Flat of the curve medicine?
Evidence from cancelled appointments

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Although many health services definitely improve health, in other cases even the best known techniques may have no effect.

Victor Fuchs (1966)

The bottom line is that a considerable amount of the care delivered in the United States is flat-of-the-curve medicine.

Victor Fuchs (2004)

…the typical enrollee in the [Rand HIE] study was on the "flat of the medical effectiveness curve," the portion where additional care was not buying medically effective care. Thus, care could fall significantly without adverse health consequences for the average person.

Jonathan Gruber (2006)

…nearly 20 percent of Medicare expenditures [are] are spent for health care with no measurable survival benefit.

Jonathan Skinner, Elliot Fisher, and John Wennberg (2005)

Estimates suggest that between one-quarter and one-half of medical spending is not associated with improved health, although this view is not without controversy.

David Cutler (2018)

Why would we be be on the flat of the curve?

Incentives for wasteful care

- Moral hazard
- Physician induced demand
- Medical care fraud
- Defensive medicine
- Market power
- Administrative bloat

Could we cut utilization without sacrificing health and longevity?

Problems with flat of the curve hypothesis

There are many margins: health care is not a single good or service.

Benefits may be flat on some margins and not others

What is the “average marginal benefit” associated with a big cut?

The plan

Quick preview

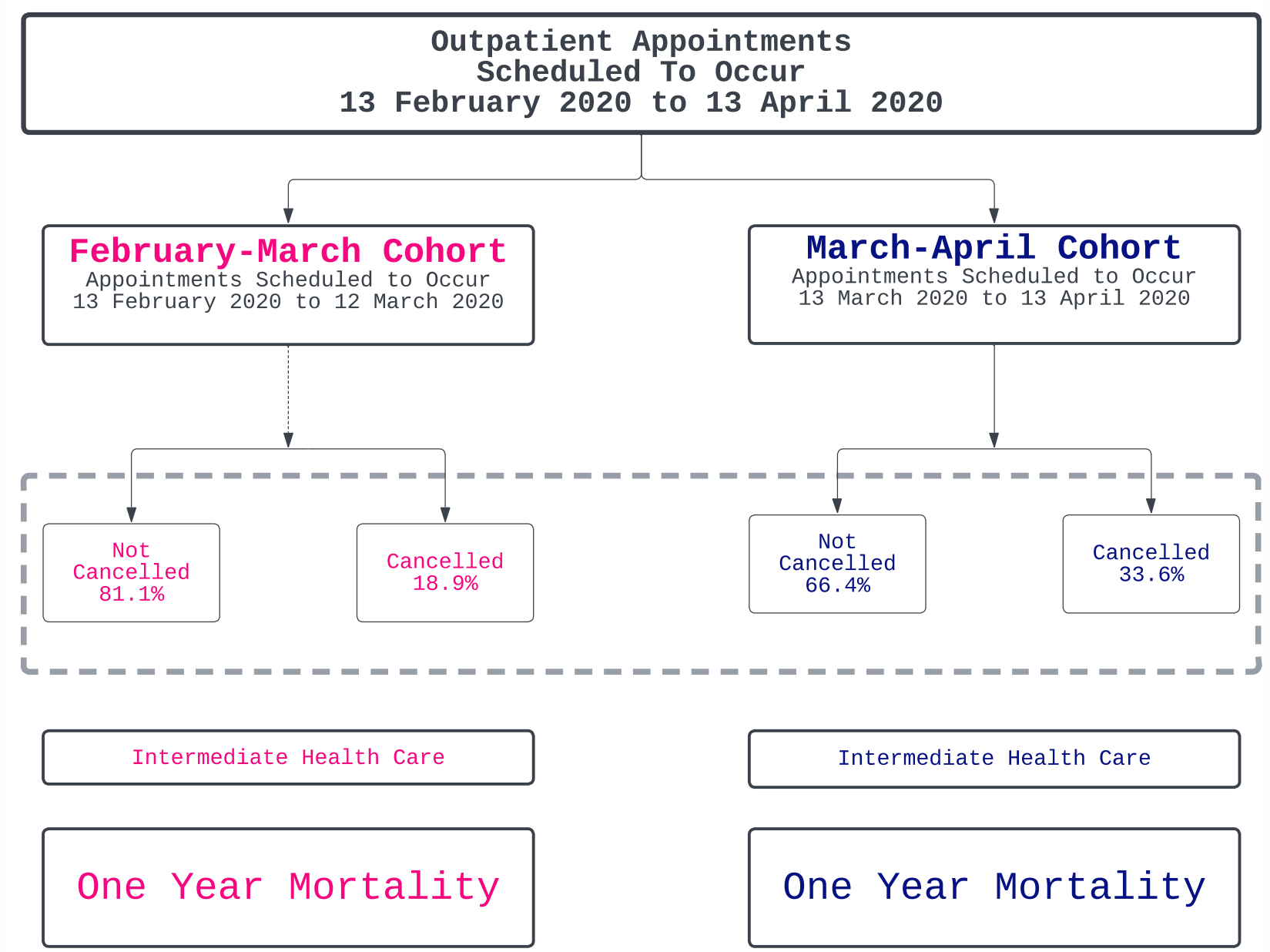
Data Sources

Methods

Results

Discussion

Preview


Outpatient Appointments
Scheduled To Occur
13 February 2020 to 13 April 2020
February-March Cohort
Appointments Scheduled to Occur
13 February 2020 to 12 March 2020
March-April Cohort
Appointments Scheduled to Occur
13 March 2020 to 13 April 2020
Not Cancelled 81.1%
Cancelled 18.9%
Not Cancelled 66.4%
Cancelled 33.6%
Intermediate Health Care
Intermediate Health Care
One Year Mortality
One Year Mortality

Key Results

First Stage

Cancellation Rate is 14.7 pp higher in Treatment Cohort

Large reduction in health care utilization

Intent to Treat

Treatment group has 4.3 extra deaths per 10,000 after one year

IV-LATE

Cancellation increases mortality risk by 29 per 10k

1 extra death for every 342 cancellations

Mechanisms

Mortality effect is driven by non-Covid Deaths

Compliers have high benefits from medical care

- Compliers are older

- Cancellation effect is much larger for people over 65

Cancellations tipped off cascade

- Cancelled visit causes fewer appointments and lab tests

- Short fall lasts about 1-3 months before catch up starts

Data Sources

HealthJump – Electronic Medical Records

Harmonized EMR – pooled from multiple providers

70 million+ patients, all payer types

Scheduling information

- Appointment date
- When was appointment booked?
- Did the appointment happen? Or was it cancelled?

Appointments and cancellations

We know the date each scheduled outpatient appointment is supposed to occur

- Unknown: exact procedure/reason for appointment
- Known: specialty of the physician hosting the appointment

We also know the date when each appointment was first booked

We know if an booked appointment was kept vs cancelled

Mortality Data

Datavant produces an annual death database for the US

- Death Masterfile + Obituary Data

Compared with death certificates, Datavant captures:

- 81% of all 2020 deaths
- 85% of all 2019 deaths

Tokenized Linkage

Common ID Variables: HealthJump and Datavant Deaths

- SSN (sometimes)
- Last Name
- First Name
- Soundex of Name
- DOB
- Zip
- Gender

Datavant receives data on HealthJump ID Variables:

- Tokenize HealthJump Records
- Same algorithm applied to Death Data

Mortality Status

Datavant contains month and year of death

We assume patient is alive if no record in Datavant Death Data

- Some deaths are missing from Datavant and so we will undercount level of mortality by about 15% to 20%

Methods

Effects of cancelled care on mortality

$$M_{ij} = \alpha + \beta_{ij} \times C_{ij} + \epsilon_{ij}$$

*Person i is dead **one year** after the scheduled appointment j.*

Causal effect of cancelled care on one year mortality rate

Appointment j was cancelled

Endogenous Unobserved Factors

Identification Strategy

Focus on appointments scheduled for February 13 to April 13

- Booked before the pandemic was a consideration

Two groups of appointments: February-March and March-April

- Comparable at baseline
- Both groups live through the same pandemic

March-April has much higher cancellation rate

March-April vs Feb-March is an instrument for cancelled care

Instrumental Variables Framework

First Stage -- Average effect of March-April appointment date on cancellations

$$C_{ij} = \pi_0 + \pi_1 \times Z_{ij} + e_{ij}$$

ITT -- Average effect of March-April appointment date on mortality

$$M_{ij} = \delta_0 + \delta_1 \times Z_{ij} + u_{ij}$$

IV-LATE -- Average effect of cancelled appointment on one year mortality among compliers

$$\delta_1 / \pi_1 = E[\beta_{ij} | Comp_{ij} = 1]$$

IV Assumptions – how do they apply?

Independence – March-April vs February-March is quasi-random

- Scheduling groups have balanced mortality risk
- No selective scheduling of healthier patients in February-March
- No seasonal scheduling patterns

Exclusion – March-April appointment date does not affect health

- Both groups live through (nearly) the same pandemic year.
- No effects of differential pandemic severity by follow up time

First Stage, Monotonicity, SUTVA have standard meaning

Analysis Plan

Balance and Evidence of Advance Booking

Mortality Effects -- First Stage, ITT, LATE (OLS and TSLS),

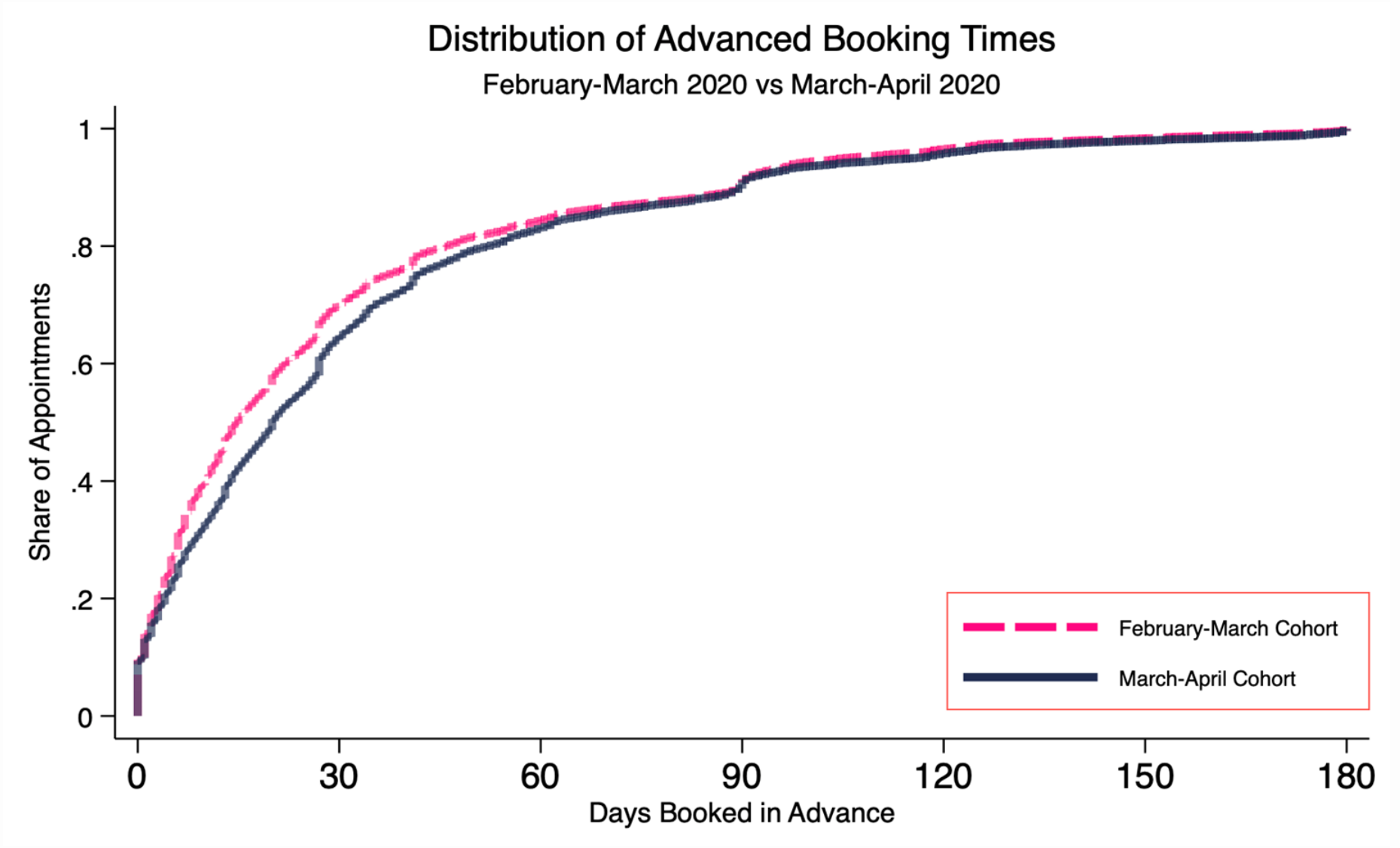
Threats to Validity

Mechanisms

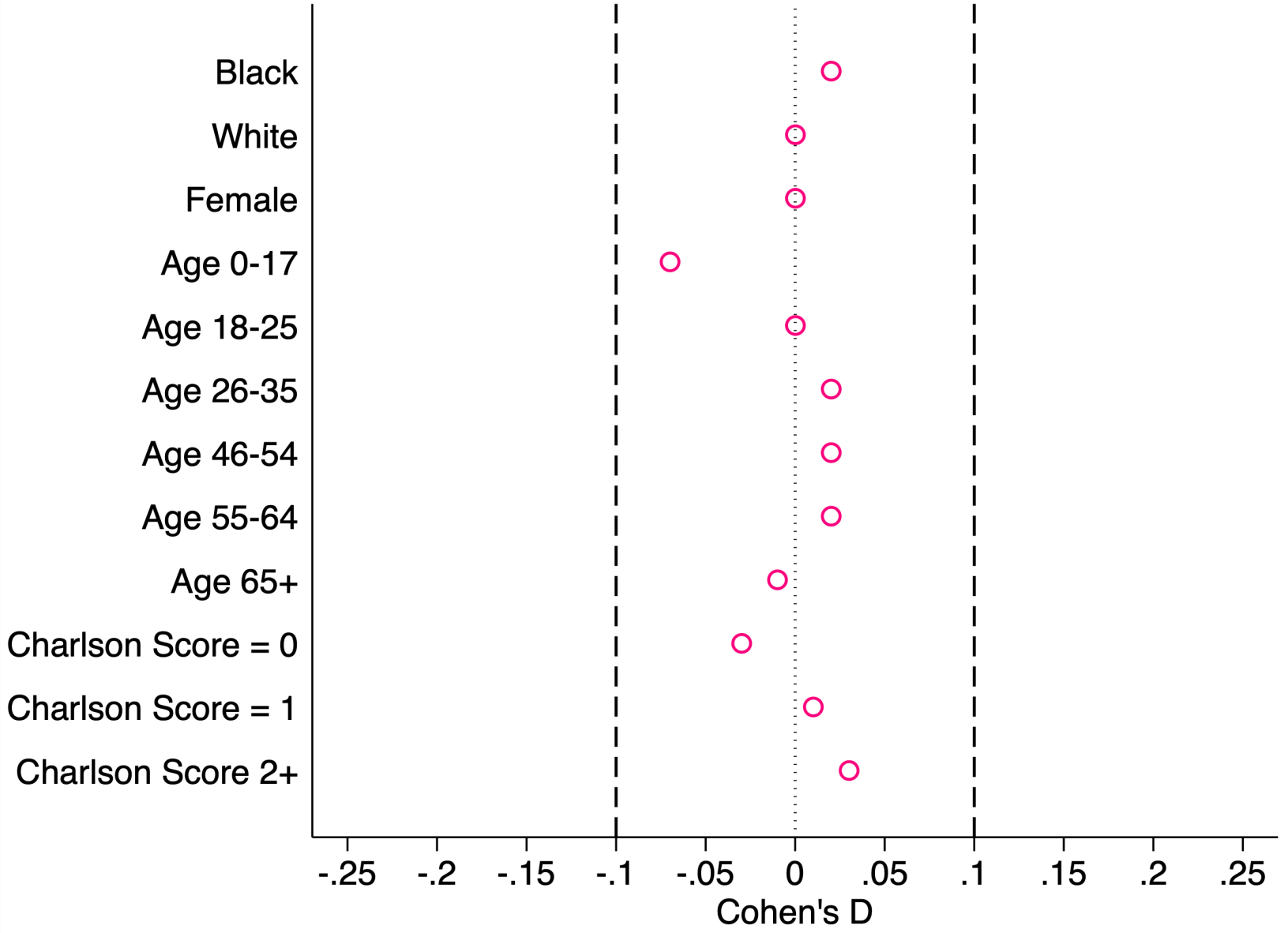
- Who are the compliers?
- Treatment effect heterogeneity
- Cascade of delayed/cancelled care

Results

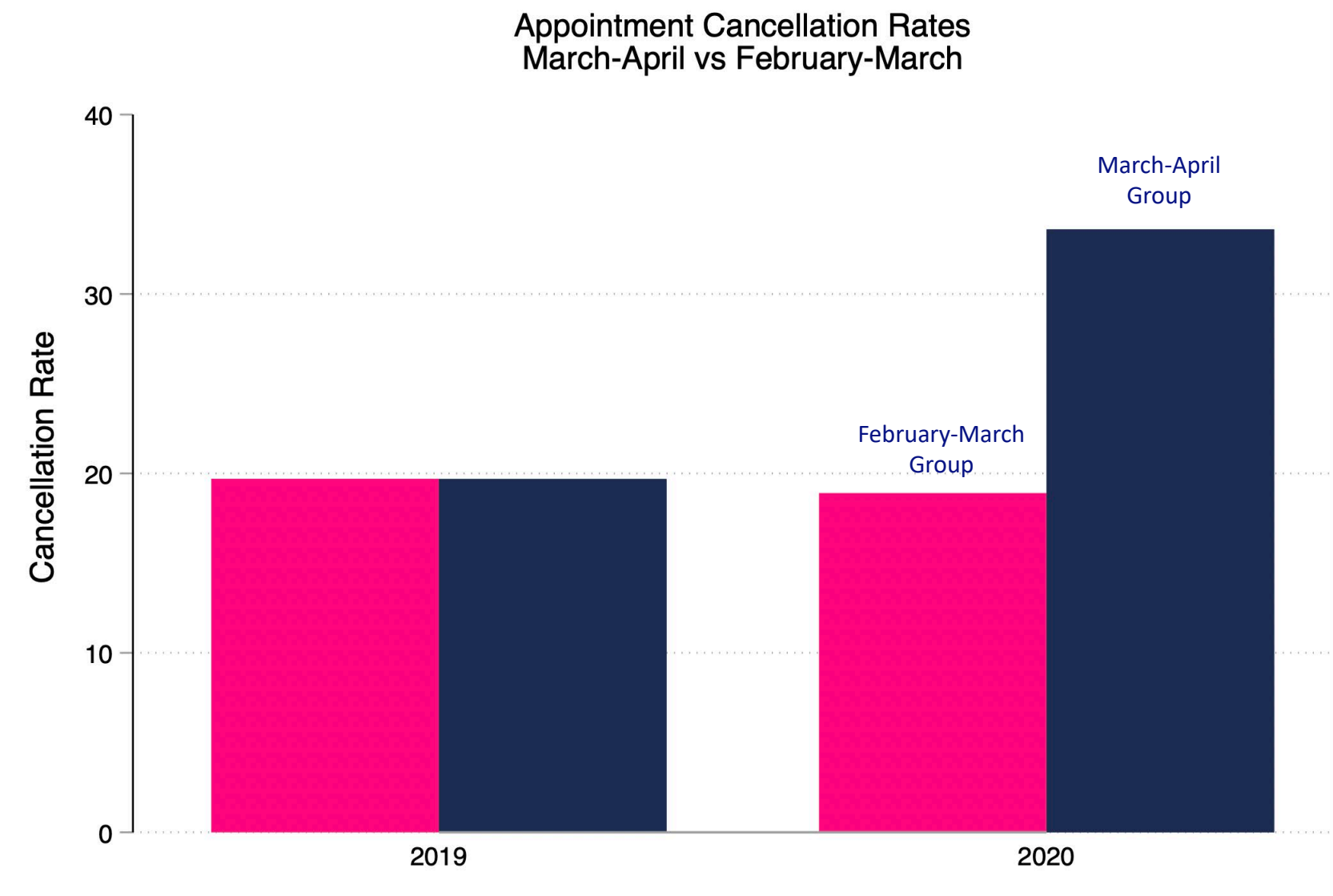
Most appointments scheduled 30+ days in advance



Balanced at baseline



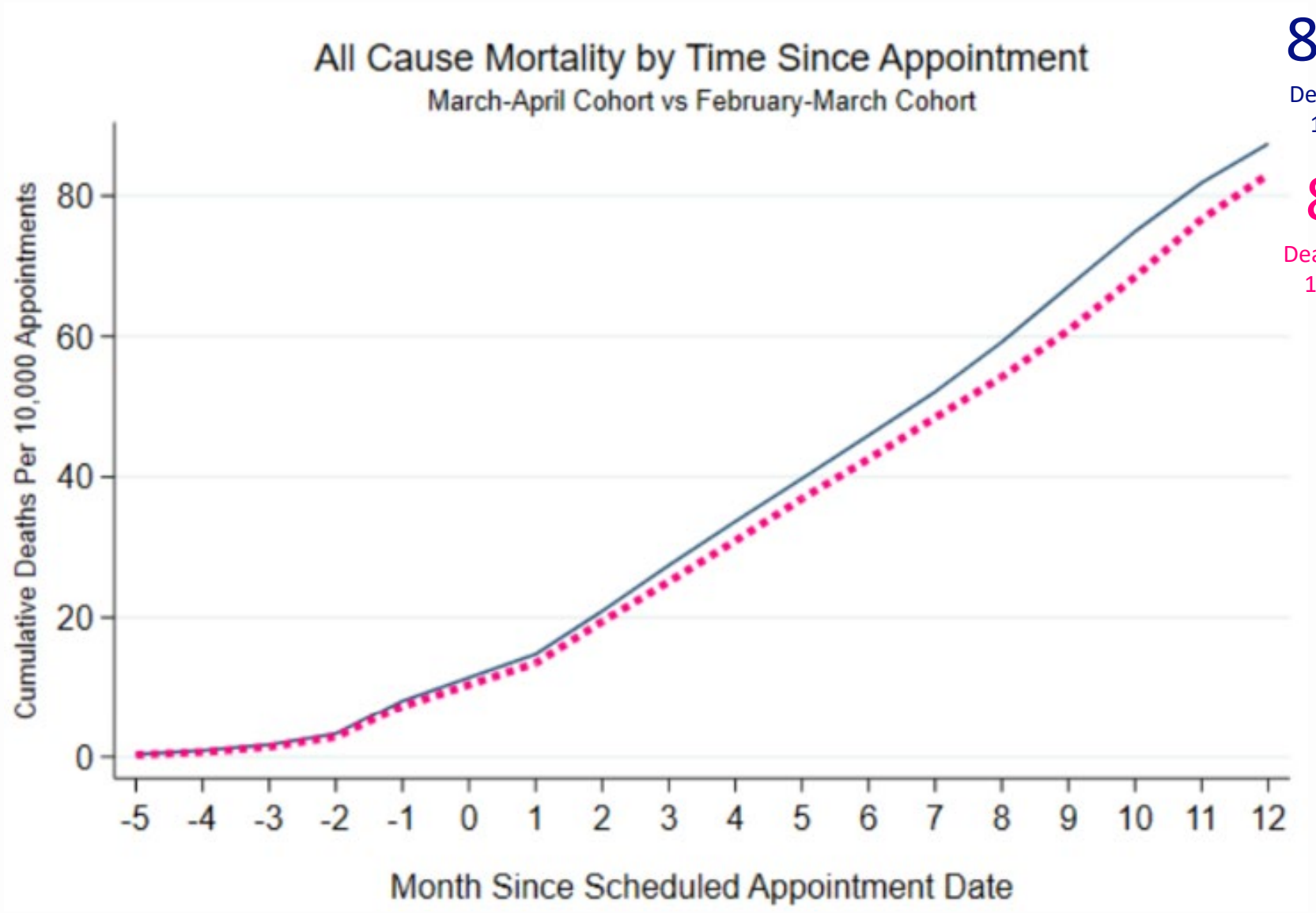
First Stage: 14.7 pp higher in March-April group



First stage regression estimates

	2020 Appointments	2019 Appointments (Placebo)
March-April	.147	-.004
	(.00041)	(.00036)
Intercept	.189	.197
	(.00026)	(.00029)
F Statistic	128,548	123
N	5,665,641	5,382,151

Cumulative Mortality – Intent To Treat



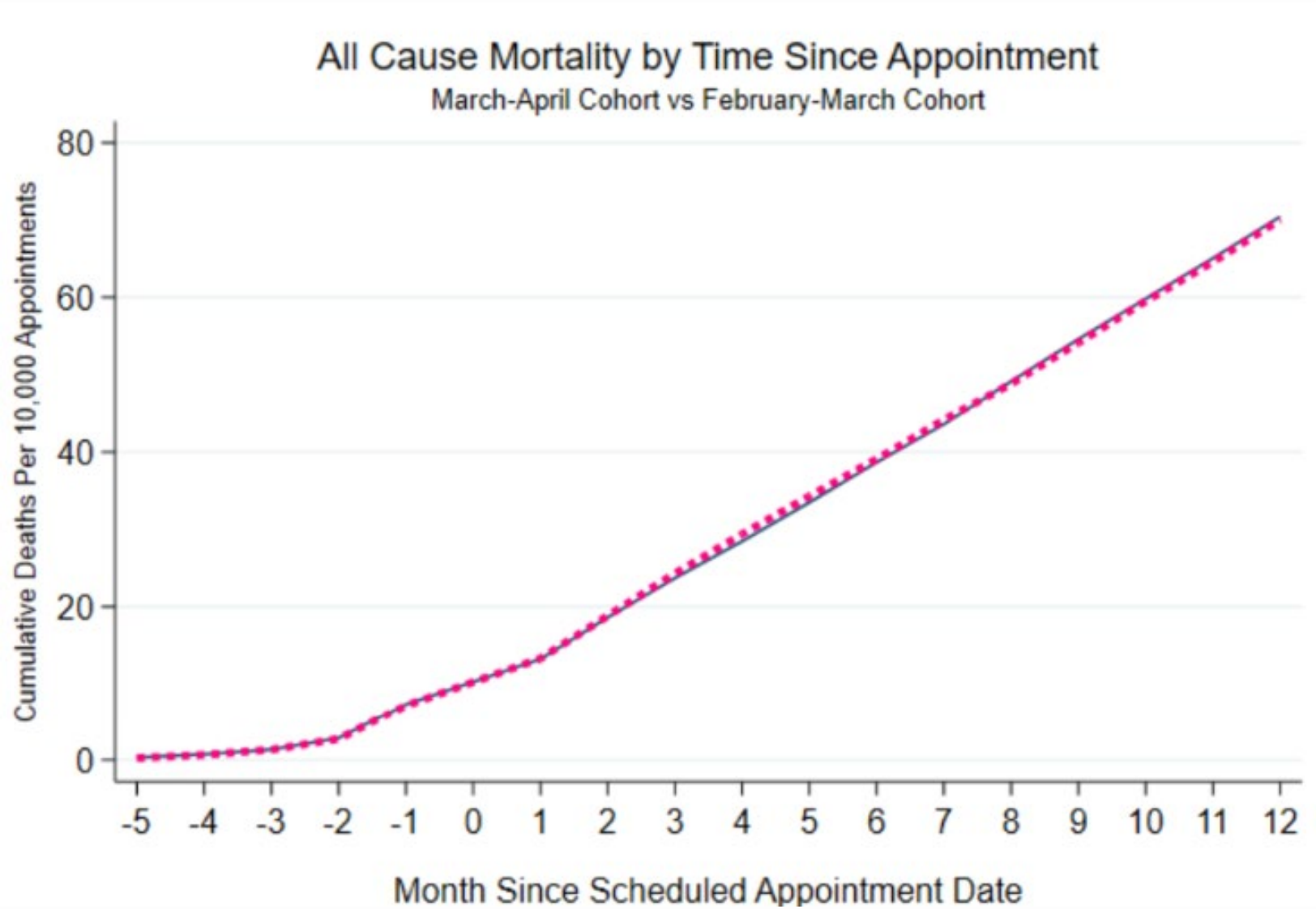
87.3

Deaths per 10,000

83

Deaths per 10,000

Placebo Check -- same comparison in 2019



Cancellation effects on one year mortality

	First Stage	ITT	IV
March-April	.147	4.3	--
	(.00041)	(0.9)	--
Cancelled		--	29.3
		--	(5.9)
Intercept	.189	83	77.5
	(.00026)	(1.6)	(1.6)
N		5,681,918	

Placebo check using 2019 data

	First Stage Effect	ITT Effect	Cancellation LATE-IV
2020	.147	4.3	29.3
	(.00041)	(0.9)	(5.9)
2019	-.004	0.4	-91.6
	(.00029)	(0.8)	(193.5)

Making sense of things

First Stage -- 14.7 pp increase in cancellation

ITT -- 4.3 deaths per 10,000 appointments at one year

Cancellation increases mortality risk by 29.3 deaths per 10,000

1 extra death for every $\left(\frac{29.3}{10{,}000}\right)^{-1} \approx 342$ cancellations

Elasticity

Mortality increases by (87.3 - 83)/83 x 100 = 5.2%

Cancellation rate: 18.7% in February-March → 33.6 in March-April.
Realized utilization fell by (66.4 - 81.3)/81.3 x 100 = -18.3%

Elasticity = 5.2 / -18.3 = -.28

A 10% cut in health care increases mortality rates by 2.8%

Threats to Validity

Ordinary Seasonality vs Special Seasonality

Cumulative mortality 12 months post-appointment date

- March-April Group: End point is March 2021
- February-March Group: End point is February 2021

2019 Placebo rules out “ordinary seasonality”

But 2020 was a very unusual year! What if there is “special” seasonality?

Robustness checks for Special Seasonality

Compare mortality at a common calendar month end point in both groups, pro-rate deaths to account for different “exposure time”

Some 2020 seasonality stories imply excess Covid-19 deaths.

- Repeat analysis -- cancellation effects on “suspected Covid mortality”

Fixed calendar month follow up

	ITT	Cancellation LATE-IV
One Year Follow Up	4.3	29.3
	(0.9)	(5.9)
Fixed Endpoint (March 2021)	6.0	40.5
	(0.9)	(5.9)
N	5,681,918	

Covid vs non-Covid Mortality

	Covid Mortality		Non-Covid Mortality	
	ITT	IV	ITT	IV
March-April	1.1	--	3.3	--
	(0.31)	--	(0.8)	--
Cancelled	--	7.2	--	22.6
	--	(2.2)	--	(5.5)
N	5,665,641			

Does cancellation effect depend on the severity of the epidemic?

External validity

Effect of missed care

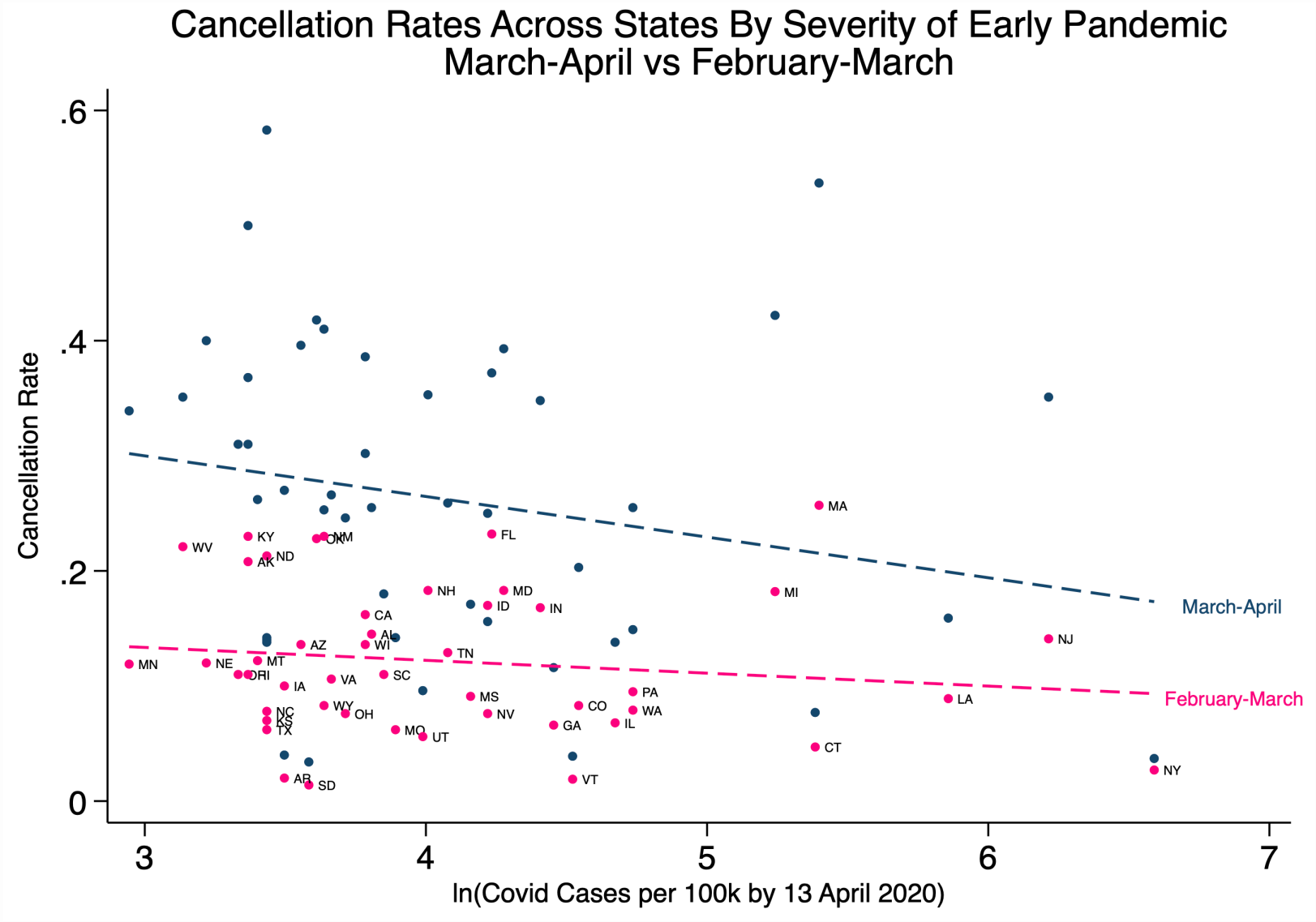
vs

Effect of missed care during pandemic?

Maybe harder to reschedule appointments during Covid?

Compare effects in places with different early pandemic severity

Cancellation shock by early pandemic conditions



If anything, cancellation had smaller effects in states with more severe early epidemics

	ITT	Cancellation LATE-IV
Pooled Model (All States)	4.3	29.3
	(0.9)	(5.9)
Epidemic Severity		
Low Early Covid States	4.8	34.9
	(1.1)	(7.7)
High Early Covid States	4.4	19.2
	(1.4)	(7.7)
N	5,665,641	

Mechanisms:
Compliers have high benefit?

Who are the compliers?

	February-March Mean	Complier Mean
Charlson Score	.46	.47
Age		
65+	.36	.48
55-64	.18	.18
46-54	.12	.10
36-45	.10	.08
26-35	.08	.06
18-25	.06	.03
0-17	.10	.06
Demographics		
Black	.09	.06
White	.49	.42
Female	.59	.59

Cancellation has larger effects on older patients

	ITT	Cancellation LATE-IV
Pooled Model (All Ages)	4.3	29.3
	(0.9)	(5.9)
Age Heterogeneity		
Under 65	2.6	22.3
	(0.6)	(5.4)
Over 65	9.8	48.9
	(2.2)	(10.7)
N	5,665,641	

Cancellation effect is larger with comorbdities

	ITT	Cancellation LATE-IV
Pooled Model (All Ages)	4.3	29.3
	(0.9)	(5.9)
Comorbidity Heterogeneity		
Charlson = 0	1.5	9.7
	(0.8)	(5.0)
Charlson ≥ 1	6.6	51.0
	(3.1)	(23.5)
N	5,665,641	

Mechanisms:
Cascade of Disruptions?

Cancelling an appointment may slow down a chain of events

Stylized Example

Focal appointments might result in ordering some tests

A follow up appointment draws samples and sends them to the lab

The labs may result in a diagnosis, with subsequent treatment

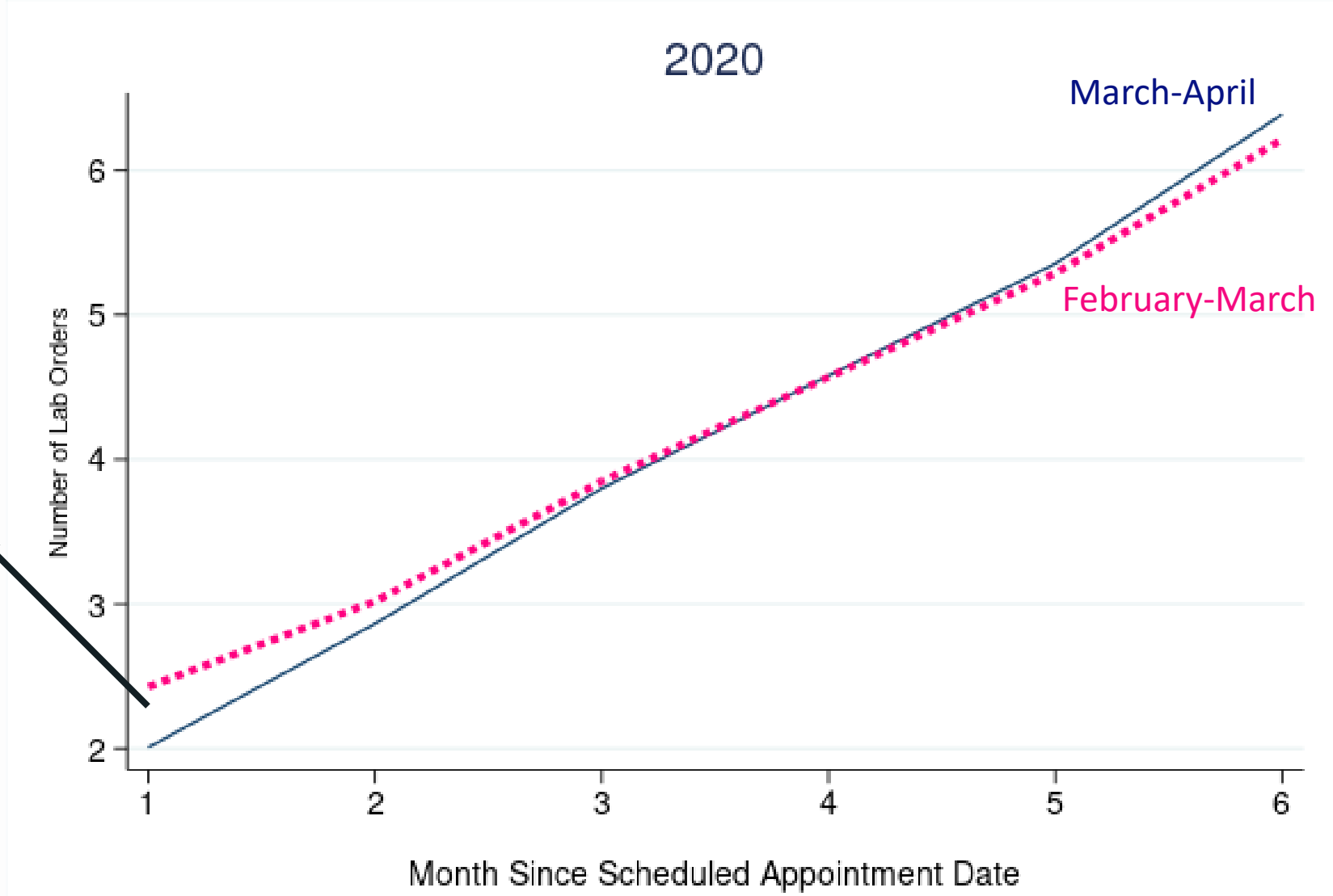
Cancelling an appointment might delay the entire chain of events.

Cumulative lab tests by exposure group

The March-April group does not just miss one appointment

The initial cancellation tips off a period of reduced care that lasts about 1-3 months

Catch up eventually means March-April has slightly more labs by 12 months



Fewer lab tests for months 1 to 3 after appointment



Cancellation LATE on subsequent lab tests

	ITT	Cancellation LATE-IV
1 Month Post	-.72	-6.0
	(.01)	(0.1)
2 Months Post	-.42	-3.5
	(.01)	(0.1)
3 Months Post	-.15	-1.3
	(.01)	(0.1)
N	5,665,641	

Discussion

Styles of research

Small area variations - compare health in places with high vs low aggregate spending

- Health is typically similar and high and low spending places

Health insurance studies - compare health and utilization with exogenous cost sharing.

- Cost sharing usually does reduces utilization but negligible effects on health.

Emergency studies (i.e. ambulance availability) - compare health outcomes when people have “sudden” health needs in scarce vs plentiful settings

- Access to care matters for health. But focus in on specific types of urgent care.

Triage rule studies - compare health outcomes of patients who do not receive health services for haphazard reasons.

- Often find that receiving the care does improve health.

How does our study fit?

Supply shock similar to designs based on ambulances

Probably different from insurance studies with price variation.

- Cost-sharing may lead people to cut back on low value services first
- When health services are simply scarce, people cut back even the service is high value and not on the “flat of the curve”.

Discussion

Results suggest that a lot of marginal medical care is actually quite valuable in producing health and reducing mortality.

- Suggests mortality rates grow by 2.8% for 10% cut in utilization

Skipping an appointment may slow down testing, diagnosis, treatment, etc.

Older patients may have particularly high value of medical care, even at the margin.

- Contrary to the standard view that health care is quite wasteful for older Medicare patients.