Bike Lanes, Congestion, and Road Safety. Evidence from New York City.*

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Cities increasingly invest in cycling infrastructure, with a primary focus on bike lanes. In this paper, we focus on New York City, and analyse the effect of such bike lanes on congestion and road safety. We combine observations of road accidents with changes in infrastructure and street-level proxies for traffic volumes and traffic speed. These proxies are obtained using trips made in yellow taxis and on public rental bikes. Our results suggest that moving from standard bike lanes (dedicated but directly next to traffic lanes) to protected paths (fully separated) slightly increases both traffic speed and flow. We find no effect, with small standard errors, of bike lanes on overall traffic accidents. The point estimates for the effect on bicycle safety have the expected sign, suggesting a reduction in accidents, but are not statistically significant.

Keywords: road safety, cycling infrastructure, congestion, accident risk.
JEL Codes: I18, J24, K32, R41

1. Introduction

Urban policy makers around the globe increasingly see cycling as an essential part of sustainable urban transport. Urban cycling is associated with benefits for public health, reductions in local and global air pollution, and increased road capacity (Gössling and Choi, 2015). However, compared to other transport modes, cycling is also associated with higher accident risk. A modal shift from cars to bicycles, for instance, can lead to more accidents (Schepers and Heinen, 2013). Therefore, many cities are investing in cycling infrastructure, often with dedicated and protected bicycle lanes, to accommodate an increase in urban cycling, while minimising road safety issues.

In this paper, we analyse the effect of bicycle infrastructure on road safety and traffic speed. We focus on New York City (NYC), where we can exploit spatial and temporal variation

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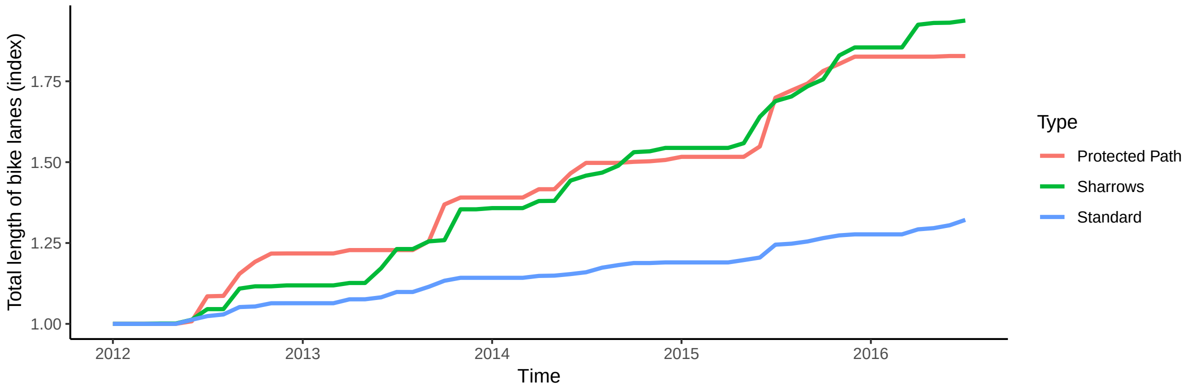


Figure 1: Growth of dedicated bike lanes in New York City over the sample period.

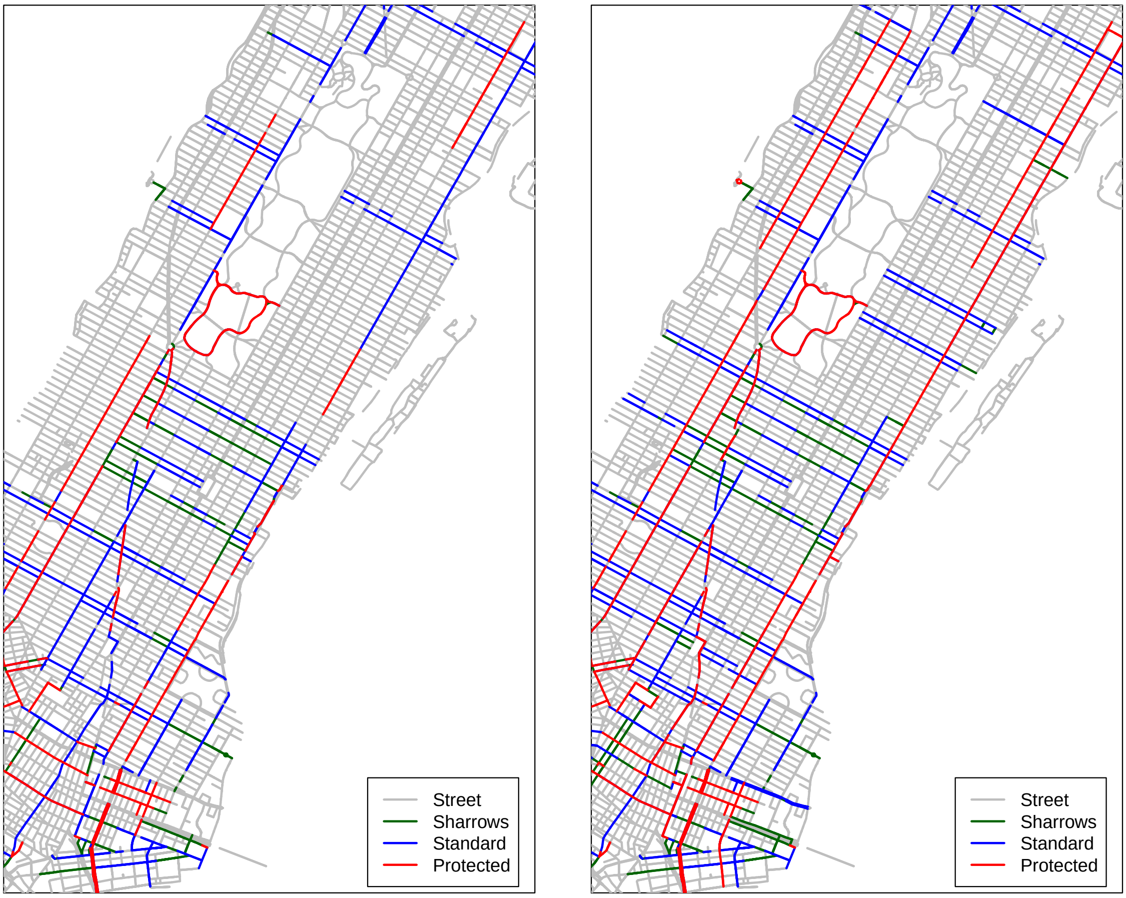
Notes: Indices are calculated per month with January 2012 as base. Protected bike path indicates a lane that is separated from other travel lanes, by parking bays, a barrier, or both. Streets with sharrows do not have dedicated bike lanes, but have marks on the road surface indicating that the road is shared between cars and cyclists. Standard bike lanes are marked on the road surface and adjacent to other travel lanes.

from recent expansion of cycling infrastructure, with a focus on installation of protected bike paths. Our paper contributes to an increasing body of literature that focuses on road safety and cycling infrastructure. Marshall and Garrick (2011) find safety benefits of bike lanes by analysing overall road safety trends in several cities in California. At a more disaggregated level, Li et al. (2017) find that installation of London's Cycle Superhighways did not increase collision rates.[1] For NYC, Gu et al. (2017) find that bike lanes are cost effective due to their road safety improvements. In a related study, Wall et al. (2016) find that bike lanes decrease the severity of accidents with cyclists involved. Further, bike lanes appear to yield most safety improvements close to intersections and on roads with high traffic volumes (Kondo et al., 2018), but are often obstructed in NYC (Basch et al., 2019).

Figure 1 shows the development of bike lanes in NYC during our sample period. The figure highlights that bicycle infrastructure in NYC grew substantially, with a 75% increase in the total length of protected bike paths. Because the increase in protected paths occurred in waves, this provides us with temporal variation that we can exploit for identification. Hereby, we can infer a causal estimate under the assumption that the exact timing of bike lane installation is random, conditional on controls and several location and time fixed effects.

This paper proceeds as follows. Section 2 describes the data and presents descriptive statistics. Section 3 explains the methods employed. Section 4 discusses preliminary results.

[1]The authors do find an increase in the number of collisions, but this is driven by increased mileage on those roads. This highlights that traffic flows are an essential control in road safety analyses.



(a) 2012

(b) 2016

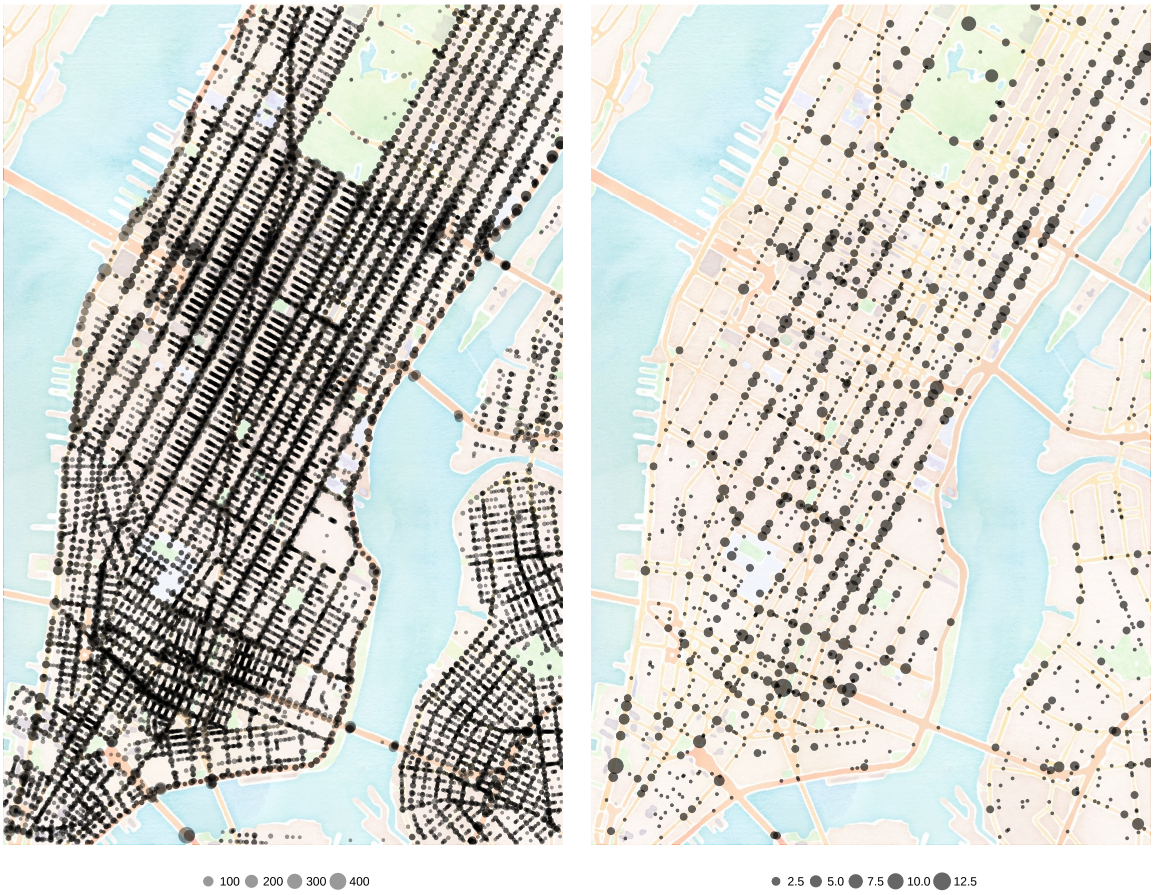
Figure 2: Map with spatial distribution of bike lanes in Manhattan between 2012 and 2016

2. Data

2.1. *Street network*

We obtain the street network in NYC from City of New York (2020f). For comparability between treated streets (those with a bike lane) and control streets, we only focus on 'normal' streets and thereby exclude highways, tunnels, trails etc. The street network is combined with bike lane information for each street segment, retrieved from City of New York (2020c). Thereby we have information on the location of each bike lane in NYC, and its installation date.

The maps in Figure 2 show the spatial distribution of cycling infrastructure in Manhattan at the start and end of our sample period (see Figure A1 in Appendix A for the whole city). The



(a) All accidents. (b) Accidents with cyclists involved.

Figure 3: Map with spatial distribution road accidents in Manhattan between 2012 and 2020
Notes: Map tile by Stamen Design, under CC BY 3.0, base layer data by OpenStreetMap, under CC BY SA.

maps highlight that NYC faced a substantial increase in bike lanes at specific streets accross and within multiple zones within the city.

2.2. *Road accidents*

We observe 1.38 million accidents (of which 38.9k with cyclists involved), as reported by New York Police Department (NYPD) between 2012 and 2019 (City of New York, 2020d). Based on the geographical location and time stamp, we assign accidents to the closest street, with time-specific bike lane properties at the time of the accident. Figure 3 shows accident locations for Manhattan, and indicates that both all accidents as well as accidents with bikes are spread around the most of the street network within our sample.

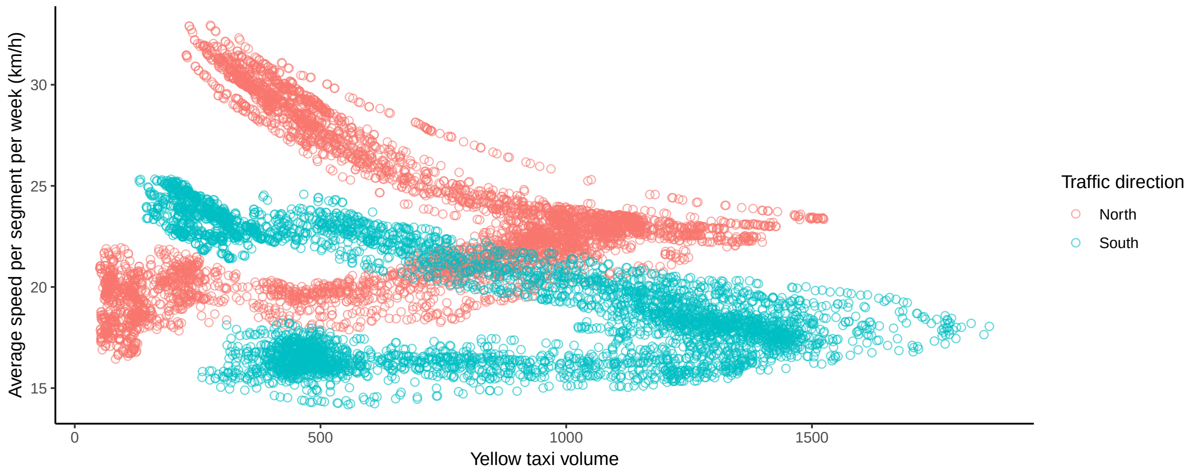


Figure 4: Flow and speed on Broadway

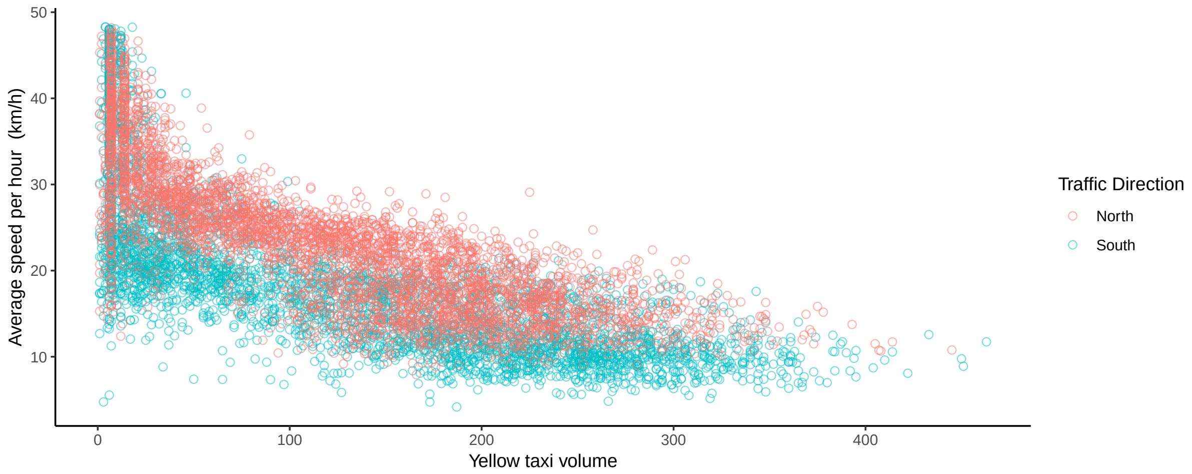


Figure 5: Flow and speed in a Census Tract 78 on Manhattan

2.3. *Taxi trips*

We observe origin-destination (OD) pairs for trips made in yellow taxis from City of New York (2020h). We use these data to construct proxies for traffic volumes and speed, where we follow Mangrum and Molnar (2017) and focus on within-road trips using the following steps. First, we exclude all taxi trips with origin and destination on different streets. Second, for these within-road trips we only include trips with the shortest path between origin and destination is equal to the distance measured by the GPS odometer. Third, for each trip we determine its contribution to average traffic speed and volume for each street segment that a trip passed.

Figure 4 shows the calculated speed and volume for an example street (Broadway on Manhattan) with two directions. As to be expected in a crowded city as NYC is, this speed-flow relationship exhibits the backward bending characteristics of the fundamental diagram of traffic flow Small et al. (2007). Similarly, Figure 5 shows that at tract level, we again observe a clear relationship between speed and flow, but this time without a backward bending part, so that we have a monotonic relationship between speed and flow over time. Both figures highlight that traffic speed is highly informative for traffic flow. We further analyse the quality of taxi flow and speed for total traffic volume using counter data obtained from City of New York (2020i), see Section 3.3 for further discussion.

2.4. *Cycling traffic volumes (not yet included).*

To get a proxy for cycling volumes, we use publicly available trip data from the public bicycle rental system (Citibike New York City, 2020). We use both trip origins, as well as within-road trips to get a proxy for cycling traffic volumes. Similarly as with the taxi data, we will test for the quality of this proxy by assessing the correlation of rental bike trips for street for which we have bike counts available from City of New York (2020b).

3. Methods

Our aim is to identify the causal effect of bike lane installation on the congestion and road safety at street level. Two main statistical challenges arise in our setting. First, bike lanes are not installed at random and targeted at unsafe streets. Second, one can expect induced demand from bike lane installation, and potentially also some sorting of within the population of cyclists. We deal with these issues by including time and location fixed effects, and by controlling for traffic volumes, both discussed in detail below. Thereby, we essentially employ a generalized difference-in-differences method, with multiple time periods.

3.1. *Specifications*

For congestion, we use speed and flow as two separate indicators. For speed we consider variants of the following general specification:

$$\log(\text{speed}_{zst}) = \phi_{zs} + \kappa_t + \beta \cdot \text{bikelane}_{zst} + \gamma \cdot \log(\text{flow}_{zst}) + \epsilon_{zst}, \tag{1}$$

where z denotes a zone (borough, neighborhood or census tract), s a street segment, and t time in months or weeks. We include two fixed effects. First, ϕ_{zs}, is a street segment fixed effect, which absorbs any unobserved time invariant characteristic of a street. Second, κ_t is a year×month fixed effect, that controls for city-wide trends and seasonality. We also estimate a variant, where we include κ_{zt}, a year×month×borough fixed effect, to absorb any within-borough time trends. For traffic flow we use a similar approach and estimate variants of:

$$\log(\text{flow}_{zst}) = \phi_{zs} + \kappa_t + \beta \cdot \text{bikelane}_{zst} + \gamma \cdot \log(\text{speed}_{zst}) + \epsilon_{zst}, \tag{2}$$

where indices and fixed effects are identical to those in (1).

For road safety we estimate similar models as above, but to accommodate the count data in the dependent variable, we will use poisson regression.[2] We consider variants of the following general specification:

$$(\#\ \text{accidents})_{zst} = \phi_{zs} + \kappa_t + \beta \cdot \text{bikelane}_{zst} + \gamma \cdot \log(\text{speed}_{zst}) + \delta \log(\text{flow}_{zst}) + \epsilon_{zst}, \tag{3}$$

where indices and fixed effects are as above. We estimate two main variants of (3) one where we use all accidents, and one where we only focus on accidents with bicycles involved.

3.2. *Endogeneity of bike lane installation*

One source of bias is endogeneity of bike lane installations. NYC planning department aims at improving road safety by targeting streets that are relatively unsafe (City of New York, 2014). We deal with this issue as follows. First, the street segment fixed effects will absorb intrinsic location characteristics of each street. Second, for each treated street, we include only a narrow time window of one year before and one year after the bike lane installation. Third, we run a robustness check where we focus on a subsample that contains only those streets that will eventually be treated. This means that we only use variation across streets that are targeted by urban planning (not yet included).

[2] We will use the algorithm as developed by Correia et al. (2019) to avoid computational burden of estimating parameters for the fixed effects.

3.3. *Traffic volume and speed*

Traffic flow and speed are essential controls in any road safety analysis. In our case, for instance, bike lanes may induce more traffic, so that accident counts increase due to increased traffic volumes, but not due a less safe road layout. Because street-level data on traffic flow and speed are only available at a few roads and time windows, we will use taxi trips to proxy these controls (see 2.3 for a description of the data).

We analyse the quality of this proxy in Table B1 in Appendix B. The results highlight that taxi volume is highly correlated with traffic volume, especially when analysing at daily level, and while including street segment fixed effects. The results also indicate that speed—in itself a strong predictor of traffic volumes—does not add much predictive power when included on top of taxi volumes.

3.4. *Effect of roadwork during installation*

The roadworks required for the installation of bike lanes are likely to disrupt traffic and thereby affecting congestion and road safety. To avoid such effects to influence our results, we will exclude any observations two months prior to a change in infrastructure. In addition, we exclude the first month after the bike lane installation has finished, to avoid any post-roadwork adjustments that can affect our results. In addition we will use NYC's roadworks databse to exclude any observations with roadworks nearby, as these not just contain installation of bike lanes (not yet included).

Table 1: Effect of bike lanes (standard) on traffic speed and flow.

	log(Traffic speed)			log(Traffic volume)		
	(1)	(2)	(3)	(4)	(5)	(6)
Bike lane	0.001	0.0004	0.004	0.007	0.007	0.020^{*}
	(0.007)	(0.007)	(0.006)	(0.011)	(0.011)	(0.011)
log(Traffic volume)		0.036^{***}	0.034^{***}			
		(0.005)	(0.005)			
log(Traffic speed)					0.104^{***}	0.099^{***}
					(0.015)	(0.014)
Street segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes		Yes	Yes	
Year × Month × Boro FE			Yes			Yes
Treated segments	409	409	409	409	409	409
Control segments	1885	1885	1885	1885	1885	1885
Clusters	6178	6178	6178	6178	6178	6178
Observations	164,546	164,546	164,546	164,546	164,546	164,546

Notes: Robust standard errors in parentheses are clustered at the level of a zone.***, **, * indicate significance at 1%, 5%, and 10%.

4. Preliminary results

4.1. *Effect of bike lanes on traffic*

In Table 1 we estimate the effect of installing a standard bike lane on streets that previously did not have any cycling infrastructure. Columns (1)–(3) show that we find no significant effect on the traffic speed. Similarly, columns (4)–(5) show that we do not detect a substantial effect on the traffic volume. Importantly, in all columns we obtain small standard errors, indicating that bike lanes have only a small effect on traffic, if at all. When we include a borough×year×month fixed effect, as in column (6), we find a small and borderline significant effect on volume suggesting, that there may be slight capacity improvements when a bike lane is installed.

Table 2 shows the effects from upgrading standard bike lanes to a protected bike path. These upgraded typically do not affect the number of lanes or width per lane, but merely separate the bike lanes by physical barriers or parking bays. In columns (1)–(2) we do not find a significant effect. In column (3) we find a significant and positive effect, indicating that a bike lane upgrade is associated with a just over 1% increase average traffic speed on a link. For traffic volumes, in columns (4)–(6) we find an even stronger effect of around 3-4%. These results suggest that upgrading bike lanes induces benefits for traffic speed and flow on that link.

Table 2: Effect of bike lane upgrade (standard to protected) on traffic speed and flow.

	log(Traffic speed)			log(Traffic volume)		
	(1)	(2)	(3)	(4)	(5)	(6)
Bike lane protection	0.013	0.011	0.014**	0.038***	0.037***	0.033***
	(0.009)	(0.008)	(0.006)	(0.014)	(0.013)	(0.010)
log(Traffic volume)		0.038***	0.041***			
		(0.015)	(0.014)			
log(Traffic speed)					0.109***	0.116***
					(0.040)	(0.038)
Street segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes		Yes	Yes	
Year × Month × Boro FE			Yes			Yes
Treated segments	155	155	155	155	155	155
Control segments	510	510	510	510	510	510
Clusters	2624	2624	2624	2624	2624	2624
Observations	39,616	39,616	39,616	39,616	39,616	39,616

Notes: Robust standard errors in parentheses are clustered at the level of a zone.***, **, * indicate significance at 1%, 5%, and 10%.

4.2. *Effect of bike lanes on accidents*

Table 3 show preliminary results for the effect of bike lanes on accidents. At this stage we do not yet control for cycling traffic, and therefore have to rely on fine grained spatial and temporal fixed effects. In columns (1) and (2) the statistically insignificant results and the small standard errors indicate that bike lanes do not affect overall accidents levels. Columns (3) and (4) show that our point estimates for the treatment effect have the expected sign, which suggest that that bike lanes may improve road safety for cyclists, but we the results are not statistically significant. Table 4 shows the results for bike lane upgrades, with results that hardly differ from those in Table 3.

Table 3: Effect of bike lanes (standard) on traffic accidents.

	(1) Accidents	(2) Accidents	(3) Bike Accidents	(4) Bike Accidents
Treatment effect	0.001	0.000	-0.076	-0.076
	(0.022)	(0.022)	(0.105)	(0.105)
log(Traffic volume)		0.025***		0.027
		(0.006)		(0.027)
log(Traffic speed)		-0.026***		-0.002
		(0.007)		(0.039)
Street segment FE	Yes	Yes	Yes	Yes
Year × Month × Boro FE	Yes	Yes	Yes	Yes
Observations	1,577,833	1,577,833	553,857	553,857

Notes: Robust standard errors in parentheses, estimated using poisson regression.***, **, * indicate significance at 1%, 5%, and 10%.

Table 4: Effect of bike lane upgrade (standard to protected) on traffic accidents.

	(1) Accidents	(2) Accidents	(3) Bike Accidents	(4) Bike Accidents
Treatment effect	0.003	0.003	-0.103	-0.104
	(0.024)	(0.024)	(0.125)	(0.125)
log(Traffic volume)		0.027*		0.085
		(0.015)		(0.058)
log(Traffic speed)		-0.071***		-0.075
		(0.022)		(0.099)
Street segment FE	Yes	Yes	Yes	Yes
Year × Month × Boro FE	Yes	Yes	Yes	Yes
Observations	226,369	226,369	99,550	99,550

Notes: Robust standard errors in parentheses, estimated using poisson regression.***, **, * indicate significance at 1%, 5%, and 10%.

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A. Appendix

A.1. *Additional maps*

Figure A1: Street network with bike lanes in New York City in 2016.

B. Additional results

Table B1: Estimation results testing predictive power of taxi trips on traffic volume.

	log(Hourly traffic volume)				log(Daily traffic volume)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Taxi volume)	0.383***	0.267***	0.200***	0.165***	0.253***	0.591***	0.579***	0.577***
	(0.014)	(0.007)	(0.007)	(0.007)	(0.009)	(0.027)	(0.027)	(0.028)
Speed (km/h)			-0.342***				-0.202***	
			(0.016)				(0.060)	
Speed 10 – 15 km/h				-0.014				-0.080
				(0.020)				(0.107)
Speed 15 – 20 km/h				-0.035				-0.109
				(0.024)				(0.108)
Speed 20 – 25 km/h				-0.120***				-0.151
				(0.025)				(0.109)
Speed 25 – 30 km/h				-0.217***				-0.225**
				(0.026)				(0.111)
Speed 30 – 35 km/h				-0.296***				-0.257**
				(0.028)				(0.120)
Speed 35 – 40 km/h				-0.416***				-0.352***
				(0.031)				(0.133)
Speed 40 – 45 km/h				-0.574***				0.088
				(0.034)				(0.153)
Speed 45 – 50 km/h				-0.707***				-0.487***
				(0.042)				(0.171)
Speed 50 – 55 km/h				-0.697***				-0.131
				(0.044)				(0.131)
Speed 55 – 60 km/h				-0.708***				-0.368***
				(0.077)				(0.136)
Speed 60 – 100 km/h				-0.676***				-0.199*
				(0.145)				(0.111)
Street segment FE		Yes	Yes	Yes		Yes	Yes	Yes
Clusters	1285	1285	1285	1285	1287	1287	1287	1287
Within R2	0.299	0.234	0.316	0.345	0.343	0.557	0.565	0.571
Observations	16,918	16,918	16,918	16,917	1,287	1,287	1,287	1,287
R^2	0.299	0.768	0.793	0.801	0.343	0.905	0.906	0.908

Notes: Robust standard errors in parentheses are clustered at the level of street segment and day for columns (1)–(4) and at the level of the date for columns (5)–(8).***, **, * indicate significance at 1%, 5%, and 10%.