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Cities in Bad Shape: Urban Geometry in India[†]

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The spatial layout of cities is an important feature of urban form, highlighted by urban planners but overlooked by economists. This paper investigates the causal economic implications of city shape in India. I measure cities' geometric properties over time using satellite imagery and historical maps. I develop an instrument for urban shape based on geographic obstacles encountered by expanding cities. Compact city shape is associated with faster population growth and households display positive willingness to pay for more compact layouts. Transit accessibility is an important channel. Land use regulations can contribute to deteriorating city shape. (*JEL* O18, R14, R23, R52, R58)

The United Nations (UN) estimates that cities will add more than 2.5 billion people by 2050, with nearly 90 percent of this increase occurring in Asia and Africa (UN 2014). This will likely trigger a massive expansion in urban land (Seto et al. 2011), with India alone predicted to require 18.6 million more hectares by 2030 (McKinsey 2010). Faced with the challenge of facilitating urban expansion, policy makers are making decisions on urban planning and infrastructural investments that will have persistent effects on the spatial configuration of economic activity within and across cities. Understanding how cities grow and which city forms best promote quality of life and economic growth is thus paramount.

This paper contributes to the debate on how to accommodate urban development by studying the economic implications of a previously overlooked feature of urban form: city shape. While largely ignored by the economics literature, the geometry of a city's footprint has long been emphasized by urban planners as important for transit accessibility and service delivery. All else being equal, a city with a more compact layout is characterized by shorter distances within the city, potentially affecting

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transit accessibility, public service delivery (such as electricity), and household and firm location choices. This, in turn, could impact firms' productivity and households' quality of life (Cervero 2001, Bertaud 2004), particularly in the developing world, where levels of service provision are lower and many city dwellers lack individual means of transportation.

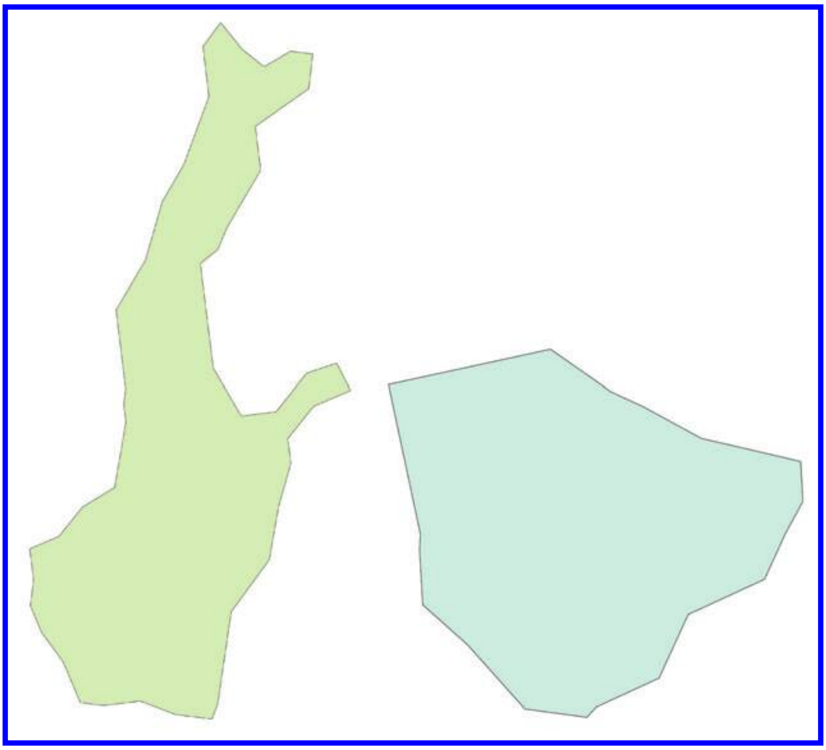
Despite a common perception that developing country cities are expanding rapidly and haphazardly (Suzuki et al. 2010, UN-Habitat 2016), we have little understanding of how the shape of urban expansion influences households and firms within and between cities. Among the key empirical challenges are the lack of data and the endogeneity of city shape, which is in itself an equilibrium outcome. By leveraging satellite-derived data and plausibly exogenous variation driven by topography, I provide the first causal estimates of the impacts of city shape on economic outcomes, in the context of Indian cities. I find that city geometry affects household location choices across urban areas: compact cities are associated with faster population growth and a negative compensating real wage differential, which suggests that they offer higher quality of life (Rosen 1979, Roback 1982).

The first contribution of this paper lies in the data and the measurement of the spatial properties of Indian cities over time. With over 470 urban agglomerations in rapid expansion (Census of India 2011) and the world's second-largest urban population (UN 2014), India is a particularly important context for studying urban form. An allegedly chaotic urban growth has been associated with sprawl and potentially distortive land use regulations (McKinsey 2010), which makes urban form an important item in the Indian policy debate. However, systematic data on Indian cities and their spatial structures is not readily available. I assemble a novel panel dataset that covers over 350 Indian cities between 1950 and 2011 and includes detailed information on each city's spatial properties, microgeography, and city-level outcomes. I trace the dynamic evolution of urban footprints by combining newly geo-referenced historical maps (1950s) with satellite imagery of night-time lights (1992–2010).

The second contribution is to quantify city compactness through a shape metric that I then embed in a standard urban economic model. I employ a shape index used in urban planning, based on the average distance between any two points in a polygon. Higher values of this index indicate a less compact urban footprint, and longer within-city distances. As an example, consider the cities of Kolkata and Bangalore (Figure 1): Kolkata has a distinctive elongated shape, stretching along the North-South axis, whereas Bangalore, roughly shaped like a pentagon, has a more compact layout. Controlling for city area, the average linear distance between any two points in the city is 27 percent longer in Kolkata than it is in Bangalore.[1] This is likely to become more pronounced over time, as I find that large cities have a tendency to deteriorate in shape as they grow.

The third contribution of this paper concerns the identification strategy. Estimating the causal impact of city shape on economic outcomes is challenging, as the spatial structure of a city at any point in time is in itself an equilibrium outcome. Urban shape is determined by the interactions of city population growth, natural constraints, and policy choices, such as land use regulations and infrastructural investments.

[1] This example is discussed in greater detail in Section II.



Shape metric	Kolkata	Normalized	Bangalore	Normalized
Disconnection, km	20.4	1.2	16	0.94
Remoteness, km	14.8	0.87	11.8	0.69
Spin, km^2	287.1	0.99	9.4	0.55
Range, km	65.2	3.83	44.5	2.62

FIGURE 1. SHAPE METRICS: AN EXAMPLE

I propose a novel instrumental variable for urban geometry that combines geography with a mechanical model for city expansion. The underlying idea is that, as cities expand in space and over time, they face geographic constraints—steep terrain or bodies of water—leading to departures from an ideal circular expansion path. The relative position in space of such constraints allows for a more or less compact development pattern, and the instrument captures this variation.

The construction of my instrument requires two steps. First, I employ a mechanical model for city expansion to predict the area that a city should occupy in a given year, based on its projected historical population growth. Using a predicted expansion path is important since the city's actual growth path would be endogenous. Second, I consider the largest contiguous set of developable land pixels within this predicted radius; these pixels together form a polygon that I denote as "potential footprint." I then instrument the shape of the actual city footprint with the shape of the potential footprint.

The resulting instrument varies at the city-year level, allowing me to focus on long differences in shape between 1950 and 2010 and abstract from time-invariant city characteristics. The identification effectively relies on changes in shape that a city undergoes over time, as a result of hitting geographic obstacles. Importantly, my instrument captures variation in the relative position of topographic obstacles, rather than the presence or the extent of particular geographic features, and its explanatory power is not limited to cities with extremely constrained topographies (e.g., coastal or high-altitude cities).

To frame the empirical question of the economic impacts of city shape, I turn to a simple framework of spatial equilibrium across cities (Rosen 1979, Roback 1982). As households and firms optimally choose where to locate, I hypothesize that they account for city shape when evaluating the trade-offs associated with different locations. Compact cities may offer advantages associated with better service delivery or with greater accessibility, stemming from the fact that all locations within the city are closer to one another. If compact shape makes a city operate more efficiently, population will flow to that city, bidding housing rents up and wages down, until utility is equalized everywhere. This argument suggests that compact cities should have, in equilibrium, larger populations and lower real wages.

With my instrument in hand, I take these reduced-form predictions to the data. I begin by demonstrating that more compact cities experience faster population growth. A one standard deviation improvement in city compactness, corresponding to a reduction in the average within-city distance of 360 meters, is associated with a 3 percent population increase. Naïve OLS estimates have the opposite sign, as they are confounded by the fact that larger and faster-growing cities also tend to have more disconnected shapes in equilibrium.

These results are robust to using different methods to delineate urban footprints and alternative shape indicators, and survive many falsification checks. One of the main threats to the identification is that the instrument may capture direct effects of local geography on city-level outcomes; for example, bodies of water can have an inherent amenity value or provide productivity advantages. Reassuringly, the instrument is not correlated with geographic characteristics such as elevation, distance from the coast, or ruggedness. To further strengthen the identification, I allow for differential responses to city shape in cities with different geographies or different soil characteristics (such as bedrock depth, presence of minerals, or crop suitability) and find very similar results. My results are also stable if I exclude from the sample cities with particular characteristics, including coastal and high-altitude cities, as well as fast- or slow-growing ones. Another concern for the identification stems from potential preexisting trends that may be correlated with historical population growth rates. I show that the results are consistent using an alternative version of the instrument, that employs a completely mechanical model for city expansion and does not rely on projected historical population.

Next, I turn to rent and wage differentials across cities. In the spatial equilibrium framework, poor accessibility and worse service delivery in non-compact cities may require cross-city compensating differentials, to the extent that households and firms cannot fully optimize against poor shape at the within-city level. For example, in a non-compact, low-accessibility city, households may be forced to live or shop in less preferable locations, if their first-best ones require excessively long trips. Consistent with this hypothesis, I find that compact cities are characterized by lower real wages. I further provide a back-of-the-envelope calculation of households' implied willingness to pay for compact shape, equivalent to 5 percent of their income for a one standard deviation improvement in compactness. Along the same lines, I calculate the implied impact of city shape on firm productivity through the lens of the model, finding negligible effects. This suggests that firms may be able to offset the negative impacts of poor shape through margins other than their cross-city location choices.

Turning to mechanisms, I consider the two main channels emphasized by urban planners: service delivery and transit accessibility. I find no meaningful impacts of city shape on the share of households connected to tap water or electricity, suggesting that disconnected shape is not standing in the way of the delivery of utilities. In contrast, several pieces of evidence point to the importance of accessibility. First, the negative impact of non-compact shape on population is mitigated in cities with a denser and better-functioning road network or a larger share of households with car access. Second, cities with worse shapes have a less dense road network, suggesting higher costs of providing infrastructure in more disconnected cities.

Furthermore, work commuting patterns may be affected by city shape. The impacts of city shape on realized commutes are a priori ambiguous: households may respond to longer potential distances by incurring longer commutes but also by giving up certain trips entirely. This is difficult to investigate empirically due to a lack of commuting surveys, but I indirectly shed light on work commuting patterns by examining the location of firms within cities. Using street addresses to geo-locate establishments, I find that firms located in non-compact cities tend to cluster in few employment sub-centers. This suggests that firms may be able to neutralize the effects of poor city shape and still take advantage of agglomeration by locating near one another, leaving it to workers to bear the costs of longer commutes. This is consistent with the interpretation of the compensating differentials discussed above, where city shape is associated with positive household willingness to pay but with no differences in firm productivity.

Finally, I consider the role of policy, specifically land use regulations, as one of the determinants of city shape. I show that more permissive vertical building limits, in the form of higher floor area ratios (FARs),[2] result in less spread-out and more compact cities. For given geography, increasing FARs by one improves compactness by one standard deviation. This provides new evidence on the potentially distortive effects of land use regulations in India, highlighting a new margin: making cities less compact (Brueckner and Sridhar 2012).

Taken together, these results indicate that the spatial configuration of cities has real consequences for the quality of life of urban dwellers, for their location patterns across cities, and, potentially, for their welfare. This has important implications for policy makers taking decisions related to urban planning or infrastructure, particularly in rapidly growing cities, and suggests that the impact of urban policies on city shape should be accounted for in cost-benefit analyses.

The rest of the paper is organized as follows. Section I provides some background on urbanization in India and reviews the related literature. Section II discusses the dataset and descriptive patterns. Section III outlines the conceptual framework. Section IV details the empirical strategy and the instrument. Section V presents my main empirical results. Section VI addresses identification threats. Section VII

[2]FARs are defined as the maximum allowed ratio between a building's floor area and the area of the plot on which it sits. Higher values are associated with taller buildings. The average FAR in the cities in my sample is 2.3.

interprets the results on wages and rents in terms of compensating differentials and provides willingness-to-pay estimates. Section VIII presents results on mechanisms and heterogeneous effects, discussing the interactions between city shape and transit, utilities, and land use regulations. Section IX concludes.

I. Background and Previous Literature

India represents a relevant and promising setting to study urban spatial structures. With a current urban population of 460 million (World Bank 2018) growing at a 2.3 percent yearly rate, India has the second-largest urban population in the world, after China, and is projected to host 250 million new urban dwellers by 2030 (McKinsey 2010). Importantly for my empirical strategy, India has a large number of cities of meaningful size, with over 50 urban agglomerations having more than one million inhabitants.

During the period studied in this paper (1950 through 2011), India experienced a massive urban transition, with the urban population growing from 62 to 377 million according to the Census. This has been accompanied by a significant physical expansion of urban footprints, at an estimated rate of 4.84 percent yearly between 1970 and 2000 (Seto et al. 2011). Urban expansion has typically occurred beyond urban administrative boundaries (Indian Institute for Human Settlements 2013, World Bank 2013), making it difficult to track in space using official administrative sources.

The more-than-proportional expansion in urban land has been associated with haphazard development and poor urban planning. Sprawl, lengthy commutes, and limited urban mobility are often cited among the perceived harms of rapid urbanization (McKinsey 2010, World Bank 2013). There is also a concern that existing land use regulations might contribute to distorting urban form (Sridhar 2010, Glaeser 2011). In particular, sprawl has been linked to vertical limits in the form of restrictive floor area ratios (Bertaud 2002 and 2004, Sridhar 2010, Glaeser 2011, Brueckner and Sridhar 2012).[3]

Literature directly related to the geometric layout of cities is scant, but a number of strands are tangentially connected to this theme. The economics literature on urban spatial structures has mostly focused on the determinants of city size and of the population density gradient, often assuming that cities are circular or radially symmetric (see Anas, Arnott, and Small 1998, for a review). The implications of city geometry are left mostly unexplored.[4] A large body of empirical literature investigates urban sprawl (see Glaeser and Kahn 2004), typically in the US context, suggesting longer commutes as one of its potential costs. Although some studies identify sprawl with non-contiguous development (for instance, Burchfield et al. 2006, in the United States; Baruah, Henderson, and Peng 2017, in Africa), which is related to the notion of "compactness" that I investigate, in most analyses the focus is on decentralization and density, neglecting differences in geometry. I focus on

[3] Another example is the Urban Land Ceiling and Regulation Act, which has been claimed to hinder intra-urban land consolidation and restrict the supply of land available for development within cities (Sridhar 2010).

[4] One exception is Bento et al. (2005), who incorporate a measure of city shape in their investigation of the link between urban form and travel demand in US cities. Differently from their approach, I incorporate time variation in urban form and I treat city shape as endogenous.

a different set of spatial properties of urban footprints: conditional on the overall amount of land used, I consider geometric properties capturing compactness, and view population density as an outcome variable.

The geometry of cities has attracted the attention of the quantitative geography and urban planning literature, from which I borrow indicators of city shape (Angel, Civco, and Parent 2010). Descriptive analyses of the morphology of cities and their dynamics have been carried out in the urban geography literature (see Batty 2008 for a review), which emphasizes the scaling properties of cities. Urban planners emphasize the link between city shape, intra-urban trip length, and accessibility, claiming that contiguous, compact, and monocentric urban morphologies are more favorable to transit (Cervero 2001, Bertaud 2004).

In terms of methodology, my work is related to that of Burchfield et al. (2006), who employ remotely sensed data to track the extent of sprawl in US cities over time. The data I employ comes mostly from night-time, as opposed to day-time, imagery, and covers a longer time span.[5] Furthermore, Saiz (2010) examines geographic constraints to city expansion and relates it to the elasticity of housing supply. I use the same definition of geographic constraints, but I employ them in a novel way to construct a time-varying instrument for city shape.

Finally, by highlighting the implications of city shape for accessibility, this paper also complements a growing literature on infrastructure, transit, and urban expansion in developing countries (Storeygard 2016, Baum-Snow et al. 2017) and India in particular (Kreindler 2018, Akbar et al. 2018, 2019).

II. Data

A. *Sources and Dataset Construction*

I assemble a city-year level dataset covering over 350 cities in the main estimation sample, for a period ranging from 1950 to 2010. I include data on the geometric properties of urban footprints, topography, and various city-level economic outcomes: in particular, population, wages and housing rents. This section discusses my primary data sources. A detailed description of data sources and methods can be found in Section A in the online Appendix.

Urban Footprints.—The first step in constructing my dataset is to trace the footprints of Indian cities at different points in time. I retrieve the boundaries of urban footprints from two sources. The first is a set of historical maps of India from the US Army Map Service, that I geo-referenced and used to trace the boundaries of urban areas as of 1950 (US Army Map Service 1955-). An example of one such map, showing the city of Mumbai, is shown in Figure 2. From these maps I am able to trace the footprints of 351 cities.

Second, I employ the DMSP/OLS Night-time Lights dataset, a series of night-time satellite imagery recording the intensity of earth-based lights for every year between 1992 and 2010, with a resolution of approximately 1 square kilometer

[5] Recently, night-time lights have been employed to detect urban markets in India by Baragwanath-Vogel et al. (forthcoming).

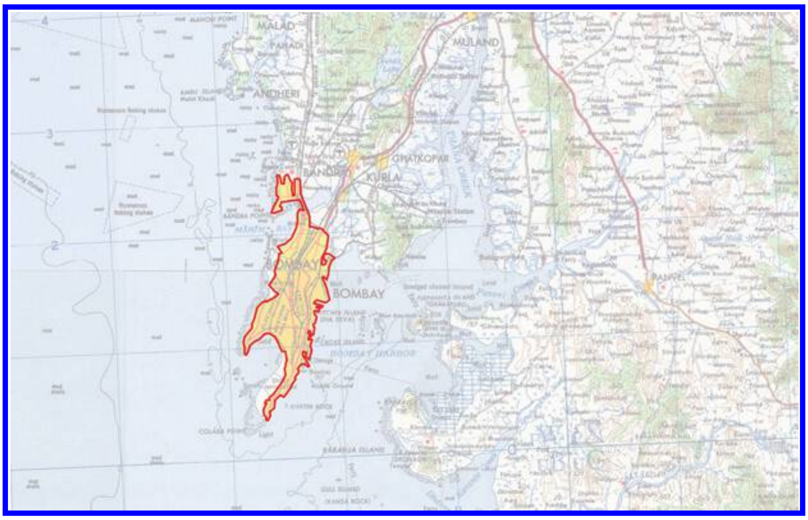


FIGURE 2. US ARMY INDIA TOPOGRAPHIC MAPS

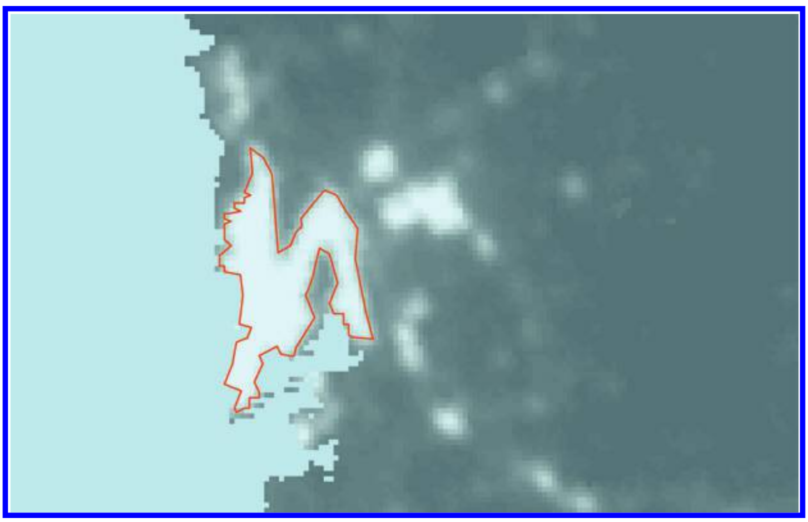


FIGURE 3. DMS/OLS NIGHT-TIME LIGHTS, YEAR 1992

(National Geophysical Data Center 1992-).[6] I use night-time lights imagery to delineate urban areas by considering spatially contiguous lighted pixels surrounding a city's coordinates, with luminosity above a predefined threshold of 35. This approach is illustrated in Figure 3. Employing higher (lower) thresholds results in more (less) restrictive definitions of urban areas and fewer (more) detected footprints overall, but does not affect the main results, as I show in Section V.[7]

[6] These data have been widely employed in the economics literature, mainly for purposes other than urban mapping, starting with the seminal work of Henderson, Storeygard, and Weil (2012).

[7] See Baragwanath-Vogel et al. (forthcoming) for a discussion of the extents of Indian urban areas delineated employing night-time lights.

In general, the resulting definition of urban areas is broad, extending beyond administrative boundaries. Through this procedure I retrieve up to 450 footprints per year.

Although this approach is not immune from measurement error, this is not a major concern in this setting since both area and shape of urban footprints will be instrumented throughout my analysis. Among other things, this addresses non-classical measurement error in the extents of urban footprints: for instance, due to a correlation between income and luminosity. Moreover, the goal is not to provide absolute estimates of urban land cover, but rather to explain changes. The long difference or fixed effects panel specifications employed throughout the paper account for differences in the definition of urban areas in different years (particularly between the US Army maps and the night-time lights).

Combining these two sources, I retrieve footprints for a total of 6,172 city-years. The main estimation sample focuses on 2010−1950 long differences and includes 351 cities.

Shape Metrics.—Next, I quantify the compactness of urban footprints in each city-year. There are many possible indexes that measure compactness, defined as the extent to which a polygon's shape departs from that of a circle. I employ the disconnection index, an indicator borrowed from the urban planning literature (Angel, Civco, and Parent 2010). The index is defined as the average Euclidean distance, in kilometers, between any two points within a polygon, as illustrated in Figure A.1 in the online Appendix.[8] For a given footprint area, higher values of the disconnection index are associated with larger distances between points in the city and a less compact shape. Online Appendix Figure A.2 provides examples of polygons with varying degrees of disconnection: elongated shapes and polygons with recesses and gaps (similar to urban areas growing around topographic obstacles) are all associated with greater disconnection relative to circular polygons with similar areas. For robustness, I also consider alternative indexes of compactness, which tend to be highly correlated with one another (see Section V).

Importantly, any compactness index based on distances within a polygon is mechanically correlated with polygon area. In order to disentangle the effect of geometry per se from that of city size, in all of my specifications I control for the area of the footprint (which in the instrumental variables specification will be separately instrumented for, as discussed in Section IV). Alternatively, the index can be normalized, computing a version that is invariant to the area of the polygon. My results are robust to this alternative approach (discussed in Section VI).

To illustrate how the index maps onto urban shape, Figure 1 displays the footprints of Bangalore and Kolkata in 2005, where Bangalore's footprint has been rescaled so that they have the same area. Among India's best-known cities, Bangalore and Kolkata have among the most and the least compact geometries.[9] The difference

[8] Section A2 in the online Appendix provides the mathematical formula. The index is calculated numerically, by sampling pairs of interior points from a polygon and averaging their distances. The shortest connecting paths used to define distance do not need to lie within the polygon.

[9] For the interested reader, Table A1 in the online Appendix shows a list of the top most and least compact cities among those with over a million inhabitants. Cities are ranked by their normalized shape index, so that the ranking is not confounded by city size.

in the rescaled disconnection index indicates that, if Kolkata had the same compact shape as Bangalore, the average potential distance within the city would be shorter by 4.4 kilometers.[10]

Outcomes.—The outcome data I consider include city population, wages, and rents. Population data at the city level for the period 1871–2011 is obtained from the Census (Office of the Registrar General and Census Commissioner, India 1871–2011)[11] available at 10-year intervals. Urban footprints, as retrieved from the night-time lights dataset, do not always have an immediate Census counterpart. The calculation of footprint-level population totals requires intermediate steps, detailed in Section A3 in the online Appendix.

Wages and rents data are not systematically available at the city level for India. I thus employ coarser, district-level data and use district urban averages as proxies for city-level averages (as in Chauvin et al. 2017). The matching between cities and districts is not one to one. I thus provide results obtained with different matching approaches (including dropping districts that include more than one city or considering only the top city in each district).

Data on wages are drawn from the Annual Survey of Industries (ASI), waves 1990 and 2010 (Central Statistics Office 1990–1991, 2009–2010).[12] The ASI consists of a series of repeated cross-sections covering manufacturing plants in the formal sector.[13]

Data on rents are drawn from the National Sample Survey (rounds 2005–2006 and 2007–2008), in which households are asked about the amount spent on rent and about the floor area of their dwelling (National Sample Survey Office 2005–2006, 2007–2008).[14] Average rents calculated from NSS data are likely to underestimate the market rental rate, due to rent control provisions in most major cities of India (Dev 2006). In the online Appendix I thus show that my results are similar if I exclude the bottom 25 percent of reported rents for each city, where it is a priori more likely to find observations from rent controlled units.

For robustness, I also employ an alternative source of data on rents: the India Human Development Survey 2005 and 2012 (Desai et al. 2005, 2012), used amongst others by Chauvin et al. (2017). An advantage over the NSS data is that respondents report not only rent but also a number of dwelling characteristics, allowing me to consider the residuals of a hedonic rents regression as an outcome.

[10] This comparison is based purely on shape, holding city area constant. Even if Bangalore has a relatively efficient geometry, the overall spatial extent of the city may well be inefficiently large, as highlighted by Bertaud and Brueckner (2005).

[11] See Section A3 in the online Appendix for details on which Census tables were used and how they were accessed.

[12] Using intermediate waves in a panel specification yields similar results.

[13] This selective coverage may affect my results, to the extent that manufacturing is systematically over- or underrepresented in cities with worse shapes. However, I examined the relationship between shape and the industry mix of cities, employing data from the Economic Census, and found no obvious patterns. The share of manufacturing appears to be slightly lower in non-compact cities, but this figure is not significantly different from zero, which alleviates the selection concern discussed above.

[14] For those who own, an imputed figure is provided. Results are similar when excluding owners from the sample.

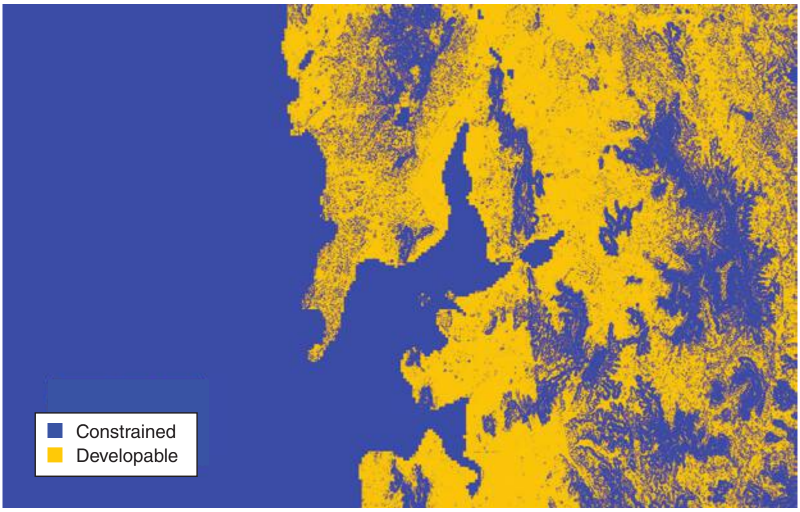


Figure 4. Developable versus Constrained Land

Other Data.—To construct my city shape instrument, I employ high-resolution data on each city's microgeography. I consider land pixels as "undevelopable" when they correspond to a water body or have a slope above 15 percent (as in Saiz 2010). Data on bodies of water and slope are drawn respectively from the MODIS Raster Water Mask (with a resolution of 250 meters) and the ASTER dataset (30 meters) (Caroll et al. 2009, NASA and METI 2011). Figure 4 illustrates this classification for the Mumbai area.

For my robustness checks, I collect data on many additional city characteristics including topography and geology controls. Furthermore, for my analyses of mechanisms and heterogeneous effects, I assemble data on infrastructure (including current road length from OpenStreetMap (OpenStreetMap contributors 2019)), firm location within cities (from street addresses in the Economic Census (Office of the Registrar General, India 2005)), availability of public services and slum population (from the Census (Office of the Registrar General and Census Commissioner, India 1981–2011)), and land use regulations (from Sridhar 2010). All these data sources are discussed in online in online Appendix, Section A.

Assembling city-year level data for Indian cities is not a straightforward exercise due to a lack of city-level sources and poor matching across different datasets. It should further be noted that data at a more disaggregated level is typically not available for India. In particular, a limitation is that I cannot systematically observe household location and commuting patterns within cities.

B. *Descriptive Statistics*

As a preliminary step to the causal investigation of the impacts of city shape, I provide descriptive evidence on the spatial properties of Indian city footprints. Summary statistics for city area and shape are provided in Table 1. Recall that shape is measured as the average within-city distance, in kilometers, with higher values of the index denoting less compact shapes. Panel A reports statistics for the full panel

Table 1—Descriptive Statistics

	Observations	Mean	Median	SD	Min	Max
Panel A. 1950, 1992–2010						
Area, km^2	5,028	73.15	24.14	191.93	0.43	3,986
Shape, km	5,028	3.58	2.60	3.29	0.35	38.21
Potential shape, km	5,028	3.16	2.65	1.88	0.42	20.03
City population	1,135	480,626	133,229	1,546,857	5,822	22,085,130
	1950	2010	2010−1950			
Panel B. Long difference						
Area, km^2	3.743	118.0	114.2			
	(7.22)	(304.15)	(298.64)			
Shape, km	1.012	4.714	3.703			
	(0.71)	(4.24)	(3.81)			
Potential shape, km	1.376	3.985	2.608			
	(0.99)	(2.30)	(1.78)			
City population	106,807	657,420	550,614			
	(325,337)	(1,968,436)	(1,703,455)			

Notes: Panel A reports descriptive statistics from the 351 cities in the main estimation sample, in all years for which data is available. City area, shape, and potential shape are observable in years 1950 and 1992–2010. City population is available for census years 1951, 1991, 2001, and 2011. Panel B reports variable averages for the 351 cities in the main estimation sample for years 1950, 2010, and for the long difference 2010−1950. For city population, 1950 and 2010 correspond to census years 1951 and 2011, respectively. Standard deviations in parentheses.

of years in which the footprints of those cities are observed. Panel B shows averages for years 1950 and 2010 and for the long difference on which most of my analyses are based.

The average city in my sample is relatively large, with a population of over 600 thousand inhabitants, a night-light-based footprint area of 118 square kilometers (about twice the land area of the borough of Manhattan), and an average within-city distance of 4.7 kilometers as of 2010. As expected, there is considerable variation in city shape across cities (partly driven by the variation in city area) and less variation for a given city over time. In 2010, the standard deviation in shape across cities was 4.2 kilometers, while the average within-city standard deviation across the years in the panel is only 1 kilometer. This is not surprising, given the path-dependence of urban form. City shape also appears to have a skewed distribution, consistent with similar patterns in the distribution of city size and area. Finally, the average within-city distance in 2010 is nearly five times larger than in 1950. While this may indicate a deterioration in urban shape over time, it is confounded by the massive expansion in the land area of urban footprints over the sample period and by differences in the methodologies used to trace urban areas in different years.

To gain further insight, rather than focusing on the absolute values, in Table A2 I examine correlates of city shape, in levels and changes. While these correlations are purely descriptive, they help establish some key stylized facts in the data and motivate my causal estimation strategy. Each row in Table A2 corresponds to a city attribute and reports OLS coefficients from two independent cross-sectional regressions: in column 1, I regress city shape in 2010 on the city attribute, controlling for 2010 city area; column 2 is analogous but the dependent variable is the 2010−1950 long difference in city shape and I control for 1950 city area. A description of the variables and a more detailed discussion of the results is provided in Section A4 in the online Appendix. Summary statistics for the correlate variables are in Table A3. Below I highlight the key patterns.

First, there is a clear positive equilibrium correlation between city size and non-compact shape, which affects the interpretation of naïve OLS regressions of shape on city-level outcomes. Panel A shows that large cities have worse shapes and tend to become less compact over time. Ranking cities by their 1951 population, cities in the lower quartile are associated with lower values of the disconnection index, whereas those in the top quartile are associated with higher values, both in levels and in changes. In Section IV, I discuss potential explanations for these patterns: the selection of topographically privileged locations when a city is originally founded, sprawl as a response to expanding infrastructure, or difficulties in enforcing urban planning regulations in rapidly growing cities.

In line with the results in panel A, panel B shows that cities with less compact shapes also have better access to electricity, tap water, and cars, likely reflecting the fact that larger settlements also have higher incomes and better public services. At the same time, disconnected cities do not appear to have a more developed road network, which could stem from the difficulty of providing road infrastructure in cities with disconnected layouts. Interestingly, the disconnection index is positively correlated with the average distance to workplace in 2011 (drawn from the Census), also pointing to more difficult transit in non-compact cities. Section VIII is devoted to further causal exploration of these patterns.

Panel C highlights that city-level geographic features associated with natural advantage (such as a city's distance from the coast or crop suitability) are not predictors of city shape. An identification strategy based on instrumenting city shape with local topography may raise concerns associated with confounding effects of local geography through natural advantage. The lack of correlation in panel C is reassuring and these concerns are further assuaged by the robustness checks discussed in Section VI.

Finally, panel D shows the correlation between city shape and a number of non-predetermined characteristics capturing initial conditions, such as distance from other cities or colonial origin. State capitals appear to have experienced a large deterioration in shape, consistent with the correlation between shape and city size. Moreover, initial shape appears to be a strong predictor of current shape, suggesting that changes in shape are more informative than levels.

III. Conceptual Framework

In this section I present a simple economic framework to motivate my empirical analysis, connecting the economic value of city shape with population, wages, and housing rents. According to the urban planning view, compact urban layouts offer households and firms advantages in terms of accessibility and public services, stemming from shorter within-city distances (Cervero 2001, Bertaud 2004). I embed this idea in a model of spatial equilibrium across cities. In this framework, households and firms optimally choose in which city to locate and, in equilibrium, they are indifferent across cities with different attributes. I hypothesize that they may value the "compactness" of a city as they evaluate the trade-offs associated with locating in different cities. Spatial equilibrium implies that, if compact shape makes a city operate more efficiently, population will flow into that city, bidding up housing costs and bidding down labor costs, until utility is equalized everywhere (Henderson 1974). Along the same lines, if compact cities offer productivity advantages, they will attract firms, which will bid up labor costs, until profits are equalized. The city-level responses of population and factor prices to changes in city shape thus allow me to shed light on the value of compact urban layouts for households and firms by revealed preferences (Rosen 1979, Roback 1982). Below I provide a brief description of the model (adapted from Glaeser 2008) to highlight the key reduced-form implications. The full model is provided in Section B in the online Appendix, along with a discussion of caveats and extensions.

Assume identical and perfectly mobile households choosing optimally where to locate among a menu of cities. Their utility depends on the consumption of a (numéraire) tradeable good C and housing H, and on a vector of city characteristics θ. Households' maximization problem reads

$$\max_{C,H} U(C,H,\theta) \quad \text{subject to} \quad C = W - p_h H, \tag{1}$$

where W is labor income and p_h is the rental price of housing (both of which are city-specific). Broadly, θ captures all utility costs and gains of living in a city. For the purposes of my discussion, it is useful to conceptualize θ as consisting of three components: "public services" θ_P, "transit accessibility" θ_T, and "consumption amenities" θ_A. All else being equal, better public services (such as electricity or water), greater accessibility, and better amenities (such as good climate) improve household utility. Denoting city shape with S, I assume that S can affect θ_P and θ_T, in line with the conjectures of urban planners.

The role of "accessibility" in this context deserves some discussion. Subsumed in this cross-city framework is a complex within-city location and travel problem that households face once they have chosen a city. This involves simultaneously choosing where to reside, work, shop, and consume leisure within the city, what mode of transportation to use, and how many trips to make out of a large menu of potential trips (Small and Verhoef 2007). A city with poor shape can be thought of as offering a worse menu of choices than one with good shape, as some of the potential trips offered are longer. Once the within-city problem is solved, commuting trips are realized in equilibrium. Note that, as a city's shape deteriorates and potential distances increase, realized trips may become longer or shorter, as one of the possible household responses is to give up certain trips entirely or substitute them with shorter ones (for example, shopping in the neighborhood instead of traveling to a far away mall). Although the within-city rent gradient may partially offset direct commuting costs (as suggested by spatial equilibrium within cities à la Alonso 1964), to the extent that households cannot fully optimize against bad shape through within-city margins, poor city shape will affect city choice and require cross-city compensating differentials. These stem from potential non-pecuniary costs associated with living in a poorly shaped city, including the disutility from living in less preferable locations so as to avoid long commutes, the sheer displeasure of sitting in traffic, or the disutility of renouncing a trip to avoid this displeasure. These "quality of life" costs are parsimoniously captured in the model by allowing S to reduce θ_T.[15]

Along the same lines, S may affect θ_P, capturing the fact that utilities can be more efficiently delivered through spatial networks in more compact cities. Note that in India public services are primarily funded by states and local taxes have an extremely limited role (Jaitley 2018), hence θ_P plausibly does not appear in the budget constraint.

Spatial equilibrium requires that indirect utility V be equalized across cities, implying

$$V(W - p_h H, H, \theta) = \bar{v}. \tag{2}$$

Embedded in (2) is the intuition that, in equilibrium, wages and rents equalize utility differences. Households implicitly pay for a better θ bundle, including better accessibility or amenities, through a combination of higher rents p_h and lower wages W.

In the production sector, competitive firms optimally choose where to locate and produce the tradeable good according to production function $C = AF(N, K, \bar{Z})$, where A represents a city-specific productivity parameter, N is labor, K is traded capital, and $\bar{Z}$ is a fixed supply of non-traded capital. Similar to households, firms may benefit from compact city shape through better access to services or because of greater accessibility, which I capture by allowing S to affect A via two components, A_P and A_T. Firms also face a within-city problem where they optimize along various margins, including choosing where to locate within a city. To the extent that they cannot fully optimize against bad shape, S will affect A and their choice of city. Normalizing the price of traded capital to 1, firms' profit maximization problem yields the following zero-profit condition:

$$\pi(W, A, \bar{Z}) = 0. \tag{3}$$

This embeds the intuition that more productive cities must pay higher wages in equilibrium, as they attract more firms.

Finally, the model features developers competitively producing housing in each city, building over a fixed supply of land. Combining the indifference condition of households, firms, and developers, the model delivers equilibrium population N, wages W, and housing rents p_h in a given city as a function of θ and A:[16]

$$Y = f(\theta, A), \quad Y \in \{N, W, p_h\}. \tag{4}$$

[15] Modeling the within-city location and travel problem solved by households is notoriously challenging both theoretically and in terms of data requirements (Small and Verhoef 2007). In Section C in the online Appendix I present a drastically simplified version of this problem by embedding a monocentric city (Alonso 1964) in a setting with constraints to urban shape. The reduced-form predictions of the within-city model are consistent with those of the cross-city framework. Empirically, pinning down the within-city responses to city shape would require more disaggregated data than what is available for India. However, in Section VIII I offer suggestive evidence on some of these responses, including firm location and work commutes.

[16] See equations (B.9), (B.10), and (B.11) in the online Appendix for closed-form solutions.

To illustrate the reduced-form predictions of the model, assume that non-compact shape S is negatively affecting households $\left(\partial\theta/\partial S < 0\right)$ but not firms $\left(\partial A/\partial S = 0\right)$. This would be the case if, for example, households located in non-compact cities faced longer commutes, or were forced to live in a less preferable location so as to avoid long commutes, while firms were unaffected—because of better access to transportation technology, or because of being centrally located within a city. All else being equal, a city with less compact shape should then have a smaller population, higher wages, and lower housing rents. Intuitively, households prefer cities with good shapes, which drives rents up and bids wages down in those locations.

Suppose, instead, that poor city geometry negatively affects both the utility of households and the productivity of firms $\left(\partial\theta/\partial S < 0, \partial A/\partial S < 0\right)$. This would be the case if firms have worse access to utilities or are prevented from taking full advantage of agglomeration spillovers in non-compact cities. The model's predictions are similar, except that the effect on wages will be ambiguous, given that now both firms and households prefer to locate in compact cities.

Motivated by the model, in Section V I begin by examining the reduced-form impacts of city shape on population, wages, and rents. Furthermore, in Section VII I discuss compensating differentials and provide estimates of the implied willingness to pay for compact shape. The evidence suggests that S affects households' quality of life (via θ) but does not have a meaningful impact on firm productivity (A) in equilibrium. In Section VIII, I investigate mechanisms, considering accessibility (θ_T) and service delivery (θ_P), and I find evidence in support of the former channel.

IV. Empirical Strategy

In this section, I propose an empirical strategy to take to the data the reduced-form predictions outlined above. To fix ideas, consider city population N as an outcome. Denote the shape of city c in year t as $S_{c,t}$, where higher values denote less compact shapes, and let $area_{c,t}$ be the area of the urban footprint. The equation of interest is[17]

$$\log\left(N_{c,t}\right) = a \cdot S_{c,t} + b \cdot \log\left(area_{c,t}\right) + \eta_{c,t}. \tag{5}$$

The main concern in estimating the above relationship is the endogeneity of urban geometry. The observed spatial structure of a city at a given point in time is the result of the interaction of exogenous factors, such as geography, and factors endogenous to population, such as the city's growth rate and policy choices. Examples of policies affecting city shape include master plans, land use regulations, that can promote more or less compact patterns, and investments in road infrastructure, that can generate distinctive patterns of urban growth along transport corridors. This induces a simultaneous correlation between city shape and city size. In general, the sign of the OLS bias will be ambiguous, as the selection effects induced by the endogenous determinants of city shape operate in different directions. Below, I provide a qualitative discussion, and in Section D in the online Appendix I provide an analytical derivation.

[17] This is the empirical counterpart of reduced-form equation (B.9) derived in the online Appendix.

One endogenous determinant of city shape is local institutional capacity. Areas with stronger state capacity tend to have better urban planning and enforcement of master plans, and may be more compact, all else being equal. At the same time, cities with stronger institutional capacity and well-functioning local governments also tend to be more successful and faster-growing cities. This may result in fast-growing cities having better shapes, for reasons unrelated to the value of compactness. This selection effect (denote it as A) would thus tend to generate a negative correlation between non-compact shape and population.

Another kind of selection effect (denote it as B) is due to the fact that population growth may make cities less compact. Mechanically, as cities grow, they tend to deteriorate in shape. Intuitively, a city is originally founded in a topographically privileged location, and as it expands over time it will typically extend into terrain that is less preferable. Furthermore, a city experiencing faster population growth may be harder to manage from an urban planning perspective, resulting in more chaotic development. There could also be effects mediated by infrastructural investment: more highways connecting into large and fast-growing cities could lead to sprawl and non-compact development (echoing Baum-Snow 2007). Finally, large cities may have more fragmented governance as they stretch over multiple administrative units (as Delhi's urban agglomeration, which covers multiple states). This may result in uncoordinated urban planning and more difficult enforcement, all leading to less compact development. All of these effects would tend to generate a positive correlation between non-compact shape and population. The OLS estimate for the impact of bad shape on city population will thus be a combination of the causal impact (via utility-equalizing population flows), gross of selection effects of type A and B discussed above.

A. *Instrumental Variable Construction*

In order to address these concerns, I employ an instrumental variables approach that exploits both temporal and cross-sectional variation in city shape. Intuitively, my identification relies on plausibly exogenous changes in shape that a city undergoes over time, as a result of encountering topographic obstacles along its expansion path. More specifically, I construct an instrument that isolates the variation in urban shape driven by topography and mechanically predicted urban growth. Such instrument varies at the city-year level, incorporating the fact that cities hit different sets of topographic obstacles at different stages of their growth.

To operationalize this identification strategy, I instrument the *actual* shape of the observed footprint at a given point in time with the *potential* shape the city can have, given the geographic constraints it faces at that stage of its predicted growth. Specifically, I consider the largest contiguous patch of developable land, i.e., land not occupied by a water body nor by steep terrain, within a given predicted radius around each city. I denote this contiguous patch of developable land as the city's "potential footprint." I compute the shape indicator of the *potential* footprint and use it as an instrument for the shape of the *actual* urban footprint. What gives time variation to this instrument is the fact that the predicted radius is time-varying, and expands over time based on a mechanical model for city expansion. Using predicted growth is important as actual growth would be endogenous.

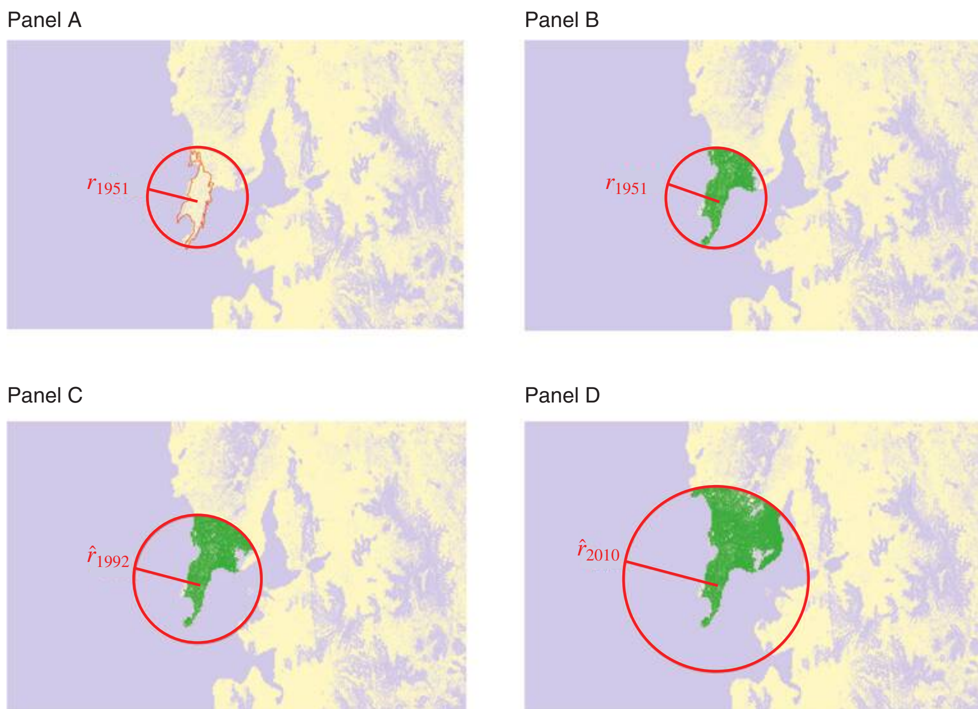


Figure 5. Instrument Construction

The procedure for constructing the instrument is illustrated in Figure 5 for the city of Mumbai. Recall that I observe the footprint of a city c in year 1950 (from the US Army maps) and then yearly between 1992 and 2010 (from the night-time lights dataset). I take as a starting point the minimum bounding circle of the 1950 city footprint (panel A of Figure 5). To construct the instrument for city shape in 1950, I consider the portion of land that lies within this bounding circle and is developable, i.e., not occupied by bodies of water nor steep terrain. The largest contiguous patch of developable land within this radius is colored in green in panel B of Figure 5 and represents what I define as the "potential footprint" of the city of Mumbai in 1950. In subsequent years $t \in \{1992, 1993, \ldots, 2010\}$ I consider concentrically larger radii $\hat{r}_{c,t}$ around the historical footprint, and construct corresponding potential footprints lying within these predicted radii (panels C and D of Figure 5).

The projected radius $\hat{r}_{c,t}$ is obtained by postulating a mechanical model for city expansion in space, that is based on a projection of the city's historical (1871–1951) population growth rates. In particular, $\hat{r}_{c,t}$ answers the following question: if the city's population continued to grow as it did between 1871 and 1951 and population density remained constant at its 1951 level,[18] what would be the area occupied by the city in year t? More formally, the steps involved are the following:

[18] Area is observed in 1950 and matched to Census population data from 1951 to calculate density in 1951.

(i) I project log-linearly the 1871–1951 population of city c (from the Census) in all subsequent years, obtaining the projected population $\widehat{pop}_{c,t}$, for $t \in \{1992, 1993, \ldots, 2010\}$.

(ii) Denoting the actual population of city c in year t as $pop_{c,t}$, I pool together the 1950–2010 panel of cities and estimate the following regression:

$$\log\left(area_{c,t}\right) = \alpha \cdot \log\left(\widehat{pop}_{c,t}\right) + \beta \cdot \log\left(\frac{pop_{c,1951}}{area_{c,1950}}\right) + \gamma_t + \varepsilon_{c,t}. \tag{6}$$

From the regression above, I obtain $\widehat{area}_{c,t}$, the *predicted* area of city c in year t.[19]

(iii) I compute $\hat{r}_{c,t}$ as the radius of a circle with area $\widehat{area}_{c,t}$:

$$\hat{r}_{c,t} = \sqrt{\frac{\widehat{area}_{c,t}}{\pi}}. \tag{7}$$

The circle with radius $\hat{r}_{c,t}$ from panels C and D of Figures 5 thus represents the area the city would occupy if it continued to grow as in 1871–1951, with unchanged density, and if the city expanded freely and symmetrically in all directions.

The variation in city shape captured by this time-varying instrument is induced by geography interacted with mechanically predicted city growth. This excludes, by construction, the variation resulting from policy choices. The instrument is also arguably orthogonal to most time-varying confounding factors—such as rule of law or local politics—that may be correlated with both city shape and the outcomes of interest. Focusing on variation induced by topography avoids the selection effects of type A discussed above (more successful cities attracting better planners). Using variation from the mechanical model for city expansion, instead of the city's actual growth, helps avoid selection effects of type B discussed above (faster growing cities deteriorating in shape).

Note that city area has to be included in the estimating equation (5) to account for the fact that, mechanically, larger cities are characterized by longer distances. However, including actual area as a control is problematic: a city's expansion in land area will reflect population growth, part of which will be a response to changes in shape. To avoid this simultaneity, I employ projected historical population as an instrument for city area, mirroring the approach I follow in the construction of the shape instrument. By predicting city area using historical population 1871–1951, I isolate the variation in city area that is driven by a city's fundamentals, and exclude the variation induced by recent responses to city shape.

[19] As a robustness check, I also consider an alternative implementation of the instrumental variables approach, that postulates a common rate of expansion for all cities, equivalent to the average rate of expansion across all cities in the sample. This alternative approach is detailed in the online Appendix Section E, and discussed in Section VI among the other robustness checks.

B. *Estimating Equations*

With this instrument in hand, I proceed to estimate the following specification:

$$\log(Y_{c,t}) = a \cdot S_{c,t} + b \cdot \log(area_{c,t}) + \mu_c + \rho_t + \eta_{c,t}, \tag{8}$$

where $Y_{c,t}$ is the outcome of interest, $S_{c,t}$ is the shape of the *actual* footprint, $area_{c,t}$ is the area of the urban footprint, and μ_c and ρ_t are city and year fixed effects.

Two regressors are endogenous: the regressor of interest $S_{c,t}$ and the control variable $\log(area_{c,t})$. The corresponding instruments are $\tilde{S}_{c,t}$, the shape of the potential footprint, and $\log(\widehat{pop}_{c,t})$, the same projected historical population used in the model for urban expansion (described above).

This leads to the following first-stage equations:

$$S_{c,t} = \sigma \cdot \tilde{S}_{c,t} + \delta \cdot \log(\widehat{pop}_{c,t}) + \omega_c + \varphi_t + \theta_{c,t} \tag{9}$$

and

$$\log(area_{c,t}) = \alpha \cdot \tilde{S}_{c,t} + \beta \cdot \log(\widehat{pop}_{c,t}) + \lambda_c + \gamma_t + \varepsilon_{c,t}. \tag{10}$$

Since many of my outcomes are not available on a yearly basis and the year-to-year variation in city shape is limited, throughout the paper I present most results as long differences, yielding the following estimating equation:

$$\Delta\log(Y_c) = a \cdot \Delta S_c + b \cdot \Delta\log(area_c) + \eta_c, \tag{11}$$

where the long differences (denoted by Δ) are taken over 2010−1950 unless otherwise indicated. The corresponding first-stage estimating equations are long difference versions of equations (9) and (10) above. This approach differences out time-invariant city characteristics.

Finally, a small subset of outcomes are available for a single cross-section, in which case cross-sectional versions of (8), (9), and (10) are estimated.

V. Main Results

In this section, I discuss first-stage estimates of the relationship between predicted and actual city shape and the impact of city shape on population, wages, and rents.

A. *First Stage*

Table 2 presents results from estimating the two first-stage equations, relating city shape (in odd columns) and area (in even columns) to the geography-based instrument described above and to projected historical population. Potential shape, as determined by topographic obstacles, is indeed predictive of actual city shape, with Angrist-Pischke and Kleibergen-Paap *F*-statistics above conventional levels (Kleibergen and Paap 2006,0 Angrist and Pischke 2009). Columns 1 and 2 present results from the baseline long difference specification employed throughout the

Table 2—First Stage

	Long difference, 2010–1950		Panel 1950, 1992–2010	
	Δ Shape, km (1)	Δ log area (2)	Shape, km (3)	log area (4)
Δ Potential shape, km	1.941	0.232		
	(0.249)	(0.0488)		
Δ log projected population	−2.226	0.0467		
	(0.484)	(0.131)		
Potential shape, km			1.503	0.185
			(0.241)	(0.0495)
log projected population			−1.354	0.213
			(0.278)	(0.122)
Observations	351	351	5,028	5,028
AP F-statistic shape	27.51	27.51	78.36	78.36
AP F-statistic area	9.14	9.14	13.60	13.60
KP F-statistic	12.86	12.86	15.97	15.97
City fixed effects			Y	Y
Year fixed effects			Y	Y

Notes: This table reports OLS estimates of the first-stage relationship between city shape and area, and the instruments discussed in Section IV. Each observation is a city in columns 1 and 2 and a city-year in columns 3 and 4. The dependent variables are the 2010−1950 long differences in city shape, in km, in column 1, and city area, in squared km, in column 2; and levels of city shape and city area in columns 3 and 4. The regressors are the shape of the potential footprint and log projected historic population, in long differences in columns 1 and 2, and in levels in columns 3 and 4. Shape is defined as the average distance between two points in the city. Columns 3 and 4 include city and year fixed effects. AP and KP F-statistics are the Angrist-Pischke and Kleibergen-Paap F-statistics respectively. Robust standard errors in parentheses (clustered at the city level in columns 3 and 4).

paper, where I consider changes in city shape and area between 2010 and 1950. Columns 3 and 4 report the equivalent specification, but in panel format, using all of the data from intermediate years as well, which yields very similar results and a slightly stronger first stage.

This exercise is of inherent interest as it sheds light on the land consumption patterns of Indian cities as a function of their geography. Interestingly, the area of the *actual* footprint appears to be positively affected by the shape of the *potential* footprint (columns 2 and 4). While this partly reflects the mechanical correlation between shape and footprint area, it also suggests that the topographic configurations that make cities less compact may also make them expand more in space. This could be because topographic constraints induce a leapfrog, more land-consuming development pattern, or could reflect an inherent difficulty in planning for parsimonious land use in constrained contexts. This also clarifies that "constrained" cities in this context should not be thought of as land-scarce in absolute terms, but rather cities where growth has to occur around topographic obstacles.

B. *Population*

Table 3 reports estimates of the impact of city shape on population, the main outcome of interest. I estimate long-difference equation (11) by IV in column 1

Table 3—Impact of City Shape on Population

	Δ log population, 2011−1951	
	IV	OLS
	(1)	(2)
Δ Shape, km	−0.0964	0.0222
	(0.0439)	(0.00721)
Δ log area	0.851	0.213
	(0.238)	(0.0338)
Observations	351	351
AP *F*-statistic shape	27.51	
AP *F*-statistic area	9.14	
KP *F*-statistic	12.86	

Notes: This table reports estimates of the impact of city shape on population. Each observation is a city. The dependent variable is the 2011−1951 long difference in log city population. The regressors are the 2010−1950 long differences in city shape, in km, and log city area. Estimation is by IV in column 1 and OLS in column 2. AP and KP *F*-statistics are the Angrist-Pischke and Kleibergen-Paap *F*-statistics respectively and are reported in column 1. Robust standard errors in parentheses.

and OLS in column 2. The results are similar in the panel version (equation (8)), reported in the online Appendix.[20]

The IV estimates show that, as cities become less compact, conditional on area, their population growth declines. The magnitudes are best understood in standardized terms. Recall that higher values of the shape index imply longer distances and less compact geometry. A one-standard deviation increase in normalized shape for the average-sized city in the panel (which has radius 4.8 kilometers) corresponds to roughly 360 meters. Holding constant city area, this increase in the average distance between points in the city is associated with a 3.5 percent decline in population. Through the lens of the model, this is consistent with households valuing compact city layouts as they choose across cities. To the extent that households value compact city shape, spatial equilibrium forces coupled with national population growth will result in population flowing into compact cities at a faster rate.

Conversely, the OLS results in column 2 indicate a positive correlation between city shape and population growth. This confirms the descriptive patterns highlighted in Section II: in equilibrium, faster growing cities are cities that grow into more disconnected shapes. Specifically, the 0.022 OLS coefficient implies a deterioration in shape of 450 meters for a 1 percent increase in population. The discussion in Section IV suggests potential channels through which this positive selection effect may operate: more difficult urban planning or governance, urban growth occurring along transit corridors, and the mechanical tendency of cities to expand into less favorable terrain.

These results are robust to employing more or less restrictive definitions of urban areas. As discussed in Section II, delineating urban areas using night-time lights

[20] In Table A4 I show that the first-stage and population results also hold in the full panel of city-years. Columns 1 and 2 show the first-stage using all city-years detected in the night-time lights and not just those in the long-difference sample of cities present in the US Army maps. Columns 3 through 6 show that the IV and OLS impacts of city shape on population are very similar using a panel specification, both in the long-difference sample (columns 5 and 6) and in the full sample (columns 3 and 4).

requires setting a luminosity threshold above which a pixel is considered "urban." In online Appendix Table A5 I provide results using a less restrictive threshold of 30 (columns 1 through 4) and a more restrictive one of 40 (columns 5 through 8). As expected, the lower threshold detects more urban areas, which end up having larger footprints; conversely, the higher threshold detects fewer urban areas and delineates smaller footprints. Despite differences in sample size and in the areas of cities, the estimated impacts of shape on population are very similar to the baseline ones.

These results are also robust to employing alternative shape indicators. In online Appendix Tables A6 and A7 I consider different shape metrics, detailed in Section A2 in the online Appendix. Again, I find similar results, with less compact cities associated with slower population growth.

C. *Wages and Rents*

Next, I examine the impact of city shape on wages and rents, which in the model provide compensating differentials to households and firms as they allocate across cities. A caveat to the empirical analyses below is that wages and rents are measured more noisily than population, as discussed in Section II (with further details provided in Section A in the online Appendix).

In Table 4, I report the IV and OLS relationship between average wages and city shape, providing suggestive evidence that non-compact cities are associated with higher wages. The dependent variable is the 2010−1990 long difference in the log urban average of individual yearly wages in the city's district, from the Annual Survey of Industries. The average yearly wage in 2010 was Rs 187,000, at 2015 purchasing power. As discussed in Section II, the ASI data are available at the district level and the matching between districts and cities is not one to one. I thus provide results for three samples: one including any city that can be matched (columns 1 and 2); one that only includes cities for which there is a one-to-one mapping with a district (columns 3 and 4); and finally a sample including only the top city in each district (columns 5 and 6). Since not all districts can be matched, the sample size is smaller than in the population sample and the first stage is also weaker. The IV estimates tend to be imprecise, with the shape coefficient being only borderline significant in column 3 and significant at the 10 percent level in column 5, but the qualitative pattern suggests a positive impact of city shape on wages, both in the OLS and in the IV.

Table 5 reports the same set of specifications for housing rents, providing suggestive evidence of lower rents in less compact cities. The dependent variable is the 2008−2006 difference of the log yearly housing rent per square meter, averaged throughout all urban households in the district, from National Sample Survey data. The average yearly rent per square meter in 2006 was Rs 703, at 2015 prices. The estimates appear only borderline significant in column 3, with a p-value between 0.10 and 0.15. Again, the lack of precision in the results can partly be attributed to data limitations: measurement error, an imperfect match between cities and districts, loss of power from smaller sample size (which also weakens the first stage), and the limited time variation in the data (drawn from two consecutive rounds of NSS data). However, subject to these caveats, the qualitative pattern that emerges is

Table 4—Impact of City Shape on Wages

	Δ log rent 2010−1990					
	All		Only districts with one city		Only top city per district	
Sample:	IV (1)	OLS (2)	IV (3)	OLS (4)	IV (5)	OLS (6)
Δ Shape, km	0.0364	0.0336	0.0728	0.0466	0.0562	0.0349
	(0.0354)	(0.0132)	(0.0470)	(0.0154)	(0.0293)	(0.0150)
Δ log area	−1.057	−0.0787	0.0542	−0.0371	−0.418	−0.0668
	(0.944)	(0.0833)	(0.368)	(0.130)	(0.435)	(0.101)
Observations	183	183	80	80	145	145
AP F-statistic shape	13.86		10.21		10.4	
AP F-statistic area	1.94		3.76		3.10	
KP F-statistic	1.67		1.76		2.28	
Average yearly wage, 1992	72	72	72	72	72	72
Average yearly wage, 2010	187	187	193	193	187	187

Notes: This table reports estimates of the impact of city shape on wages. Each observation is a city. The dependent variable is the 2010−1990 long difference in the log urban average yearly wage in the city's district. The regressors are the 2010−1992 long differences in city shape, in km, and log city area. Estimation is by IV in odd columns and OLS in even columns. In columns 3 and 4 the sample is restricted to districts with only one city. In columns 5 and 6 the sample is restricted to the top cities in their respective districts. AP and KP F-statistics are the Angrist-Pischke and Kleibergen-Paap F-statistics respectively. Average yearly wages are in thousand 2018 rupees. Robust standard errors in parentheses.

Table 5—Impact of City Shape on Rents

	Δ log rent 2008−2006					
	All		Only districts with one city		Only top city per district	
Sample:	IV (1)	OLS (2)	IV (3)	OLS (4)	IV (5)	OLS (6)
Δ Shape, km	−0.606	0.000310	−0.486	−0.0172	−0.697	0.0145
	(0.521)	(0.0472)	(0.310)	(0.0675)	(0.648)	(0.0476)
Δ log area	−2.367	−0.0101	−1.245	−0.101	−1.955	−0.0594
	(2.145)	(0.0902)	(1.044)	(0.108)	(2.094)	(0.0970)
Observations	262	262	134	134	215	215
AP F-statistic shape	9.60		14.77		5.11	
AP F-statistic area	3.00		6.12		2.80	
KP F-statistic	1.67		2.93		1.20	
Average yearly rent per m^2, 2006	703	703	705	705	700	700
Implied willingness to pay	−0.133		−0.151		−0.168	
$0.16 \cdot \beta_{\text{Rents}} - \beta_{\text{Wages}}$	(0.082)		(0.072)		(0.107)	
	[0.104]		[0.037]		[0.115]	

Notes: This table reports estimates of the impact of city shape on housing rents. Each observation is a city. The dependent variable is the 2008−2006 long difference in the log urban average of housing rent per square meter in the city's district. The regressors are the 2008−2006 long differences in city shape, in km, and log city area. Estimation is by IV in odd columns and OLS in even columns. In columns 3 and 4 the sample is restricted to districts with only one city. In columns 5 and 6 the sample is restricted to the top cities in their respective districts. AP and KP F-statistics are the Angrist-Pischke and Kleibergen-Paap F-statistics respectively. Average yearly rents are in 2018 rupees. The implied willingness to pay is calculated as discussed in Section VII and is based on coefficients from this table and Table 4. Robust standard errors in parentheses, p-values in brackets.

quite consistent: the impact of disconnected shape on rents is negative in the IV and close to zero in the OLS.

These patterns are similar if I exclude from the calculation of average rents the bottom 25 percent of the rents distribution in a district, which may be more likely to belong to rent-controlled units (see Table A8 in the online Appendix).

In online Appendix Table A9, I show similar qualitative results using an alternative source of rents data, the Indian Human Development Survey (IHDS) (Desai et al. 2005). The correlation between the IHDS and the NSS data is positive but weak (0.3), reflecting measurement error in both sources. Nevertheless, the sign of the impact of city shape on rents is still negative in the IV and positive in the OLS. In column 3 and 4 of Table A9 the dependent variable is a rent residual, obtained from a hedonic regression of rents on housing attributes provided in the IHDS survey (details are provided in the online Appendix). The qualitative pattern of lower rents in less compact cities is preserved.

Taken together, the finding of higher wages and lower rents in non-compact cities is consistent with a compensating differential interpretation. In the model, if compact city shape provides advantages in terms of quality of life or productivity, compact cities will be characterized by higher rents and wages that may be higher or lower depending on whether households or firms value compact shape the most. To the extent that households value city shape more than firms, they will bid wages up in compact cities. I discuss the magnitudes and interpretation of this compensating differential through the lens of the model in Section VII.

VI. Threats to Identification

In this section, I address the main threats to identification, focusing on population as an outcome variable. I begin by discussing concerns related to direct effects of geography, followed by confounding by initial conditions or diverging trends. Finally, I discuss an alternative estimation strategy that employs a single instrument and does not rely on controlling for projected historical population.

A. *Direct Effects of Geography*

The exclusion restriction for the shape instrument requires that potential shape only affects the outcomes of interest though the constraints that it posits to urban form. One of the major identification threats is that the instrument may be correlated with geographic characteristics that have direct time-varying impacts on the outcomes of interest. For example, the topographic constraints that affect city shape, such as coasts and slopes, may also make cities intrinsically more or less attractive for households and/or firms. Indeed, the literature documents many channels through which physical geography affects local development: amongst others, see Combes et al. (2010); Rosenthal and Strange (2004); and Barr, Tassier, and Trendafilov (2011) on geology, density, and agglomeration; Burchfield et al. (2006) on local geography and density; Bleakley and Lin (2012) on coastal configurations and ports; Nunn and Qian (2011) on potato suitability and urbanization; and Nunn and Puga (2012) on ruggedness and local economic development. In particular, the reader may worry about geographic features that have inherent consumption amenity value (e.g., coasts or lakes), production amenity value (e.g., the presence of mineral deposits, or fertile land), or that may impact construction costs (e.g., terrain ruggedness or bedrock depth).

These direct effects of geography could bias the IV results in different directions. For example, if the instrument picked up the effect of coasts and the latter were landscape amenities, the estimated effects of bad shape on population would be biased towards positive values. Conversely, if potential shape were less compact in areas with particularly deep bedrock, the IV impacts of shape on population could be biased towards more negative values, as they would be mediated by higher construction costs in those cities (Barr, Tassier, and Trendafilov 2011).

Below, I show that the IV results are unlikely to be driven by confounding effects of these geographic characteristics. As a preliminary step, in online Appendix Table A10, I show that the instrument is uncorrelated with most of these geographic variables. Each row reports the coefficient from a separate OLS regression. In column 1, I report pairwise correlations between changes in potential shape 2010−1950 and a number of predetermined city characteristics, including elevation, distance from the coast, distance from the nearest river or lake, distance from mineral deposits, terrain ruggedness (capturing slope), bedrock depth (which the literature has linked to high-rise construction costs, population density, and ultimately agglomeration), and crop suitability (that may be higher near cities with bodies of water). For completeness, in column 2 I provide the same correlations for the projected population instrument (used to control for city area). A description of the controls is provided in Section A4 and summary statistics are reported in Table A3 in the online Appendix. Reassuringly, changes in potential shape are uncorrelated with most of these characteristics.[21]

In Table 6, I show that the IV estimates for the impact of city shape on population are robust to controlling for all of the characteristics listed above. I report the same IV specification as in Table 3, column 1, augmented with time-invariant geography controls. This amounts to allowing for differential changes across cities with different geographic characteristics. All point estimates are very similar to the baseline one of −0.096, assuaging concerns of confounding.

In online Appendix Table A11, I provide IV results for different sample cuts. My results are minimally affected by excluding from the sample coastal and mountainous cities, high-ruggedness cities, cities near rivers or lakes, cities with minerals, cities with high bedrock depth, and cities with high crop suitability. This is reassuring that the results are not driven by a very peculiar set of compliers: most cities are affected in their shape by the position of topographic constraints, and not only those with particular topographies.

The lack of correlation between the shape instrument and geographic variables such as elevation or distance to the coast may appear surprising, since potential shape is calculated based on constraints stemming from steep slopes and bodies of water. Importantly, the instrument's variation does not stem from the generic presence of bodies of water or steep slopes, nor from the presence of particularly large obstacles (e.g., a mountain or lake), but rather from the relative position in space

[21] There is a weak correlation between changes in potential shape and distance from mineral deposits. This is addressed in Table A11 by showing that the results are robust to excluding cities near mineral deposits.

TABLE 6—IV IMPACT OF CITY SHAPE ON POPULATION, ROBUSTNESS TO CONFOUNDING TRENDS

	Δ log population, 2011−1951						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Shape, km	−0.0976	−0.0964	−0.103	−0.0923	−0.0993	−0.0872	−0.0888
	(0.0453)	(0.0426)	(0.0472)	(0.0428)	(0.0445)	(0.0395)	(0.0391)
Δ log area	0.857	0.851	0.887	0.839	0.874	0.799	0.798
	(0.244)	(0.229)	(0.258)	(0.232)	(0.244)	(0.215)	(0.211)
Control	−0.00556	−4.03e−09	−0.00285	0.000845	−0.000397	−0.0223	0.190
	(0.0167)	(0.000115)	(0.00237)	(0.000544)	(0.000319)	(0.0103)	(0.123)
Observations	351	351	351	351	351	351	351
AP *F*-stat shape	27.32	29.64	26.71	28	26.62	30.06	32.25
AP *F*-stat area	8.89	9.37	8.41	9.37	8.69	10.34	9.75
KP *F*-stat	12.44	13.63	11.90	12.93	12.11	14.27	15.68
Characteristic	Elevation	Distance from coast	Distance from river/lake	Distance from mineral deposit	Ruggedness	Bedrock depth	Crop suitability

Notes: This table reports the same IV specification as in Table 3, column 1, augmented with time-invariant controls, described in Section A4 in the online Appendix. Summary statistics are in Table A3 in the online Appendix. Robust standard errors in parentheses.

of these constraints. In fact, a city could be very "constrained" in terms of share of land lost to bad topography, but may still be able to expand in a compact way. For example, suppose all topographic obstacles are concentrated East of the center of a city. This will not prevent the city from expanding in a relatively compact way on the West side. On the other hand, if a city is surrounded by obstacles in multiple directions, it will have to grow around those obstacles generating a less compact pattern. This is the variation that the instrument is capturing.

B. *Initial Conditions and Preexisting Trends*

The estimation of the population response to changes in city shape may be confounded by underlying city-specific trends, potentially driven by fundamentals or initial conditions. Controlling for projected historical population growth 1871–1951 through the city area instrument partially addresses these concerns, as it allows changes in city shape to only affect deviations from the city's long-run path. However, there is still a concern of changes in cities' fundamental trends that are not captured by past projected growth. I address these concerns by showing that my baseline results are very similar when controlling for a battery of city characteristics and across various sample cuts. I also present falsification tests using instrument leads and future changes.

In online Appendix Table A12, I consider potential diverging trends by initial conditions, extending the tests of Table 6 to include non-predetermined characteristics as controls. The first-stage and IV estimates are qualitatively similar to the baseline ones. In columns 1 through 3, I control for initial shape at the beginning of the sample, allowing cities that start out with different constraints to evolve along different paths. Not surprisingly, in this more demanding specification instruments are weaker, but the qualitative impacts of city shape are preserved. In columns 4 through 6, I control for direct British rule, which may be associated with particular city management or urban planning approaches (Baruah, Henderson, and Peng 2017), and in columns 7 through 9 I include a capital city dummy, motivated by the strong correlation between capital cities and non-compact shape highlighted in Table A2. Again, results are very similar.

In Table A13 I present additional sample cuts based on non-predetermined characteristics. In columns 1 through 9, I consider cities with different population growth patterns and show that the first-stage and IV results are very similar when excluding particular sets of cities. In columns 1 though 3, I exclude cities that at any point during the years in the panel have experienced negative population growth from one year to the other. In columns 4 though 6, I exclude fast-growing cities, defined as cities whose 2011 − 1951 growth rate was in the top tenth percentile. In columns 5 and 6, I exclude the slow-growing cities, defined as the bottom 10 percent growers. Again, this is reassuring that the compliers are not a peculiar set of cities. Along the same lines, in columns 10 through 12 I exclude the top 10 percent most constrained cities. The definition of "constrained" refers to the share of land within the 2010 city radius that is lost to topographic constraints.[22]

To further assuage the concern of underlying pre-trends, in Table 7 I provide a falsification test regressing changes in outcomes on instrument leads and future instrument changes. Reassuringly, past changes in population are not predicted by future values of the instrument. Specifically, in column 1, I regress 2001 − 1951 population changes on 2005 and 2010 instruments; in column 2, I consider 2001 − 1991 population changes as a dependent variable instead. In column 3, I regress 1991 − 1951 population changes on instruments measured in 1995 and 2000. Finally, in column 4 I regress 1991 − 1951 changes in shape on 2010 − 2001 changes in the instruments. None of the shape coefficients are statistically different from 0, and many of the point estimates are positive (the opposite sign of the main effects). Table A14 in the online Appendix includes a similar test for rents and wages, which shows no pattern that would be suggestive of pre-trends correlating with the shape instrument.

C. *Single-Instrument Specification*

Employing projected historical population in the construction of the shape instrument and as an instrument for area may raise identification concerns. The identifying assumption is that projected historical population predicts actual city area and shape, but does not affect current population and other outcomes other than through "deep fundamentals" uncorrelated with shape. A violation of the exclusion restriction may arise if historical population growth 1871–1951 not only predicted current population and city expansion through fundamentals, but also affected it through shape itself. This could be the case if city shape also followed a long-run trend and the 1871–1951 population growth partially responded to it.

[22] This is similar to the measure that Saiz (2010) relates to housing supply elasticity. This robustness check suggests that the results are not driven by particularly constrained (and thus potentially more supply-inelastic) cities. In future work, a richer model could characterize the impacts of topographic constraints and shape on housing supply elasticity, to fully disentangle them from those driven purely by geometry. I discuss this in Section B in the online Appendix.

TABLE 7—FALSIFICATION TEST WITH LAGGED OUTCOMES, POPULATION

	Δ log population, 2001−1951 (1)	Δ log population, 2001−1991 (2)	Δ log population, 1991−1951 (3)	Δ log population, 1991−1951 (4)
2005 Potential shape, km	0.0237	0.076		
	(0.129)	(0.0494)		
2010 Potential shape, km	0.0157	−0.0361		
	(0.0910)	(0.0344)		
1995 Potential shape, km			0.0601	
			(0.196)	
2000 Potential shape, km			−0.00273	
			(0.183)	
Δ Potential shape, km, 2010 − 2001				−0.0509
				(0.0407)
2005 log projected population	−4.524	−0.561		
	(0.823)	(0.356)		
2010 log projected population	4.387	0.515		
	(0.806)	(0.347)		
1995 log projected population			−4.087	
			(0.848)	
2000 log projected population			3.933	
			(0.831)	
Δ log projected population, 2010−2001				1.996
				(0.417)
Observations	238	238	267	267

Notes: This table presents a falsification test to show that the shape instrument is not correlated with past population growth rates. Each observation is a city. The dependent variables are long differences of log population and the regressors are levels and long differences of the instruments. Estimation is by OLS. Robust standard errors in parentheses.

These concerns can be assuaged by an alternative identification strategy that does not rely on using projected historical population at any stage. This alternative approach, detailed in Section E in the online Appendix, involves normalizing both sides of equation (4) by city area. The ensuing estimating equation has population density as an outcome and normalized city shape as the only explanatory variable, which is treated as endogenous. The corresponding instrument is a normalized version of potential shape, based on topographic obstacles encountered along a city's predicted expansion path. However, in this alternative version, the city's predicted expansion path is not based on historical population growth, but is completely mechanical, based on the average rate of city expansion in the panel.

The results of this estimation are reported in Table 8. Column 1 reports the first stage, showing that potential normalized shape is a strong predictor of actual normalized shape. Column 2 reports IV estimates for the impact of normalized shape on population density, showing that population density declines as normalized shape deteriorates. The magnitudes are consistent with the estimates from the baseline specification: as normalized shape deteriorates by one standard deviation, population density declines by approximately one standard deviation.

Table 8—First Stage and Impact of City Shape on Population, Single Instrument

	Δ Normalized shape	Δ Population density	
	First stage	IV	OLS
	(1)	(2)	(3)
Δ Potential normalized shape	0.0996		
	(0.0188)		
Δ Normalized shape		−171.8	−22.19
		(37.32)	(7.806)
Observations	351	351	351
AP F-statistic shape	28.05	28.05	
KP F-statistic	21.07	21.07	
Mean dep var in levels, 2010	0.964	6.568	
Mean dep var in levels, 1950	1.066	29.872	

Notes: This table reports estimates of the impacts of city shape on population, employing the strategy discussed in Section E in the online Appendix. Column 1 reports the first stage of actual normalized shape on potential normalized shape. Columns 2 and 3 report the IV and OLS estimates of the impact of normalized shape on population density, measured in thousand inhabitants per square km. All variables are expressed as 2010−1950 long differences (2011−1951 for population). The construction of the instrument is based on a purely mechanical model for city expansion. Normalized shape is the area-invariant version of the disconnection index (see Section A2 in the online Appendix). The mean and standard deviation of normalized shape in the panel are respectively 0.96 and 0.08. AP and KP F-statistics are the Angrist-Pischke and Kleibergen-Paap F-statistics respectively. Robust standard errors in parentheses.

VII. Compensating Differentials and Willingness to Pay

In this section, I provide an interpretation of the reduced-form results on wages and rents from Section V through the lens of the model. In a Rosen-Roback framework, higher real wages in disconnected cities can be interpreted as the implicit premium that households pay in order to live in cities with more compact shapes. To calculate households' willingness to pay for city shape, I begin by expressing households' indifference condition (2) as a log-separable function, which can be derived from a Cobb-Douglas utility function:

$$\log(W) - \alpha\log(p_h) + \log(\theta) \;=\; \log(\bar{v}), \tag{12}$$

where α is the share of housing in consumption.

Differentiating (12) with respect to S provides a way to quantify the extent to which S affects indirect utility via θ:

$$\frac{\partial\log(\theta)}{\partial S} \;=\; \alpha\frac{\partial\log(p_h)}{\partial S} - \frac{\partial\log(W)}{\partial S}. \tag{13}$$

The marginal willingness to pay for a unit improvement in S equals the difference between the semi-elasticity of housing prices to S, weighted by the share of housing in consumption α, and the semi-elasticity of wages. As an empirical counterpart of (13), I estimate the following:

$$\hat{\lambda}_\theta \;=\; \alpha\hat{B}_P - \hat{B}_W \tag{14}$$

where $\hat{B}_P$ and $\hat{B}_W$ are estimates of the reduced-form impact of city shape S on, respectively, log rents and wages. To calibrate α, I compute the share of household expenditure devoted to housing for urban households, according to the NSS Household Consumer Expenditure Survey data in my sample. This figure amounts to 0.16.[23]

Estimates of $\hat{\lambda}_\theta$, obtained from pooling the IV regressions of Tables 4 and 5, are reported at the bottom of Table 5. The willingness to pay for a one kilometer improvement in city shape ranges between 0.13 and 0.17 log points, depending on the specification, with p-values between 0.04 and 0.12. In standardized terms, this implies a willingness to pay between 4.7 and 6 percent for a one standard deviation improvement in city compactness, corresponding to an increase in the average within-city distance of approximately 360 meters.[24] Note that relying on OLS, as opposed to IV estimates of $\hat{B}_P$ and $\hat{B}_W$ would yield smaller willingness-to-pay estimates, ranging between 1 and 2 percent.

A. *Discussion*

The positive estimated willingness to pay for good shape $\hat{\lambda}_\theta$ can be interpreted as evidence that households view compact shape as affecting their quality of life as they evaluate the trade-offs associated with different cities. Through a more structural lens, this estimate can also be useful to sign and bound potential welfare effects of city shape.

First, λ_θ can be viewed as an upper bound for welfare effects of deteriorating shape, to the extent that reality is somewhere in between a scenario with infinitely elastic or infinitely inelastic supply of urban dwellers (Donaldson and Hornbeck 2016). With a fixed total urban population at the country level, equilibrium indirect utility $\bar{v}$ will increase everywhere if θ increases in one city. In the Cobb-Douglas case, λ_θ coincides with the welfare impact of a one unit improvement in shape in all cities. The assumption of a fixed total population is extreme, as many migrants into cities are coming from the countryside rather than reallocating across cities. The alternative extreme assumption is that of a perfectly elastic supply of migrants to cities, with indirect utility being pinned down by a reservation utility in the countryside. In this scenario, any improvement in θ will result in larger city populations but no welfare change, which provides a lower bound of zero for the welfare effect of city shape.

Furthermore, in a richer model with heterogeneous households, the Rosen-Roback indifference conditions will hold for the marginal household, but there will be welfare impacts on inframarginal households. Intuitively, the latter will not be perfectly compensated for bad shape through higher real wages and their utility will be affected by changes in θ. The welfare impacts on those households will depend on the relative elasticity of labor and of housing supply, with a lower local elasticity of labor implying a larger household incidence (Moretti 2011). Analyzing

[23] While this figure may seem low, it is consistent with the evidence from other developing countries (Chauvin et al. 2017). Employing the IHDS data as an alternative source I find a similar number.

[24] In order to evaluate this magnitude, this figure could be compared to estimates of the value of other amenities. However, no such estimates are available for India. As a reference, covering 360 additional meters on foot twice a day takes about nine minutes, or two percent of an eight-hour working day.

distributional impacts of deteriorating city shape requires a richer model incorporating landlords and tenants as well as heterogeneous incomes and/or migration costs and is left for future research.

The calculation of λ_θ is subject to a number of caveats, that could be addressed in future work. While the notion of compensating differentials based on rents and wages is very general, the calculation above relies on Cobb-Douglas functional form, implying homothetic preferences and a constant housing expenditure share. Which functional form best describes housing expenditure in a developing country setting is an open question.

Second, the model does not allow for heterogeneous agents to sort into locations based on their preferences or skills. This particularly affects the interpretation of the estimated impact of shape on wages. The latter may reflect sorting and differences in the skill composition of the workforce (Combes, Duranton, and Gobillon 2008), which I cannot control for given the information in the ASI data.[25] The estimated compensating differentials should be thus thought of as an underestimate of true equalizing differences for those with a strong preference for compact layouts, and an overestimate for those with weak preferences.

Third, the model assumes that the housing supply elasticity is the same across cities. Allowing for heterogeneity across cities would affect the magnitude of the response of rents and wages: to the extent that good shape positively affects household utility, in more inelastic cities the impacts on population and wages would be attenuated and the impact on rents would be amplified (in absolute terms).

Furthermore, the model implicitly assumes that S only affects θ. A richer model, providing a micro-foundation for how city shape affects households and firms, may also allow for city shape to affect other objects, including the elasticity of housing supply.

Finally, the model does not allow for externalities. With congestion, $\hat{\lambda}_\theta$ would understate the true willingness to pay for compact shape, as it would be estimated gross of equilibrium congestion effects.

B. *Implied Productivity Impacts*

Next, I consider the implied productivity impacts of city shape on firms, dA/dS. Similar to the calculation for households, I begin by expressing firms' indifference condition (3) under the assumption of a Cobb-Douglas production function:

$$(1-\gamma)\log(W) = (1-\beta-\gamma)\Big(\log\big(\bar{Z}\big) - \log(N)\Big) + \log(A) + \kappa_1, \tag{15}$$

where parameters β and γ represent the shares of labor and tradeable capital in a Cobb-Douglas production function.

[25] In Section VIII, I discuss evidence that compact cities have a larger share of slum dwellers, which may suggest sorting of lower-skill workers into compact cities. However, the wages of slum dwellers are unlikely to be driving my results, as the ASI data that I employ only covers the formal sector.

Totally differentiating (15) with respect to S allows me to pin down the effect of S on productivity as

$$\frac{\partial \log(A)}{\partial S} = (1-\beta-\gamma)\frac{\partial \log(N)}{\partial S} + (1-\gamma)\frac{\partial \log(W)}{\partial S}. \tag{16}$$

I estimate the empirical counterpart of the above as

$$\hat{\lambda}_A = (1-\beta-\gamma)\hat{B}_N + (1-\gamma)\hat{B}_W, \tag{17}$$

where $\hat{B}_N$ is the estimated reduced-form impact of shape on population.

Setting β to 0.4 and γ to 0.3 (as in Glaeser 2008), IV-based estimates of $\hat{\lambda}_A$ range from -0.12 percent (under the most conservative point estimates of $\hat{B}_W$) to 0.8 percent for a one standard deviation deterioration in city shape. In the pooled specification, none of the estimates are statistically different from zero (with p-values ranging from 0.5 to 0.9).[26]

These estimates appear very small, suggesting that city shape does not affect firms in the cross-city equilibrium. This does not indicate that a city's layout is ex ante irrelevant for firms. Rather, the interpretation is that firms do not require a compensation for poor city geometry through factor prices, whereas households do. Put differently, in equilibrium, firms may be able to optimize against "bad" shape, in a way that households cannot. This may be related to the relative location of households and firms within cities. This hypothesis is explored in Section VIII, where I investigate how firms respond to city shape in their location choices within cities, by looking at the spatial distribution of employment.

VIII. Mechanisms and Heterogeneous Effects

The urban planning literature emphasizes two main channels through which the compactness of city layouts may affect households and firms: transit (θ_T and A_T in the model) and public service delivery (θ_P and A_P). Shorter distances improve accessibility and may facilitate the provision of infrastructure, as well as ease the delivery of services provided through spatial networks, such as water and electricity (Cervero 2001, Bertaud 2004). In what follows I provide evidence on both channels, showing that accessibility is plausibly the main mechanism. I also discuss heterogeneous effects of city shape shedding further light on the way in which disconnected cities operate.

A. *Accessibility and Transit*

In this section, I begin by discussing the heterogeneous impacts of city shape as a function of a city's infrastructure and ease of transit, taking infrastructure as given. I then discuss the equilibrium relationship between city shape and infrastructural

[26] Utilizing OLS, as opposed to IV estimates, yields positive and statistically significant impacts of bad shape on productivity in the 1.1–1.4 percent range, in line with the OLS pattern of more disconnected cities being the larger and plausibly most productive cities.

Table 9—Heterogeneous Effects of Infrastructure and Transit

	Δ log population, 2011−1951							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Shape, km	−0.247	−0.41	−0.173	−0.152	−0.163	−0.316	−0.29	−0.227
	(0.115)	(0.205)	(0.0829)	(0.0507)	(0.0611)	(0.125)	(0.114)	(0.0971)
Δ Shape × roads	7.48e−06	0.000167	0.0109	0.249	0.386	0.000356	0.000772	0.000197
	(3.44e−06)	(7.75e−05)	(0.00455)	(0.0763)	(0.211)	(0.000142)	(0.000292)	(9.46e−05)
Δ log area	1.192	1.468	0.997	0.864	0.882	1.482	1.421	1.269
	(0.462)	(0.665)	(0.347)	(0.216)	(0.267)	(0.532)	(0.492)	(0.410)
Observations	336	336	336	123	123	246	246	246
AP *F*-stat interaction	911.41	35.14	328.24	41.95	36.37	504.84	517.16	305.6
AP *F*-stat shape	10.29	4.60	13.07	7.66	8.34	6.31	7.07	7.54
AP *F*-stat area	4.91	3.16	6.57	10.32	12.02	3.38	3.63	4.37
KP *F*-stat	7.95	5.67	9.96	9.79	8.41	6.06	6.39	7.09
Interaction variable	Roads 2019	Roads 1981	State roads 1981	Proximity	Grid conformity	Cars 2011	Cars 2001	State cars 1984
Mean interaction variable	695	150	1.517	0.001	0.132	19	8	105

Notes: This table reports the same IV specification as in column 1of Table 3, augmented with interactions between city shape and the transit-related variables indicated in each column. Roads 2019 is the total length of roads in a city's 2010 lit-up shape, as reported in 2019 in Openstreetmap. Roads 1981 is the length of city urban roads in 1981 from the Census. State roads in 1981 is to the total length of urban roads in a state in 1981. All road length variables are in km. Proximity is an index of distance accessibility, from Akbar et al. (2018). Grid conformity is a measure of the regularity of a city's primary road grid from Akbar et al. (2019). Cars 2011 indicates the number of households with a car, from the Census, in thousands. Cars 2001 is analogous for 2001. State cars 1984 is the number of motor vehicles registered in a state. State variables are drawn from the Ministry of Road, Transport, and Highways and normalized by state urban area (in square km). Further details can be found in Section A5 in the online Appendix. AP and KP *F*-stats are the Angrist-Pischke and Kleibergen-Paap *F*-statistics respectively. Robust standard errors in parentheses.

provision. Finally, I provide suggestive evidence on the location of firms and commutes to work.

Heterogeneity by Infrastructure.—Recall that my shape indicator is based on Euclidean distances between points in a city, abstracting from the road network and transport technology. All else being equal, a well-functioning road network should mitigate the impacts of bad shape: for example, a disconnected city with a fast highway may ultimately be very accessible.

In Table 9 I show that the negative impacts of shape on population are indeed mitigated in cities with better-functioning within-city transit. I augment my baseline IV specification with interactions between shape and a number of transit-related variables that capture how easy commutes are in the city: road length (columns 1 through 3), indices capturing the functionality of the road network from Akbar et al. (2018, 2019) (columns 4 and 5),[27] and availability of cars (columns 6 through 8). The sources and construction of each variable are detailed in Section A5 in the online Appendix. All interaction terms yield positive coefficients: while bad

[27] The grid conformity index (column 4) measures the extent to which a city's current road network is laid out as a regular grid; it correlates with better vehicular mobility. The proximity index (column 5) is a city-level measure of distance accessibility capturing how easy it is to reach shopping centers, train stations, restaurants, and other amenities within a city.

shape tends to reduce population growth, the effects are attenuated for cities where commutes are plausibly easier due to better road infrastructure and motorized means of transportation.

While these results are highly suggestive, I caution that they can only be interpreted causally if one takes infrastructure as given. In reality, infrastructure provision is simultaneously determined with urban shape (as discussed in detail below) and affected by city income, which may confound the estimation of the interaction terms in Table 9. I mitigate endogeneity concerns through various approaches: I consider lagged interaction variables (in columns 2 and 7) and employ state-level, instead of city-level variables (columns 3 and 8). One specific concern is that cities with better infrastructure tend to be higher-income, more successful cities. To assuage this source of confounding, in Table A15 I replicate the estimation of Table 9 additionally controlling for the number of banks in 1981 as a proxy for city income (Office of the Registrar General and Census Commissioner, India 1981). While this is admittedly an endogenous control, including it does not change the main estimates, suggesting that the interactions with infrastructure are not solely capturing income differences.

City Shape and Provision of Infrastructure.—Below I elaborate on the equilibrium relationship between city shape and infrastructure. Urban infrastructure is jointly determined with city shape and the sign of the reduced-form relationship between the two is a priori ambiguous. On the one hand, infrastructural provision is an endogenous response to changes in a city's layout: as built-up areas expand, the road network also tends to expand to service these areas. At the same time, infrastructure is a co-determinant of a city's layout: new built-up areas often arise around transit corridors. This two-way relationship tends to generate a *positive* correlation between bad shape and urban road length. On the other hand, topographic obstacles that lead to disconnected shape may also increase the costs of providing infrastructure, resulting in a *negative* correlation between bad shape and urban road length. Similar arguments can be made regarding road quality.[28]

In panel A of Table A16, I empirically examine the equilibrium relationship between city shape and road length. I find that disconnected cities tend to have a shorter road network, conditional on city area, both in absolute and in per capita terms. In columns 1 through 8 I consider roads in 2019 as measured from OpenStreetMap (OpenStreetMap contributors 2019). I report estimates from a cross-sectional version of my benchmark IV and OLS specification, where regressors are defined in 2010 levels. Bad shape is associated with shorter total length of roads (columns 1 and 2) and motorways (columns 3 and 4). A one standard deviation in normalized shape (approximately 360 additional meters) is associated with a 6 percent shorter road network (column 1). The pattern is similar when considering road length per 2011 population (columns 5 through 8). Although precision varies, these results are qualitatively similar in the OLS (even columns) and in

[28] Bad topography may increase the cost of maintaining or upgrading roads, resulting in lower road quality in cities with poor shapes. At the same time, planners may choose to compensate for poor accessibility by investing in road quality, for example increasing the number of lanes of the main city's artery. Thus, the relationship between city shape and infrastructure quality is a priori ambiguous.

the IV specifications (odd columns). In columns 9 through 12, I consider a specification in changes, where the dependent variable is the difference between 2019 OpenStreetMap road length and 1981 urban road length from the Census. While weaker, the negative IV estimates confirm the pattern highlighted thus far. The OLS estimates are positive, in line with the spurious correlation between city growth and deteriorating shape. Taken together, these results suggest that as cities expand to become more disconnected, the road network is not keeping up, plausibly due to higher costs of providing infrastructure in topographically constrained settings. Thus, poor city shape may hurt accessibility not only directly, but also by making infrastructural provision more costly.

For the interested reader, in panel B of online Appendix Table A16, I consider indexes related to the internal functioning of city transit from Akbar et al. (2019). Some of the evidence points to moderately worse mobility in disconnected cities, as measured by within-city transit speeds. In Section A5 in the online Appendix I provide details on the construction of these indexes and caveats to the interpretation of the corresponding regression results.

Commuting and Within-City Responses to City Shape.—The evidence provided thus far points to transit accessibility as one of the key channels through which city shape affects households. The question may then arise on how city shape maps to commuting behavior. The theoretical prediction is ambiguous: all else being equal, disconnected city shape is associated with lower accessibility and higher *potential* costs of travel within the city. However, *realized* commuting costs may be higher or lower, depending on households' elasticity of demand for trips and on the endogenous location of employers and retailers within the city. As a city becomes more disconnected, households may respond through different margins: one is to incur longer commutes, but others include locating closer to one's job and giving up some trips entirely. For example, they may choose to shop in their neighborhood instead of taking a lengthy trip to their preferred mall. This would result in shorter, rather than longer realized commutes in disconnected cities. Moreover, firms may respond to deteriorating shape by dispersing throughout the city or forming new business districts to be closer to their workers or clients: if a city becomes more polycentric as it becomes more disconnected, commutes should also shorten.[29]

The lack of systematic data on Indian households' location patterns and travel behavior limits the scope for investigating the within-city responses to poor accessibility in a conclusive way. With this in mind, I provide two pieces of evidence on the endogenous responses of firms and workers to city shape, examining the location of firms within cities and households' distance to workplace.

In Table 10, columns 1 and 2, I consider the clustering of firms within cities and show that disconnected cities do not have more dispersed employment. Specifically, I use street addresses and reported employment of productive establishments from the 2005 Economic Census (Office of the Registrar General, India 2005) to detect

[29] Models of endogenous sub-center formation emphasize firms' trade-off between a centripetal agglomeration force and the lower wages that accompany shorter commutes in peripheral locations. See Anas, Arnott, and Small (1998) for a review of the literature on polycentricity.

Table 10—Employment Centers and Work Trips

	log number subcenters, 2005		log average distance to work, 2011			
			Car		Walk	
	IV	OLS	IV	OLS	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shape, km	−0.0951	−0.0644	0.00257	0.0143	−0.00314	−0.0138
	(0.0537)	(0.0165)	(0.0181)	(0.00470)	(0.0193)	(0.00453)
log area	0.683	0.577	−0.0171	−0.0649	0.0781	0.115
	(0.150)	(0.0520)	(0.0758)	(0.0243)	(0.0824)	(0.0230)
Observations	200	200	238	238	238	238
AP *F*-statistic shape	7.47		5.02		5.02	
AP *F*-statistic area	21.77		16.74		16.74	
KP *F*-statistic	4.82		4.44		4.44	

Notes: This table reports cross-sectional estimates of the impact of city shape on the number of employment subcenters in 2005 (columns 1 and 2) and average reported distance to work in 2011 (columns 5 through 8). Each observation is a city in columns 1 and 2 and a district in columns 5 through 8. In columns 1 and 2, the dependent variable is the log number of employment subcenters in a city in 2005, detected using the method described in Section F in the online Appendix based on establishment addresses from the Economic Census. In columns 5 through 8, the dependent variable is the log weighted average distance to work of workers in a district, from the 2011 Census. Columns 5 and 6 consider workers commuting by car and columns 7 and 8 consider workers commuting on foot. The regressors are city shape, in km, and log city area, measured in 2005 (columns 1 and 2) and 2010 (columns 5 through 6). Estimation is by IV in odd columns, and OLS in even columns. AP and KP *F*-statistics are the Angrist-Pischke and Kleibergen-Paap *F*-statistics respectively. Robust standard errors in parentheses.

employment sub-centers using the approach developed by McMillen (2001).[30] Employment sub-centers are identified as locations that have significantly larger employment density than nearby ones and that have a significant impact on the overall employment density function in a city. Details on the data and the procedure are provided in the online Appendix, in Sections A6 and F, respectively. I estimate a cross-sectional version of the benchmark OLS and IV specification with the log number of employment sub-centers as a dependent variable, for year 2005. Subject to the limitations of cross-sectional inference and small sample size, less compact cities have, if anything, fewer subcenters, a pattern found both in the IV and the OLS.

This is consistent with the interpretation that, as cities grow into more disconnected shapes, firms continue to cluster in a few locations within a city, plausibly so as to take advantage of agglomeration, and they leave it to workers to bear the costs of longer commutes.[31] This is also in line with the findings discussed in Section VII that poor shape has meaningful impacts for households, but has negligible impacts on firms in equilibrium.

This interpretation also suggests that disconnected cities should be characterized by longer trips to work in equilibrium. Absent commuting data at the city level, in columns 3 through 6 of Table 10 I consider a noisy district-level proxy for work commute length derived from the 2011 Census. The latter provides a breakdown of

[30] I geo-code the street addresses of productive establishments covered in the fifth Economic Census using Google Maps. I retrieve consistent coordinates for approximately 240 thousand establishments in about 190 cities.

[31] In the model, firms compensate workers for these longer commutes with high wages. Firms are able to pay higher wages in more disconnect cities because poorly shaped cities have smaller population and returns to labor are decreasing (see Section B in the online Appendix).

workers in a district by travel mode and reported distance to work, by coarse bins (0–1, 2–5, 6–10, 11–20, 21–30, 31–50, and above 50 kilometers). I calculate weighted average distance to work separately for workers commuting by car and on foot. Additional details on the construction of this variable are provided in Section A4 in the online Appendix. I report a cross-sectional version of the benchmark IV and OLS specifications, for year 2010. In the OLS (columns 4 and 6), poor shapes are associated with longer commutes by car and shorter commutes on foot. This could point to two heterogeneous kinds of responses to deteriorating shape: those with cars endure longer commutes, whereas those without cars choose locations of work and/or residence that are closer to one another. Plausibly, many of the workers who report walking to work are employed in local informal jobs, which may be an alternative to formal employment in inaccessible parts of the city. I caution that this result is not robust as the corresponding IV estimates (columns 3 and 5) are small and insignificant (albeit with the same sign). Noisy results are to be expected given the inherent limitations in the data: the unit of observation is the district (larger than the city) and the distance bins are probably too coarse to capture differences in commuting length in medium and smaller cities.[32]

B. *Public Services*

The second channel through which city shape may affect households and firms is public service delivery. More compact layouts may reduce the cost of providing services such as water, electricity or sewerage, resulting in higher levels of access. In Table 11 I examine the impact of city shape on households' access to electricity and tap water, but I do not find any meaningful effects. Specifically, I consider the 2011−1991 long difference in the log number and share of households with access to electricity (panel A) and tap water on premises (panel B). When considering the total number of households, OLS estimates indicate a positive correlation between disconnected shape and service access (columns 2 and 6), plausibly due to the fact that larger cities tend to have worse shape. However, when examining the share of households with access (columns 3, 4, and 7 and 8), both OLS and IV estimates are close to zero.

These results appear to run counter the prediction of the urban planning literature and the findings of Baruah, Henderson, and Peng (2017), who find worse service access in African cities that are more sprawled. However, one reason may be that service access in urban India is quite high to begin with: in 1991, the shares of households with access to electricity and tap water were 82 percent and 70 percent respectively. Furthermore, the urban planning argument may be more relevant for services delivered along a centralized grid, while electricity and water access in urban India is also granted through decentralized means such as small-scale private service providers (Kariuki and Schwartz 2005). These decentralized solutions may provide a way around the difficulty of servicing the more disconnected parts of a city.

[32] Recall that the median value of the disconnection index is 2.6 kilometers.

TABLE 11—IMPACT OF CITY SHAPE ON PUBLIC SERVICES

	A. Electricity				B. Tap water			
	Δ log number households, 2011−1991		Δ log share households, 2011−1991		Δ log number households, 2011−1991		Δ log share households, 2011−1991	
	IV (1)	OLS (2)	IV (3)	OLS (4)	IV (5)	OLS (6)	IV (7)	OLS (8)
Δ Shape, km	0.229	0.0741	0.0268	−0.00279	0.185	0.0815	−0.0167	0.00459
	(0.152)	(0.0103)	(0.0249)	(0.00227)	(0.113)	(0.0156)	(0.0380)	(0.0122)
Δ log area	1.685	−0.0948	0.340	0.0398	1.427	−0.176	0.0823	−0.0409
	(1.789)	(0.0544)	(0.311)	(0.0160)	(1.517)	(0.0716)	(0.467)	(0.0527)
Observations	201	201	201	201	201	201	201	201
AP *F*-stat shape	8.88		8.88		8.88		8.88	
AP *F*-stat area	2.49		2.49		2.49		2.49	
KP *F*-stat	1.77		1.77		1.77		1.77	

Notes: This table reports estimates of the impact of city shape on public services. The specifications reported are similar to those in Table 3. The dependent variables are the 2011−1991 long differences in the log number (columns 1, 2, 5, and 6) and share (columns 3, 4, 7, and 8) of households with service access. Columns 1 through 4 report results for electricity and columns 5 through 8 report results for tap water. The regressors are the 2010−1992 long differences in city shape, in km, and log city area. Estimation is by IV in odd columns and OLS in even columns. The average shares of households with electricity and tap water in 1991 are, respectively, 0.82 and 0.7. AP and KP *F*-stats are the Angrist-Pischke and Kleibergen-Paap *F*-statistics respectively. Robust standard errors in parentheses.

TABLE 12—IMPACT OF CITY SHAPE ON SLUM POPULATION

	Δ log slum population, 2011−1981		Δ log slum population share, 2011−1981	
	IV (1)	OLS (2)	IV (3)	OLS (4)
Δ Shape, km	−0.154	−0.0387	−0.167	−0.0502
	(0.0798)	(0.0149)	(0.0823)	(0.0143)
Δ log area	0.651	0.0378	0.702	−0.0614
	(0.760)	(0.107)	(0.757)	(0.103)
Observations	200	200	200	200
AP *F*-statistic shape	15.98		15.98	
AP *F*-statistic area	4.08		4.08	
KP *F*-statistic	6.17		6.17	

Notes: This table reports estimates of the impact of city shape on slum population. The specifications reported are similar to those in Table 3. The dependent variables are 2011−1981 long differences in the log number (columns 1 and 2) and share (columns 3 and 4) of slum households in a city. The regressors are 2010−1950 long differences in city shape, in km, and log city area. Estimation is by IV in odd columns and OLS in even columns. The average share of slum households in 1981 is 0.2. AP and KP *F*-statistics are the Angrist-Pischke and Kleibergen-Paap *F*-statistics respectively. Robust standard errors in parentheses.

C. *Slum Population*

Complementary to the investigation of the impact of city shape is the question of which types of households bear the costs of poor city shape. On the one hand, compact cities may be more favorable to the poor because they may offer better connectivity to jobs and services. However, lower real wages in compact cities may reduce the housing floor space that the poor can afford and price them out of the formal market (Bertaud 2004).

While I cannot systematically observe household income, I examine the share of slum dwellers from the Census (Office of the Registrar General and Census Commissioner, India, 1981 and 2011). In Table 12 I show that cities with less compact shapes have overall fewer slum dwellers, both in absolute terms (columns 1 and 2) and relative to total population (columns 3 and 4). The dependent variables are 2011−1981 long differences in the log number and share of slum households as identified by the Census and the regressors are defined as 2010−1950 long differences. Results are similar in the IV and OLS specifications. Two interpretations are possible. The first is that higher equilibrium rents in compact cities are forcing more households into sub-standard housing. The second relates to sorting of poorer migrants into cities with more compact shapes, possibly because of their lack of individual means of transport and consequent higher sensitivity to commute lengths.[33]

D. *Land Use Regulations and City Shape*

Taken together, the evidence presented in this paper suggests that poor city shape affects household location choices and potentially their quality of life. Given that most cities cannot expand radially due to their topographies, an important question arises on the role of policy and on what kind of land use regulations best accommodate city growth. Below I provide evidence on the interactions between land use regulations, urban growth, and city shape by focusing on a controversial regulatory tool: Floor Area Ratios (FARs).

FARs are restrictions on building height expressed in terms of the maximum allowed ratio of a building's floor area over the area of the plot on which it sits. Higher values allow for taller buildings. The average value of FARs in my sample is 2.3, a very restrictive figure compared to international standards. Previous work has linked conservative FARs in Indian cities to suburbanization and sprawl (Sridhar 2010, Bertaud and Brueckner 2005).

In Table 13, I show that restrictive FARs lead to less compact city shapes. I employ data on FARs in 55 Indian cities as of 2005, from Sridhar (2010).[34] I report the two first-stage equations, linking potential shape and projected historical population to city shape and area, augmented with interactions between each of the two instruments and FARs. Given the small number of cities, in order to leverage more time variation in the data, I present a panel version of the two first-stage equations, similar to columns 3 and 4 in Table 2. The interaction between projected population and FARs has a negative impact on city shape (column 1) and city area (column 2). This suggests that cities with laxer FARs may expand less in space (consistent with Sridhar 2010), and may expand in a more compact fashion than their projected

[33] These results may raise concerns related to the interpretation the wages results from Section VC: lower wages in more compact cities may be driven by low-productivity workers disproportionately locating in these cities, consistent with my findings on slum dwellers. Recall, however, that my wage sample covers the formal sector only and is therefore unlikely to include a large share of slum workers.

[34] Given that FARs are updated infrequently, these mid-2000s data are a reasonable proxy for FARs in place throughout the sample period.

TABLE 13—IMPACT OF FLOOR AREA RATIOS ON CITY SHAPE

	Shape, km (1)	log area, km^2 (2)
log projected population	2.995	1.981
	(2.755)	(0.788)
log projected population × FAR	−1.975	−0.705
	(1.023)	(0.319)
Potential shape, km	0.158	−0.184
	(1.182)	(0.232)
Potential shape, km × FAR	0.667	0.137
	(0.487)	(0.107)
Observations	1,182	1,182
City fixed effects	Y	Y
Year fixed effects	Y	Y

Notes: This table reports estimates of the relationship between Floor Area Ratios (FARs), city shape, and area. Each observation is a city-year. Columns 1 and 2 are similar to columns 3 and 4 in Table 2, augmented with interactions between FARs and each of the instruments. Estimation is by OLS. All specifications include city and year fixed effects. Standard errors clustered at the city level in parentheses.

growth would imply. A one standard deviation increase in FARs (0.6) is associated with an absolute reduction in the shape index of roughly 1 kilometer for each percent increase in projected population.

In other words, higher FARs may slow down the deterioration in city shape that fast city growth entails: if growing and topographically constrained cities are allowed to grow vertically, they will not expand horizontally as much and will plausibly remain more compact. These findings are particularly important for the larger cities in India, as they are those with the most pronounced natural tendency to deteriorate in shape and also those with the most restrictive FARs (Sridhar 2010).

IX. Conclusion

In this paper I examine the causal economic implications of city shape in the context of India, exploiting variation in urban form driven by topography. Embedding city shape in a classic urban economics model, I connect the notion of geometric city compactness with that of spatial equilibrium across cities, and provide novel causal evidence that city compactness affects urbanization patterns. Less compact urban layouts, conducive to longer within-city distances, are associated with lower quality of life and potential welfare costs for households, primarily driven by worse accessibility. This is particularly important for the largest cities in India, that have a tendency to become less compact over time.

As India prepares to accommodate an unprecedented urban growth in the next decades, the challenges posed by urban expansion are gaining increasing importance. On the one hand, policy makers are concerned about the perceived harms of haphazard urban expansion, including sprawl and limited urban mobility (World Bank 2013). On the other hand, existing policies, especially land use regulations, are viewed as potentially distortive of urban form (Glaeser 2011, Sridhar 2010).

This paper contributes to informing the policy debate on both fronts. Although this study focuses on geographic obstacles (which are mostly given) in order to gain identification, there is a range of policy options to prevent the deterioration in connectivity that fast city growth entails and to mitigate the negative impacts on bad shape, for example by improving urban mobility. My findings also suggest that urban connectivity can be indirectly improved by promoting more compact development through land use regulations: restrictive FARs, among the most controversial of such regulations, result in less compact footprints. This suggests that any distortive effects on urban morphology should be accounted for when evaluating the costs of land use regulations. A number of other urban planning practices and regulations currently in place in Indian cities have been viewed as conducive to sprawl (Bertaud 2002) and could be explored in future work.[35]

In future research, it would be interesting to provide a richer theoretical microfoundation for the effects of city shape on the behavior of households and firms, shedding further light on the channels through which city shape matters. A richer model could also be used to investigate heterogeneous distributional effects and to pin down welfare consequences. More disaggregated data at the sub-city level will be required to empirically investigate these ramifications.

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[35] Examples include: the Urban Land Ceiling Act, which has been claimed to hinder intra-urban land consolidation; rent control provisions, which prevent redevelopment and renovation of older buildings; regulations hindering the conversion of land from one use to another; and, more generally, complex regulations and restrictions in central cities, as opposed to relative freedom outside the administrative boundaries of cities.

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