.214	239.228	264.285	235.109	322.474	288.443
	(21.151)	(22.139)	(21.169)	(26.683)	(28.010)	(21.138)
Hospital admissions by MH disorders	-0.951	-0.798	-0.889	-1.980	-1.487	-1.151
	(0.286)	(0.266)	(0.287)	(0.749)	(0.343)	(0.402)
MH hospital spendings	-0.157	-0.143	-0.153	-0.118	-0.218	-0.197
	(0.038)	(0.033)	(0.035)	(0.043)	(0.039)	(0.044)
Deaths of despair	-0.022	-0.012	-0.013	-0.029	-0.029	-0.018
	(0.034)	(0.031)	(0.032)	(0.035)	(0.040)	(0.036)
Homicides	0.149	0.225	0.157	0.324	0.155	0.214
	(0.042)	(0.041)	(0.045)	(0.100)	(0.051)	(0.056)

Note: This table reports our main average effects for different specifications. The average effects are defined by the average of the DID estimators for the non-negative event-times. Standard errors in parenthesis are computed using a municipality-level clustered bootstrap. Controls include municipality GDP per capita, PBF spending per capita, a series of indicators for age-by-gender population bins, state×year fixed effects, and linear trends of pre-treatment characteristics. Pre-treatment municipality characteristics included are: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. Column 1 presents the results of our main specification. In column 2, we exclude the controls from our main specification. Column 3 shows the results for a specification that adds to the main specification linear trends of time-invariant characteristics, namely: Theil index, poverty rate, unemployment rate, illiteracy rate, share of rural population, log of population, log of social spending, number of mental health providers, number of mental health offices, municipality area, altitude, distance to capital, temperature, and rainfall. In column 4 we report the results of our main specification restricting the sample so as to have a balanced panel. In column 5, we consider a specification with eight years after the event.

B. Empirical Strategy

We start by defining our causal estimand of interest. Let $D_{m,t}$ denote our treatment dummy. For our main empirical strategy, it indicates whether a municipality m gained a CAPS for the first time in year t. We are interested in the average treatment effects across the municipalities that sequentially implemented a mental health center after 2002. That is, (m, t) cells such that $D_{m,t-1} = 0$ and $D_{m,t} = 1$ for any pair of consecutive time periods $t-1$ and t. Let $\mathcal{S}(k)$ denote the set of switching cells observed $k \geq 0$ periods away from the treatment year ($t + k \leq 2016$). Our primary causal estimand is

$$\beta(k) := \frac{1}{\#\mathcal{S}(k)} \sum_{(m,t)\in\mathcal{S}(k)} Y_{m,t+k}(1) - Y_{m,t+k}(0),$$

where $Y_{m,t+k}(1)$ and $Y_{m,t+k}(0)$ are the potential outcomes with and without treatment of municipality m at period $t+k$, respectively. $\beta(k)$ is the average treatment effect across all groups of switchers, k periods after a group starts to receive the treatment.

Under the usual parallel trends assumption, the outcome evolution among the non-switchers can be used as the counterfactual evolution of the switchers, and a DID estimator that compares the outcome of both groups before and after the intervention can estimate average treatment effects among the switchers. We now present such an estimator. Let $\mathcal{S}(t,k)$ be the set of municipalities m that received a CAPS for the first time at a particular period $t \in [2003, 2016-k]$. In our setting, this means that $D_{m,t-1} = 0$ and $D_{m,t} = \ldots = D_{m,t+k} = 1$. Let $\mathcal{C}(t,k)$ be the set of cities such that $D_{m,t-1} = D_{m,t} = \ldots = D_{m,t+k} = 0$. For a fixed event-time $k \geq 0$, we can estimate a 2×2 DID for the cohort of municipalities that implemented a CAPS at t:

$$DID(t,k) := \frac{1}{\#\mathcal{S}(t,k)} \sum_{m\in\mathcal{S}(t,k)} \left(Y_{m,t+k} - Y_{m,t-1}\right) - \frac{1}{\#\mathcal{C}(t,k)} \sum_{m\in\mathcal{C}(t,k)} \left(Y_{m,t+k} - Y_{m,t-1}\right).$$

$DID(t,k)$ compares the evolution of the mean outcome between $t-1$ and $t+k$ in two sets of groups: the municipalities that gained a CAPS at the period $t \leq 2016-k$, and those remaining untreated until $t+k$. Under the assumption that the mean outcome of municipalities in $\mathcal{S}(t,k)$ and $\mathcal{C}(t,k)$ would evolve in parallel in the absence of CAPS, $DID(t,k)$ estimates the average treatment effect for the municipalities that implemented a CAPS at period t, k periods later. We can then define our estimator for $\beta(k)$, which is a weighted average of the $DID(t,k)$ estimators:

$$DID(k) := \sum_{t \in [2003, 2016-k]} \frac{\#\mathcal{S}(t,k)}{\#\mathcal{S}(k)} DID(t,k).$$

The CAPS' implementation process across municipalities has been taking place slowly and steadily over the years. Therefore, differences over $\{DID(k)\}_k$ may be the result of not only dynamic treatment effects but also compositional changes arising from the fact that late switchers will have many missing post-CAPS years. For instance, if municipalities select themselves into treatment based on expected future gains, the dynamic effects for early-treated cities may be different from those that gained a CAPS later and have few post-CAPS years. In our primary analysis, we will look up to five years post-intervention. About 70% of our treated units had a CAPS in operation for at least 5 years. We also consider an estimator that restrict the dynamic effects only for cities that have at least five periods of post-CAPS observations as a robustness check.[1]

We also estimate pre-treatment parameters and use them to assess the credibility of the underlying identifying assumptions. In particular, we use placebo estimators that replace the "long differences" $Y_{m,t+k} - Y_{m,t-1}$ (across municipalities that switched from untreated to treated at t and those remaining untreated until $t+k$) with "short differences" $Y_{m,t'} - Y_{m,t'-1}$ for all $t' < t$. These pre-treatment effects should be equal to zero under basically the same assumption that guarantees that $E[DID(k)] = \beta(k)$.

[1]In this case, since the composition of municipalities is the same across all event times, longer-run dynamic effects cannot be biased due to compositional changes. However, the loss of groups used to compute the dynamic effects can lead to less informative inference.