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	Strictly speaking: Exa punishment and s	mining teacher use of student outcomes	
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March 18, 2022

Motivation		
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Big Picture		
Motivation		

- Extant research has identified a variety of negative academic and long-run effects from exclusionary discipline (Chu & Ready, 2018; Lacoe & Steinberg 2018; Novak, 2019; Bacher-Hicks et al., 2019).
- Exclusionary discipline leads students to disengage with school (Pyne, 2019) and, troublingly, exhibits racial bias in its use (Skiba et al., 2011; Barrett et al., 2021; Shi & Zhu, 2021).
- Scholars have begun to examine school-related factors that shape the use of discipline.
  - Teacher diversity reduces Black-White gap in referrals (Lindsey & Hart, 2017)
  - Principal variation in use of punishment (Sorensen et al., 2021)
  - Policies on use of exclusionary punishments (Craig & Martin, 2019; Eden, 2017; Lacoe & Steinberg, 2018)
- Teachers' contribution to the production of discipline and impacts on student achievement remains an open question.

Motivation		
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Big Picture		
Research Q	uestion	

- How does teacher use of referrals affect students' academic outcomes?
- How does racial bias in teachers' use of referrals impact student outcomes?

	Data and Methods	
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Data		
North Caro	lina Data	

- Data from North Carolina Education Research Data Center (NCERDC)
- Contains full universe of traditional public school students
  - Provides student test scores in 3rd-8th grade
  - Provides matched teacher and student identifiers
  - Provides rich information about teachers
- Restrict sample to self-contained classrooms in grades 3-5 from 2008-2013
- Analytic sample: 155,287 students, 10,856 teachers, 28,408 classrooms, 1,200 schools

	Data and Methods	
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Identification strategy		
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$$P_{ijct} = \alpha_{jt} + \gamma_1 P_{i,t-1} + \gamma_2 A_{i,t-1} + \varepsilon_{ijct}$$
(1)

- *P<sub>ijct</sub>* represents student-level counts of referrals for subjective infractions
- $\gamma_1$  and  $\gamma_2$  capture the contribution of prior year referrals and achievement
- $\alpha_{it}$  is a teacher-year fixed effect

$$P_{ijct} = \rho_{1jt} \textit{black}_i + \gamma_{1jt} P_{i,t-1} + \gamma_{2jt} A_{i,t-1} + \varepsilon_{ijct}, \forall t \in \{j\}$$
(2)

• *rho*<sub>1</sub> captures the conditional difference in Black-White referrals assigned within teacher-year

	Data and Methods	
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Identification strategy		
Effect of Re	ferral lise	

 $Y_{ijcgst} = \beta_1 \widehat{\alpha}_{jt} + \beta_2 Z_j + \beta_3 X_i + \gamma_1 Y_{i,t-1} + \omega M_c + \varphi_s + \psi_g + \tau_t + \varepsilon_{ijcgst}$ (3)

- *Y<sub>ijcgst</sub>* represents student-level measures of academic outcome (absences, math scores, ELS scores)
- $\hat{\alpha}_{jt}$  represents our estimated teacher contribution to use of referrals (measure of punitiveness, measure of bias)
- Controls for lagged outcomes; student and teacher observables; class-level observables; school, grade, and year FE.
- Bootstrapped standard errors with 500 replications.

	Results	
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Teacher punitiveness		

## Effect of teacher punitiveness on academic outcomes

	(1)	(2)	(3)	(4)
	Absences	Chronically	ELA	Math
Punitiveness	0.494***	0.011***	-0.041***	-0.068***
	(0.06)	(0.00)	(0.01)	(0.01)
Observations	313,326	313,326	313,326	313,326
R-squared	0.363	0.139	0.645	0.671
All teacher controls	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
All student controls	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Lagged Absences	$\checkmark$	$\checkmark$		
Lagged test Scores	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
School, grade, and year FE	$\checkmark$	✓	$\checkmark$	$\checkmark$

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10.

	Results	
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Teacher punitiveness		

## Spillover effect of teacher punitiveness

	(1)	(2)	(3)	(4)
	Absences	Chronically	ELA	Math
Punitiveness	0.122	0.004	-0.099***	-0.123***
	(0.09)	(0.00)	(0.01)	(0.01)
Observations	266,190	266,190	266,190	266,190
R-squared	0.366	0.135	0.654	0.692
All teacher controls	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
All student controls	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Lagged Absences	$\checkmark$	$\checkmark$		
Lagged test Scores	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
School, grade, and year FE	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10.

		Results	
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Teacher bias			
Effect of te	acher bias		

 $\checkmark$ 

 $\checkmark$ 

	(1)	(2)	(3)
	Absences	ELA	Math
Panel A. White S			
Bias	-0.064**	-0.003	-0.006*
	(0.03)	(0.00)	(0.00)
Observations	118,746	118,746	118,746
R-squared	0.364	0.609	0.646
Panel B. Black S			
Bias	0.385***	-0.015**	-0.034***
	(0.06)	(0.01)	(0.01)
Observations	51,152	51,152	51,152
R-squared	0.327	0.590	0.612

 $\checkmark$ 

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.10.

All controls

		Conclusion
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Conclusion		
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Conclusions		

- Teachers play an important role in the disciplinary pipeline and their behaviors in this area have consequential impacts on students
- Teachers who respond more harshly to minor infractions have less productive classrooms in general
  - Student absenteeism increases
  - Student achievement decreases in both ELA and math
  - The impact on student achievement spills over to students who did not receive referrals
- Racial bias in teachers' use of referrals has negative impacts concentrated on the recipients of the bias
- Overall effects of bias seem quite modest and independent from measures of teacher effectiveness

			Conclusion
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Conclusion			

## Thank You! Comments welcome. Contact: sbholt@albany.edu

		Conclusion
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Conclusion		

## Distribution of Punitiveness



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		Conclusion				
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Distribution of Bias						
	Data and Methods 000	Data and Methods Results 000 000				



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