Causal Inference Lab

인과추론과 실무 : 9. Synthetic Control Method

가짜연구소 인과추론팀

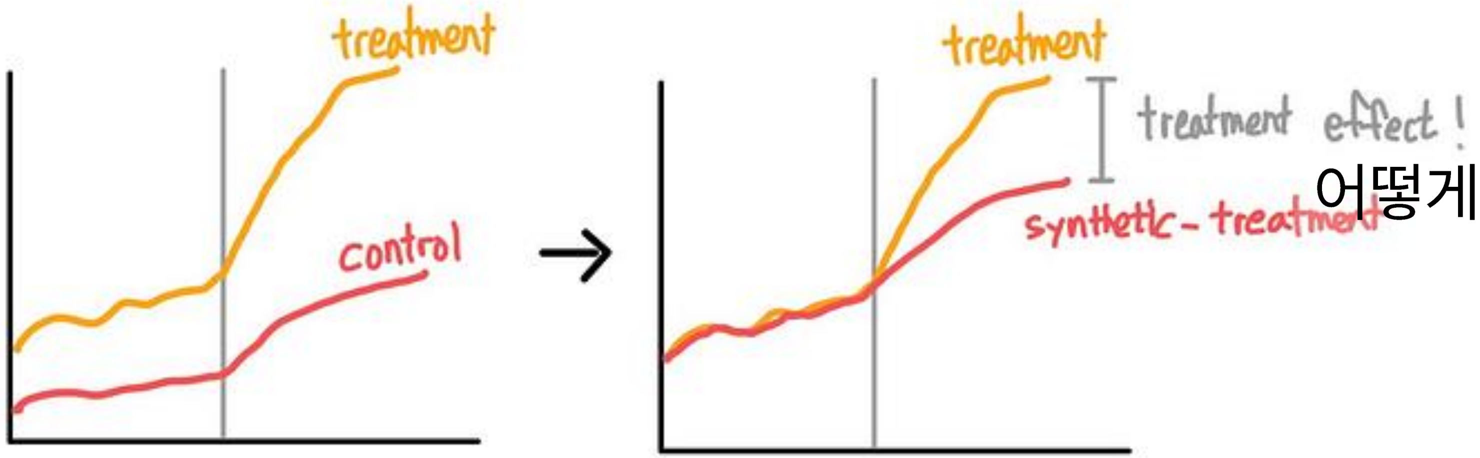
발표자 : 손지영

Difference-In-Difference와 Synthetic Control

같은 목적, 다른 접근

Parallel trend 가정을 지키지 않아도 됨

인과추론을 위해 어떤 counterfactual 추정
DID: Simple average -> SC: Weighted average



어떻게 Weight 을 주어야 하는가?

Source : https://medium.com/@chyun55555/synthetic-control-method-for-causal-inference-basics-with-simple-mathematics-c61fc42fd472

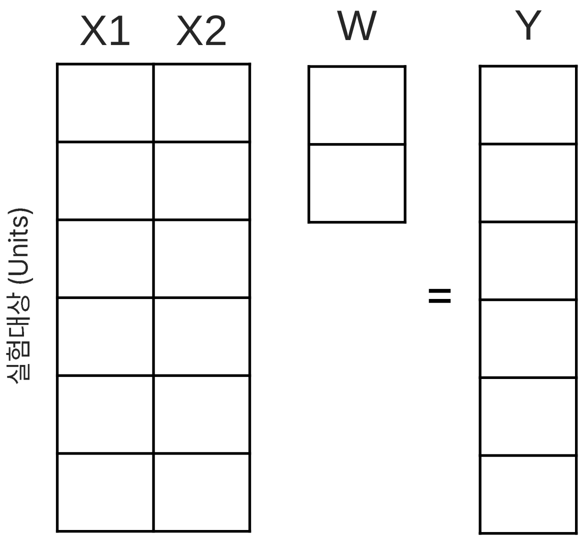
9-1. Synthetic Control Method

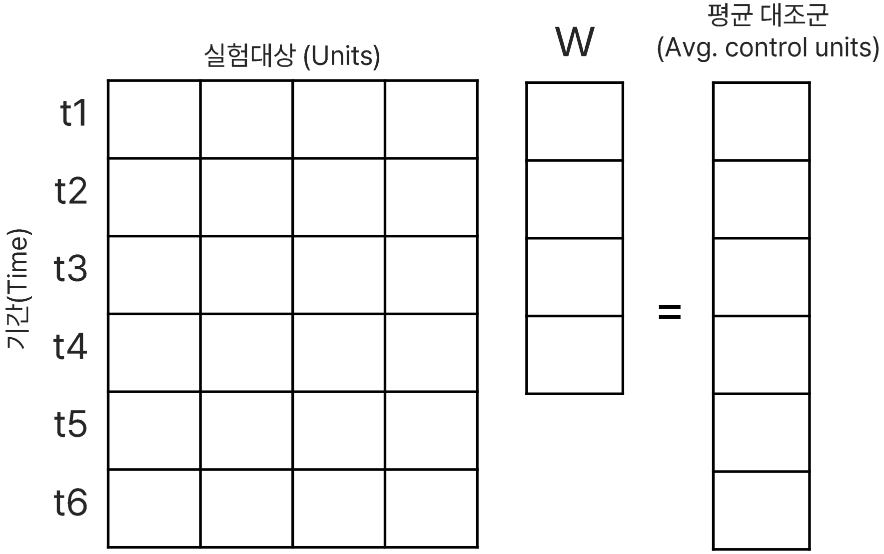
통제집단합성법과 수평 회귀분석

처치 이전기간을 사용하여 대조군을 결합함으로써 실험군의 평균 결과를 잘 근사할 수 있는 방법 찾기

$$\hat{\omega}^{sc} = \arg\min \left\| \bar{y}_{Pre,tr} - Y_{Pre,co}\,\omega_{co} \right\|^2$$

대조군의 결과를 특성으로 사용해서 실험군의 평균 결과를 예측하는 회귀





통제집단합성법과 수평 회귀분석

온라인 마케팅 데이터
(outcome) app_download -> app_download_pct

마케팅여부

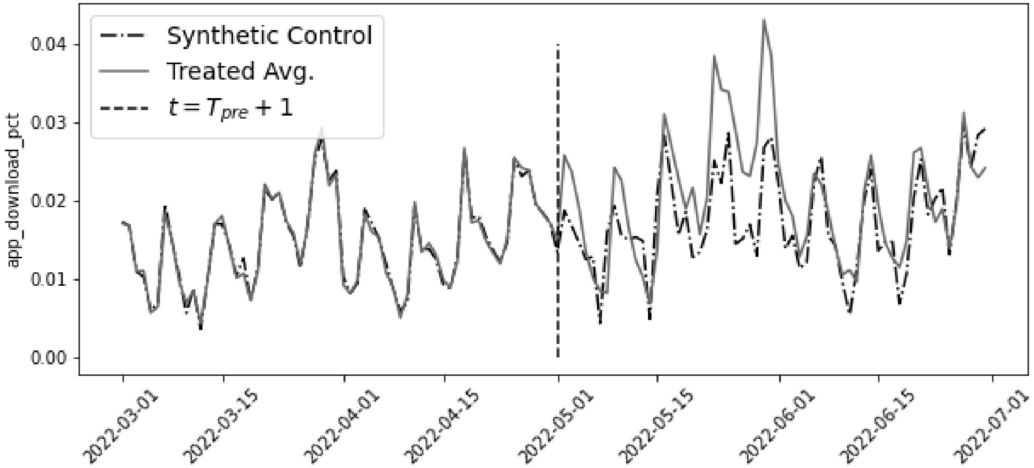
covariates (경쟁사 일별 다운로드 수)

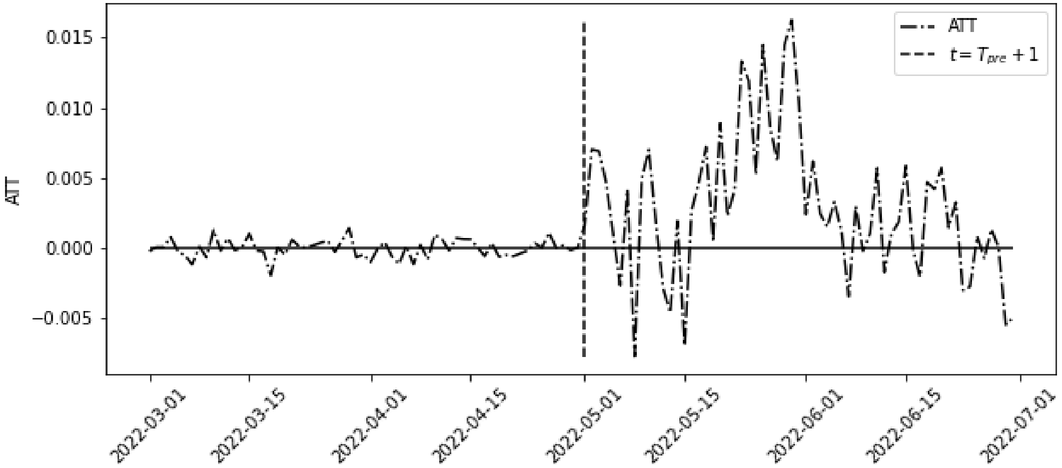
	app_download	population	city	state	date	post	treated	app_download_pct	comp_download_pct
0	3066.0	12396372	sao_paulo	sao_paulo	2022-03-01	0	1	0.024733	0.026280
1	2701.0	12396372	sao_paulo	sao_paulo	2022-03-02	0	1	0.021789	0.023925
2	1927.0	12396372	sao_paulo	sao_paulo	2022-03-03	0	1	0.015545	0.018930
3	1451.0	12396372	sao_paulo	sao_paulo	2022-03-04	0	1	0.011705	0.015858
4	1248.0	12396372	sao_paulo	sao_paulo	2022-03-05	0	1	0.010067	0.014548

city	sao_paulo	porto_alegre	joao_pessoa
date			
2022-03-01	0.024733	0.004288	0.022039
2022-03-02	0.021789	0.008107	0.020344
2022-03-03	0.015545	0.004891	0.012352
2022-03-04	0.011705	0.002948	0.018285
2022-03-05	0.010067	0.006767	0.000000

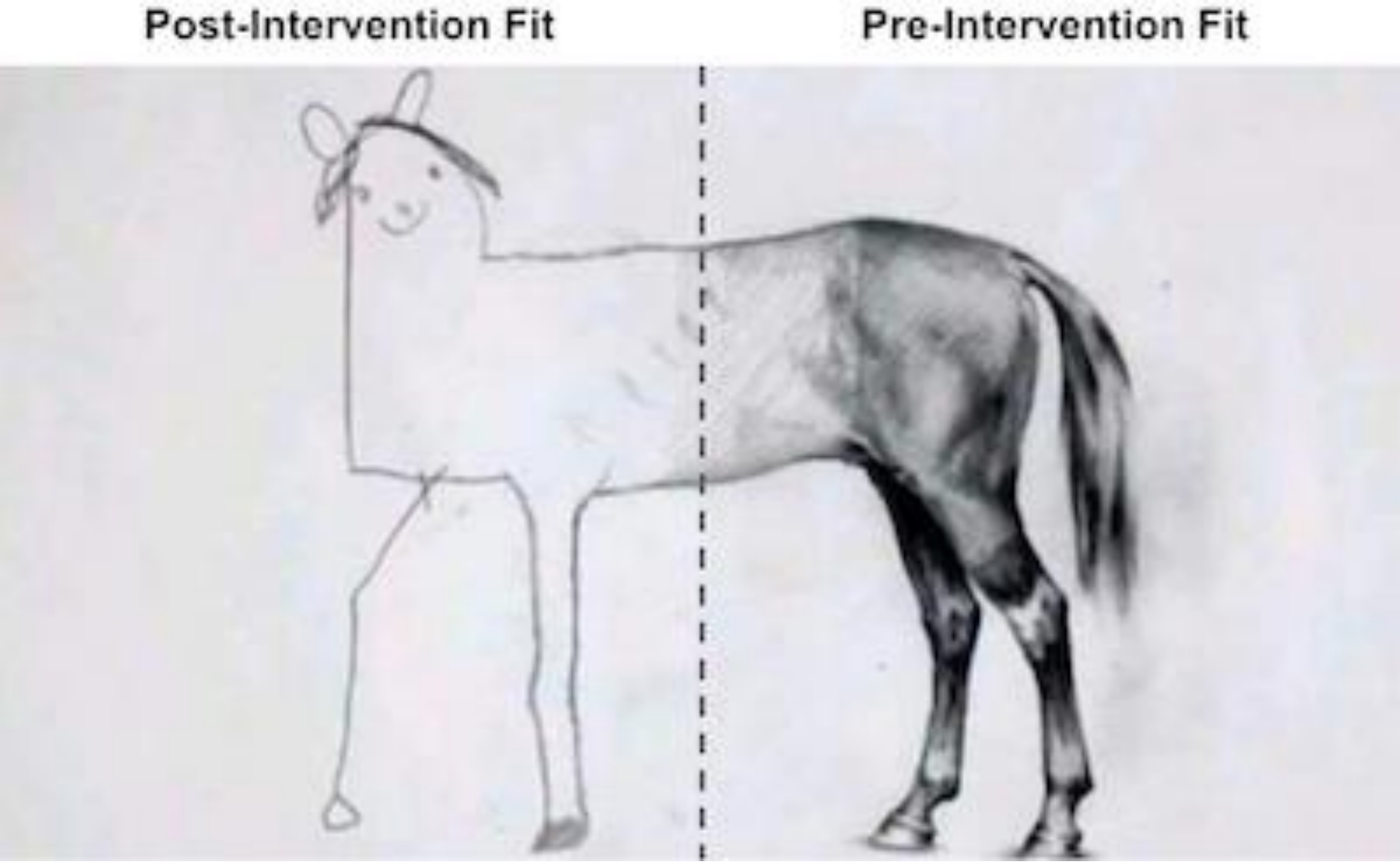
통제집단합성법과 수평 회귀분석

1. 효과가 정점에 이르기까지 일정 시간이 걸리고, 그 후 점차 줄어듦
2. ATT의 크기 = OLS 모델의 잔차. 0에 가까우면 좋은가?






```
array([-0.65 , -0.058, -0.239,  0.971,  0.03 , -0.204,  0.007,  0.095,
        0.102,  0.106,  0.074,  0.079,  0.032, -0.5  , -0.041, -0.154,
       -0.014,  0.132,  0.115,  0.094,  0.151, -0.058, -0.353,  0.049,
       -0.476, -0.11 ,  0.158, -0.002,  0.036, -0.129, -0.066,  0.024,
       -0.047,  0.089, -0.057,  0.429,  0.23 , -0.086,  0.098,  0.351,
       -0.128,  0.128, -0.205,  0.088,  0.147,  0.555,  0.229])
```



> 단순 회귀는 대조군을 구성할 때 사용하지 않음. 일반화 되지 않고 과적합 되는 경향이 존재함.

Source : [Causal Inference for the Brave and True - 15 Synthetic Control]

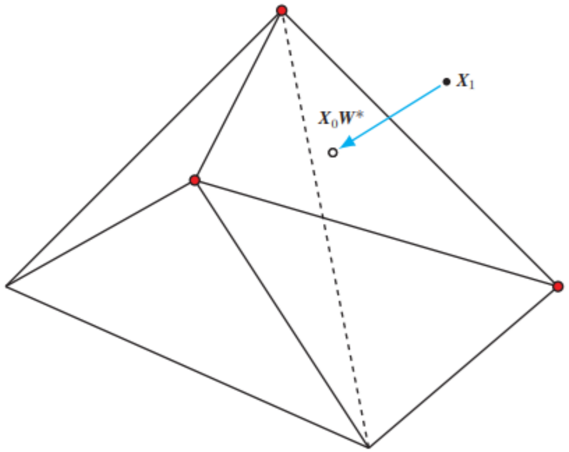
표준 통제집단합성법

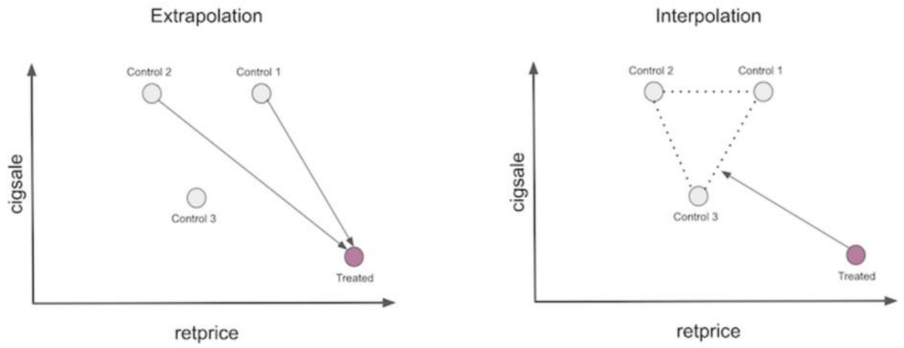
1. 가중치는 모두 양수
2. 가중치의 합은 1

$$\hat{\omega}^{sc} = \arg\min \left\| \bar{y}_{Pre,tr} - Y_{Pre,co}\omega_{co} \right\|^2$$

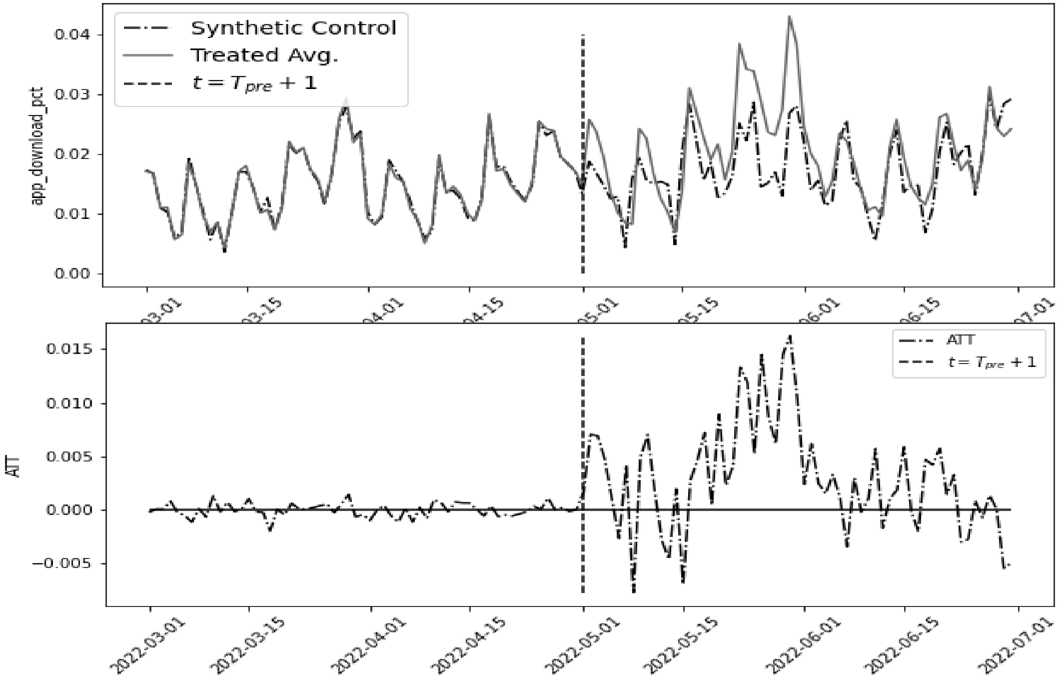
$$\boxed{s.t \sum \omega_i = 1 \; and \; \omega_i > 0 \; \forall_i}$$

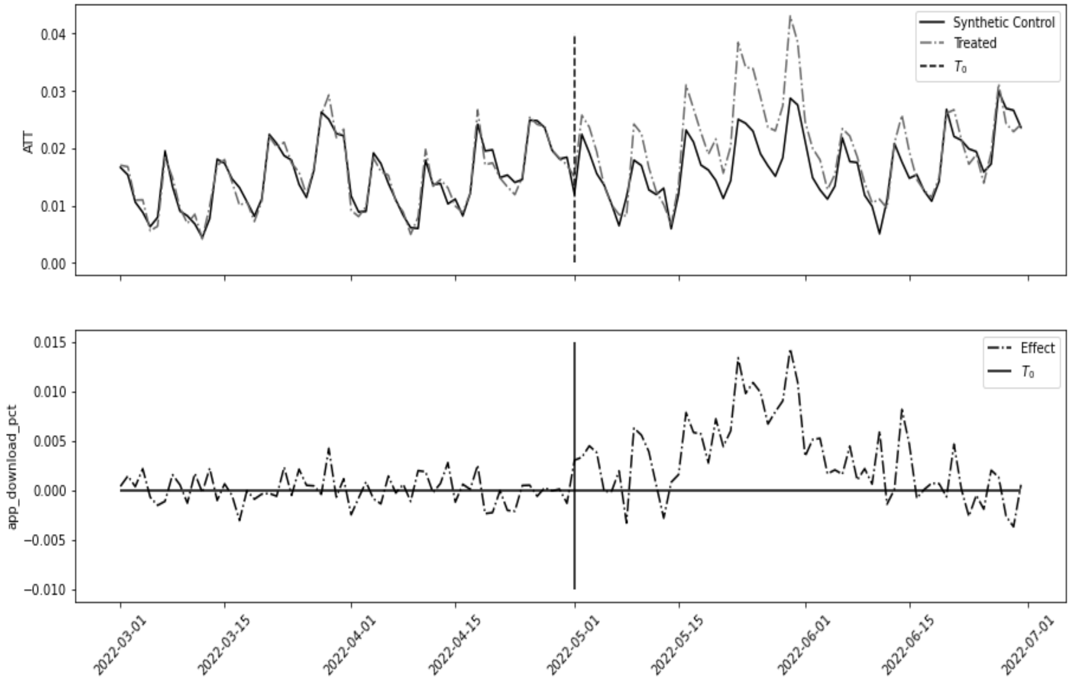
Convex combination이 되도록 하여 외삽을 피하는데 있음.
> 과적합의 위험을 감소시키기 위한 것





표준 통제집단합성법



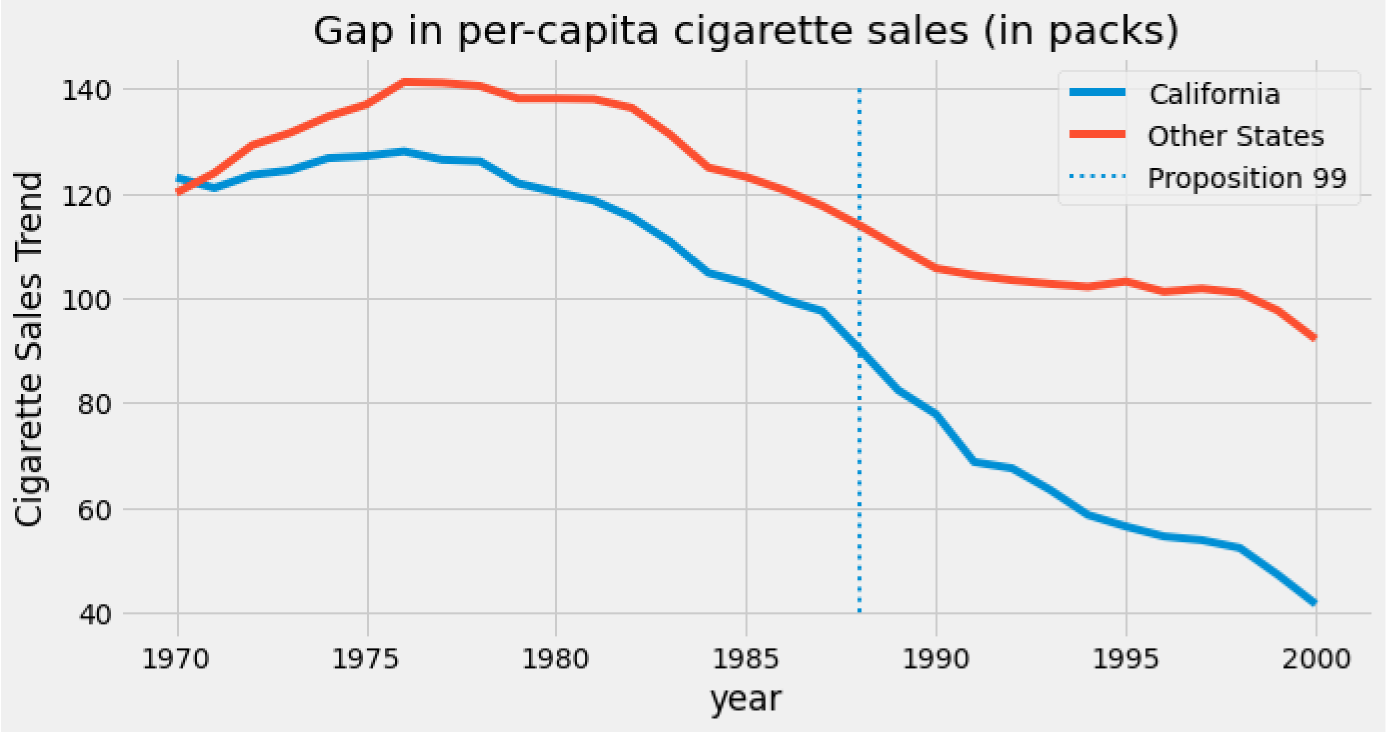



```
array([-0.65 , -0.058, -0.239,  0.971,  0.03 , -0.204,  0.007,  0.095,
        0.102,  0.106,  0.074,  0.079,  0.032, -0.5  , -0.041, -0.154,
       -0.014,  0.132,  0.115,  0.094,  0.151, -0.058, -0.353,  0.049,
       -0.476, -0.11 ,  0.158, -0.002,  0.036, -0.129, -0.066,  0.024,
       -0.047,  0.089, -0.057,  0.429,  0.23 , -0.086,  0.098,  0.351,
       -0.128,  0.128, -0.205,  0.088,  0.147,  0.555,  0.229])
```

```
array([-0.   , -0.   , -0.   , -0.   , -0.   , -0.   ,  0.076,  0.037,
        0.083,  0.01 , -0.   , -0.   , -0.   , -0.   , -0.   , -0.   ,
        0.061,  0.123,  0.008,  0.074, -0.   ,  0.   , -0.   , -0.   ,
       -0.   , -0.   , -0.   , -0.   , -0.   ,  0.   , -0.   ,  0.092,
       -0.   , -0.   ,  0.   ,  0.046,  0.089,  0.   ,  0.067,  0.061,
        0.   , -0.   , -0.   ,  0.088,  0.   ,  0.086, -0.   ])
```

캘리포니아 발의안 제 99호 담배세가 소비에 미치는 영향 분석

1988년 캘리포니아는 발의안 제 99호: 담배세 및 건강 보호법을 통과
이 법안이 실제로 담배 소비를 줄였는지, 그리고 얼마나 효과적인지 평가



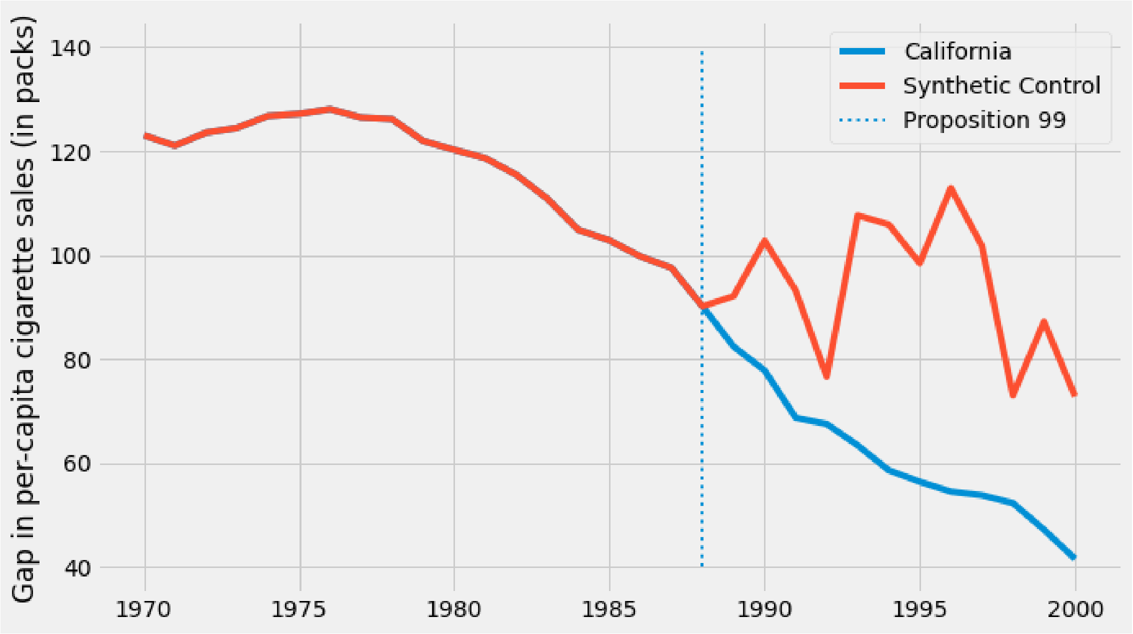

```
cigar = (pd.read_csv("data/smoking.csv")
         .drop(columns=["lnincome","beer", "age15to24"]))

cigar.query("california").head()
```

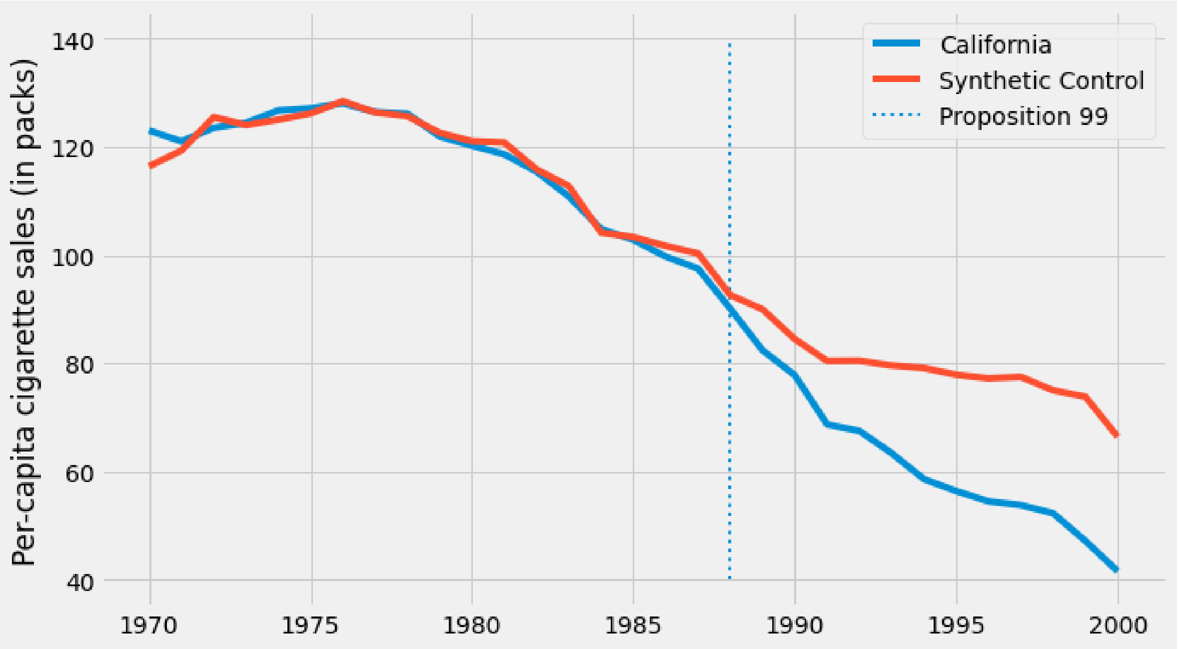
	state	year	cigsale	retprice	california	after_treatment
62	3	1970	123.000000	38.799999	True	False
63	3	1971	121.000000	39.700001	True	False
64	3	1972	123.500000	39.900002	True	False
65	3	1973	124.400002	39.900002	True	False
66	3	1974	126.699997	41.900002	True	False

(covariates) retprice: the cigarette retail price,
(outcome) cigsale: the per-capita sales of cigarettes in packs.

Source : [Causal Inference for the Brave and True - 15 Synthetic Control]

캘리포니아 발의안 제 99호 담배세가 소비에 미치는 영향 분석






```
from sklearn.linear_model import LinearRegression
weights_lr = LinearRegression(fit_intercept=False).fit(X, y).coef_
weights_lr.round(3)
```

```
array([-0.436, -1.038,  0.679,  0.078,  0.339,  1.213,  0.143,  0.555,
       -0.295,  0.052, -0.529,  1.235, -0.549,  0.437, -0.023, -0.266,
       -0.25 , -0.667, -0.106, -0.145,  0.109,  0.242, -0.328,  0.594,
        0.243, -0.171, -0.02 ,  0.14 , -0.811,  0.362,  0.519, -0.304,
        0.805, -0.318, -1.246,  0.773, -0.055, -0.032])
```

```
calif_weights = get_w(X, y)
print("Sum:", calif_weights.sum())
np.round(calif_weights, 4)
```

```
Sum: 1.000000000000424
```

```
array([0.    , 0.    , 0.    , 0.0852, 0.    , 0.    , 0.    , 0.    ,
       0.    , 0.    , 0.    , 0.    , 0.    , 0.    , 0.    , 0.    ,
       0.    , 0.    , 0.    , 0.113 , 0.1051, 0.4566, 0.    , 0.    ,
       0.    , 0.    , 0.    , 0.    , 0.    , 0.    , 0.    , 0.    ,
       0.2401, 0.    , 0.    , 0.    , 0.    , 0.    ])
```

Source : Causal Inference for the Brave and True - 15 Synthetic Control

통제집단합성법과 공변량

온라인 마케팅 데이터
(outcome) app_download -> app_download_pct

마케팅여부 / covariates (경쟁사 일별 다운로드 수)

	app_download	population	city	state	date	post	treated	app_download_pct	comp_download_pct
0	3066.0	12396372	sao_paulo	sao_paulo	2022-03-01	0	1	0.024733	0.026280
1	2701.0	12396372	sao_paulo	sao_paulo	2022-03-02	0	1	0.021789	0.023925
2	1927.0	12396372	sao_paulo	sao_paulo	2022-03-03	0	1	0.015545	0.018930
3	1451.0	12396372	sao_paulo	sao_paulo	2022-03-04	0	1	0.011705	0.015858
4	1248.0	12396372	sao_paulo	sao_paulo	2022-03-05	0	1	0.010067	0.014548

city date	sao_paulo	porto_alegre	joao_pessoa
2022-03-01	0.024733	0.004288	0.022039
2022-03-02	0.021789	0.008107	0.020344
2022-03-03	0.015545	0.004891	0.012352
2022-03-04	0.011705	0.002948	0.018285
2022-03-05	0.010067	0.006767	0.000000

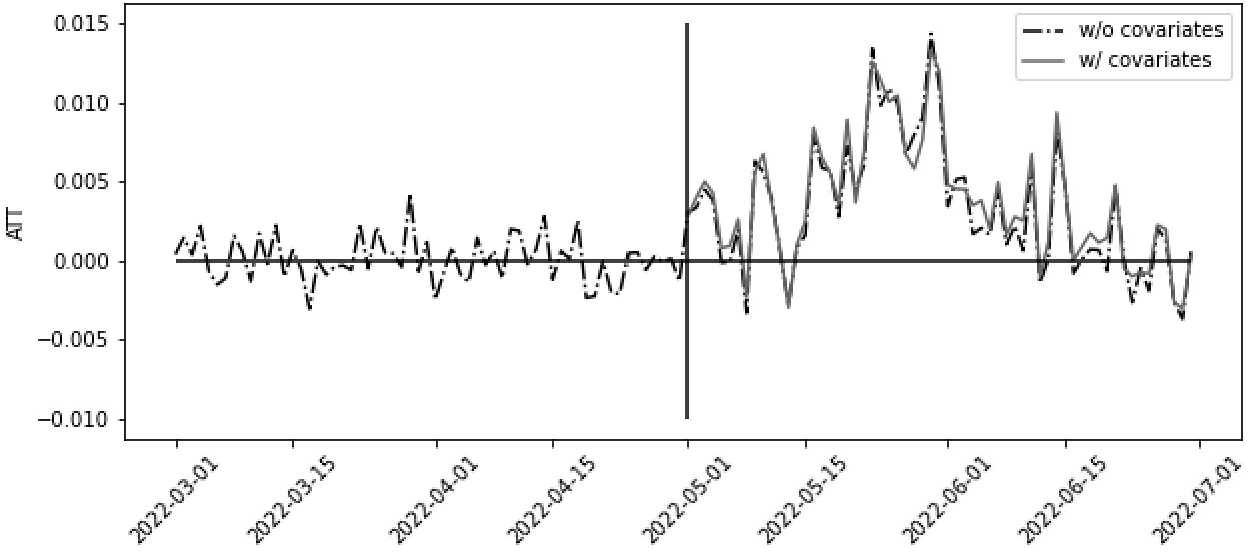
Source : 실무로 통하는 인과추론 with 파이썬

통제집단합성법과 공변량

pre-treatment를 모두 고려하면 좋음
: outcome에 영향을 주는 covariates이 있으면 고려하면 좋다.
: pre-treatment 기간이 짧은 경우

$$\widehat{\omega}^{sc} = \arg\min \left\| \bar{y}_{Pre,tr} - \sum \boxed{V_k^*} X_{k,pre,co}\, \omega_{co} \right\|^2$$

$$\text{s.t} \sum \omega_i = 1 \; and \; \omega_i > 0 \; \forall_i$$



Source : 실무로 통하는 인과추론 with 파이썬

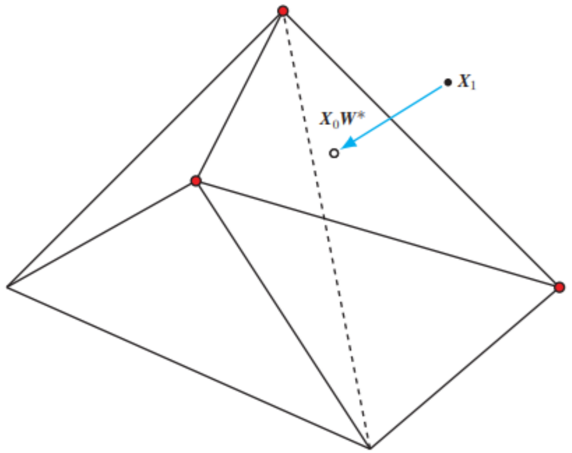
통제집단합성법과 편향 제거

1. 가중치는 모두 양수
2. 가중치의 합은 1

$$\widehat{\omega}^{sc} = \arg\min \left\| \bar{y}_{Pre,tr} - Y_{Pre,co}\omega_{co} \right\|^2$$

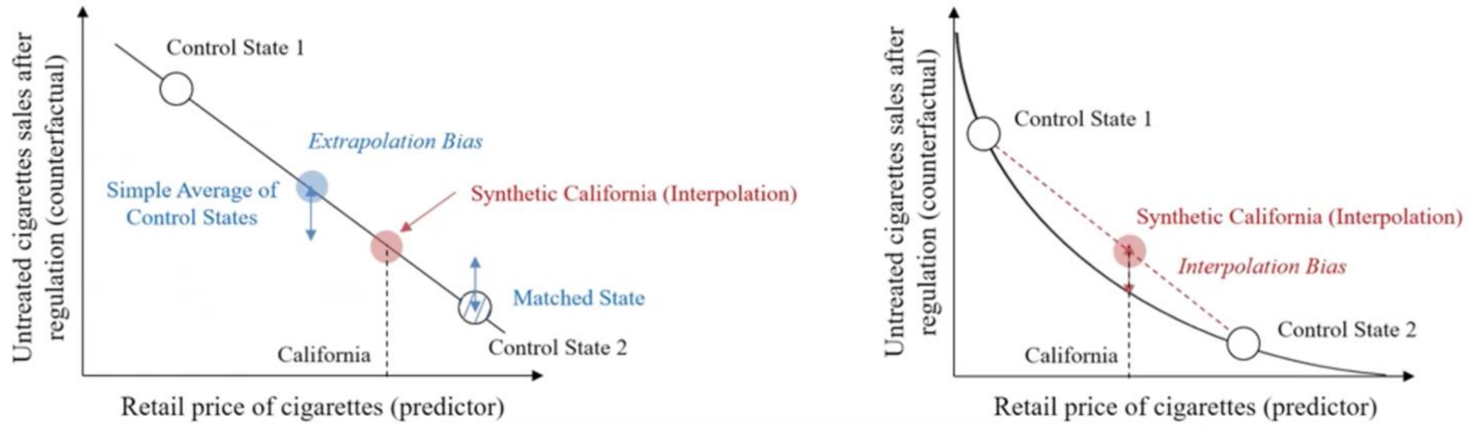
$$\boxed{\text{s.t} \sum \omega_i = 1 \; and \; \omega_i > 0 \; \forall_i}$$

Convex combination이 되도록 하여 외삽을 피하는데 있음.
> 과적합의 위험을 감소시키기 위한 것

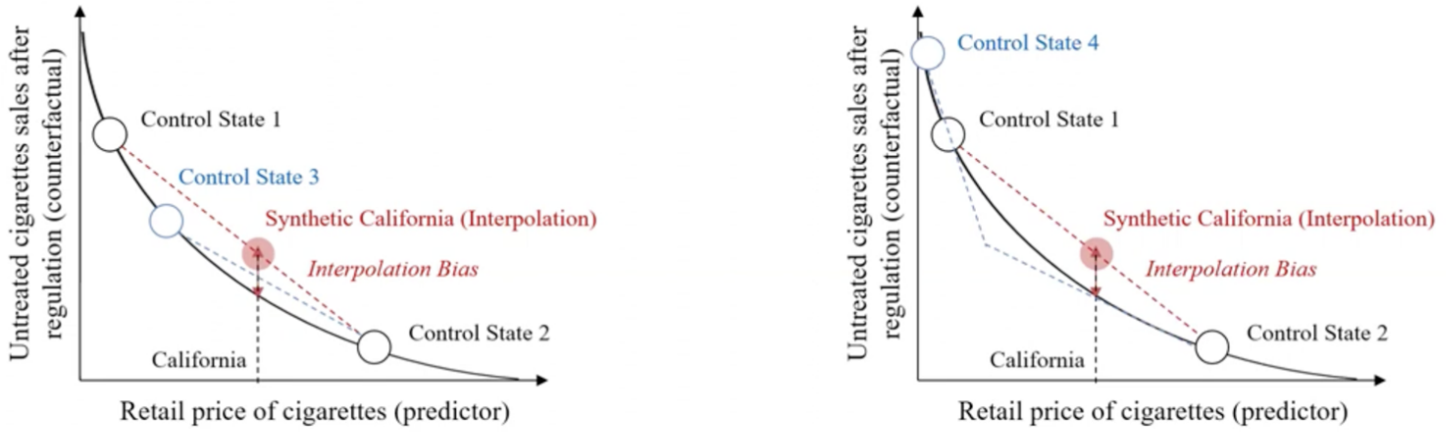


통제집단합성법과 편향 제거

Example: Impact of California anti-tobacco legislation



Example: Impact of California anti-tobacco legislation



(1) Add Closer control units
(2) Allowing for extrapolation

Source : [7-4 Week] 통제집단합성시 발행할 수 있는 편향

통제집단합성법과 편향 제거

교차 검증(cross-fitting)

1. 개입 전 기간을 K개의 블록으로 나누어, 각 블록의 크기는 $\min\{\frac{T_{pre}}{K}, T_{post}\}$설정
2. 각 블록을 홀드아웃 셋으로 취급하고 $Y^{-k}_{pre,co}$와 $Y^{-k}_{pre,tr}$에 대한 통제집단 합성 모델을 적합시킴
   $-k$는 훈련 셋에서 블록을 삭제한다는 의미
3. 홀드아웃 데이터 $Y^{k}_{pre,co}$와 를 사용하여 이 가중치로 표본 외 예측
   예측값과 관측값 사이의 평균 차이는 편향에 대한 추정값

k번째 폴드에서 개입된 집단(처리집단)의 예측값

k번째 폴드를 제외한 나머지 데이터에서 최적화된 가중치

$$\widehat{Bias}^k = avg(Y^k_{pre,tr} - Y^k_{pre,co}\hat{\omega}^{-k})$$

k번째 폴드에서 합성된 통제집단의 예측값

$A = \pi r^2$

$$\widehat{ATT}^k = Y_{pre,tr} - Y_{post,co}\hat{\omega}^{-k} - \widehat{Bias}^k$$

Source : 실무로 통하는 인과추론 with 파이썬

통제집단합성법 가정과 검증

1. Convex Hull Condition
2. No Anticipation
3. No Confounding Events
4. No Interference (SUTVA)
5. No Structural Breaks

Source : [Week 7-3] 통제집단합성법의 가정과 검증

통제집단합성법 가정과 검증

1. Convex Hull Condition
: pre-treatment -> 차이가 얼마나 적은 지

해결방안: normalized 해서 Convex 내에 둘수 있음.

ex) 캘리포니아 예제 - 전체 담배판매량 -> 인구당 담배판매량

```
cigar = (pd.read_csv("data/smoking.csv")
         .drop(columns=["lnincome","beer", "age15to24"]))

cigar.query("california").head()
```

	state	year	cigsale	retprice	california	after_treatment
62	3	1970	123.000000	38.799999	True	False
63	3	1971	121.000000	39.700001	True	False
64	3	1972	123.500000	39.900002	True	False
65	3	1973	124.400002	39.900002	True	False
66	3	1974	126.699997	41.900002	True	False

cigsale: the per-capita sales of cigarettes in packs.

	app_download	population	city	state	date	post	treated	app_download_pct
0	3066.0	12396372	sao_paulo	sao_paulo	2022-03-01	0	1	0.024733
1	2701.0	12396372	sao_paulo	sao_paulo	2022-03-02	0	1	0.021789
2	1927.0	12396372	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.015545
3	1451.0	12396372	sao_paulo	sao_paulo	2022-03-04	0	1	0.011705
4	1248.0	12396372	sao_paulo	sao_paulo	2022-03-05	0	1	0.010067

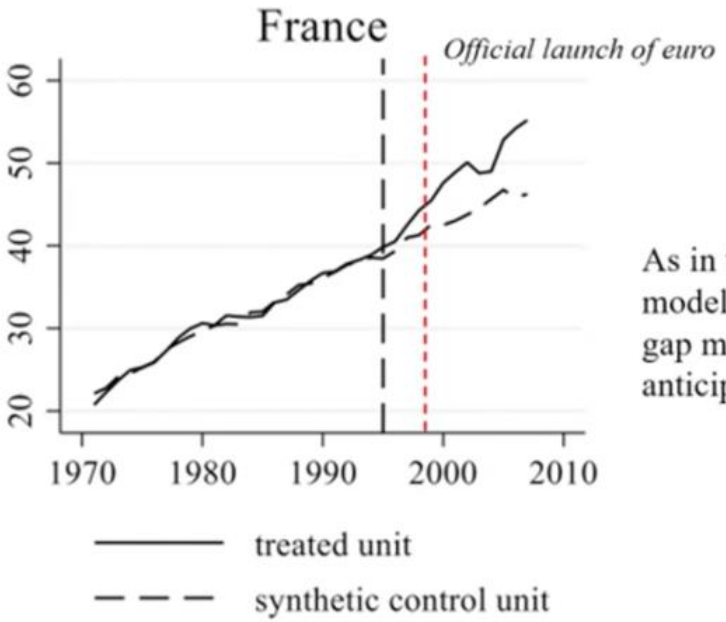
Source : [Week 7-3] 통제집단합성법의 가정과 검증

통제집단합성법 가정과 검증

2. No Anticipation
: 실제 처치보다 미리 영향을 받는 경우

해결방안: Backdating

- Example: Effect of joining European Monetary Union on labor productivity (Zhuang et al. 2023)



As in the event-study DID model, the pre-treatment gap may be indicative of anticipation effects.

"Although the euro was officially launched in 1999, members started working on the Maastricht Treaty requirements after the treaty went into effect in 1993. Therefore, we backdate the treatment year to 1995 to estimate the full extent of the treatment effect, accounting for members' anticipation." (p. 294)

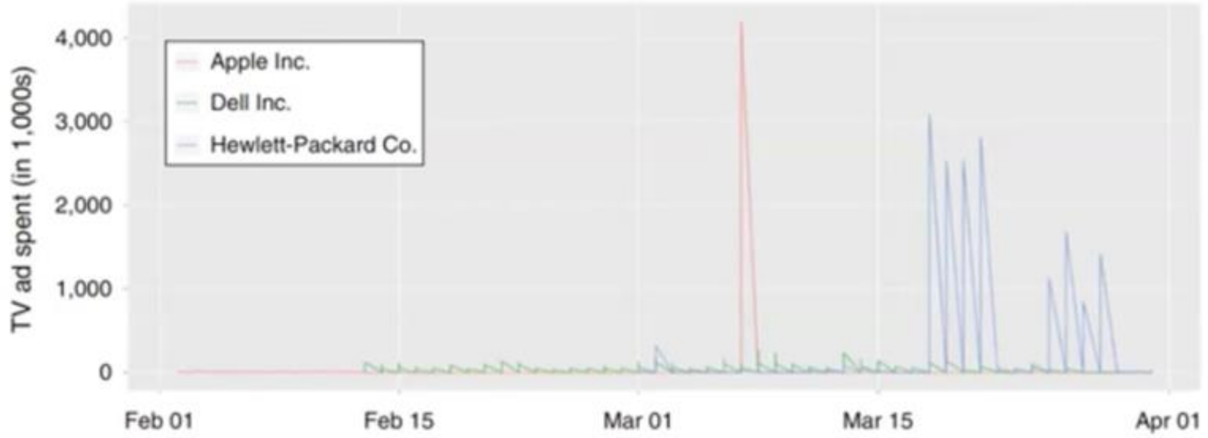
통제집단합성법 가정과 검증

3. No confounding Events
4. No Interference (SUTVA)
: 변화가 없었는지 검증

해결방안: Donor pool에서 제외

"A second assumption is that only the focal brand undergoes the treatment during the intervention period and that the donor brands contributing to the synthetic brand do not undergo similar confounding events." (p. 869)

"A fourth assumption is that HP [treated unit] undergoes no other changes in the other marketing variables during the intervention period, such as changes in price, channels, products, and promotions." (p. 870)



"With one exception, these searches did not reveal any major changes during the intervention period in channels, products, pricing, or promotion… the only major change in marketing reported was the uploading of the TV campaign on HP's YouTube channel." (p. 871)

Abadie, A., 2021. Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, 59(2), pp.391-425.
Tirunillai, S. and Tellis, G.J., 2017. Does offline TV advertising affect online chatter? Quasi-experimental analysis using synthetic control. *Marketing Science*, *36*(6), pp.862-878.

Source : [Week 7-3] 통제집단합성법의 가정과 검증

통제집단합성법 가정과 검증

5. No Structural Breaks
:안정적으로 유지되는가? 분석 기간동안 break가 없어야 함
만약에 중간에 다른 브랜드의 광고 전략에 변화가 있었다면?

- Example: Effect of TV advertising on online chatter (Tirunillai and Tellis 2017)

Figure 4. Average Weekly Advertising Across Different Media of HP

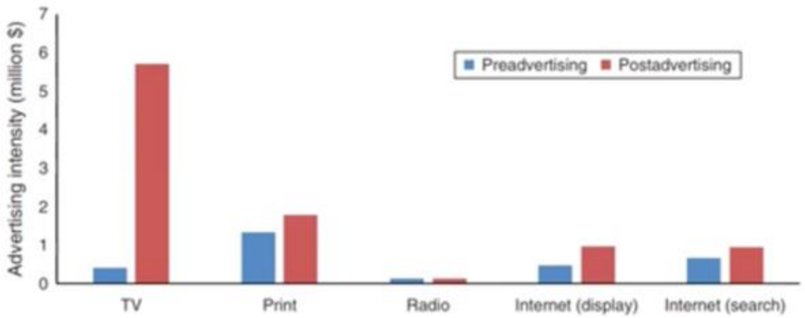
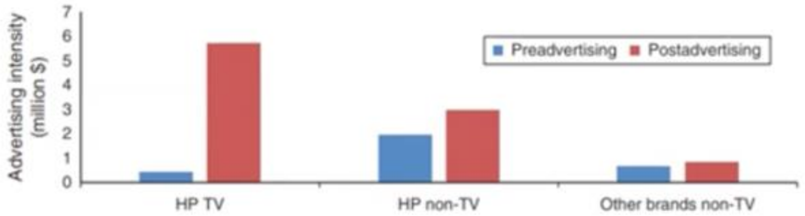


Figure 5. Average Weekly Advertising by Top Brands on Non-TV Media vs. HP TV



Note. "Non-TV" includes print (including Sunday, national, local, and Hispanic newspaper and magazine and business-to-business), radio (national, local, and spot), Internet display, and outdoor display advertising.

"*A third assumption is that no major changes in advertising on other channels (radio, print, and online display and search) occur for HP and other brands during the treatment period.*" (p. 870)

Tirunillai, S. and Tellis, G.J., 2017. Does offline TV advertising affect online chatter? Quasi-experimental analysis using synthetic control. *Marketing Science*, *36*(6), pp.862-878.

통제집단합성법 가정과 검증

Trade-off
: Including close control units for a better fit vs. Excluding close control units to prevent spillovers

- Example: Impact of reunification on West Germany

"As explained above, if countries that compose the synthetic control for West Germany, like Austria, suffered from the negative effects of the German reunification, then we would expect the synthetic control estimator to be attenuated. That is, in this case, the synthetic control estimate would provide a lower bound on the magnitude of the causal effect of the German reunification on GDP per capita in West Germany." (Abadie 2021, p. 410)

: Longer pre-treatment period for a better fit vs. Shorter pre-treatment periods to avoid structural breaks

Source : [Week 7-3] 통제집단합성법의 가정과 검증

9-2. Synthetic Control Method
: Industry Cases

현금 결제 시도의 사례

문제 배경
라틴 아메리카와 인도 등 신용카드 사용이 적은 시장에서 현금 결제를 도입

1. **거스름돈 문제:** 운전자가 거스름돈을 준비해야 하는 불편함.
2. **서비스 요금 징수 문제:** 운전자가 Uber에 돈을 빚지는 상황 발생 가능.

해결방안
운전자에게 현금 결제 요청을 알리는 기능을 도입

A/B 테스트의 어려움

- **스필오버 효과:** 한 그룹의 처리가 다른 그룹에 영향을 미침.
  - 현금 결제를 선호하는 운전자가 많아지면, 카드 결제는 다른 운전자에게 넘어가게 되어 시장 전체에 영향을 미침.

Source : [Nick Jones, Sam Barrows: Uber's Synthetic Control | Pydata Amsterdam 2019]

현금 결제 시도의 사례

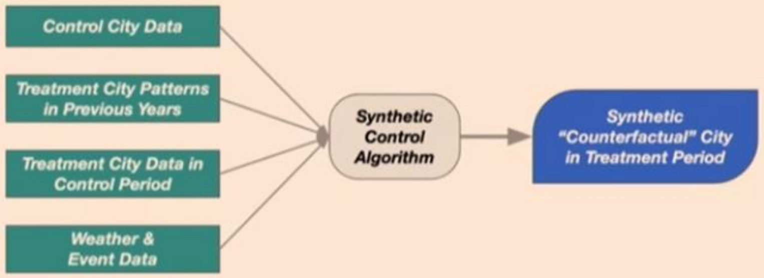
대안 방법

- 사전-사후 비교: 특정 시점 이전과 이후를 비교.
- 스위치백 설계: 특정 기간 동안 번갈아 가며 처리를 적용.
- 합성 통제 방법
  - 장점)
    - 정확한 인과 효과 추정: 여러 변수를 통제하여 보다 정확한 결과 도출 가능.
  - 단점)
    - 외부 충격: 결과 왜곡 가능성.
    - 작은 효과 감지 어려움: 효과 크기가 작을 경우 분석 어려움.
    - 사용자 간 이질성 분석 어려움: 도시 수준에서 집계하므로 개별 사용자 분석 어려움.
    - 사전 계획 필요: 명확한 계획 없으면 결과 조작 위험

Source : Nick Jones, Sam Barrows: Uber's Synthetic Control | Pydata Amsterdam 2019

현금 결제 시도의 사례

How Do We Form Our Synthetics?



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How Do We Form Our Synthetics?

We form a synthetic model of Sao Paulo

$$y_t^{SAO} = F(y_t^{RIO}, y_t^{SAN}, y_t^{LIM}, \dots, y_{t-l}^{SAO}, z_t; \theta)$$

where $\boldsymbol{y}^{SAO}$ denotes the data in Sao Paulo, $\boldsymbol{y}^{RIO}$, $\boldsymbol{y}^{SAN}$, $\boldsymbol{y}^{LIM}$ are control cities, and $\boldsymbol{z}$ is other data like weather, traffic, holidays, etc.

We assume a structure $\boldsymbol{F}$ and a loss function $\boldsymbol{L}$ over pre-treatment data, and solve

$$\hat{\theta} = \arg\min_{\theta} \mathcal{L}(\{y_t^{SAO}, F(\dots;\theta)_{t \text{ before treatment}})$$

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How Do We Estimate Treatment Effect?

Our treatment effect at time $\boldsymbol{t}$ in Sao Paulo is then

$$\hat{\beta}_t^{SAO} = y_t^{SAO} - \hat{y}_t^{SAO} = y_t^{SAO} - F(y_t^{RIO}, y_t^{SAN}, y_t^{LIM}, \dots, y_{t-l}^{SAO}, z_t; \hat{\theta})$$

We can do average treatment effect across cities and dates

$$\hat{\beta} = \sum_{\text{cities } j} \sum_{\text{periods } t} \hat{\beta}_t^j \mathbf{1}_{\{j \text{ treated in } t\}}$$

We can do inference by comparing how extreme $\hat{\beta}$ looks compared to estimated treatment effects in placebo data.

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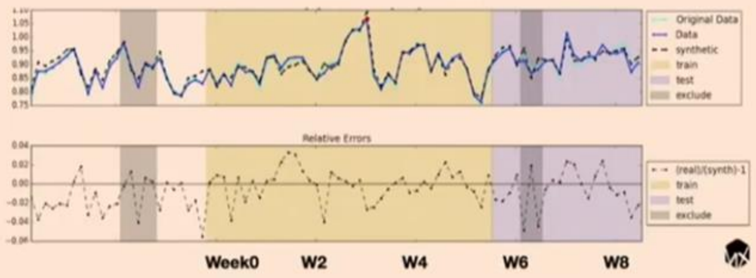
It Actually Works!!

Using synthetic control we've been able to model some surprisingly irregular time series.

Sao Paulo ~ 23% Rio de Janeiro + 10% Santiago + 6% Lima + ...



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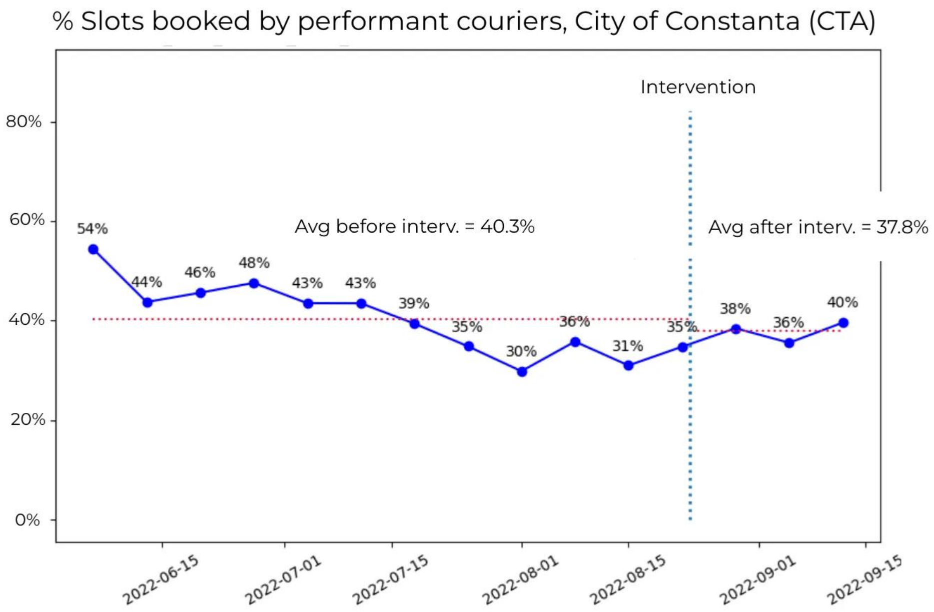
Source : [Nick Jones, Sam Barrows: Uber's Synthetic Control | Pydata Amsterdam 2019]

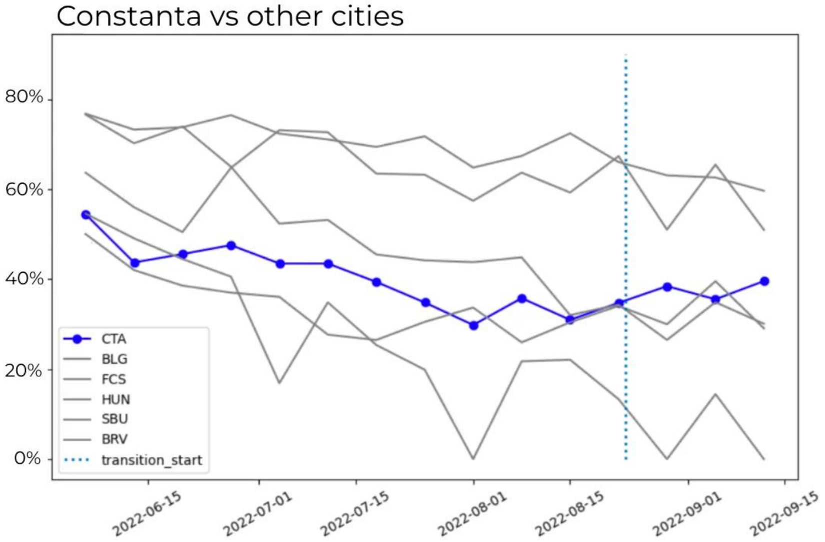
신규 피처 및 알고리즘 개선 평가 사례

Introduction

At Glovo, we are always developing new features and algorithms or improving the current ones. But how do we measure the impact of every change? The simplest way to measure it is to make a comparison between before and after. Look at the example below, where we implemented a new algorithm to rank the couriers and would expect more slots booked by performant couriers. Comparing the average metrics before the intervention and after it, **we see a reduction of 2.5pp (37.8% — 40.3%). So, if we take this at face value, as an estimate of the treatment effect, can we conclude that the new algorithm is worse than the previous one?**

The metric we're looking at is the % slots booked by performant couriers. We want this metric to be as high as possible because the best couriers provide the best service to our customers. It's impossible to run an AB test at courier level randomization in the city because we can't simply split the city in half, as one group would impact the other. A switchback test is not possible either, because changing the algorithm implied changes in the app and it would operationally be an overkill. Neither could we compare one city with another (matching or clustered randomization), because we wouldn't have enough cities to achieve power. So, we were quite tight in terms of possibilities for experimentation.

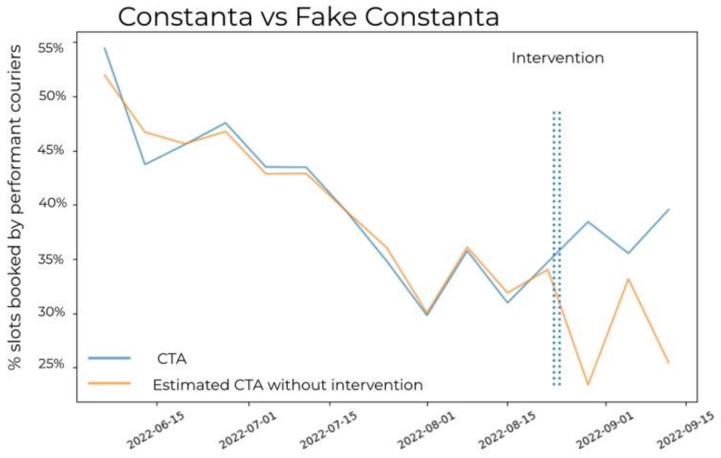


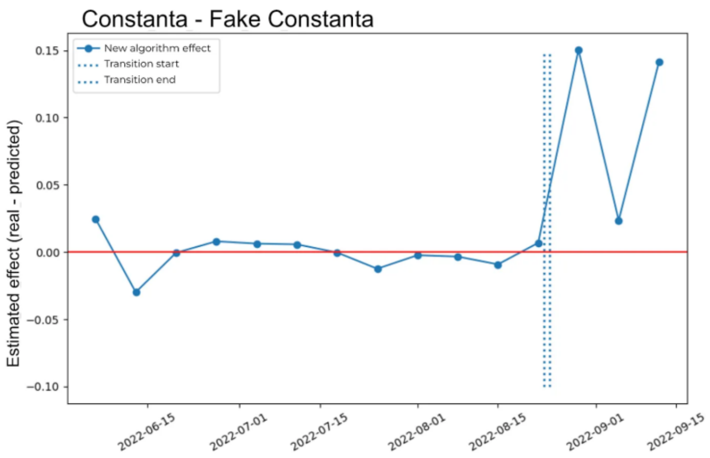


Source : The Glovo tech blog - An intro to Synthetic Controls in real life

신규 피처 및 알고리즘 개선 평가 사례

$$y_0 \approx w_{BLG} y_{BLG,0} + w_{FCS} y_{FCS,0} + w_{SBU} y_{SBU,0} + w_{BRV} y_{BRV,0}$$



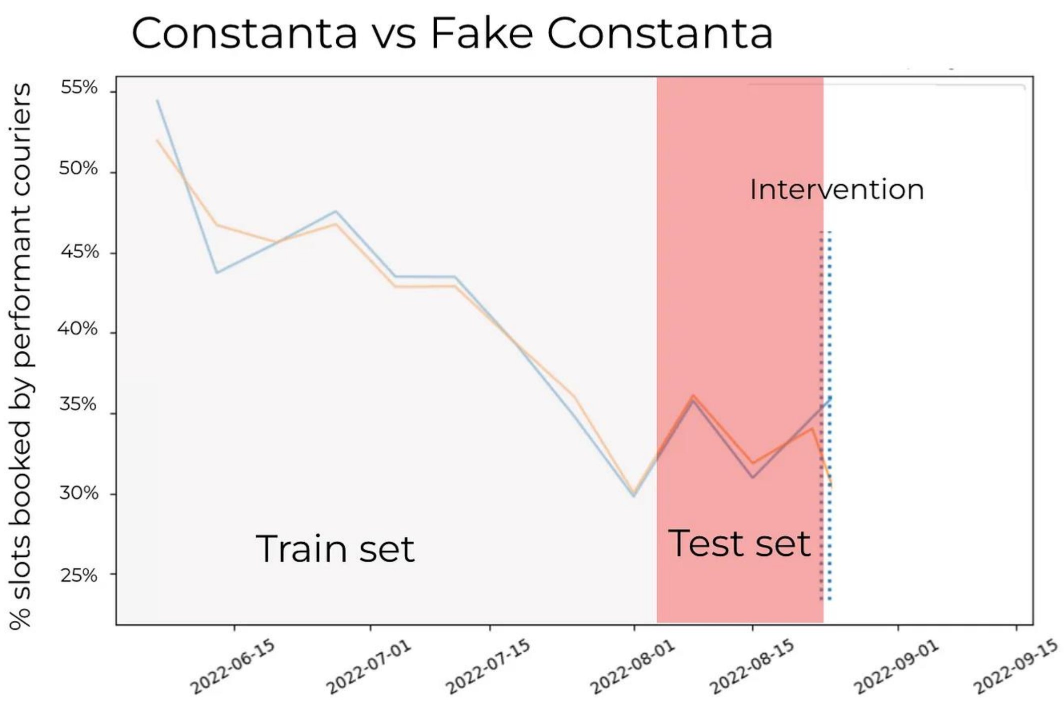


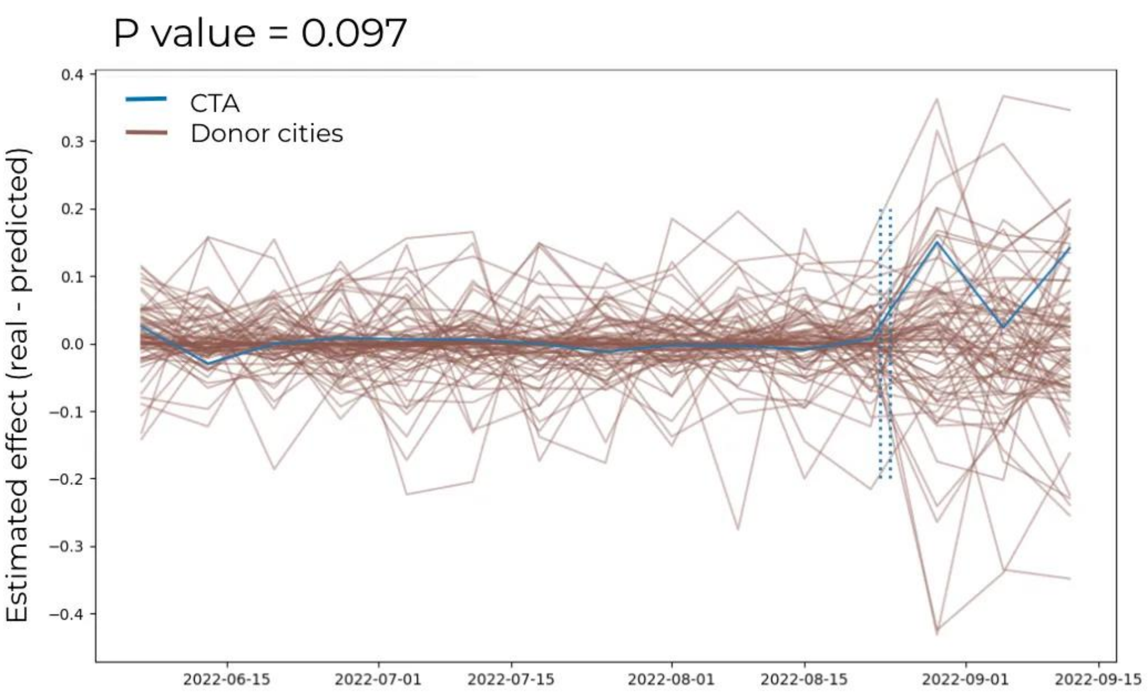
Donor city	Country	Weight
Blagoevgrad	Bulgaria	25%
Focșani	Romania	23%
Hunedoara	Romania	20%
Tuzia	Bosnia and Herzegovina	18%
Sibiu	Romania	6%
Resita	Romania	4%
Ruse	Bulgaria	2%
Mamaia	Romania	2%
Celje	Slovenia	1%
Sum	**-**	**100%**

Source : The Glovo tech blog - An intro to Synthetic Controls in real life

신규 피처 및 알고리즘 개선 평가 사례

평가방법





Source : The Glovo tech blog - An intro to Synthetic Controls in real life

Xandr 사례
디지털 광고 공간을 사고 파는 대규모 거래소 운영

OpenRTB (실시간 입찰) 요청
- 사용 가능한 광고 공간(배치)
- 광고 형식 (배너 또는 비디오)
- 선택 사항 및 사용자 지정 필드

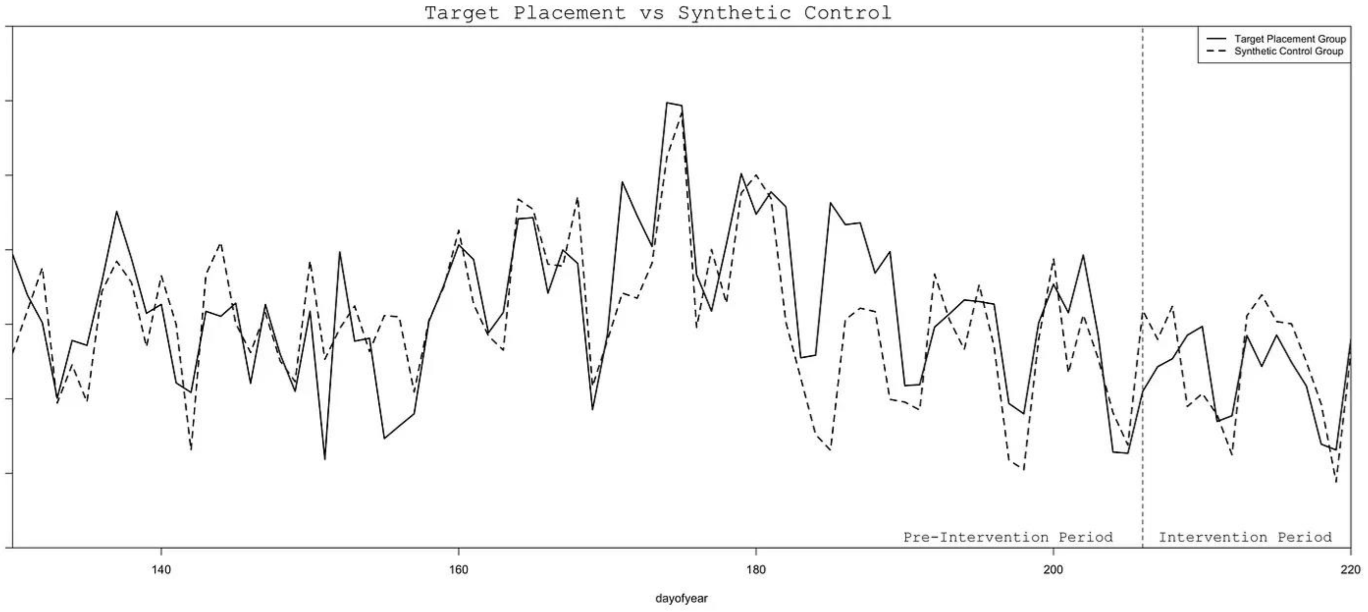
How (and how not) to approach the problem

Let's consider only one specific placement (i.e., ad slot) for now, which we call our target unit. This makes the problem more manageable. Say we would like to make some change to an OpenRTB request but want to know what effect this will have on our revenue. How can we make sure we estimate the true causal effect and not some spurious correlation or noise?

Source : Data Science at Microsoft - Causal inference using synthetic controls

Xandr 사례
새로운 OpenRTB 요청 변경이 수익에 미치는 영향

1. Donor pool 구성
   a. 1개 퍼블리셔와 협력하여 퍼블리셔가 보유한 다른 모든 배치(아마도 수십 개 또는 수백 개) 중에서 먼저 우리의 목표와 "유사한" 약 10개의 배치 하위 집합을 식별
2. 우리는 7월 25일에 "새로운 OpenRTB 요청 보내기"을 시행.
   a. 그 후 8월 7일까지의 2주를 실험 또는 치료 후 기간으로 사용



Weight	Unit Name
0.000	7648
0.000	2290
0.806	1263
0.000	7747
0.000	5605
0.194	4261
0.000	1239
0.000	3034

Unit weights found by the synthetic control method. Only two of the units have weights that are non-zero. Note that they sum to one, which makes interpretation quite easy.

Source : Data Science at Microsoft - Causal inference using synthetic controls

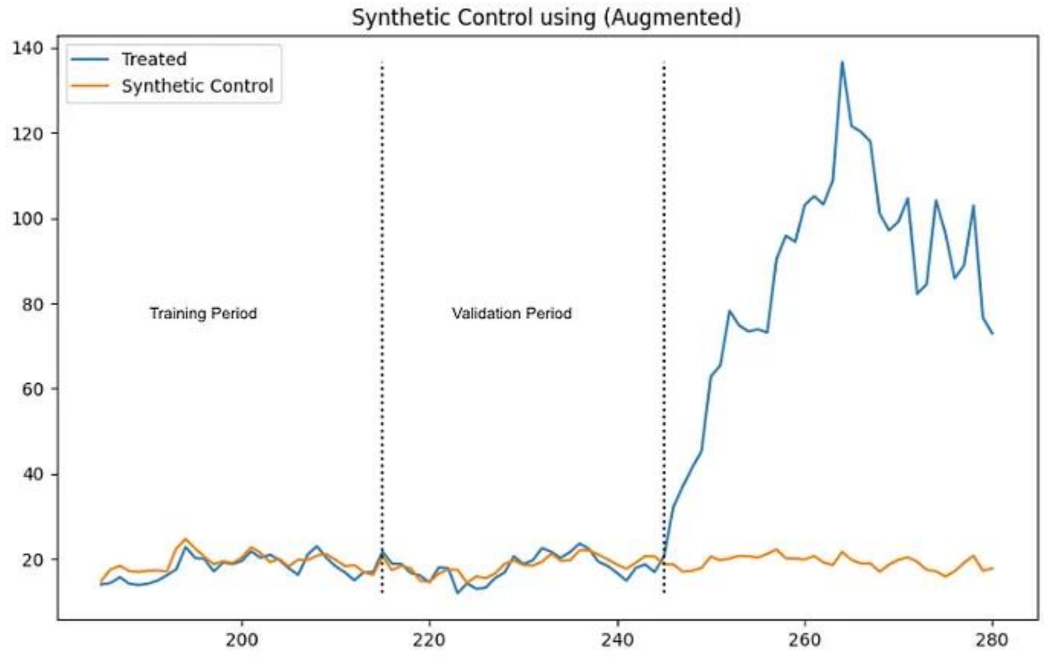
A Systematic Framework for Evaluating Game Events

Claire Willeck, Yimeng Tang

In Netflix Games DSE, we are asked many causal inference questions after an intervention has been implemented. For example, how did a product change impact a game's performance? Or how did a player acquisition campaign impact a key metric?

While we would ideally conduct AB tests to measure the impact of an intervention, it is not always practical to do so. In the first scenario above, A/B tests were not planned before the intervention's launch, so we needed to use observational causal inference to assess its effectiveness. In the second scenario, the campaign is at the country level, meaning everyone in the country is in the treatment group, which makes traditional A/B tests inviable.

Our framework utilizes a variety of synthetic control (SC) models, including Augmented SC, Robust SC, Penalized SC, and synthetic difference-in-differences, since different approaches can work best in different cases. We utilize a scale-free metric to evaluate the performance of each model and select the one that minimizes pre-treatment bias. .



Source : Netflix techblog - Round 2:A Survey of Causal Inference Applications at Netflix

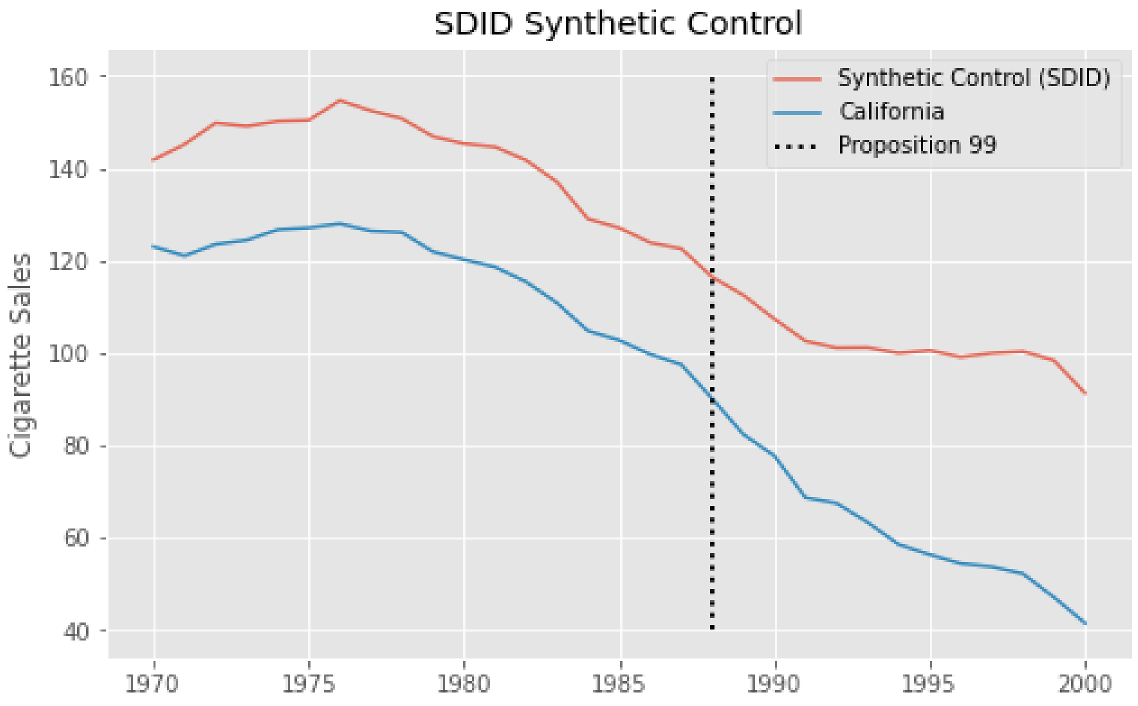
No robust approach of causal inference using synthetic control

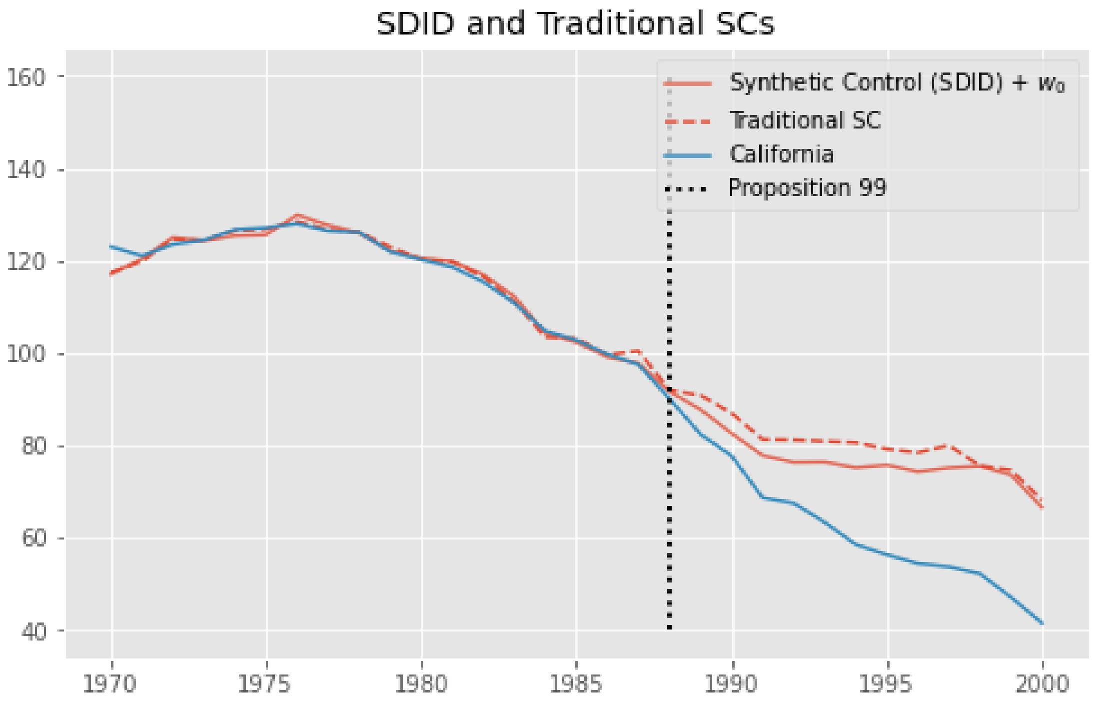
Another commonly-used approach is to use the synthetic control methodology to conduct causal inference study. The idea is to find a synthetic control group and use a time series of the outcome prior to the marketing intervention from control to predict the outcome during the marketing intervention (counterfactual) and then measure the lift between the counterfactual and actual. Since we will measure the app download, in this case, we can try to build a relationship between Android and iOS two platforms. However, given the fact that our campaigns across different marketing channels are optimized on a regular basis, the distribution of Android versus iOS is constantly changing. As a result, there is no easy way to build a robust synthetic control model to conduct such causal inference study.

Source : DOORDASH ENGINEERING - Adapted Switch-back Testing to Quantify Incrementality for App Marketplace Search Ads

9-3. Synthetic Difference-In-Difference

Synthetic Difference-In-Difference





DiD ATT: -27.349
SC ATT: -19.5136
SDID ATT: -15.6054

Source : [Causal Inference for the Brave and True - 25 - Synthetic Difference-in-Differences]

Synthetic Difference-In-Difference

Synthetic Control
: 주로 처리 전후의 결과 차이를 분석하는 데 중점

Synthetic Difference-in-Differences
: SDID에서는 Difference-in-Differences 접근법을 사용하여 시행 전후의 시간적 변화를 분석하고, 이를 처리 그룹과 합성 대조 그룹 사이에서 비교하여 효과 추정

따라서 SDID는 시간이 지남에 따른 효과의 변화를 더 정확히 파악할 수 있는 장점이 있음.

감사합니다
Q&A

참고자료

1. [Week 7-1] 통제집단합성법 (Synthetic Control Method)
2. [Week 7-2] 통제집단합성법 분석모형
3. [Week 7-3] 통제집단합성법의 가정과 검증
4. [Week 7-4] 통제집단 합성 시 발생할 수 있는 편향
5. Causal Inference for the Brave and True
    a. 15 - Synthetic Control
    b. 25 - Synthetic Difference-in-Differences
6. Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects
7. https://medium.com/@chyun55555/synthetic-control-method-for-causal-inference-basics-with-simple-mathematics-c61fc42fd472
8. Nick Jones, Sam Barrows: Uber’s Synthetic Control | Pydata Amsterdam 2019
9. The Glovo tech blog - An intro to Synthetic Controls in real life
10. Data Science at Microsoft - Causal inference using synthetic controls
11. Netflix techblog - Round 2:A Survey of Causal Inference Applications at Netflix
12. DOORDASH ENGINEERING - Adapted Switch-back Testing to Quantify Incrementality for App Marketplace Search Ads
13. research facebook - regression adjustment with synthetic controls in online experiments