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Review

Ride-Hailing and Road Traffic Crashes: A Critical Review

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Ride-hailing businesses, including Uber and Lyft, have reshaped road traffic since they first began operating in the United States approximately a decade ago. It follows that ride-hailing may also alter the incidence and distribution of road traffic crash injuries and deaths. The available evidence relating ride-hailing to crashes is critically reviewed in this article. We present a theoretical model that synthesizes the hypothesized mechanisms, and we identify common methodological challenges and suggest priorities for future research. Mixed results have been reported for the overall incidence of road traffic crash injuries and deaths, likely due to heterogeneous impacts on vehicular traffic flow (e.g., increasing the volume of vehicles); on vehicle-, person-, and event-level characteristics (e.g., reducing alcohol-impaired driver crashes); on road-user types (e.g., increasing pedestrian crashes); and on environmental conditions (e.g., reducing crashes most substantially where public transit access is poorest). The lack of a well-developed theory of human mobility and methodological challenges that are common to many ecological studies impede exploration of these sources of moderation. Innovative solutions are required to explicate ride-hailing's heterogeneous impacts, to guide policy that can take advantage of the public health benefits of ride-hailing, and to ensure that research keeps pace with technological advances that continue to reshape road traffic use.

accidents, traffic; bicycling; distracted driving; driving under the influence; land travel; motor vehicles; pedestrians

Abbreviation: DD, difference-in-differences.

Ride-hailing has had a substantial impact on road traffic use around the world. Since the first paying passenger connected with an owner/operator driver through the Uber mobile application on July 5, 2010 (1), transactions through ride-hailing companies (also known as ridesharing and transportation network companies) have grown exponentially. Uber facilitated 1.9 billion rides in just the fourth quarter of 2019 (2) and its largest US competitor, Lyft, provides more than 1 million trips per day (3). Although ride-hailing still composes a small fraction of road use in most US metropolitan areas, the services account for up to 13% of vehicle miles traveled in some cities (4). The impacts on urban transportation systems are far-reaching, including increasing traffic congestion and air pollution (5) and devastating the business model for taxis (6). A logical question for public health is whether a technology that demonstrably affects road traffic use also affects the burden of injury and death due to road traffic crashes. This question is critical because ride-hailing is forecasted to continue its rapid growth around the world, and road traffic crashes are among the leading causes of morbidity and mortality globally—accounting for 1.3 million deaths worldwide and 70 million disability-adjusted years of life lost each year (7).

Here, we critically review and synthesize available evidence examining the impacts of ride-hailing on road traffic crash injuries and fatalities. We present a unifying theoretical model that describes the many pathways through which the exposure may affect the outcome, explore methodological challenges that affect studies of these associations, and identify critical gaps for the field to address through future research efforts. We include peer-reviewed and non–peer-reviewed studies, such as reports, theses, and working papers, because unpublished sources are among the most highly cited documents in this nascent research area.

A DECADE OF RIDE-HAILING SERVICE; HALF A DECADE OF RESEARCH

Brazil and Kirk published the first peer-reviewed study of ride-hailing and road traffic crashes in *American Journal of Epidemiology* in 2016 (8). The authors selected the 100 most populous US counties and used publicly available reports to manually code a dichotomous variable measuring the presence or absence of Uber services within these counties for each month from 2005 to 2014. Outcomes were counts per county-month of road traffic fatalities overall, road traffic fatalities in which drivers were alcohol impaired, and road traffic fatalities that occurred on weekends and holidays (a marker of alcohol involvement) (9). In difference-in-differences (DD) analyses, ride-hailing was not associated with any of the crash-fatality outcomes.

Brazil and Kirk's work is an instructive example of the state of the science, because most studies published in the intervening 5 years have used similar data and methods to examine similar outcomes. Most were set in the United States (10–24), apart from a handful of others conducted in Brazil (25), Chile (26–28), South Africa (29), Spain (30), and the United Kingdom (31). Other authors also examined associations with overall injury or fatal crash incidence (13, 15, 16, 18–23, 25–27, 29, 31) or with alcohol-involved injury or fatal crash incidence (10–15, 18, 22, 24, 26, 27, 30). In most studies, researchers used quasi-experimental designs (11–19, 21, 25–31). Data were commonly structured as spatial ecological panels, aggregated within spatial units (e.g., cities, counties) and over multiple time periods (e.g., weeks, months). Two-dimensional panels composed of space–time units (e.g., city-weeks; county-months) often included dichotomous measures of ride-hailing availability and road traffic crash incidence, and authors used conventional statistical methods to relate the exposure to the outcome while controlling for data structures and possible confounders. Like Brazil and Kirk, authors of most of the other studies used a DD approach (11, 12, 14–19, 25, 26, 29, 31), which measures intervention effects while accounting for global time trends that affect ride-hailing and non–ride-hailing sites alike. In other studies, researchers used 1-dimensional structures to cleverly assess associations within a single location over time, for example, using interrupted time-series analyses (13, 27).

Although published studies share many methodological traits, the results of analyses examining overall incidence of injury and fatal crashes are surprisingly mixed. In several studies in the United States (8, 13, 18) and the United Kingdom (30), authors found Uber's presence was not associated with crash fatalities; but authors of the studies from Brazil (25), Chile (26–28), South Africa (29), and 2 from the United States (15, 22) found the presence of ride-hailing services were negatively associated with crash fatalities. In another analysis of US cities (19) and in a small-area study in New York City (20), researchers found positive relationships for injury and fatal crashes. Attention has turned in recent years to understanding how different researchers using comparable analytic methods, sometimes in the same geographic settings, could arrive at such divergent results. Explanations can be separated into the theoretical and the methodological.

A THEORETICAL MODEL OF RIDE-HAILING AND ROAD TRAFFIC CRASH INJURY AND DEATH

Theoretical explanations for the discrepant findings from studies of ride-hailing and the overall incidence of injury and fatal crashes center on possible heterogeneous effects. Figure 1 presents a theoretical model that summarizes the causal paths implied in prior studies, emphasizing heterogeneous impacts between component parts of vehicular traffic flow (volume, speed, pattern), vehicular traffic characteristics (person level, vehicle level, and trip level), and road traffic crash victims (motorists, pedestrians, cyclists, motorcyclists). Conditions of the social environment (e.g., ride-hailing policies) and physical environment (e.g., public transit access) will further modify these effects, variously strengthening or weakening each of the theorized associations over time and from location to location. Moderation by environmental conditions will also affect the proportion of road traffic crashes that result in injury and death. In the presence of these many competing pathways, ride-hailing may affect injury and death in some settings but not in others, and average associations may be inflated or attenuated depending on which pathways are tested, controlled for, and ignored. In the following paragraphs, we explore each mechanism.

Foundational epidemiologic concepts suggest that ride-hailing could be associated with increased incidence of road traffic crashes due to changes in vehicular traffic flow. Evidence suggests that ride-hailing is associated with greater volume of vehicles using the roadway network (5), in part because up to 50% of driver time is spent traveling without a passenger (32). In epidemiologic terms, the presence of more vehicles will produce increases in expected crash incidence because of the greater size of the population at risk, which, in turn, will produce increases in the number of expected injuries and deaths (33). Researchers have accounted for road traffic volume methodologically by carefully selecting space–time units in a way that minimizes bias due to unknown denominators (20), or statistically by using estimated road traffic volume (21) or large space–time units in which conditioning through model or variable specification can account for most of the variation in vehicular traffic flow (8, 31). However, relationships between ride-hailing and vehicular traffic volume may not be dose responsive, because greater volume is negatively related to average speed, because of congestion. Lower average speeds will result in fewer crashes relative to the number of vehicles using the roadway. Beyond these global effects, ride-hailing could also shift traffic patterns, meaning it could affect the spatial and temporal distribution of vehicular traffic flow within small geographic areas over time. Ride-hailing drivers may operate at different days and times and along different routes compared with other forms of transportation, altering the size of the local population at risk. Controls for local vehicular traffic flow, therefore, are important, particularly when using smaller spatial or temporal scales as the units of analysis.

In addition to global and local features of vehicular traffic flow, characteristics of the vehicles and people traveling through the roadway network will also contribute to

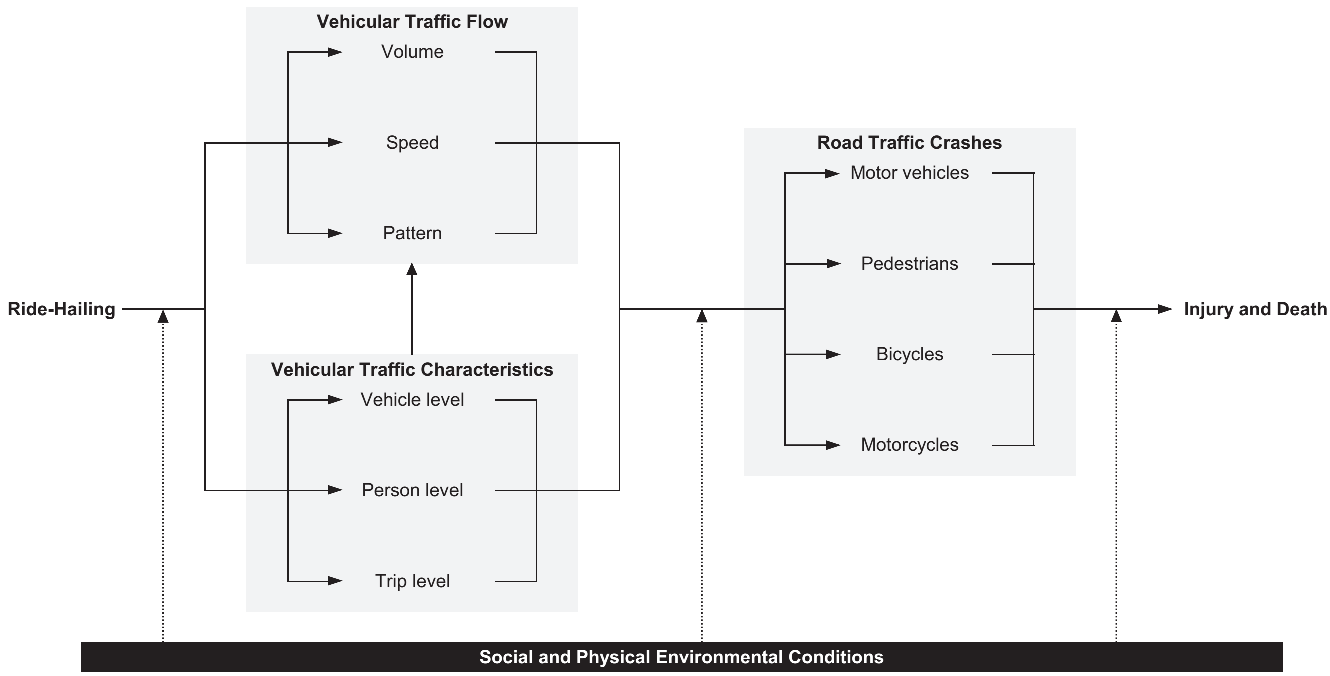

Figure 1. Theoretical model of ecological associations between ride-hailing and injury and death due to road traffic crashes.

heterogeneity in associations between ride-hailing and road traffic crash injury and death. In the United States, the average age of all registered vehicles is 11.9 years (34), whereas Uber requires that vehicles be no more than 12 model-years old (35), meaning that ride-hailing vehicles are likely to be newer and to have improved safety features (e.g., lane departure warnings) (36, 37) compared with the vehicles they replace. However, ride-hailing vehicles likely travel many more roadway miles than non–ride-hailing vehicles, and wear and tear could increase crash risks (e.g., due to worn brakes). Variation in the population of drivers and passengers may also matter. Compared with the general population, ride-hailing passengers tend to be younger and wealthier, and ride-hailing drivers are younger and more likely to be male (38–40). The younger age of ride-hailing drivers reflects the fact that relatively little driving experience is necessary to become a driver for leading companies (41, 42); both younger age and less experience may increase crash risks. Trip-level causes operate through a similar mechanism. Ride-hailing drivers could be more distracted (e.g., by glances away from the road) and be more fatigued (e.g., due to long shifts). A larger population of distracted and fatigued drivers would mediate associations between ride-hailing and road traffic crashes.

Alcohol impairment is a trip-level characteristic of vehicular traffic that has received considerable empirical attention. Following Brazil and Kirk (8), in almost all published studies of ride-hailing and road traffic crashes, authors considered alcohol-involved injury or fatal crash incidence as directly measured outcomes (8, 11–15, 18, 22–24, 26, 27, 30) or they used well-justified proxies (e.g., nighttime crashes) (15, 16, 26, 30) or antecedents (e.g., arrests for driving while impaired) (12, 17, 21, 23). In 1 study, self-reports of alcohol-impaired driving were examined (43). The mechanism motivating these studies is that ride-hailing could replace trips by alcohol-impaired drivers because ride-hailing will lower the prospective financial and convenience costs of taking alternate forms of transportation compared with driving while impaired (44). That is, because ride-hailing is often easier and cheaper to access than taxis and public transit, people who would otherwise choose to drive after drinking will instead choose to purchase a ride. The collective evidence generally supports this explanation, though results of some studies are null (8, 18, 43) and important caveats apply. Rationalist theories of behavioral economics may not be directly relevant to people who are alcohol impaired and who may momentarily inflate self-evaluations of driving ability or discount future consequences (45). Conversely, if alcohol-impaired individuals are rational, they may conclude it is too costly to pay for ride-hailing relative to driving themselves, given that the absolute risk of crashing or being arrested for driving while impaired is low (8). Furthermore, conceptualizing alcohol-impaired driving as a mediator assumes trips by ride-hailing drivers are less risky than trips by alcohol-impaired drivers, which will depend on other vehicle-level, person-level, and trip-level characteristics of the drivers and passengers, including whether drivers are, themselves, alcohol impaired. Ride-hailing companies require that drivers not be under the influence of any alcohol (46, 47), so this mechanism is plausible in locations where detection and enforcement of impaired driving is greater (48). However, relative associations are small (24, 29), meaning that a very large number of ride-hailing trips is required to produce meaningful reductions in alcohol-impaired driving at a population level.

Another source of heterogeneity may exist between road user types. Crash risks related to ride-hailing could be greater for vulnerable road users, such as pedestrians, bicyclists, motorcyclists, than for motor vehicle drivers. For example, ride-hailing drivers use road shoulders and other roadway space (e.g., driveways, local roads) that pedestrians and bicyclists prefer in order to pick up and drop off passengers. Different impacts according to road user type have been assessed in 2 studies. The authors found increased crash incidence for pedestrians (19, 20) but not for bicyclists (20). Although there are many such mechanisms by which ride-hailing could differently affect crash incidence for different road user types, few studies have considered these associations.

After accounting for vehicular traffic flow, vehicular traffic characteristics, and different risks for road user types, differences in social and physical environmental conditions could contribute to further variation in associations between ride-hailing and road traffic crash injuries and fatalities. The potential pathways for this variation are innumerable, and statistical moderation could affect any of the putative causal relationships at any stage. For example, greater access to public transit could attenuate impacts of ride-hailing on trip-level vehicular traffic characteristics—specifically alcohol-impaired driving—because people who have been drinking might be less likely to drive in these settings in the first place. Impacts may be greater in higher-income areas, where ride-hailing use is likely to be greater (28). Similarly, roadway conditions could modify associations between vehicular traffic characteristics and road traffic crashes. Ride-hailing is associated with excess crash risks for pedestrians in small areas of New York City (20). Physical infrastructure to separate pedestrians and motor vehicles would reduce the strength of this association at high-risk locations (49).

Another important source of moderation is local policies that regulate who can work as a ride-hailing driver and when, where, and how long they can drive; and how, where, and when prospective passengers can access trips. For example, ride-hailing companies require the use of a credit card to access services in some countries, which will then modify the impact of ride-hailing if differences between populations with and without credit cards are associated with crash risks. Likewise, there are important differences in road use and road traffic conditions between countries that could moderate the associations of interest, including differences in alcohol-impaired driving incidence (48), vehicle maintenance (36), and the types of vehicles used by ride-hailing drivers (50). Finally, crash incidence does not perfectly predict injury and fatality incidence, because of many conditions in the social and physical environment (51, 52), including socioeconomic resources dedicated to clinical treatment for traumatic injury (53). Despite the many potential sources of moderation by environmental conditions, empirical investigations are few, but preliminary findings confirm that impacts may be considerable (18, 19, 27).

METHODOLOGICAL CONSIDERATIONS

It is no coincidence that in most studies of ride-hailing and road traffic crashes, researchers use the same basic, spatial ecological design. The approach can be easily implemented using publicly available data, it allows researchers to account statistically for known confounders (e.g., total vehicle-miles traveled), it permits subgroup analyses and tests for moderation, it corresponds geographically to the administrative boundaries within which ride-hailing companies typically structure service availability, and results are easily interpretable. The design is well suited theoretically to the research question at hand because access to ride-hailing will affect aggregate behaviors among the whole population of drivers, not just among individual ride-hailing drivers or passengers at the time of a trip. For example, fewer people own motor vehicles after ride-hailing services launched (54) in the United States, but not in France (55), so travel patterns are likely to be affected on aggregate in that country.

However, the agreement between spatial ecological study designs and the theorized impacts of ride-hailing on road traffic crashes can be deceptive. Researchers must still make important operational decisions that could introduce bias and may have contributed to variation in the results of prior studies. One such challenge that is common to many ecological analyses is how best to measure exposure. In most cases, the optimal solution will depend on the theoretical mechanism linking the exposure and the outcome. Some theorized associations between ride-hailing and road traffic crash injuries and deaths imply a direct causal mechanism (e.g., ride-hailing increased the overall volume of vehicles and resulted in more crashes). Studies examining these associations will ideally use precise measures of ride-hailing volume, such as trip counts, although such data are rarely available. Other associations between ride-hailing and road traffic crashes imply an indirect causal mechanism (e.g., ride-hailing availability alters individuals' decisions to drive after drinking alcohol). For these associations, access to ride-hailing may be best measured by other means, including dichotomous indicators for ride-hailing's presence or absence within space–time units (56). Though often unavoidable, these imperfect solutions could introduce aggregation bias, which will attenuate associations toward null if ride-hailing trips are nondifferentially distributed with respect to the outcome. Differential misclassification could bias associations in either direction. Ride-hailing service-use data are not available in most settings, so researchers have developed imaginative solutions to model exposure, including assessing temporally lagged associations (8, 11), simultaneously accounting for stepped and linear associations (27), using counts of internet searches for ride-hailing companies (19, 23), and exploiting policy changes that abruptly affect ride-hailing availability (13).

Variation in study results may also arise because of avoidable biases. Discordance between spatial units of analysis and the spatial scale over which ride-hailing actually affects crashes could lead authors to erroneously conclude there is no association, due either to aggregation bias (when using units that are too large) or sparse data problems (when using units that are too small). Associations could be confounded by selection bias if inclusion of study locations is related to a moderator. For example, ride-hailing was associated with fewer alcohol-involved crashes in 2 of 4 US cities, perhaps because of the presence of salient environmental conditions (13). In a study in which researchers assess global associations and include only cities where these environmental conditions were present (whatever they happened to be), only negative associations might be found between ride-hailing and alcohol-involved crashing; in a study in which cities were included where the condition was absent, null, or perhaps even positive, associations might be found. Selection bias could also affect external validity. Note that the bulk of research on ride-hailing focuses on the United States, where the relatively high rates of traffic fatalities may impede generalization to other high-income settings. The near-absence of research in low-income countries, many of which have even higher rates of road traffic crash fatalities than the United States (7), is another important gap.

The chosen analytic strategy is another potential source of bias. Spatial ecological panel analyses, including DD and time-series analyses, are generally well suited to the quantitative research questions embedded in the theoretical model, but they include strong assumptions that, if violated, could affect study results. For example, conventional DD analyses separate pretreatment from posttreatment periods and assume parallel trends among treatment and control groups (57). But ride-hailing was introduced at different times across settings, requiring the use of staggered DD analyses that make more restrictive assumptions, including parallel variance-weighted trends (58–60). Whether violations of these assumptions contribute to heterogeneous findings is not clear.

RESEARCH GAPS AND FUTURE CHALLENGES

Figure 1 presents a theoretical model that explains how similar studies of ride-hailing and road traffic crash injury and death could produce different results. Some of the causal mechanisms have empirical support. For example, it is increasingly clear that ride-hailing directly affects vehicular traffic flow, including volume, speed, and pattern through the roadway network (5, 31). And there is now moderately strong observational evidence that ride-hailing reduces incidence of alcohol-involved crashes (10–15, 18, 22, 24, 26–29). Nevertheless, many gaps in the evidence base remain. The role of vehicular traffic characteristics other than alcohol impairment are largely abstruse or untested, including whether the theorized vehicle-, person-, and trip-level characteristics mediate associations between ride-hailing and road traffic crashes. In only a small handful of studies have researchers assessed whether ride-hailing is differentially associated with crash risks according to road user type. Evidence regarding moderation by environmental conditions is mostly absent. Sources of variation should be explored within and between urban settings, and it is not clear how findings from studies in the United States generalize to those from other countries (e.g., where ride-hailing regulations differ; passenger vehicles are less commonly used; urban planning promotes less sprawl; road design facilitates safer conditions) (57). Given the discordant results between studies in the United States and the few conducted in other countries, and the substantial variation across countries in salient environmental conditions, more work in other countries is needed.

Gaps in the theoretical and empirical base connecting ride-hailing and road traffic injuries reflect a much wider gap in human geography research. Since the "mobilities turn" of the early 2000s—when many social science disciplines began to acknowledge movement between places as an essential element of human behavior rather than an analytic inconvenience (61)—geographers have identified an impressive array of person-, trip-, and environmental-level determinants of travel patterns. However, this empirical progress has occurred despite the lack of a grand theory of mobility that explains where, when, and how individuals with certain characteristics travel through space over time (62). Advances in theories of mobility are essential for identifying other sources of variation in ride-hailing use with respect to where ride-hailing is used (e.g., urban vs. suburban), when ride-hailing is used (e.g., daytime vs. nighttime), how ride-hailing is used (e.g., complementing vs. competing with public transit), and who the passengers and drivers are (e.g., younger vs. older people). Understanding heterogeneity in ride-hailing use, in turn, will help identify sources of heterogeneity in associations with road traffic crash injuries and deaths. Researchers have examined some of these sources, but in no studies, to our knowledge, have their linkages with crashes been formally tested (40).

Concurrent to developing the theoretical base, methodological advances are essential for overcoming obstacles related to feasibility and data availability. Novel approaches such as synthetic control (63), generalized autoregressive models, and recently developed DD methods that include time-varying controls can address possible violations of the restrictive assumptions (64–66). Experimental studies will be an important complement to the available quasi-experimental studies; however, this research will likely be limited to individual-level analyses, because altering ride-hailing access for whole populations is impractical. Creative study designs will be required to simulate environmental-level access to ride-hailing for individual study participants. Qualitative studies could also assist hypothesis generation, focusing on questions such as barriers to diffusion of technology and decisions about when, where, and why to use ride-hailing. Above all, researchers must attend to the possibility that seemingly minor methodological differences (e.g., using different spatial or temporal scales; failing to control adequately for vehicular traffic flow) could contribute to variation in findings.

Another important development is that ride-hailing service use data have become available in select markets. In the United States, the cities of New York and Chicago have publicly released trip-level data collected by their respective departments of transportation, with trip origins and trip destinations masked within small geographic areas (e.g., census tracts). These data allow assessment of moderation by environmental conditions within, but not between, cities (20). Uber has released trip-level data for 3 studies, including 2 published in 2021 (17, 22, 23), in which the authors examined associations between ride-hailing and alcohol-involved crash incidence. Data are indexed to prevent researchers from accessing commercially sensitive information, but these examples are a promising development that, if it continues, will allow more rigorous assessment of ride-hailing's impacts, including of associations other than for alcohol-involved crashes.

Despite the many theoretical and empirical gaps, authorities are already enacting policies to capitalize on the possible benefits of ride-hailing. A New England hospital provided free trips to clinical staff to reduce fatigued driving (67); a conglomerate in Columbus, Ohio, issued ride-hailing vouchers valid for travel to and from the city's hospitality zones on weekend evenings (24). Pairing theoretically informed interventions with rigorous scientific evaluation methods will help identify the impacts of ride-hailing on road traffic crashes and other outcomes. A body of literature evaluating policies that address vehicular traffic flow, vehicular traffic characteristics, and road user types in different environmental settings will illuminate sources of heterogeneity. These findings will guide recommendations about the optimal conditions for enacting ride-hailing–based interventions to maximize public health benefits while minimizing unintended negative consequences.

CONCLUSIONS

Ride-hailing has reshaped urban transportation systems in just 1 decade. Researchers have made important early strides toward understanding its impacts on road traffic crash injuries and fatalities. The collective evidence suggests, with some exceptions, that the technology likely reduces alcohol-involved crashes; however, these declines could be wholly offset by increases in other crashes and may not be experienced in all urban settings. Furthermore, negative impacts on other public health–related outcomes such as air pollution, worker rights and protections, and passenger safety may negate ride-hailing's positive impacts on traffic crash outcomes (5, 15). Low- and middle-income countries will likely experience the balance of benefits and harms differently, because of the presence of different social and physical environmental moderators (68, 69). Sources of heterogeneity are unclear, and there is much theoretical and methodological work to be done to encourage global health gains during the next decade of ride-hailing (and the technological advances that follow). There may be even more untapped benefits to realize if ride-hailing companies can find a way to further position ride-hailing as a substitute for private vehicle use. Reducing crash incidence without increasing traffic congestion and air pollution would truly signal innovation in the public health arena.

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