Akbar, Prottoy; Couture, Victor; Duranton, Gilles; Storeygard, Adam

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Mobility and congestion in urban India

By Prottoy Akbar and Victor Couture and Gilles Duranton and Adam Storeygard

We develop a methodology to estimate robust city-level vehicular speed indices, exactly decomposable into uncongested speed and congestion. We apply it to 180 Indian cities using 57 million simulated trips measured by a web mapping service. We verify the reliability of our simulated trips using a number of alternative data sources, including data on actual trips. We find wide variation in speed across cities that is driven more by differences in uncongested speed than congestion. Denser and more populated cities are slower, only in part because of congestion. Urban economic development is correlated with faster speed despite worse congestion.

JEL: R41, O18
Keywords: urban transportation, roads, traffic congestion, travel speed determinants, cities

Using a popular web mapping and transportation service, we generate information for more than 57 million simulated trip instances by motor vehicle in 180 large Indian cities. We leverage a number of alternative data sources, including data on actual trips, to verify the reliability of our simulated trips. We use these trips to estimate indices of mobility (speed) in these cities. The indices that we develop provide a novel decomposition of overall speed into uncongested speed and the congestion delays caused by traffic. This decomposition allows us to compare the importance of uncongested speed with that of congestion in generating speed variation across cities. Then, we examine how population, roadway characteristics, geography, and indicators of urban economic development correlate with speed, uncongested speed, and congestion delays. Finally, we consider walking and transit trips, and we replicate most of this investigation in the United States.

* Akbar: Aalto University and Helsinki Graduate School of Economics (email: prottoy.akbar@aalto.fi). Couture: Vancouver School of Economics, University of British Columbia (email: victor.couture@ubc.ca). Duranton: Wharton School, University of Pennsylvania (email: duranton@wharton.upenn.edu). Storeygard: Department of Economics, Tufts University (email: Adam.Storeygard@tufts.edu). This work is supported by the World Bank, the Zell Lurie Center for Real Estate at the Wharton School, the Fisher Center for Urban and Real Estate Economics at Berkeley-Haas, and we also gratefully acknowledge the support of the Global Research Program on Spatial Development of Cities at LSE and Oxford funded by the Multi Donor Trust Fund on Sustainable Urbanization of the World Bank and supported by the UK Department for International Development. We appreciate the comments from Leah Brooks, Ben Faber, Nicole Fortin, Michael Gechter, Ejaz Ghani, Ed Glaeser, Vernon Henderson, Ki-Joon Kim, Gabriel Kreindler, Emile Quinet, Christopher Severen, Kate Vyborny, and participants at conferences and seminars. Hero Ashman, Xinzhong Chen, Lin Fan, Cindy Feng, Allison Green, Xin Yu Ma, Gao Xian Peh, Serena Xu, Jungsoo Yoo and Xianya Zhou provided us with excellent research assistance. We are immensely grateful to Sam Asher, Geoff Boeing, Arti Grover, Nina Harari, and Yue Li for their help with the data as well as to Hugh MacMullan for his initial 17 support. The views expressed here are those of the authors and not of any institution they may be associated with.
To the best of our knowledge, our paper provides the first systematic multi-city investigation of urban travel in a developing country. Our main substantive findings are the following. First, there are large differences in speed across Indian cities. A factor of nearly two separates the fastest and slowest cities. To illustrate this, figure 1 plots the speed of travel by motorized vehicles throughout the day in a particularly fast (large) Indian city, Thrissur, and in a particularly slow city, Kolkata.

Second, variation in speed across cities is driven primarily by uncongested speed, not by congestion delays. In figure 2 we observe on average mild variation across hours of the day for our sample of 180 cities. A very poor city like Santipur in West Bengal is slower than average at all times, even at night in the absence of traffic. We see instead wider intra-day differences in speed in the largest cities, particularly close to their center, as illustrated by Mumbai in the figure. While Mumbai is slow because it is highly congested, especially around its center, it is the exception, not the rule. More generally, an index of uncongested speed explains more than 50% of the variance in overall speed across cities. Simple welfare computations suggest that gains from a 10% improvement in uncongested speed—which we find is about one standard deviation of the uncongested speed distribution across cities—are much larger than existing estimates of the gains from optimal congestion pricing. These findings challenge the conventional wisdom that traffic congestion is the main reason why some cities are slow and some are fast. To take one prominent example, a recent report by the Boston Consulting Group \cite{bcg} claims that Kolkata has the most traffic congestion among the four largest Indian cities. We find that Kolkata is in fact the least congested of the four, but the slowest because of low uncongested speed. This distinction has important policy implications, because uncongested speed cannot be improved by congestion pricing, ride-sharing promotion or restriction, or other policies often proposed to combat congestion.

Third, travel is generally slow in Indian cities, even outside peak hours. In addition to Thrissur and Kolkata, figure 1 also plots comparable speed data for the corresponding fastest US city with population above one million, Kansas City, and the slowest one, New York. Even the slowest large US city is generally faster than the fastest Indian city, Thrissur. Finally, we find that denser, more populated cities are slower, that there is a hill-shaped relationship between city per capita income and speed, and that a city’s speed is related to its geography and road network. Specifically, cities that are flatter, with fewer waterbodies, more roads and streetlights, and a more grided network are faster.

This investigation is important for three reasons. First, there is an extreme paucity of useful knowledge about urban transportation, especially in developing countries. As a first building block towards a more serious knowledge base on

\footnote{Two new studies focusing on a single developing city complement our cross-city investigation: \cite{kreindler} studies the welfare impact of congestion pricing in Bangalore, and \cite{akbar} measure the cost of congestion in Bogotá.}
Figure 1. Speed throughout the day, two Indian vs. two US cities

Note: Mean speed for trips with length between 5 and 10 kilometers. New York and Kolkata are the slowest, and Kansas City and Thrissur the fastest, cities with a population over one million in their country according to our calculations described in sections III and IV below.
Figure 2. Speed throughout the day in India

Note: Mean speed for trips with length between 5 and 10 kilometers. Central Mumbai refers to trips that take place on average within 5 kilometers of the center of Mumbai. See section [ ] for further details.
urban transportation, some stylized facts are needed. For instance, we need to know how slow travel is in developing cities beyond the anecdotal evidence offered by disgruntled travelers. Equally important objects of interest are the differences between cities, between different parts of the same city, across times of day within the same city, and across days of the week for the same trip (reliability). We hope that our results, methodology, and data can help guide policy and future research on urban transportation in developing countries.

Second, there is a popular view that urbanization and economic development lead to ever larger cities and increased rates of motorization, and that these two features will eventually lead to complete gridlock. We do find evidence of congestion in the largest Indian cities. However, economic development also brings about better travel infrastructure which facilitates uncongested mobility.

Third, urban transportation in developing countries is prioritized for massive investments. For instance, transportation is the largest sector of lending by the World Bank and represents more than 18% of its net commitments as of 2019. Among the many problems that these investments are trying to remedy, the lack of urban land devoted to the roadway is widely perceived to be a chief cause behind slow speed and urban congestion. Providing an assessment of the determinants of speed to guide policy is thus fundamental. For instance, we find suggestive evidence that higher travel speeds in Indian cities are associated with a more regular grid network and more major roads.

Our investigation raises three challenges. The first is methodological. We propose a new approach to measure travel speed from trip information, and to decompose travel speed into uncongested speed and delays caused by congestion. The second is a travel data challenge. There is no comprehensive source of data about urban transportation in Indian cities. Our approach is to collect data on predicted travel time from a popular website, Google Maps (GM). For each city, we designed a sample of trips and sampled each trip at different times on different days. A key concern is that trips simulated on GM may not accurately represent actual travel conditions in Indian cities. To address this concern, we perform a

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2 In richer countries, much of our knowledge stems from representative surveys of household travel behavior. These surveys nonetheless have clear limitations, including a lack of precision in what travelers report. They are also prohibitively expensive to carry out broadly in developing countries. For the US, the Bureau of Transportation Statistics reports a cost per household of perhaps $300 to produce the National Household Transportation Survey or about $40 million in total (see [http://onlinepubs.trb.org/onlinepubs/reports/nhts.pdf](http://onlinepubs.trb.org/onlinepubs/reports/nhts.pdf), last accessed, 22 April 2020.)

3 Several software and data services such as Inrix and TomTom propose popular measures of congestion for a large sample of world cities. These services do not make the details of their methodology public. It seems that they monitor either specific roads or average traffic speed. We show below that measures of average speed are problematic and perform poorly. Uber Mobility provides travel times for a smaller sample of cities (just 5 in India). We argue below that they lead to substantial overestimates of speed. [https://google.com/maps](https://google.com/maps), last accessed, 20 May 2021. A number of new studies, which we discuss later in the paper, also use GM to measure traffic in a developing city, notably Kreindler (2016), Hanna, Kreindler and Olen (2017), and Akbar and Duranton (2018). Our approach, which we document explicitly in our replication archive, allows for considerably larger scale data collection with GM. Alternative approaches include direct GPS records for particular vehicles such as taxis (Mangrum and Molnar, 2017), or sensors, which usually track traffic only on the most important arterials (for instance, Geroliminis and Daganzo, 2008; Yang, Purevjav and Li, 2020).
number of exercises that demonstrate the reliability of GM as a source of travel data in a developing country. In particular, we commissioned a smartphone app that records actual trips in many Indian cities, and we compare trips from this app with trips simulated from GM. To further demonstrate the reliability of our simulated trips, we show that our city speed indices vary little across various trip sampling methodologies, type of trip destinations, origin and direction of travel, or time of day. Finally, we face the challenge of consistently defining and measuring the cities in which we sample simulated trips. To answer this challenge, we rely on a wide variety of sources including the census of India, OpenStreetMap, and satellite imagery.

I. Data collection

In this section we provide an overview of our data. Further details about our data sources are in online Appendix A and Appendix B. The construction of the variables we use is described in online Appendix C.

A. City sample and city-level data

United Nations (2019) reports the locations of the 181 cities in India that reached a population of 300,000 by 2018. We initially define the spatial extent of these cities as the surrounding or nearest polygon composed of contiguous 1-kilometer grid cells characterized as urban land circa 2014-15 in the Settlement Model (Smod) of the Global Human Settlements Layer (GHSL; Pesaresi and Freire 2016). Where multiple United Nations (2019) cities fall within the same polygon, we split the polygon following a procedure described in online Appendix A. For trip sampling purposes we restrict attention to 40-meter pixels defined as built-up in 2014 according to GHSL’s built-up layer (Corbane et al. 2018). Our final city boundaries include a 500-meter buffer around the built-up pixels of each city. After dropping one city (Thanjavur) for which the Smod boundary is clearly inappropriate, we are left with an estimation sample of 180 cities.

We compute city population from the 2011 census as the sum of underlying town/village (fourth administrative level) populations, accounting for partial overlap. We use an analogous approach for a variety of other variables from the 2011 Census (share of households with a car or motorcycle, inventory of streetlights and paved and unpaved roads, and binned average commute length for urban non-agricultural workers by mode and district, etc.) and from the Employment and Unemployment Survey of the National Sample Survey (NSS-EUE) 2011–12 for earnings.

Using the same delineation of cities, we also measure the extent of their road network by road class using data from OpenStreetMap via GeoFabrik and processed through OSMnx (Boeing 2017). We develop a number of measures of shape for the road network in each city. We also use OpenStreetMap to compute the length of rivers and coastlines in each city. We collect weather variables from Meteostat to match our trip data, elevation data for all road intersections from GM’s
elevation API, and nightlight satellite data. For comparison, we also compute similar variables for a corresponding sample of 139 US metropolitan areas.

Online Appendix table C.1 reports summary statistics for our sample of Indian cities. They are on average large, with a mean population over 1.2 million, and fast growing, having more than doubled in population since 1990. There is substantial variation across cities in road infrastructure stocks and rates of access to personal motorized transportation.

B. Trips data

We define a trip as an ordered pair of points (origin and destination) within the same city. A trip instance is a trip taken at a specific time. Our target sample for city $c$ is $15 \sqrt{\text{Pop}_c}$ trips, where $\text{Pop}_c$ is the projected 2018 population of city $c$ from United Nations (2019). We collect 21 trip instances per trip, to ensure variation across times of day and different days. For a city with a population of one million, for instance, our sampling strategy thus targets 15,000 trips (7,500 in each direction between the trips’ endpoints) and 285,000 trip instances. All trips are restricted to be at least one kilometer between origin and destination because GM results are less reliable for very short trips, few of which we expect to be motorized anyway.

We collect about eight instances per trip across times of day to roughly match the weekday distribution of actual trips in the 2009 US National Household Travel Survey (NHTS). We oversample sparse overnight periods, and sample weekends at half the rate of weekdays. We collect about 13 additional instances of each trip at the same time of day as one of those original eight (within a five minute window) to measure reliability.

We sample across four broad classes of trips, each designed to reflect key aspects of urban travel: radial, circumferential, gravity, and amenity trips. Radial trips join a randomly located point within 1.5 kilometers of a city’s center with another point in the city, either approximately 2, 5, 10, or 15 kilometers away, or at a distance percentile drawn from a uniform distribution. These trips are those predicted by the standard monocentric model of cities. This model provides a reasonable first-order characterization of the distribution of population, density, and land and house prices in cities of many countries (see Duranton and Puga, 2015 for a survey).

Circumferential trips, orthogonal to radial trips, join a randomly located origin at least 2 kilometers from the city center with a destination at approximately the same radius but displaced approximately 30 degrees clockwise or counterclockwise.

Gravity trips join a random origin with a destination in a random direction, at a distance that is drawn from a truncated Pareto distribution with shape parameter 1 and support between 1 kilometer and 250 kilometers. Both commutes and city trips in general have been shown to reflect this distance distribution in many contexts (e.g. Berlin (Ahfeldt et al., 2015) and Bogotá (Akbar and Duranton, 2015).
Amenity trips join a random origin with a destination corresponding to one of 12 amenity types (e.g. schools, recreation, religion). We systematically search Google Places for all establishments of each type in a city to identify the most popular business categories associated with them. Then, we use these categories as search keywords on GM to identify the most “prominent” trip destination (according to GM) within a reasonable radius of each trip origin. The weighting of trips across these amenity types is based on a mapping of amenity types to trip purposes whose share we draw from the 2017 US NHTS.

Using the sampling scheme above, we successfully simulated 57,103,181 trip instances in GM, covering 1,366,566 location pairs and 2,730,969 trips across all cities and trip design strategies between June 5 and November 13 of 2019. For each trip instance, we record origin, destination, time/day, trip type, and estimated length in meters and duration in seconds of GM’s recommended route under current traffic conditions (which we sometimes refer to as real-time), as well as the duration required for the same route without traffic. For comparison, we also collect 52,158,502 trip instances in 139 cities in the US.

We use the ‘throughpoints’ provided by GM to characterize the route of a trip. Combining this information about trip route with detailed data on the road network from OpenStreetMap, we compute the share of each trip that takes place on different classes of roads (motorways, primary roads, etc), the number of intersections, and the number of turns against traffic along the trip’s route. Using data on establishments from Google Places, we compute the density of establishments along the trip’s route. We also use elevation data to compute the gross slope up and down associated with each trip.

We also collect one instance of each trip via walking, which is time-invariant, and several instances via transit. Walking unsurprisingly shows little variation in speed across cities, and transit data are problematic for our purposes, because GM uses only scheduled, as opposed to actual, transit times, and is restricted to formal transit. While we recognize that these modes are important, particularly for poorer residents, we thus limit discussion to some brief comments below and online Appendix A. Finally, we note that since within-city rail is extremely limited in India, our measures of on-road travel are relevant to public transit travel times as well.

Some basic trip statistics for Indian cities are reported in panel A of table 1. Mean travel speed is 23.6 kilometers per hour, which is slow relative to the speeds reported for New York City and Kansas City in Figure 1. That said, 23.6

In online Appendix G, we show that we get essentially identical results about the speed of cities with a random 0.1% subsample. Our full sample is however necessary to show robustness to more directed subsampling.

GM’s estimated duration without traffic is consistent with the information we get by sampling each trip approximately 21 times. Specifically, the correlation across all trips between GM’s log uncongested speed and log speed of the fastest instance of a trip is 0.96 in our sample. The corresponding duration correlation is 0.99.
Table 1—Trip statistics

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Trip statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>percentile:</td>
<td>Mean St. dev. 1 10 25 50 75 90 99</td>
</tr>
<tr>
<td>Panel A: Sample: all trip instances (N=57,103,181)</td>
<td></td>
</tr>
<tr>
<td>Speed</td>
<td>23.6 6.9 11.6 15.6 18.6 22.7 27.5 32.7 43.8</td>
</tr>
<tr>
<td>Duration</td>
<td>15.7 12.7 3.6 6.0 8.2 12.1 18.4 29.1 67.7</td>
</tr>
<tr>
<td>Duration (no traffic)</td>
<td>13.8 10.3 3.4 5.6 7.5 10.9 16.2 25.4 55.0</td>
</tr>
<tr>
<td>Trip length</td>
<td>6.5 6.6 1.3 1.9 2.8 4.5 7.3 13.3 34.8</td>
</tr>
<tr>
<td>Effective length</td>
<td>4.4 4.8 1.0 1.3 1.8 2.9 4.9 9.8 24.5</td>
</tr>
<tr>
<td>Panel B: Sample: all cities (N=180)</td>
<td></td>
</tr>
<tr>
<td>Mean speed</td>
<td>24.1 3.8 14.9 19.2 21.8 24.0 26.3 29.4 34.0</td>
</tr>
<tr>
<td>Mean duration</td>
<td>13.9 3.9 8.4 10.3 11.3 12.8 15.2 19.4 30.0</td>
</tr>
<tr>
<td>Mean duration (no traffic)</td>
<td>12.4 3.2 7.6 9.4 10.1 11.6 13.6 16.9 23.8</td>
</tr>
<tr>
<td>Mean trip length</td>
<td>5.6 2.0 2.6 3.7 4.2 5.1 6.7 8.1 12.4</td>
</tr>
<tr>
<td>Mean effective length</td>
<td>3.8 1.3 1.9 2.5 2.8 3.5 4.6 5.5 8.2</td>
</tr>
</tbody>
</table>

Note: Durations are in minutes, lengths in kilometers; and speeds in kilometers per hour.

kilometers per hour is faster than the sometimes apocalyptic descriptions found in the popular press. Similar observations can be made for trip duration and length. The average trip under actual traffic conditions lasts about 14% longer than its counterpart without traffic. We keep in mind that we oversampled trips taken at night and return to this issue below. Finally, the average trip is about 50% longer than its “effective” (haversine) length.

Panel B reports naive mean city analogs of panel A statistics. We note considerable differences in mean speed across cities. The standard deviation across cities is 3.8 kilometers per hour, more than half the standard deviation across trips of 6.9 in table 1. Mean speed for the slowest city is 14.2 kilometers per hour whereas it is more than twice as high for the fastest city at 34.4. We show below that these wide raw speed differences remain once we adequately control for features of our sampling strategy.

C. Accuracy of Google Maps speed estimates

In this section we provide several pieces of evidence that GM’s estimates of trip speed are accurate, even in small cities. First, we show that their source data are likely to have excellent coverage. Next, we provide evidence of variation of travel time estimates over time, suggesting that real-time data is used in general, even within small cities. We also document variation in travel times during holidays and strikes that is consistent with GM providing real-time data. Finally and most
importantly, we compare the GM estimates to actual trip speed data from other data sources.

GM’s speed estimates are based on the location and speed of mobile phones using the Android operating system, as well as other phones running Google software, especially GM. Accurate measurement thus requires that many drivers are providing information.

A natural concern is that travel times predictions are worse in cities with lower mobile phone penetration. This is unlikely to affect our results. As of 2017, 63% of people across all of urban India had smartphones (see online Appendix B for details of all web-based sources). Given rapid growth from only 20% in 2013, this is surely an underestimate for 2019. In setting up their phones, users may choose to opt out of sending information to Google. However, the opt-out rate, which Google does not publish, would have to be extremely high to affect our results. Crucially, to estimate slowed traffic on a block, GM only needs one vehicle with a phone, and by definition, time-varying congestion implies many vehicles. Put together, this suggests that all cities have enough phones to generate high-quality speed estimates. Furthermore, using data from the GSM Association, we compute that more than 99% of the area of all sample cities had 2G (or better) coverage.

Even if GM has access to all of these data, it might not use them to provide real-time traffic data, reporting instead modeled averages, perhaps especially in smaller cities. In order to test for this, we looked for variation in trip duration (reported in seconds) and trip length (reported in hundreds of meters) across instances of the same trip occurring at the same time of day (within a 5-minute band) on a different weekday. We find that in the average city, 97% of peak-time trips show variation across instances on different days within a five-minute time-of-day window. In no city does this value fall below 78%. We believe that this is strong evidence that GM is using real-time traffic information to calculate travel speed in all cities.

We also estimate differences in travel speed during public holidays and strikes that took place during weekdays of our main data collection period, from June to November 2019. We find that most public holidays are associated with statistically significant changes in travel speed. In about two thirds of the cases, travel is faster during public holidays, typically between 0.5% faster like a typical Saturday and 4.5% faster like a typical Sunday, and in about quarter of the cases it is slower. The Ganesh Chaturthi festival in various states accounts for about half of these latter cases. This festival is a major Hindu celebration, which in many parts of India is associated with large processions. When we assess the effects of major strikes on travel speed in major Indian cities, we find that, unlike public holidays, they are associated with slower traffic in a majority of cases. Online

\textsuperscript{7}For more than 90% of the pairs of instances of the same trip within a five-minute interval, the lengths are within less than 1% of each of each other, suggesting that the variation in duration is not caused by some randomization of routes by GM. Excluding the 20% of trips for which we observe a variation of less than 6 seconds makes no change to our results below. After discarding these trips and re-estimating our speed index below, the correlation with our preferred speed index is 0.998.
Appendix B describes more precisely how we estimate the effects of these events on speed and reports more detailed results. Overall they strongly suggest that GM uses real-time data to simulate travel time.

To evaluate the accuracy of simulated GM trips in a broad set of cities, we collected information on actual trips using an app designed for us by Intents Mobi, a mobile app developer. We summarize this evaluation here, and provide detailed descriptions, figures, and tables in online Appendix D. Our Intents app was available everywhere in India, and it paid drivers per kilometer traveled, at a rate that was higher at night and in smaller cities. Our app asks drivers to record trip start and end, and collects driver geo-location at every second in between. After collecting trips from early September to mid-December 2019, and removing trips with implausible length or speed, we end up with 90,894 weekday trips in 89 cities. This sample is too small for city-specific analysis, so we divide it into large (population rank 1 to 20), medium (20 to 60), and small (over 60) cities.

We first compare the speed of actual Intents trips to that of our sample of simulated trips. We find that Intents trips are faster than simulated trips, with an especially large gap at night. This discrepancy occurs because Intents trips are much longer at night than during the day, and longer trips tend to be faster than shorter trips. After conditioning out trip length and distance to the city center (as in our main analysis described in Section II), time of day discrepancies disappear and our simulated and Intents samples display remarkably similar time patterns throughout the day. However, Intents trips remain somewhat faster.

To explore this issue further, for each Intents trip we query a corresponding trip on GM that starts at the same time of day and takes the same route. Comparing the speed of Intents trips to their GM replications, we find remarkably similar speeds throughout the day. This holds in all three city size bins, although results are noisier in small cities, where night time trips are rare. Android phone users are orders of magnitude more numerous than users of our app, so GM may still accurately measure speed at night in small cities. As an example of how the Intents and GM data display similar variation over time and across cities, online Appendix D shows that after controlling for trip characteristics, the average speed difference between night time (11 PM to 6 AM) and peak time (10 AM to 2 PM and 4:30 PM to 9 PM) trips in large cities is 29.4% in our main simulated GM sample, 28.0% in the Intents data, and 31.7% in the GM replication of Intent trips. In medium sized cities, the night time vs peak time differences in these three samples is 20.5%, 21.9%, and 21.9%. Overall, this replication exercise supports our use of GM to measure hourly speed patterns in Indian cities.

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8Intents recruited drivers through online ads targeted at frequent drivers, like Ola or Uber drivers. We did not collect information about drivers.
9Many cities have very few trips. Delhi has a large sample of 35,500 trips, and 13 cities have samples between 1,000 and 7,500 trips.
10This suggests that the differences with our main sample of GM trips are due to the special nature of the Intents sample. In particular, professional drivers may be reluctant to enter narrow residential roads. In addition, despite our best efforts we are not confident that the Intents data is well-partitioned into trips. Replicating Intents trips directly greatly attenuates these problems.
The other relevant source of information on the speed of a large number of actual trips we are aware of is Kreindler (2018), who shows that trip speeds from GM are very close to speeds for actual trips of both cars and motorcycles in Bangalore, measured with a custom-designed smartphone app.

Finally, in online Appendix E, we also provide a comparison between our data and information provided by Uber Movement about travel speeds in five large cities in our sample. This comparison is complicated by the manner in which Uber Movement aggregates its information. Instead of travel times of actual trips, Uber Movement reports times between zones by averaging travel times from Uber trips that pass through these zones. As we show, this greatly undersamples the beginnings and ends of trips, and these beginnings and ends are considerably slower than the middle parts. Because of this, Uber Movement reports speeds that are substantially faster than our trips. We show that we can nonetheless closely approximate the speed figures obtained from Uber Movement data once we appropriately distort our treatment of GM trip instances and, in particular, focus on travel speeds for the middle parts of trips or only consider longer trips.

II. A methodology for measuring mobility

A. A general conceptual framework

We model travel as a consumption problem. Potential travelers select trips, such as errands or commutes, from a large set of potential destinations and times, simultaneously with other decisions about household location and vehicle ownership. Fully modeling this presents intractable theoretical challenges and data requirements, so we drastically simplify it by creating a price index measured for each city. This approach has three key features: a chosen good (a trip), a price (inverse speed), and a consumption basket that is comparable across cities.

In each city, we can consider a number of residential locations and attempt to measure the cost of a ‘typical’ trip. The data requirements are still considerable but no longer overwhelming. The pitfalls of this approach are the same as those associated with typical price indices. Not knowing the preferences (or idiosyncratic prices) of households, it is unclear how travel costs (i.e. the prices) should be aggregated.

To minimize these pitfalls, we will show that our speed indices do not depend on how we weight different kinds of trips. This is because slower cities are slower at all times, for all types of trips, and throughout the city. As a result, we need not rely on a particular utility specification to tell us how to weight, say, a trip to the train station at peak hour on a weekday relative to a trip to a shopping destination on the weekend.

\[11\]

While generalized transportation costs involve money, time, and several dimensions of travel comfort and travel conditions (Small and Verhoef 2007), here we focus on travel time and reliability. This generalization is not as extreme as it seems. First, if we think of travel time as home production and value it between 50% and 100% of the wage, as is customary in the literature, it represents a large share
B. Measuring mobility

We want to measure the ease of going from an origin to a destination in cities. We focus on the speed of road travel using a motorized vehicle. Data from the 2011 Indian census suggests that 46% of urban commutes, and 55% of urban commutes longer than 1 kilometer, are by motorized road transport. Measuring the speed of travel in a city raises a number of challenges since trips differ considerably in their length, location of origin and destination, time and day of departure, and mode.

The simplest approach is to compute a measure of mean speed for a given city:

\[
S_{m}^{c} = \frac{\sum_{i\in c} D_{i}}{\sum_{i\in c} T_{i}},
\]

where \(c\) denotes a city and \(i\) is a trip instance. Because we sum the length \(D_{i}\) of all trip instances in city \(c\) and divide by the sum of trip durations \(T_{i}\), the ratio \(S_{m}^{c}\) is a length-weighted measure of travel speed. It is straightforward to define the corresponding unweighted mean.

Means are attractive because of their simplicity and ease of computation. However, means may not be comparable across cities in our case. Most importantly, trip length and distance to the center differ systematically across cities. As we show below, these characteristics are important determinants of trip speed. We can condition them out by estimating the following type of regression:

\[
\log S_{i} = \alpha X_{i}^{t} + s_{f(e)}^{c(i)} + \epsilon_{i},
\]

where the dependent variable is log trip speed \((S_{i} = D_{i}/T_{i})\), \(X_{i}\) is a vector of characteristics for trip instance \(i\), \(s_{f(e)}^{c(i)}\) is a fixed effect for city \(c\), and \(\epsilon_{i}\) is an error term.

If trip characteristics are appropriately centered and the errors are normally distributed, \(S_{c}^{f(e)} = \exp \left( s_{c}^{f(e)} + \hat{\sigma}^{2}/2 \right)\) is a measure of predicted speed for a typical trip in city \(c\) where \(\hat{\sigma}\) is the estimator of the standard deviation of the error term \(\epsilon\). Note that for simplicity we often directly use the estimated city fixed effects, \(s_{c}^{f(e)}\), as an index of speed.

Equation (2) does not specify the exact content of the vector of characteristics \(X\). For now we simply note that the purpose of these controls is to ensure that we are comparing like trips across cities, just as products in a city-level price index must be comparable across cities. Somewhat more precisely, in estimating a city’s relative ability to supply fast travel, we want to hold demand conditions constant. We defer discussion of individual controls to section III where we also of the overall cost of travel. Second, many other components of travel costs such as gas consumption and vehicle depreciation are positively correlated with travel time. Safety however may be negatively correlated, though some features that improve traffic flow may improve pedestrian safety.
report results.

In online Appendix F, we consider more flexible variants of this model that allow the intercept and vector of coefficients to vary across cities. We also estimate variants from a broad class of mobility indices derived from logit (Ben-Akiva and Lerman, 1985) or CES utility specifications. In particular, we develop a model in which travelers choose a departure hour, and the city-specific ‘quality’ of each hour is calibrated to fit the hourly departure shares in the Intents trip data.

It is important to keep in mind that the observations used to estimate equation (2) and its variants are simulated trips, not actual trips. This presents both benefits and costs. The main advantage of our approach is that trips are exogenously chosen. Unlike Couture, Duranton and Turner (2018), who use travel survey data, we do not need to worry about the simultaneous determination of variables like trip length and speed, which could affect the estimates of city fixed effects in equation (2).

Conceptually, our approach is similar to measuring price indices from store price tags instead of from consumers’ transactions.

This exogeneity is also a potential limitation of our method. The trip instances that we query do not correspond to actual trips and may not be representative of the travel conditions faced by urban travelers. If our trips are far enough from representative, and if the relative speed of various types of trips varies across cities, then our speed indices will be mismeasured.

To this criticism, we have three answers. The first is that as noted in Section I.B, some of the trips we simulated were designed to resemble actual trips in other contexts where we do have representative data such as Bogotá, Berlin, and the United States, with respect to either their direction and length, or their destination type and frequency. We can also weight our simulated trips to match the time pattern of our Intents sample of actual trips in Indian cities. Second, we show below that the economic significance of the trip type indicators in equation (2) is small when we introduce a comprehensive set of controls for other trip characteristics. Third and most important, our large sample allows us to estimate speed indices for each trip type, destination, time of day, distance to city center, and various other subsamples. These indices are all highly correlated with our baseline index. As argued earlier, this result implies that our indices do not depend in an important way on the particular utility weight that each simulated trip could receive.

C. Disentangling two sources of mobility: uncongested speed and congestion.

Speed can naturally be decomposed into two components: an uncongested or “free flow” speed, and a congestion factor. To separate the “intrinsic” slowness of a city from its congestion, we can adapt the approach proposed above. To measure speed, we use the log of actual trip speed as dependent variable in equation (2).

12 For instance, travelers may take longer trips when travel speed is faster. In addition, the (simulated) trip instances that we query do not affect real traffic conditions.
and estimate city fixed effects $\hat{f}_c$ that we can interpret as an index of speed. To construct an index of uncongested speed, we estimate the same equation with the log of speed in the absence of traffic returned by $\text{GM} \left( S_{int} = D_i / T_{int} \right)$ as the dependent variable. The resulting city fixed effects $\hat{n}^t_{fc}$ are our index of uncongested speed.

To measure congestion, we repeat the same estimation using the difference between log trip duration with and without traffic, $\log T_i - \log T_{int}^t$, as the dependent variable. While strictly speaking, the resulting estimated city fixed effects, $\hat{f}_c$, are a measure of delay, we can interpret them as a broad index of congestion, which we call the congestion factor.

Because uncongested and congested speeds are defined using the same trip length, $\log T_i - \log T_{int}^t = \log S_{int} - \log S_i$. The congestion factor is thus equal to the difference between log speed without and with congestion. Since these three dependent variables are linearly related, and the three regressions use the same sample and covariates, the three fixed effects are also linearly related. A city’s congestion factor is the difference between its uncongested speed index and its speed index:

$$ f_c = \hat{n}^t_{fc} - \hat{s}^t_{fc} $$

This result is useful on two counts. First, it provides us with an exact city-level decomposition of speed into uncongested speed and congestion, which we exploit below. Second, when we regress these three city fixed effects on the same set of city determinants below, the estimated coefficients conveniently add up.

### D. Measuring travel time unreliability

Empirical studies in other contexts find that travelers care not only about travel speed, but also about reliable trip duration [Brownstone and Small [2005]]. For example, unexpected late arrival at work has a cost distinct from that of a predictably long commute. Measuring unreliability for a large sample of trips over many routes is challenging using traditional methods (loop detectors, GPS devices, or recall diaries). Our empirical design using $\text{GM}$ is uniquely well-suited for this exercise because we can query the same trip at the same time (within a five-minute time window) on different weekdays.

As in [Brownstone and Small [2005]], we measure unreliability for a given trip departing at a given time using the percentiles of the travel time distribution across different weekdays. In particular, we compute the unreliability of a trip as the ratio of the 90th to the 50th percentile of its travel time distribution net of city-specific effects for each weekday, to account for, say, systematically faster Thursdays in one city and Mondays in another. We then compute unreliability

---

13 The standard deviation of arrival times is also a common measure of unreliability. Using a high percentile of the trip time distribution has the advantage of capturing travelers’ special aversion to being
indices for each city, using the unreliability ratio of each trip as a dependent variable in the regression in equation (2) with all other controls except weather (which is part of what we want to capture in measuring unreliability). The scope of our unreliability analysis is broader than any previous attempts in the literature, and offers the first cross-city evidence on travel time unreliability.

III. Trip-level results

Before an in-depth analysis of speed indices and their correlates, we first estimate a number of variants of the generic regression described by equation (2).

We expect longer trips to be faster, as drivers use faster roads. We also anticipate slower trips closer to the city center, both because of higher congestion, as expected in monocentric cities, and likely also due to shorter blocks, more intersections, and narrower streets. Our core set of controls thus includes log trip length and log average distance to the city center. It also includes departure time (in 30 minute periods) and day indicators since travel speed generally differs by time of day and day of the week. We expect variations in travel speed throughout the day to be driven by differences in the demand for travel and perhaps by non-travel uses of the roadway, such as parking or retail. We also introduce trip type indicators to condition out any sampling differences. In addition, including weather conditions at the time of the trip ensures that such idiosyncratic factors are not driving our results either. Our benchmark specification includes these core controls and city fixed effects. We call these fixed effects “broad” because they absorb all other variation across cities.

In addition, we consider an extended set of controls which includes trip attributes related to the specific route: gross gradients upward and downward, the length share along motorways, primary, secondary, tertiary, residential and other roads, and the numbers of intersections, turns against traffic, and establishments passed. With extended trip controls, the resulting city fixed effects are “narrow” in the sense that they are net of the direct effect of route characteristics on each trip and only include the indirect effects of city attributes (such as roads). While these effects are informative, we prefer the “broad” fixed effects as our benchmark because of our focus on cross-city differences: they allow us to estimate overall effects of city characteristics on speed.

A first series of results is reported in table 2. Column 1 regresses log trip speed on city fixed effects and most core controls: day, time, trip type and length. Column 2 repeats the specifications of columns 1 on a sample of only weekday trips. Column 3 introduces log distance to city center and weather indicators. Column 4 includes regression weights ensuring that the total weight of all trips taken during any half hour of day is proportional to the share of trips taken during that half hour in the Intents data on actual trips. Column 5 adds controls for very late

\[\text{(Brownstone and Small 2005)}\]

14 They also remove average cross-city variability in weather conditions from the city fixed effects, but we show in the online Appendix that this makes little quantitative difference.
<table>
<thead>
<tr>
<th>Table 2—Determinants of log trip speed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<tr>
<td></td>
</tr>
<tr>
<td>log trip length</td>
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<td></td>
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<tr>
<td>log distance to center</td>
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<tr>
<td></td>
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<tr>
<td>Gross gradient up</td>
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<td></td>
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<tr>
<td>Gross gradient down</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Share primary roads</td>
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<tr>
<td></td>
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<tr>
<td>Share secondary roads</td>
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<tr>
<td></td>
</tr>
<tr>
<td>Share tertiary roads</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Share resid. roads</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Share other roads</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Share missing roads</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>log # intersections</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>arsinh # right turns</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>arsinh # establishments</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Type: circumferential</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Type: gravity</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Type: amenity</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>City effect</td>
</tr>
<tr>
<td>Day effect</td>
</tr>
<tr>
<td>Time effect</td>
</tr>
<tr>
<td>Weight</td>
</tr>
<tr>
<td>Weather</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R²</td>
</tr>
</tbody>
</table>

Note: 180 cities in each column. OLS regressions with city, day, and time of day (for each 30 minute period) indicators. Log speed is the dependent variable in all columns. Robust standard errors in parentheses. a, b, c: significant at 1%, 5%, 10%. Sample sizes for columns 2 and 6 apply to columns 2–5 and 6–7, respectively. Share of road classes are measured as a function of trip length. Motorways are the reference category. The reference category for trip type is radial trips. Weather indicators for rain (yes, no, missing), thunderstorms (yes, no, missing), wind speed (16 indicator variables), humidity (15 indicator variables), and temperature (5 indicator variables).
upward and downward gradients, and for the share of each OSM road class along a trip’s route. Columns 6 and 7 add controls for the number of intersections, the number of turns against traffic, and the number of Google Places establishments along a trip’s route.

We find that longer trips are faster: the elasticity of trip speed with respect to trip length is 0.22 in columns 1 and 2. This is a prominent feature of urban transportation data in other contexts.\(^{15}\) Regressing log trip speed on log trip length without any further control yields an $R^2$ of 0.31. Unsurprisingly, trips further from the center are also faster. In columns 3 and 4, the elasticity of trip speed with respect to distance to the center is 0.08, implying that a trip at 10 kilometers from the center of a city is nearly 20% faster than a trip one kilometer from the center.

In column 1 and 2, we find fairly large differences of up to 7% in speed between different types of trips. These differences become much smaller once we add a control for distance to city center in column 3 to 7. This result is reassuring, and suggests that the design of our hypothetical trips is not driving our results. We also find minimal differences between days of the week, except that Sundays are about 4.5% faster.

In column 3, we introduce weather controls and find modestly lower speed during adverse weather conditions. Comparing columns 3 and 4 shows that results are similar after re-weighting trips to ensure that the total weight of trips within each half hour of the day matches the departure shares from actual trips in Indian cities (Intents data).

Column 5 shows that driving uphill is slower, but not driving downhill. The coefficients on each road class are consistent with OSM road classification. That is, trips on primary roads are 10 percent slower than trips on motorways (the excluded road class), trips on secondary roads are even slower, and so on. Column 6 shows that trips on routes with more intersections and turns against traffic are slower, but the effect of intersections disappears in column 7 after controlling for the number of establishments near the trip route, which is negative and highly significant.

Our results do not depend on the specific choices we made when choosing our benchmark specification. Online Appendix table G.1 reports several variants of Table 2, column 4, including subsamples for peak hours, high peak hours, commutes (radial inward in the morning and outward in the evening), night only and day only.\(^{16}\) Key elasticities change little, and as we show below, city effects

\(^{15}\) Couture, Duranton and Turner (2018) estimate a larger elasticity close to 0.40 using self-reported US data where the measure of trip duration also includes a fixed time cost of getting into one’s vehicle and entering traffic. Using self-reported data, Akbar and Duranton (2018) find an even larger elasticity for Bogotá travelers, because their sample also includes transit trips, with even larger fixed time costs. Using analogous GM data for the same Bogotá trips, Akbar and Duranton (2018) find an elasticity of 0.21, very close to the elasticity estimated here. We experimented with adding the square of log trip length, and estimate very small coefficients for these higher order terms that are generally not significant.

\(^{16}\) We define as peak all the 30-minute periods where traffic, as measured from our preferred trip regression, is at least 20% slower than uncongested speed: 10 AM to 2 PM and 4:30 to 9 PM. High peak is
As expected, we also observe fluctuations in travel speed across times of day. In figure 3, which mirrors figure 2 but isolates hour effects, the dark line with small triangles plots the speed relative to 1:30 - 2 AM for each thirty-minute period estimated in column 4 of table 2 for all cities. The gap between the fastest time in the middle of the night and the slowest at 6:30 PM - 7 PM is slightly more than 25%. We also note that morning peak hours are more muted than the evening peak hours.

The figure also plots the same time profile estimated only on the decile of largest

\footnote{Since India is a vast country with a single time-zone, within-day fluctuations may be attenuated by the timing of sunrise and sunset, which differs across sampled cities by up to about two hours. A variant of figure 3 using the time of each trip relative to local sunrise and sunset is virtually indistinguishable from figure 3.}

when traffic is at least 25% slower than uncongested speed, from 6 to 8 PM. For ‘commutes’, we consider inward radial trip during the morning peak and outward radial trips during the evening peak.

\footnote{Since India is a vast country with a single time-zone, within-day fluctuations may be attenuated by the timing of sunrise and sunset, which differs across sampled cities by up to about two hours. A variant of figure 3 using the time of each trip relative to local sunrise and sunset is virtually indistinguishable from figure 3.}
Table 3—Ranking of the 10 slowest, most congested, and fastest cities

<table>
<thead>
<tr>
<th>Rank</th>
<th>City</th>
<th>State</th>
<th>Index</th>
<th>City</th>
<th>State</th>
<th>Index</th>
<th>City</th>
<th>State</th>
<th>Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Bhiwandi</td>
<td>Maharashtra</td>
<td>-0.34</td>
<td>Bangalore</td>
<td>Karnataka</td>
<td>0.18</td>
<td>Ranipet</td>
<td>Tamil Nadu</td>
<td>0.26</td>
</tr>
<tr>
<td>2</td>
<td>Kolkata</td>
<td>West Bengal</td>
<td>-0.31</td>
<td>Mumbai</td>
<td>Maharashtra</td>
<td>0.16</td>
<td>Cherthala</td>
<td>Kerala</td>
<td>0.21</td>
</tr>
<tr>
<td>3</td>
<td>Santipur</td>
<td>West Bengal</td>
<td>-0.28</td>
<td>Delhi</td>
<td>Delhi</td>
<td>0.15</td>
<td>Malappuram</td>
<td>Kerala</td>
<td>0.20</td>
</tr>
<tr>
<td>4</td>
<td>Arrah</td>
<td>Bihar</td>
<td>-0.28</td>
<td>Chennai</td>
<td>Tamil Nadu</td>
<td>0.13</td>
<td>Karur</td>
<td>Tamil Nadu</td>
<td>0.20</td>
</tr>
<tr>
<td>5</td>
<td>Bihar Sharif</td>
<td>Bihar</td>
<td>-0.27</td>
<td>Guwahati</td>
<td>Assam</td>
<td>0.12</td>
<td>Karnal</td>
<td>Haryana</td>
<td>0.19</td>
</tr>
<tr>
<td>6</td>
<td>Mumbai</td>
<td>Maharashtra</td>
<td>-0.26</td>
<td>Bhiwandi</td>
<td>Maharashtra</td>
<td>0.11</td>
<td>Kayamkulam</td>
<td>Kerala</td>
<td>0.19</td>
</tr>
<tr>
<td>7</td>
<td>Bangalore</td>
<td>Karnataka</td>
<td>-0.24</td>
<td>Pune</td>
<td>Maharashtra</td>
<td>0.11</td>
<td>Palakkad</td>
<td>Kerala</td>
<td>0.18</td>
</tr>
<tr>
<td>8</td>
<td>Patna</td>
<td>Bihar</td>
<td>-0.24</td>
<td>Hyderabad</td>
<td>Telangana</td>
<td>0.11</td>
<td>Kanhangad</td>
<td>Kerala</td>
<td>0.18</td>
</tr>
<tr>
<td>9</td>
<td>Shillong</td>
<td>Meghalaya</td>
<td>-0.24</td>
<td>Kolkata</td>
<td>West Bengal</td>
<td>0.10</td>
<td>Bhiwara</td>
<td>Rajasthan</td>
<td>0.17</td>
</tr>
<tr>
<td>10</td>
<td>English Bazar</td>
<td>West Bengal</td>
<td>-0.24</td>
<td>Shillong</td>
<td>Meghalaya</td>
<td>0.09</td>
<td>Shimoga</td>
<td>Karnataka</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Note: The speed index is measured by the city effect estimated in column 4 of table 2 and is centered around its mean. The congestion factor is measured from a similar regression using log trip duration minus log trip duration in absence of traffic as dependent variable, and centered around its mean.

The patterns are much more marked. The slowest periods in the evening are now more than 35% slower than the fastest. This pattern is slightly more accentuated when restricting to Mumbai, the second most congested city in our sample, and considerably more so in Central Mumbai, where peak travel is about half as fast as travel in the middle of the night. By contrast, travel speed in Santipur, though very slow in general (see above), varies little throughout the day.

We finally turn to city effects. As argued above, we can interpret them as speed index values. They measure (log) trip speed in cities after conditioning out log trip length, log trip distance to the center, day and time of day effects, and effects of weather. The standard deviation of the speed index is 0.116. The slowest city is 29% slower than the mean while the fastest city is 30% faster. This 83% speed difference between the slowest and fastest city is extremely large. We compare our results for India to analogous results for the US below.

Table 3 reports the ten slowest, most congested, and fastest cities. The ten slowest include three of the four largest cities in India, as well as three in Bihar, the poorest state. The ten most congested include seven of the ten largest cities. To interpret the magnitudes for congestion, it is important to keep in mind that the congestion factor of a city is relative. It is estimated conditionally on time effects (and other controls in the regression) and it reflects a log deviation from uncongested speed. So with a congestion factor of 0.10, Kolkata is about 10% slower, relative to its uncongested speed, than the average across all trips in all cities. As made clear by the speed fluctuations throughout the day reported in figure 3, the mean trip across cities experiences some congestion. Hence, the congestion factor of a city captures congestion over and above average congestion. This index is negative for cities like Santipur, which experience less congestion.
than the average. Finally, the ten fastest cities are all relatively small, and disproportionately in the southern states of Kerala and Tamil Nadu.

In online Appendix G (table G.2), we investigate the robustness of our speed index to a wide variety of specification and sample choices. Our speed index is not sensitive to restricting our sample to specific areas of the city, or specific times of the day, or specific types of trips. Our speed index also is highly correlated with more sophisticated indices that resemble standard price indices (e.g. Laspeyres), and with indices derived from discrete choice models that allow for rich substitution patterns across trips. We conclude that our speed index provides a robust characterization of travel cost differences across cities, because slow cities tend to be slow at all times, for all types of trip destinations, and across the city.

To complete our description of trip-level results, we document significant unreliability in travel time across urban India. Across different weekdays during peak times, trip times at the 90th percentile are on average 6% slower than median trip times. In more than 80% of cities in our sample, average unreliability is between 4% and 8%. Trip time is more unreliable in larger cities, with an average unreliability of 8% for cities in the top population decile. The most congested cities are also the most unreliable, with a correlation between our congestion and unreliability indices of 0.89.

To put these numbers in perspective, Brownstone and Small (2005) conclude that Californian morning commuters value the 90th to 50th percentile difference in travel time 95% to 140% as highly as they value median travel time. In our data, the population-weighted average peak travel delay is about 21%, and the population-weighted average unreliability is 7%. This suggests that the cost of unreliability is about a third of that of travel delay.

IV. Decomposition: uncongested speed and congestion

In this section, we decompose our indices of speed into speed in the absence of traffic (uncongested speed) and the congestion factor following equation (3). This relationship allows us to perform two useful exercises: an exact decomposition of the variance in our speed index, and a simple analysis to compare the welfare gains from faster uncongested speed with those from reduced congestion.

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18 We emphasize that appropriately estimating a city speed index requires accounting for trip-length differences. For instance, a mean speed index computed from equation (1) has a fairly low rank correlation of 0.68 with our benchmark speed index. As noted in Couture, Duranton and Turner (2018) for US metropolitan areas, means of speed do not provide good descriptions of speed in cities, because trip length has a large explanatory power on trip speed, and average trip length varies systematically across cities. This highlights the importance of using entire trip instances as units of analysis, instead of trip segments or travel speed at discrete locations.

19 This is perhaps an underestimate as our data from GM assume optimal re-routing depending on traffic conditions. Travelers without the benefit of information on current traffic or unwilling to re-route may face even more unreliable travel times, as well as longer delays. GM may also overestimate unreliability if it captures variation that is known in advance to commuters.
Table 4—Variance decompositions of our baseline speed index

<table>
<thead>
<tr>
<th>Sample</th>
<th>Cities</th>
<th>All trips</th>
<th>High peak trips</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Uncongested speed</td>
<td>Congestion factor</td>
</tr>
<tr>
<td>All</td>
<td>180</td>
<td>0.701</td>
<td>0.126</td>
</tr>
<tr>
<td>Smallest 50%</td>
<td>90</td>
<td>0.813</td>
<td>0.062</td>
</tr>
<tr>
<td>Largest 50%</td>
<td>90</td>
<td>0.632</td>
<td>0.179</td>
</tr>
<tr>
<td>Largest 25%</td>
<td>45</td>
<td>0.528</td>
<td>0.224</td>
</tr>
<tr>
<td>Largest 10%</td>
<td>18</td>
<td>0.477</td>
<td>0.238</td>
</tr>
</tbody>
</table>

Note: Full trip sample. High peak hours are 6–8 PM

A. Variance decomposition

The variance of the speed index is equal to the sum of three terms: the variance of the uncongested speed index, the variance of the congestion factor, and minus twice the covariance between the uncongested speed index and the congestion factor. As shown in the first row of Table 4, the variance of the uncongested speed index accounts for 70% of the variance of our benchmark speed index while that of the congestion factor accounts for only 13%. This is a striking finding. Differences in speed between Indian cities are mostly driven by differences in their uncongested speed, not by differences in how congested they are. It is consistent with the findings of Table 3, which show much more variance across cities in overall speed than in congestion.

A possible caveat here is that, despite a weighting scheme that relies on actual trips, our data oversample trips at night and this may bias our speed index towards uncongested speed. Performing the same exercise with indices computed only from trips taken at high peak hours between 6 and 8 PM, we find that the uncongested speed index still represents 57% of the variance of the speed index whereas the congestion factor represents only 26%.

The second row shows that congestion explains very little speed variation across smaller cities, even at peak times. This is unsurprising. Smaller cities are mostly uncongested but experience large differences in uncongested speed. By contrast, the largest cities face more similar uncongested speed but are congested to different degrees.

In rows 3–5, we restrict the sample to the largest 50%, 25%, and 10% of cities. The two sets of differentials (overall and high peak) shrink further. However, in all cases the contribution of uncongested speed remains larger than that of congestion, even at high peak hours in the top decile of cities (although the difference is now small).
In online Appendix table H.1, we show that the role of congestion expands as we limit attention to city centers, especially at high peak hours and in larger cities. Variance in uncongested speed still however represents a substantial share of overall variance across cities in all samples. We also repeat the same decomposition for each type of trip separately and find roughly similar results for the respective roles of uncongested speed and congestion.

**B. Valuing improvements in uncongested speed and congestion.**

The valuation of an improvement in uncongested speed depends on how much of that improvement is crowded out by peak time congestion. Our cross-city data does not offer opportunities to causally identify the extent of crowding out from congestion. However, we note that if crowding out was extensive, then cities with faster uncongested speed would also experience more congestion. We find instead a small negative (-0.29) correlation between our uncongested speed and congestion indices.\(^{20}\) Also consistent with the idea that uncongested speed improvements are not crowded out by rising congestion, our cross-city regressions below show that characteristics of road networks (mileage of major roads, street lighting, and grid-like structure) are all positively associated with higher uncongested speed but not with congestion. This lack of evidence for strong network congestibility is also consistent with existing findings in developing cities from Akbar and Duranton (2018) in Bogotá and Kreindler (2018) in Bangalore.\(^{21}\)

If we assume that any changes in congestion are small, then improvements in uncongested speed translate almost one-to-one into time saving gains, even at peak times. So, a one standard deviation improvement in uncongested speed, equivalent to uncongested speeds that are 10 percent faster, translates into time savings of 10 percent.\(^{22}\) In contrast, gains from congestion pricing in Akbar and Duranton (2018) and Kreindler (2018) are smaller than one percent of travel costs.\(^{23}\)

On the benefit side of any cost-benefit analysis, these estimates suggest that gains from achieving a one standard deviation improvement in uncongested speed could be many times larger than the gains from introducing optimal congestion pricing.

Finally, we note that the monetary value of time savings from a standard deviation (10 percent) improvement in uncongested speed would be larger in cities where workers have higher value of travel time, higher motor vehicle commute costs.\(^{24}\)

\(^{20}\) Another way to see this is from a bivariate cross-city regression: a 1% increase in uncongested speed is associated with a 1.12% increase in actual speed, with a standard error of 0.03% and an \(R^2\) of 0.88.

\(^{21}\) In characterizing how road networks are less congestible than previously thought, Kreindler (2018) highlights the linear relationship between travel speed and the number of vehicles on the road, while Akbar and Duranton (2018) highlight the role of side roads in relieving congestion on major roads at peak time.

\(^{22}\) We ignore additional welfare gains from induced demand.

\(^{23}\) The gains from congestion pricing would likely be higher near the center of large cities. For instance, Yang, Purevjav and Li (2020) estimate that optimal congestion pricing in Beijing would increase traffic speed by 4 percent in the city overall, and by 11 percent within the city center (within the third ring road).
share, and longer commute length. In online Appendix J, we express these gains in monetary units, and explore cross-city heterogeneity. We find a population-weighted average yearly gains per worker of 1,157 INR (about 16 USD) for vehicle commuters in the 100 cities with the largest Census sample of workers. The largest yearly gains per worker are 2,696 INR (about 38 USD) in Delhi, a city with high wages and a high share of vehicle commuters.

V. Correlation of speed indices with city characteristics and urban development

We now explain speed using city characteristics. We first consider basic demographic and geographic characteristics. Population and area are likely to be of central importance, as previous work has found that denser and more compact cities are slower in the US (Glaeser and Kahn [2004]; Couture, Duranton and Turner [2018]). Uneven terrain requires steep and/or circuitous roads that decrease driving speed and can also create bottlenecks. Similarly, water bodies limit road construction and can force traffic onto a limited set of causeways or bridges. To the extent that many cities form around harbors and rivers, these bottlenecks often occur in historical centers with high density.

We next consider road infrastructure. Major roads, street lighting, and a regular grid all have the potential to facilitate faster driving. Major roads are typically wider, better paved, and in some cases restricted access. All this facilitates faster driving in the absence of traffic. Street lighting also makes it possible to drive faster early or late in the day. It may also proxy more broadly for higher quality roads. The shape of the street network is also often alleged to play an important role in helping vehicles flow. Angel (2008) and Fuller and Romer (2014) highlight grids in particular.

Finally, we consider correlates of urban economic development, chiefly wage levels. Richer cities may be able to facilitate driving in more subtle ways than the infrastructure measures above, including perhaps fewer non-traveling users of the roadway and better adherence to traffic rules in addition to better design, construction, and maintenance. Richer cities may also face more vehicles and faster population growth adding to congestion.

Table 5 reports results for our benchmark speed index in columns 1–3. Columns 4–6 and 7–9 report the same specifications predicting the benchmark uncongested speed and congestion indices, respectively. Because the speed index is equal to the uncongested speed index minus the congestion factor and we estimate the same specifications for all three dependent variables in each column, each coefficient

24 They save 5.5 minutes in travel time per work day from the speed increase, valued at vehicle commuters’ average wage. In the US, Small and Verhoef’s (2007) review of the literature suggests valuing travel time at 50% percent of the hourly wage, while Goldszmidt et al. (2020) find 75% and document significant cross city heterogeneity. Kreindler (2018) estimates 400% using experimental data from Bangalore. We pick a value of 100 percent to remain conservative while accounting for the possibility of higher valuation in developing countries due to road or vehicle quality or other costs like fuel that are relatively more important there.
in column 1–3 is equal to the analogous coefficient in column 4–6 minus the analogous coefficient in column 7–9.

Column 1 of table 5 considers basic demographic and geographic characteristics. Because our dependent variable is a measure of log speed, we can interpret the population and area coefficients as elasticities. For city population, we estimate an elasticity of -0.15. For city area, the elasticity is of opposite sign and equal to 0.17. These two variables explain 36% of the variation in speed across Indian cities. Further controls added in subsequent columns have little impact on these results.

These results suggest a large density effect since an increase in population keeping land area constant is an increase in population density. An elasticity of the cost of travel with respect to population density of -0.15 to -0.19, as implied by the results of table 5, is comparable in magnitude to the analogous elasticity of housing price at the center of French cities of 0.21 estimated by Combes, Duranton and Gobillon (2019). To the extent that we can compare India with France, these results are suggestive that much of the urban costs measured by Combes, Duranton and Gobillon (2019) reflect slower travel in denser cities.

At the same time, the mostly offsetting nature of the coefficients on population and urban land area in column 1 implies that, unlike density effects, population effects are small when we allow land area to adjust. Consistent with this, we estimate an elasticity of about -0.04 when regressing our preferred speed index on log city population alone (not shown).

In columns 4–9, we see that consistent with our earlier decompositions of overall variance, most of the effect of city population and city area on speed works through uncongested speed. At least in part, we attribute this large effect of population density to shorter blocks, narrower roads, and perhaps a greater prevalence of light signals in denser areas. Consistent with this interpretation, in a regression not reported here we find that when we measure uncongested speed with “narrow” city fixed effects (i.e. from a trip-level regression that conditions out gross gradients, intersections, establishments passed, turns against traffic and road shares), the magnitude of the coefficient on city population in the column 6 specification falls by nearly a third to -0.11, fairly close to the analogous US coefficient of -0.08. For the congestion factor, we find an elasticity of city density of 0.037 in column 7 that varies little across specifications.

Consistent with expectations, hills and water bodies reduce speed, primarily through uncongested speed, but they noticeably increase congestion as well.

The density of major roads has a robust positive impact on speed, mostly through uncongested speed, while their effect on the congestion factor is a precisely estimated zero. We think these findings reflect two facts. First, major roads are engineered to be faster than other roads in the absence of traffic. Second, the absence of an effect on the congestion factor is consistent with the fundamental law of ‘major roads’ congestion: more major roads attract new traffic and eventually leave congestion unchanged (Duranton and Turner 2011).
Street lights and a road network that conforms more to a grid also increase speed via uncongested speed. Together, these three infrastructure measures notably increase the share of explained variance in speed from 0.47 to 0.62.

Column 3 of table 5 further includes average earnings per industrial worker, in USD per day, and its square. We find evidence of a hill shape: speed first increases with income and then declines. The elasticity of speed with respect to city income is 0.046 at the bottom decile of city income and -0.030 at the top decile, while the turning point corresponds to a city close to the eighth decile of income. Examining the separate effects of income on uncongested speed and the congestion factor in columns 6 and 9, we find that the shape of the income-speed relationship reflects two opposing forces. Uncongested speed improves with income throughout essentially the whole distribution, perhaps because of better roads. The congestion factor also increases with income in the top half of the income distribution, consistent with our findings below on car ownership, which also rises with income.

To assess the importance of the various explanatory variables we consider in table 5, we measure how the $R^2$ changes when we remove an explanatory variable or a block of explanatory variables from the full specification for the speed index in column 3, for which the $R^2$ is 0.64. Starting from this full specification minimizes the role of omitted variables, relative to interpreting marginal contributions of added variables to $R^2$, and is in that sense consistent with the decomposition framework of Gelbach (2016). Removing population lowers the $R^2$ of this regression to 0.23. Removing the geography variables (area, variance of elevation and length of rivers and coasts) has a smaller effect: the $R^2$ falls to 0.51. We obtain a similar result when we remove the three roads variables (with the length of the roadway having the strongest effect). Finally, removing the income variables has only a marginal effect on the $R^2$ as it falls to 0.62.

It is also interesting to conduct the same exercise for uncongested speed and congestion because both are affected by the same factors as speed. For uncongested speed, the $R^2$ of the full specification in column 6 of table 5 is 0.60. It falls to 0.21 without population, 0.42 without the roads variables, 0.50 without geography, and 0.59 without income. For congestion, the $R^2$ of the full specification in column 9 of table 5 is 0.51. It falls to 0.39 without population, 0.43 without topography, 0.44 without income, and 0.50 without the roads variables.

Hence, city population is the key determinant of both speed and uncongested speed ahead of roads and topography while income only plays a modest role. For congestion, population is less fundamental but still the most important determinant ahead of topography and income, while roads play essentially no role. The similarity of the results between speed and uncongested speed is consistent with our decomposition above, which shows that most of the variation in speed is accounted for by uncongested speed.

Online Appendix table I.2 provides consistent evidence on the importance of variables based on the coefficients on standardized versions of our explanatory variables.
Table 5—Correlates of city indices

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>(1) Speed index</th>
<th>(2) Uncongested speed</th>
<th>(3) Congestion factor</th>
<th>(4) Uncongested speed</th>
<th>(5) Congestion factor</th>
<th>(6) Uncongested speed</th>
<th>(7) Congestion factor</th>
<th>(8) Uncongested speed</th>
<th>(9) Congestion factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>log population</td>
<td>-0.15&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.19&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.18&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.12&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.16&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.15&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.037&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.038&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.035&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>log area</td>
<td>0.17&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.10&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.096&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.14&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.074&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.070&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.025&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.030&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.026&lt;sup&gt;a&lt;/sup&gt;</td>
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<tr>
<td>Elevation variance</td>
<td>-0.033&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.034&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.036&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.022&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.024&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.027&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.011&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.0097&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.0089&lt;sup&gt;a&lt;/sup&gt;</td>
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<tr>
<td>Water length</td>
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<td>-0.14&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.16&lt;sup&gt;a&lt;/sup&gt;</td>
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<td>0.058&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.053&lt;sup&gt;b&lt;/sup&gt;</td>
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<tr>
<td>log major roads</td>
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<td>0.069&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.077&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.073&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.0074&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.0038&lt;sup&gt;a&lt;/sup&gt;</td>
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<td></td>
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<tr>
<td>log street lights</td>
<td>0.014&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.010&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.010&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.0088&lt;sup&gt;c&lt;/sup&gt;</td>
<td>-0.0041&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.0015&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
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<tr>
<td>Network</td>
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<td>0.29&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.24&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.25&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.054&lt;sup&gt;a&lt;/sup&gt;</td>
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<td></td>
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<tr>
<td>Earnings</td>
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<td>0.016&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.016&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.013&lt;sup&gt;a&lt;/sup&gt;</td>
<td>(0.0088)</td>
<td>(0.0079)</td>
<td>(0.0039)</td>
<td></td>
<td></td>
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<tr>
<td>Earnings&lt;sup&gt;2&lt;/sup&gt;</td>
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<td>-0.00086&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.0013&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td>(0.00053)</td>
<td>(0.00048)</td>
<td>(0.00023)</td>
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<td></td>
</tr>
</tbody>
</table>

Note: 180 observations in each column. OLS regressions with a constant in all columns. The dependent variable of columns 1, 2, and 3 is the city fixed effect estimated in the specification reported in column 4 of table 2. The dependent variable of columns 4, 5, and 6 is the city fixed effect of an analogous regression using uncongested speed as dependent variable. The dependent variable of columns 7, 8, and 9 is the city fixed effect of an analogous regression using the congestion factor as dependent variable. Robust standard errors in parentheses. <sup>a</sup>, <sup>b</sup>, <sup>c</sup>: significant at 1%, 5%, 10%. Log population is constructed as described in the main text from the 2011 census. Elevation variance is the variance of the elevation of the nodes of the road network (where elevations are measured in meters and the variance is divided by 1000). Water length is the length of all coast and rivers measured in thousands of kilometers. Log major roads is log kilometers of motorways, primary, secondary, and tertiary roads within the city. Log street lights is the log of the number of kilometers of roadway with lights from the 2011 census. The network shape variable used in column 4 measures the share of edges in the road network that conform to the grid’s main orientation, i.e. whose compass bearing are within 2 degrees of the modulo 90 modal bearing in the network. It measures how grid-like the city is. Income is measured with industrial earnings in USD per day. An F-test rejects the joint insignificance of both earnings variables at 1% in columns 3 and 9. The same tests marginally fails to reject it at 10% in column 6.

Online Appendix table I.1 considers three additional regressors. First, population growth in the previous three decades is significantly associated with more congestion, but also with faster uncongested travel. Overall the positive effect via uncongested speed appears to dominate, though not significantly so. While we leave a deeper investigation of these results for future research, we emphasize that they are inconsistent with typical claims that rapid urban population growth in developing countries is necessarily associated with worse mobility. Congestion may worsen with population growth but this negative effect is more than offset...
by faster roads. Second, having more cars is significantly associated with more congestion, but also with faster uncongested speed (although not significantly), so the overall effect on speed is small and not significant. Motorcycles, which take up less space and can weave through traffic, are associated with less congestion and faster travel. Again, causal identification is beyond our scope here, but these results are consistent with motorcycles taking up less room than cars, but inconsistent with them being a response to congestion. Third, a greater concentration of city population, as measured by a spatial Gini coefficient, is associated with slower uncongested speed but also less congestion. This is an intriguing result which suggests that the distribution of population within cities matters in determining their mobility as often claimed by urban planners (e.g., Ewing and Cervero, 2010). We again leave a deeper investigation of this issue to future research.

Online Appendix tables I.2 and I.3 provide further robustness checks. In particular, online Appendix table I.2 shows that our results are robust to alternative measures of population, roads, road network, and income. We also fail to provide evidence regarding two measures of road quality, potholes per kilometer and mileage of paved roads, perhaps because of substantial data limitations. Online Appendix table I.3 shows that our key results are not sensitive to the choice of our benchmark speed index as dependent variable. Interestingly, we estimate very similar results for a daytime and a nighttime speed index. We also find that using the ‘narrow’ city fixed effects, which we estimate controlling for extensive trip characteristics, has only minimal effects on our key results. In particular, we find that the length and shape of the city road network still matter even after conditioning out many attributes of the route taken by each trip. In other words, road networks may have important external effects on a given trip.

Although our findings above are generally stable across a wide variety of specifications, they may be subject to bias due to omitted city-level variables. In results reported in online Appendix K, we control for city fixed effects, using within-city variation in population, area, and roads, at the level of concentric rings (0 to 3 kilometers from the center, 3 to 5, 5 to 10, 10 to 15, and 15 and beyond) to gain further insights. Within cities, rings with more population and less area within city boundaries are slower, just as in the across-city results above.

VI. Extensions: walking, transit, and comparison with the US

A. Walking and transit

While roughly half the households in the average city in our data have a private vehicle—sometimes a car but more often a motorcycle—we recognize that city dwellers in India also often walk and use transit. To investigate these two alternative modes of travel, we collected walking and transit travel time data, described in Online Appendix A, for all our trips. We abstract from other costs including transit fares and safety concerns associated with public transit, especially for women, e.g., Borker (2020).
Walking speeds vary little across trips. Mean walking speed is 4.8 kilometers/hour with a standard deviation of 0.1 kilometers/hour. We first estimate the determinants of walking speed in the same manner as table 2. Walking is modestly faster on residential and other small roads and downhill. The standard deviation of city effects is unsurprisingly small at 0.02 and even 0.008 after excluding one mountainous city (Aizawl). An assessment of city-level determinants analogous to table 5 confirms the importance of changes in elevation: they account for 76% of the cross-city variation in walking speed.

Turning to transit, the data have two important limitations. GM only appears to return transit information for formal transit, and only based on official timetables. This ignores informal transit and delayed or canceled service in formal transit. With these caveats in mind, we first note that only about 18% of our trip instances have a transit alternative that we define as ‘viable’: it requires less than an hour wait, and is strictly faster than walking. Despite this selection, viable transit trips take on average 2.9 times as long as driving trips when considering total trip time, which includes walking to and from the stop/station and waiting for the bus/train, in addition to the time in transit, and still 2.5 times as long when considering only time in transit.

For 148 cities, we can estimate indices analogous to our baseline mobility index for transit. The results, analogous to table 2 columns 4 and 7, are reported in online Appendix table L.1. We find that longer trips are faster and that trips expected to use higher road classes are faster. However, unlike private vehicle speed, transit speed does vary by trip type. Radial trips are sizeably faster whereas circumferential trips are slower. This arguably reflects the monocentric structure of many transit networks.

We also note that, unlike with walking, cross-city variation in transit speed is large. The standard deviation of our transit mobility index is about twice that of our baseline mobility index for private vehicles. This variation does not seem to be due to sampling variation as these indices are precisely estimated. The rank correlation between our mobility index for transit and our baseline mobility index (for private vehicles) is low at 0.18. Although we must remain cautious given the limitations of our transit data, this suggests that transit speed depends much more on the coverage and frequency of transit than on driving speed.

B. Comparison with the US

In the Introduction, we showed that motorized travel in two large Indian cities is slow compared to their US counterparts. Here we provide more comprehensive

\footnote{Even though we rely on timetables, the fact that transit speed decreases less than driving speed at peak hours is suggestive here, as long as published schedules take average traffic into account at all. Also, most of the variation in transit indices is unexplained; unlike driving, transit indices show few robust associations with city characteristics. Interestingly, we find a negative association between transit speed and city population when transit speed is computed using time in transit but not when using total trip time. Again this is suggestive of our main conclusion about transit and the importance of system coverage and frequency.}
comparisons between Indian and US cities. Online Appendix M provides more details. In particular, online Appendix tables M.1–M.4 report US analogs to Tables 1, 2, 3 and 5.

Sampled trips in American cities are 70% faster on average than those in Indian cities. Trip level regressions in both countries show that trip length and city and time of day effects explain the majority of variation across trips, though even more so in the US. The log trip length coefficient is 25–50% larger in the US, highlighting the greater availability and speed advantage of highways and other fast road classes. Other trip speed determinants work in the same direction in both countries, and similarly have relatively small explanatory power.

Perhaps unsurprisingly, there is greater speed heterogeneity across cities in India: the speed difference between top and bottom deciles is 25% in the US and 36% in India. A variance decomposition shows that our key finding on the importance of uncongested speed also holds in the US: speed differences across US cities are also driven more by uncongested speed than by congestion. However, the covariance term plays a much bigger role than in India. The correlation between the congestion factor and uncongested speed is -0.29 in India and a staggering -0.82 in the US. In other words, congested cities in the US are also slower in the absence of traffic, presumably due to shorter blocks, red lights, and other ‘permanent’ features.

Finally, city-level correlates of speed are broadly similar between the two countries, but three key interesting differences. First, the US population-speed elasticity is nearly a third lower, but it has even more explanatory power despite less variation to be explained. Second, physical geography explains less variation in the US. Third, roads and road networks show weaker effects in the US. These differences are all consistent with significantly more roadway in US cities attenuating the effects of greater population, offsetting the effects of a difficult geography, and perhaps running into diminishing marginal benefits for travel speed.

VII. Conclusions and policy implications

We propose a novel approach to comparing vehicular speed across cities, and decomposing it into uncongested speed and a congestion factor. We apply it using novel large scale data on simulated trips in 180 Indian cities collected from GM. We document large mobility differences across cities, and find that slow speed is primarily due to cities being slow all the time rather than congested at peak hours. We do nonetheless find an important role for congestion in the largest cities, especially close to their centers.

Several city attributes are consistently correlated with speed and its components. We find that population and land area are key correlates of city speed. Higher population density is strongly associated with slower uncongested speed as well as more congestion. Physical geography features including waterbodies and varying elevation are associated with slower uncongested travel and more congestion, while more roads and streetlights and a more gridded street network
are associated with faster uncongested travel, but not with congestion. Higher income cities have higher uncongested speed, but also higher congestion, leading to a hill-shaped relationship between income and overall speed.

Overall, these indicators of urban infrastructure and economic development are associated with faster speed despite worse congestion, contrary to a conventional wisdom that urban growth and development condemns developing cities to complete gridlock. While in principle variation in uncongested speed could reflect many city attributes beyond those we consider here in our regressions, such as vehicle stock or driving culture, we interpret it as being primarily due to the quality of the road network. Most old cars can be driven 45 kilometers per hour (the 99th percentile of our trip speed distribution), and we speculate that GM’s algorithm is likely to pick out a high percentile of the block speed distribution it observes in order to distinguish motorized from non-motorized vehicles.

We hope that this first set of cross-city evidence on urban travel speed and congestion in a developing country can help guide policy and future research, in three key directions. First they suggest that attention to congestion can be focused on the centers of India’s largest cities. Second, the comparison with American cities imply that country-specific policies are necessary, and that using our data sources and methodology to study other countries individually may uncover distinctive patterns. Third, in most Indian cities travel is slow at all times, not just peak times, and a simple welfare analysis suggests that modest improvements in uncongested speed would generate substantial gains relative to even optimal congestion pricing. Thus, consistent with work by Akbar and Duranton (2018) and Kreindler (2018) on individual cities, standard policy recommendations like congestion pricing, HOV lanes, or other types of travel restrictions may do little to improve mobility. We would therefore like to encourage researchers to also study policies and investments that generate faster uncongested speed. Our paper provides a first set of results suggesting a modest positive role for the design of a regular network grid and the presence of more major roads, but much work remains to be done in terms of identifying cost-effective ways to build faster urban networks.

The data and methods we have developed can teach us much more. Speed is only one component of accessibility, the other being proximity to destinations. In ongoing work, we are developing complementary measures of accessibility in Indian cities. They may also help us understand how transportation affects urban land use patterns and property prices. Relative to more traditional travel surveys, the information used here is less complete but can be gathered at a small fraction of the cost and much higher frequency than the typical 5 to 8 year gap between consecutive traditional travel surveys, and allows for the evaluation of policy changes in the short-run (Kreindler, 2016; Hanna, Kreindler and Olken, 2017). We believe future studies of this type will shed useful light on many aspects of transportation policy in cities, as well as recovery from shocks such as natural disasters.
REFERENCES


