Measuring Welfare Gains from Relaxation of Land-Use Restrictions: The Case of India's Building-Height Limits

by

Jan K. Brueckner
Department of Economics
University of California, Irvine
e-mail: jkbrueck@uci.edu

and

Kala Seetharam Sridhar
Public Affairs Center
Bangalore, India
e-mail: kala@pacindia.org

May 2012, revised August 2012

Abstract

This paper estimates the effect of building-height limits on the spatial sizes of Indian cities. Regression results show that height limits, which are imposed in draconian fashion in India, cause spatial expansion of its cities, as predicted by the theoretical model of Bertaud and Brueckner (2005). The regression coefficients, by yielding the implied reduction in the area of an average city from a marginal increase in its height limit, allow computation of the annual saving in commuting cost for the city's edge resident when the limit is relaxed. This cost saving, which is an exact measure of the common welfare gain for each urban resident, can be scaled up to yield the aggregate consumer gain in a typical city from relaxation of India's restrictive height limits. For a moderate height-limit increase, this gain equals 106 million rupees.

Measuring Welfare Gains from Relaxation of Land-Use Restrictions: The Case of India's Building-Height Limits

by

Jan K. Brueckner and Kala Seetharam Sridhar*

1. Introduction

Some of the world's most dramatic land-use restrictions are found in India. Cities in India impose draconian building-height limits, which enforce low-rise land-use patterns in urban areas that would otherwise resemble the high-rise metropolises of Hong Kong or Singapore. These restrictions are imposed via limits on a building's "floor-area ratio," or FAR, which equals the floor space contained in a building divided by the area of its lot.[1] If a building entirely covers its lot, FAR approximately equals the number of floors in the building, although partial lot coverage makes the floor count greater than FAR. The draconian nature of Indian FARs is seen in Table 1, which shows FAR values in the central business districts of some of the world's major cities, including Mumbai, Delhi and Chennai (the source is World Bank (2012)). FARs in the CBDs of these three Indian cities are at most 3.5 (and less than 1.5 in Mumbai and Chennai), far lower than the values of 10 or more seen in other major metropolises.[2]

Various explanations have been offered for India's use of stringent height restrictions. Under one view, urban planners fear that the high population densities resulting from looser height limits would overwhelm inadequate urban infrastructure (sewers, water and gas lines, roads, parking, storm drains). Another view holds that Indian planners have an innate dislike of high densities, which are seen as reducing the quality of urban life, prompting the tight FAR restrictions.[3]

Whatever the motivation, urban economic theory shows that height limits have far reaching impacts on cities that go beyond their direct effect on the skyline. As shown by Bertaud and Brueckner (2005), a height limit leads to urban sprawl, causing a city to expand spatially in a natural response to the land's restricted ability to accommodate the urban population.[4] In addition, a height limit raises housing prices throughout the city, again reflecting a reduction in the housing "supply" that the land is able to provide. This price escalation matches the stratospheric real estate prices seen in some Indian cities, particularly Mumbai. A height limit also *raises* building heights in parts of the city where they remain lower than the limit, ironically undermining the intent of the restriction. Finally, a height limit makes the urban residents worse off through a combination of higher housing prices and longer commutes to the center. As shown by Bertaud and Brueckner (2005), an exact monetary measure of the per capita welfare loss is given by the increase in commuting cost for a resident living at the now-more-distant edge of the city (the housing price is unchanged for this resident).

The ultimate goal of the present paper is to quantify the welfare effect of Indian building-height limits by measuring the *welfare gain* from a *relaxation* of the height restriction in a typical city. This exercise is carried out by first estimating the empirical relationship between the spatial sizes of Indian cities and their FAR limits. This regression, which itself constitutes an important contribution of the paper, shows the expected inverse relationship (with a higher FAR making a city more compact). Using the estimated FAR coefficient, the reduction in land area, and thus the reduction in distance to the city's edge, from a unit increase in FAR can be computed. Then, using an independent estimate of commuting cost per kilometer, the reduction in the edge resident's annual commuting cost is computed, giving the per capita welfare gain. Finally, this gain is scaled up by the city's population to get the aggregate consumer welfare gain. If loosening the FAR limit entails no resource cost, then this welfare gain is a measure of the consumer benefit from doing so.[5] If, on the other hand, infrastructure improvements would be needed to allow a higher FAR, then the cost of such improvements would be subtracted from the welfare gain to arrive at the net consumer benefit from relaxing the limit. Since calculations of the monetary gain from relaxing land-use restrictions are exceedingly rare in the literature, the paper's results in this regard are highly noteworthy.[6] For another study calculating such gains, see Cheshire and Sheppard (2002), whose focus is the United Kingdom.

In addition to these welfare calculations, the paper's regression results, which show the effect of building-height limits on the urban footprints of Indian cities, are themselves an important contribution, as just noted. This contribution extends a growing body of work exploring the determinants of the spatial sizes of cities. These papers, which include Brueckner and Fansler (1983), McGrath (2005), Spivey (2008), Deng et al. (2008), and Paulsen (2012), present regression results relating urban spatial areas to variables identified as important by urban economic theory: population, income, commuting cost per km, and agricultural land rent. Like this prior work, the regressions reported in the present paper control for these other determinants of urban spatial sizes while measuring the additional effect of a city's FAR limit. In doing so, the paper mirrors the approach of two additional papers that attempt to gauge the effects of land-use restrictions on urban footprints: Wassmer (2006) and Geshkov and DeSalvo (2012). Along with an FAR variable, Geshkov and DeSalvo also include a variety of other land-use restrictions in their urban-spatial-size regression (urban growth boundaries and minimum lot-size restrictions, for example), while Wassmer relies on more general indicators of the presence of growth-management policies. Another related study is Sridhar (2010), which investigates the connection between urban density gradients (rather than spatial areas) and FAR limits in Indian cities (see also Sridhar (2007)).

The paper is also connected to a literature exploring the effect of various land-use regulations on housing prices. This literature, which includes contributions by Pollakowski and Wachter (1990), Quigley and Raphael (2005), Ihlanfeldt (2007), Glaeser and Ward (2009) and others, finds that land-use regulations tend to raise housing prices.[7] Although the urban footprint rather than the price of housing is the focus of the present paper, FAR limits do indeed put upward pressure on prices, as noted above.

The plan of the paper is as follows. Section 2 reviews the analysis of Bertaud and Brueckner (2005), which establishes the theoretical connection between a city's spatial size and its FAR limit. Section 3 discusses the data and presents the regression results, and Section 4 computes the welfare gain from relaxation of a city's FAR limit. Section 5 offers conclusions.

2. Theory

The theory is based on the standard monocentric city, where all employment is in the CBD and each household earns the same income. Existing cities do not conform exactly to these assumptions, but the resulting model offers a useful approximation to reality. Following the standard approach, Bertaud and Brueckner (2005) (hereafter BB) derive the main variables in the urban model as functions of distance to the CBD, denoted x, and the common utility level of urban residents, denoted u. The following variables are functions of x and u: the rental price per square foot of housing, $p(x,u)$; land rent per acre, $r(x,u)$; dwelling size in square feet, $q(x,u)$; and housing capital per acre of land, $S(x,u)$. As usual, p, r, and S are decreasing functions of x, while q is increasing in x. The housing price p falls with x to compensate for higher commuting costs at more distant locations, and dwelling size q rises with x in response. Mirroring the decline in p, land rent r falls with distance, equalizing the profits of housing developers across locations, and capital per acre S falls with x in response to the relative cheapening of the land input.

In the model, building height is represented by housing floor space per acre of land, which is effectively equal to FAR. Floor space per acre depends on capital per acre via the production function $h(S)$, which exhibits the usual diminishing returns. Assuming one person per dwelling, population density (people per acre) at distance x from the center is then equal to housing floor space per acre divided by floor space per dwelling, or $h(S(x,u))/q(x,u)$.

The building-height limit imposes a restriction on floor space per acre or FAR, requiring that h does not exceed a specified limit denoted $\widehat{h}$. Since S is decreasing in x, the height limit will bind in the central part of the city, where $h(S(x,u))$ would ordinarily be high. However, the x value where the constraint initially binds is endogenously determined. Letting $\widehat{x}$ denote this value, housing floor space per acre will equal $\widehat{h}$ for $x \leq \widehat{x}$, while equaling $h(S(x,u))$ for $x > \widehat{x}$.

The utility level u is endogenously determined in the model along with $\widehat{x}$. The equilibrium conditions that determine the values of these variables along with the endogenous distance $\overline{x}$ to the edge of the city are as follows:

$$r(\overline{x},u) = r_a \tag{1}$$

$$h(S(\widehat{x},u)) = \widehat{h} \tag{2}$$

$$\int_0^{\widehat{x}} 2\pi x \frac{\widehat{h}}{q(x,u)} dx + \int_{\widehat{x}}^{\overline{x}} 2\pi x \frac{h(S(x,u))}{q(x,u)} dx = N. \tag{3}$$

The first condition is the usual urban boundary condition, requiring equality of urban rent and agricultural rent (denoted r_a) at $\overline{x}$. The second condition says that the height limit becomes binding at $\widehat{x}$, and the third condition says that the urban population N fits in the city. Note that $\widehat{h}/q(x,u)$ is population density at x values inside $\widehat{x}$ while $h(S(x,u))/q(x,u)$ gives population density outside $\widehat{x}$. Weighting these densities by the area measure $2\pi x dx$ and integrating out to $\overline{x}$ gives the population fitting in the city, which must equal N.

BB prove that the $\overline{x}$ value satisfying (1)–(3) is larger than the equilibrium $\overline{x}$ value in the absence of a height limit, which is determined by dropping (2) from the set of equilibrium conditions and setting $\widehat{x}$ in (3) equal to zero. BB also show that the u value given by (1)–(3) is lower than the equilibrium u in the absence of a height limit. Thus, imposition of the height limit causes spatial expansion of the city while reducing the utility level of urban residents. Conversely, *elimination* of the height limit makes the city more compact while raising utility. BB's argument does not apply directly to the effect of a marginal relaxation of the height restriction, but an extension of the argument establishes that a marginal increase in $\widehat{h}$ is like a total relaxation in that it leads to a decrease in $\overline{x}$ and an increase in u. In other words,

$$\frac{\partial \overline{x}}{\partial \widehat{h}} < 0, \qquad \frac{\partial u}{\partial \widehat{h}} > 0. \tag{4}$$

Since $p(x,u)$ is decreasing in u, the rise in utility resulting from the increase in $\widehat{h}$ leads to a decline in the price per square foot of housing throughout the city. This price decline, along with the shorter commutes made possible by the more-compact city, are the sources of the welfare gain that accompanies relaxation of the height limit. BB show that the monetary value of the welfare gain from eliminating the height limit is the reduction in commuting cost for the resident living at the edge of the city, who is now closer to the center but experiences no change in p.[8] Analogously, the monetary value of the welfare gain from a marginal increase in $\widehat{h}$ is also captured by the reduction in the edge resident's commuting cost.

As noted above, imposition of a height limit raises building heights in the part of the city where the limit is not binding. This effect is shown in Figure 1, which compares the building-height patterns in cities with and without a height restriction.[9] Note that a marginal increase in $\widehat{h}$ would raise the horizontal line in the figure while reducing building heights in locations where the limit is not binding.

A second physical effect of the height limit is a reduction in dwelling sizes throughout the city, a response to escalation in the price p per square foot of housing (note that this effect occurs even while the city's land area is increasing). Table 2, which shows floor area per person in Mumbai and several cities from other countries, appears to confirm this prediction. While the floor-area differences shown partly reflect income disparities, the contrast between the values for Shanghai and Mumbai, cities with similar income levels, is striking. A second international comparison, shown in Table 3, appears to confirm the model's prediction that height limits create urban sprawl, raising $\overline{x}$. The table shows that the percentage of Mumbai's population living within 10 km of the CBD is far lower than in the comparison cities. Some of this difference might be due to Mumbai's peninsular topography, but Hong Kong also has unusual topographical features.

The next section of the paper further explores the effect of height limits on the spatial sizes of Indian cities, using regression analysis.

3. Data and Regression Results

3.1. Data and variables

Data are compiled for a cross section of Indian cities from a variety of sources: the Census of India (for population and area; Registrar General of India (2001)), a review of individual cities' land-use rules (for FAR), National Council of Applied Economic Research (2002), or NCAER (for household income levels), and the Indian Government Planning Commission (2012) (for agricultural income per capita). The central variable in the empirical model is the building-height measure, denoted **FAR**. This variable is set equal to the maximum FAR value, either residential or commercial, allowed anywhere in the municipality, as of 2006. Some regressions use the dummy variable **highFAR**, which indicates whether the city's FAR value is greater than or equal to 3. Although the model focuses solely on residential land-use (with all jobs concentrated in a dimensionless CBD), a variable based only on residential FARs would overlook the role of business building heights in determining the size of the urban footprint. More generally, since nonresidential FAR values provide a fuller picture of land-use restrictiveness in a city, their use in construction of the **FAR** variable is appropriate. Confirming this view, regressions using the maximum residential FAR as the height measure perform less well than those reported below.

The dependent variable in the regressions is the spatial size of the municipality in square kilometers, which is measured in 2001 and denoted **area**. The log of area, which is used in some regressions, is denoted **larea**. The 2001 population of the municipality is denoted **pop**, and the measure of urban income per household is denoted **urbinc**. This latter variable is drawn from a survey of 2002 income levels in Indian cities carried out by the NCAER (2002). In addition to population and urban income, an important determinant of urban spatial areas is agricultural rent r_a, which appears in the boundary condition (1) above. Although the US Census contains a measure of agricultural land values by county, no such variable is available for India. As a proxy for r_a, the regressions use a measure of agricultural income per capita for the years 2003-2004, denoted **aginc**.[10] Since productive agricultural land that commands a high rent will also be associated with high agricultural incomes, this variable appears to be a suitable proxy. No easily constructed measure of commuting cost per km, another important determinant of urban spatial sizes, is available for India, matching the obstacles in measuring this variable encountered by previous authors. As a result, the basic regressions do not attempt to control for commuting cost. However, later regressions include dummy variables for the individual Indian states, which control for differences in fuel taxes (a determinant of commuting costs) along with other factors.

The sample consists of 101 Indian municipalities with populations of at least 10,000 where data for all the variables was available. An alternative approach would have been to focus on metropolitan areas rather than municipalities, using the FAR value for the major city as the variable explaining the area of the entire metropolis. However, since this latter area (known as the Urban Agglomeration (UA)) is often much larger than the major city's area, the empirical connection between the urban footprint and the FAR measure would have been weakened and not easily observed.

Summary statistics for the variables are presented in Table 4. The numbers show a broad range of spatial areas and populations. The **aginc** variable similarly varies substantially (by a factor of 20) between its minimum and maximum values, although **urbinc** only varies by a factor of two. The average value of the maximum permissible **FAR** is 2.87, with minimum and maximum values of 1.0 and 4.125, respectively. The mean of **highFAR** shows that 60% of the sample cities have maximum **FAR** values of at least 3. In the regressions, the **pop** variable is divided by 100,000, while the income variables are expressed in thousands of rupees.

3.2. Regression results

The exploration of different empirical specifications showed that the regression results are somewhat sensitive to the functional form of the equation. For comparison purposes, results for both linear and semilog regressions are presented below, with other specifications omitted.[11] Table 5 shows the basic regression results for the linear and semilog specifications, using alternatively **FAR** and **highFAR** as the height-limit measure. The **FAR** coefficient is negative and significantly different from zero at the 10% level in the linear regression in column 1, but insignificant in the semilog regression in column 2. But the **highFAR** coefficients are negative and strongly significant in both the linear and semilog specifications. These results suggest that looser building-height limits, as reflected in larger FAR values, lead to more-compact cities with smaller spatial areas, as predicted by the theory.

The **pop** coefficients are positive and significant in all the regressions, indicating that populous cities occupy larger land areas than cities with smaller populations. In addition, all of the **urbinc** coefficients are positive and significant, indicating that higher-income cities take up more space, as predicted by the urban model. All of the **aginc** coefficients are negative, suggesting that higher agricultural incomes (and thus higher agricultural land rents) lead to more-compact cities, as predicted by the model. However, only the coefficient in the semilog regression containing **highFAR** is significant, and its significance level is only 10%.

Overall, the results in Table 5 are reasonably consistent with the standard predictions of the urban model while also showing the expected negative impact of a higher FAR on the spatial areas of Indian cities. However, it could be argued that, being a policy variable chosen by the city government, **FAR** (or alternatively **highFAR**) should be treated as endogenous. Table 6 presents the results of two-stage least squares regressions that attempt to correct for the possible endogeneity of **highFAR**, relying on two instrumental variables. The instruments are a dummy variable indicating that the government for the state containing the city is controlled by the Congress party as of 2012 (denoted **party**), and a variable measuring the population growth of the city between 1950 and 2000 (**growth**). Since the Congress government in 1991 spearheaded India's economic reforms, states where the Congress party is in power would tend to be more reformist and thus allow liberal FARs. Note that while the city government or the urban development authority sets height limits, choices are frequently constrained by state policies (the state of West Bengal, for example, imposes a maximum nonresidential FAR of 2.75). As for the **growth** instrument, population growth could affect the incentives to impose land-use restrictions in two possible directions. High growth could impart pressure to relax building-height limits, but it could alternatively breed resistance to further growth and thus tighter limits, implying either a positive or negative effect of **growth** on **highFAR**. The means of **party** and **growth** are 0.35 and 7.06, respectively.

Although two-stage least squares estimates using the **FAR** variable are not satisfactory, **highFAR** works better. The first column of Table 6 shows the first-stage regression relating **highFAR** to the exogenous variables and the instruments (given the 0-1 nature of **highFAR**, the regression is a linear probability model). Only the **growth** coefficient is significant, with the confidence level almost reaching 5%. Its negative sign appears to indicate that high growth increases resistance to further growth, with a city tightening its FAR limits. The joint F statistic for the two instruments is significant only at the 10% level, and the fact that its value of 2.77 is well below the desirable value of 10 indicates that the instruments are "weak." This outcome, along with the lack of explanatory power of the other exogenous variables in the first-stage regression and its low R^2 (0.14), may limit confidence in the second-stage regressions shown in the second and third columns of Table 6. Nevertheless, although some statistical significance is lost, the coefficient signs are the same as in Table 5. The coefficients of **highFAR** are negative, with the semilog coefficient significant, and the **urbinc** and **aginc** coefficients are respectively positive and negative, with two significant at the 10% level. The **highFAR** coefficient in the semilog regression is twice the absolute size of the OLS coefficient in Table 5, but whether this magnitude reflects the elimination of simultaneity bias or the subpar first-stage regression is unclear.

State dummy variables can be added to the regression, as noted above, and this specification leads to somewhat stronger results.[12] These variables capture a variety of relevant factors that may vary across cities, including state FAR limits, other political and regulatory factors, and interstate variation in fuel taxes (which affect commuting costs). The state dummies are also likely to capture differences in the productivity of the agricultural areas surrounding cities more effectively than the **aginc** variable, thus obviating the need for its use. The state-dummy specification works best with the variables **highFAR** and **larea**, and the OLS results are shown in the first column of Table 7.[13] As can be seen, **highFAR**'s coefficient is significantly negative, while the coefficients of **pop** and **urbinc** are both positive and significant. A number of the state dummies also have significant effects on **larea**. Since the presence of these variables helps control for omitted factors that affect building-height limits, concern about bias in the coefficient of **highFAR** is reduced.

Even though endogeneity concerns are lessened, the remaining columns of Table 7 present two-stage least squares results. Since the **party** variable is collinear with the state dummies, it is dropped, leaving **growth** as the only instrument. This variable's coefficient is again negative and now strongly significant (eliminating concerns about instrument weakness), and the regression's R^2 is much improved. However, relative to OLS, precision is lost in the second-stage regression, with the coefficients of both **highFAR** and **pop** no longer significant. Nevertheless, the magnitudes of the point estimates are close to those in the OLS regression, suggesting that simultaneity bias may not be present in the OLS case. This view is confirmed by application of the Hausman-Wu test. In particular, the coefficient of the fitted value of **highFAR** is insignificant when this variable is included in an augmented OLS regression like that in column 1. Thus, Table 7's OLS regression provides reliable evidence that less-restrictive height limits lead to more-compact cities.

4. The welfare gain from relaxing a city's FAR limit

With the empirical results confirming that a higher FAR limit leads to a reduction in a city's spatial size, the estimated coefficients can be used to compute the consumer welfare gain from an increase in FAR. Since the goal is to derive the gain from a "marginal" increase in FAR, chosen to equal to 1.0, the results from the regressions using the **FAR** variable rather than the dummy **highFAR** must be used.

The linear regression from Table 5 implies that a unitary increase in **FAR** reduces an average city's spatial size by 19.23 square km. Using the mean **area** value of 81.65 from Table 4, this shrinkage represents a 23.6% reduction in spatial area. To check this implication of the linear regression, the percentage reduction in area from the semilog regression can also be computed, even though the **FAR** coefficient is not statistically significant. The point estimate in that regression implies that a unitary increase in **FAR** reduces **larea** by -0.196, which translates to a percentage area reduction of 18%.[14]

Taking the approximate midpoint of these two percentage values, a unitary increase in FAR reduces the average city's spatial area (equal to 81.65) by about 20%, or 16.33 square km. Assuming a circular city, this area reduction in turn implies a reduction of the city's radius by 0.54 km.[15] Using some new underlying data along with BB's method for deriving commuting cost, the estimate of commuting cost per km per year is 969 Rs. (see the Appendix for details).[16] Using this value, the annual commuting cost saving for the city's edge resident is then equal to $969 \times 0.54 = 523$ Rs. As proved by BB, this value equals the welfare gain for each city resident from relaxation of the FAR limit. With annual income estimated at 70,900 Rs. by the same methodology, this gain is 0.7% of income, an appreciable value. Table 8 presents the steps in these calculations.

To get the aggregate consumer welfare gain from a unitary increase in FAR, the 523 Rs. value can be multiplied by the number of households in an average city. Assuming 3.7 people per household (the value from the Indian census) and using Table 4's average population figure, the number of households in the average city is $750{,}000/3.7 = 202{,}700$. Multiplying by 523, the aggregate consumer welfare gain then equals 106.0 million Rs. For comparison purposes, commuting-cost savings representing the same 0.7% percentage of income in the US would aggregate to $999.6 million in a city of this size.[17]

The cost of any infrastructure improvements needed to support the higher FAR must be subtracted from the 106 million Rs. value to reach the net consumer welfare gain from relaxation of the height limit. Arriving at the cost of such improvements is, of course, mostly an engineering matter.[18] A parallel calculation could compute the gains from a greater relaxation of FAR limits, which would put Indian cities nearer to international norms (recall Table 1).

5. Conclusion

This paper has estimated the effect of building-height limits on the spatial sizes of Indian cities. Regression results show that height limits, which are imposed in draconian fashion in India, cause spatial expansion of its cities, as predicted by the theoretical model of Bertaud and Brueckner (2005). The regression coefficients, by yielding the implied reduction in the area of an average city from a marginal increase in its height limit, also allow computation of the annual saving in commuting cost for the city's edge resident when the limit is relaxed. This cost saving, which is an exact measure of the common welfare gain for each urban resident, can be scaled up to yield the aggregate consumer gain in a typical city from relaxation of India's restrictive height limits, a value equal to 106 million Rs. for an average city. Indian policymakers should take note of this welfare gain, comparing it to any extra infrastructure costs necessitated by a higher FAR, in contemplating whether to modify the country's strict land-use policies.

Recognition of the welfare gain from a higher FAR might undercut a perception that such policy changes are business-friendly rather than pro-poor. More generally, by showing that more-compact cities closer to international FAR norms are better for consumers, saving them money on housing and commuting costs, this paper offers an important addition to Indian policy debates. Its lessons could be especially useful in formulating land-use policies for newer cities and the outlying areas of existing cities, where much of India's future growth is likely to occur.

Appendix

To compute the time-cost component of commuting cost, the wage is estimated at 22.6 Rs. per hour. This figure is based on a daily wage of 158 Rs. per day and a 7-hour work day (with an exchange rate of 53.72 Rs. per dollar, one rupee represents two U.S. cents). This daily wage figure is derived by taking the average of minimum daily wages for workers in the information-technology, garment, and construction industries. Based on discussions with the Karnataka Department of Labor, these sectors accounted for a majority of Bangalore's work force in 2012 (Karnataka is the state containing Bangalore). The wage data were drawn from the department's Karnataka Labor Journal (http://labour.kar.nic.in/labour/cur%20mw%202011-12.pdf). Commuting time is assumed to be valued at 60 percent of the wage, yielding a value per hour of 13.6 Rs. Assuming a traffic speed of 20 kilometers per hour, time cost is then $13.6/20 = 0.68$ Rs. per km.

BB estimate the money cost of travel using Bangalore bus fares, which are distance-based and involve a cost per kilometer of 0.40 Rs. Adding this money cost to the time cost, commuting cost per km is then $0.68 + 0.40 = 1.08$ Rs.

Multiplying this value by 2 to convert to a round trip basis, and multiplying again by 6 workdays per week and 44 workweeks per year, and again by 1.7 workers per household (Bangalore's value, from the census), annual commuting cost per kilometer for a household is $1.08 \times 2 \times 6 \times 44 \times 1.7 = 969$ Rs. per year. Note that the 70,900 Rs. income figure in the text shares these assumptions, coming from multiplication of the 158 Rs. daily wage by 6, again by 44 and again by 1.7 (then rounding to the nearest hundred).

Finally, it should be noted that bigger cities such as Bangalore, Delhi, Mumbai and Kolkata have public-transport options, which the typical resident in these cities uses. Many smaller cities included in the data set do not have such options, with the result that commuting cost per km for them might be higher. Savings in commuting costs from a relaxation of FAR limits could thus be understated by applying the above calculations to smaller cities.

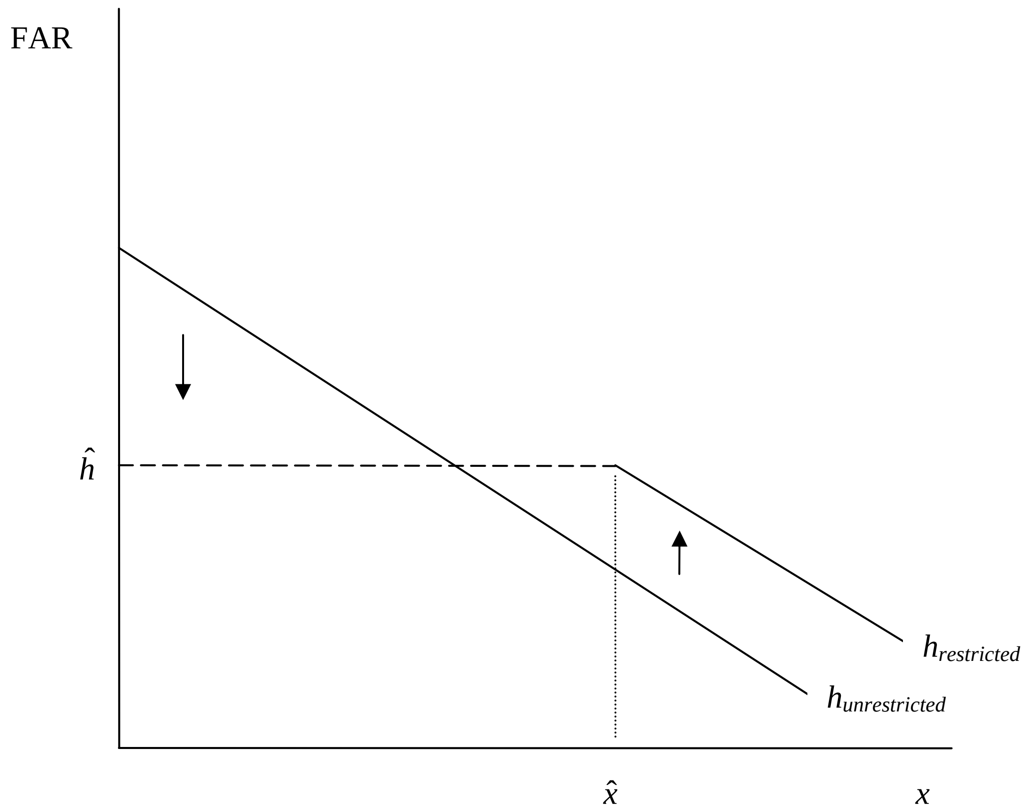

Figure 1: Building-height pattern under an FAR limit

Table 1: Center-City FAR Values

City	FAR
Sao Paulo	1
Mumbai	1.33
Chennai	1.5
Delhi	1.2–3.5
Amsterdam	1.9
Venice	2.4
Paris	3
Shanghai	8
Vancouver	9
San Francisco	9
Chicago	12
Hong Kong	12
Los Angeles	13
New York	15
Denver	17
Tokyo	20
Singapore	12–25

Source: World Bank (2012)

Table 2: Floor Area Per Person (sq. m.)

City	Area
Copenhagen	43.9
Stockholm	41.0
Berlin	37.9
Helsinki	34.2
Warsaw	24.5
Shanghai	13.1
Mumbai	2.9

Sources: Bertaud (2011), City of Helsinki Urban Facts (2008)

Table 3: Population Living Close to the CBD

City	*Urbanized area population**	*Number within 10 km of CBD*	*Share in %*
Moscow	10.7	3.1	29
Bangkok	6.6	3.3	50
Hong Kong	7.0	3.4	48
Paris	9.8	4.5	46
Jakarta	13.2	5.2	39
Seoul	9.6	6.2	64
Shanghai	14.5	7.1	49
Mumbai	18.2	2.2	12

**in millions; source: Bertaud (2002)*

Table 4: Summary Statistics

VARIABLE*	*mean*	*std. dev.*	*min*	*max*
area	81.65	108.30	1.8	603
FAR	2.87	0.62	1.0	4.125
highFAR	.604	.49	0	1
pop	753,529	1,709,769	10,195	1.20e+7
urbinc	61,834	9475	47,901	92,617
aginc	4056	2023	535	11,952

Units: area is in square km, incomes are in rupees per year, and populations are actual values

Table 5: Basic Regressions

VARIABLES	(1) area	(2) larea	(3) area	(4) larea
FAR	-19.23†	-0.196		
	(-1.899)	(-1.105)		
highFAR			-40.84**	-1.014**
			(-3.278)	(-4.994)
pop	3.950**	0.0209*	3.961**	0.0220**
	(8.231)	(2.481)	(8.552)	(2.908)
urbinc	2.968**	0.0581**	2.657**	0.0461**
	(3.516)	(3.916)	(3.229)	(3.435)
aginc	-2.547	-0.0637	-3.042	-0.0911†
	(-0.792)	(-1.128)	(-0.982)	(-1.805)
Constant	-66.20	0.677	-75.45	1.571†
	(-1.042)	(0.607)	(-1.461)	(1.867)
Observations	101	101	101	101
R^2	0.701	0.411	0.721	0.527

t-statistics in parentheses

** $p<0.01$, * $p<0.05$, $^{\dagger}p<0.10$

Table 6: 2SLS Regressions

VARIABLES	(1) highFAR (*1st stage*)	(2) area	(3) larea
highFAR		-67.30	-2.328*
		(-1.239)	(-2.245)
pop	0.00233	4.003**	0.0240*
	(0.626)	(8.318)	(2.616)
urbinc	-0.0107	2.266†	0.0267
	(-1.601)	(1.976)	(1.220)
aginc	-0.0257	-4.033	-0.140†
	(-1.013)	(-1.080)	(-1.968)
party	-0.116		
	(-1.089)		
growth	-0.0104†		
	(-1.978)		
Constant	1.464**	-31.63	3.746†
	(3.765)	(-0.310)	(1.921)
Observations	101	101	101
R^2	0.140	0.707	0.321
F stat. for inst.	2.77†		

t-statistics in parentheses

** p<0.01, * p<0.05, †p<0.10

Table 7: Regressions with State Dummies

VARIABLES	(1) larea *OLS*	(2) highFAR *1st stage*	(3) larea *2SLS*
highFAR	-3.915*		-4.439
	(-2.503)		(-0.935)
pop	0.0466**	0.00726**	0.0503
	(3.537)	(15.35)	(1.461)
urbinc	0.0441**	-0.00286**	0.0424*
	(3.348)	(-3.507)	(2.100)
andhra prad.	-0.334	-0.368**	-0.555
	(-0.279)	(-5.389)	(-0.248)
assam	4.085*	0.669**	4.412
	(2.569)	(7.960)	(1.367)
bihar	3.336*	0.615**	3.637
	(2.407)	(8.650)	(1.243)
jharkand	4.371**	0.648**	4.688
	(2.811)	(7.821)	(1.499)
haryana	-1.306	-0.298**	-1.480
	(-1.042)	(-3.912)	(-0.759)
karnataka	0.113	-0.452**	-0.139
	(0.0889)	(-6.581)	(-0.0555)
kerala	4.051**	0.634**	4.364
	(2.938)	(9.351)	(1.444)
madhya prad.	0.157	-0.383**	-0.0631
	(0.127)	(-5.469)	(-0.0280)
maharashtra	-0.235	-0.344**	-0.430
	(-0.211)	(-5.422)	(-0.214)
orissa	0.408	-0.355**	0.202
	(0.319)	(-4.715)	(0.0929)
rajasthan	1.011	-0.475**	0.740
	(0.703)	(-5.947)	(0.271)
tamil nadu	3.089*	0.616**	3.394
	(2.290)	(9.232)	(1.155)
uttar prad.	0.296	-0.412**	0.0612
	(0.245)	(-6.235)	(0.0260)
west bengal	2.321†	0.643**	2.640
	(1.672)	(9.501)	(0.862)
growth		-0.00195**	
		(-3.182)	
Constant	1.092	0.527**	1.398
	(0.705)	(6.211)	(0.459)
Observations	101	101	101
R^2	0.736	0.991	0.736

t-statistics in parentheses

** p<0.01, * p<0.05, †p<0.10

Table 8: Calculation of Aggregate Consumer Welfare Gain from a Unit Increase in FAR

Percentage reduction in city area (avg. of linear and semilog effects)	20%
Area reduction in square km (0.20 × 81.65)	16.33
Reduction in city's radius in km	0.54
Reduction in edge resident's commuting cost (0.54 × 969 Rs. per year per km)	523 *Rs.*
Aggregate annual welfare gain (523 × 750,000/3.7)	106.0 *million Rs.*

References

Arnott, R.J., MacKinnon, J.G. 1977. Measuring the costs of height restrictions with a general equilibrium model. *Regional Science and Urban Economics* 7, 359-375.

Bertaud, A., 2002. Note on transportation and urban spatial structure. Paper presented at the World Bank ABCDE conference, April (available at *http://alain-bertaud.com*).

Bertaud, A., 2011. Mumbai FAR/FSI conundrum. The perfect storm: The four factors restricting the construction of new floor space in Mumbai (available at *http://alain-bertaud.com*).

Bertaud, A., Brueckner, J.K., 2005. Analyzing building-height restrictions: Predicted impacts and welfare costs. *Regional Science and Urban Economics* 35, 109-125.

Brueckner, J., Fansler, D., 1983. The economics of urban sprawl: Theory and evidence on the spatial size of cities. *Review of Economics and Statistics* 55, 479-482.

Cheshire, P., Sheppard, S., 2002. The welfare economics of land use planning. *Journal of Urban Economics* 52, 242-269.

City of Helsinki Urban Facts, 2008. *Major Cities in Northern Europe: Statistical Comparisons*, Helsinki, Finland.

Deng, X., Huang, J., Rozelle, S., Uchida, E., 2008. Growth, population and industrialization, and urban land expansion in China. *Journal of Urban Economics* 63, 96-115.

Geshkov, M.V., DeSalvo, J.S., 2012. The effect of land-use controls on the spatial size of U.S. urbanized areas. *Journal of Regional Science*, in press.

Glaeser, E.L., Ward, B.A., 2009. The causes and consequences of land use regulation: Evidence from Greater Boston. *Journal of Urban Economics* 65, 265-278.

Government of India, Planning Commission, 2012. Statewise District Domestic Product Data. *http://www.planningcommission.nic.in/plans/stateplan/index.php?state=ssphdbody.htm*, accessed August 14, 2012.

Ihlanfeldt, K.R., 2007. The effect of land use regulation on housing and land prices. *Journal of Urban Economics* 61, 420-435.

McGrath, D., 2005. More evidence on the spatial scale of cities. *Journal of Urban Economics* 58, 1-10.

National Council of Applied Economic Research, 2002. *India Market Demographics Report*. New Delhi.

Paulsen, K., 2012. Yet even more evidence on the spatial size of cities: Urban spatial expansion in the US, 1980-2000. *Regional Science and Urban Economics* 42, 561-568.

Pollakowski, H.O., Wachter, S.M., 1990. The effects of land-use constraints on housing prices. *Land Economics* 66, 315-324.

Quigley, J.M., Raphael, S., 2005. Regulation and the high cost of housing in California. *American Economic Review* 95, 323-328.

Registrar General of India, 2001. *Census of India*. Primary Census Abstract Tables. New Delhi.

Spivey, C., 2008. The Mills-Muth model of urban spatial structure: Surviving the test of time? *Urban Studies* 45, 295-312.

Sridhar, K.S., 2010. Impact of land use regulations: Evidence from Indias cities. *Urban Studies* 47, 1541-1569.

Sridhar, K.S., 2007. Density gradients and their determinants: Evidence from India. *Regional Science and Urban Economics* 37, 314-344.

Wassmer, R., 2006. The influence of local urban containment policies and statewide growth management on the size of United States urban areas. *Journal of Regional Science* 46, 25-65.

World Bank, 2012. *India: Urbanization Beyond Municipalities*. Washington, D.C.

Footnotes

[*]Some of the data for this study were gathered when the second author was supported by the visiting Sir Ratan Tata Trust fellowship at the Institute for Social and Economic Change, Bangalore. We are also grateful to Lalita of the Public Affairs Foundation and to Jinkalappa, Joint Labor Commissioner, Karnataka Department of Labor, for assistance in, respectively, locating and intepreting some of the data. We thank Heikki Loikkanen of the University of Helsinki for help in locating data for some of the international comparisons, and we are also grateful to Shirish B. Patel and V.K. Phatak for extensive comments on the paper. Finally, we thank two referees for useful comments.

[1]In India, the acronyms FAR and FSI (denoting "floor space index") are used interchangeably.

[2]The FAR value for Chennai was recently raised to 3.5, after the gathering of the data used in Table 1.

[3]FAR violations do occur, and Sridhar (2010) reports the evidence that most violations in Bangalore are due to the unduly low FAR limits permitted.

[4]For an earlier analysis of the effects of building-height limits, see Arnott and MacKinnon (1977). See also Bertaud (2011) for a discussion of height limits in the Indian context. Regarding urban sprawl, a term laden with controversy, the sprawl generated by a height limit is inefficient, whereas the spatial expansion of cities generated by other forces is benign in the absence of any underlying market failures or policy-induced distortions.

[5]This welfare measure is incomplete, however, because it ignores the change in rental income of landowners, which is affected by relaxation of the height limit. The measure can thus be viewed as a consumer-oriented measure of the change in social welfare.

[6]BB carry out an illustrative calculation of the gain from eliminating Bangalore's height limits. However, to do the calculation, they were forced to speculate on the resulting reduction in the commuting distance for the city's edge resident. Here, by contrast, the regression results directly yield the magnitude of the commuting-distance reduction from a marginal increase in FAR.

[7]Whereas Quigley and Raphael (2005) and Ihlanfeldt (2007) use indexes of the restrictiveness of land-use regulations in their regressions, Pollakowski and Wachter (1990) and Glaeser and Ward (2009) measure the price effects of specific regulations (for example, a minimum lot-size requirement). Since a housing-price increase is a direct monetary measure of welfare

loss, these papers therefore are among the few other studies in the literature that estimate the welfare losses from specific land-use regulations.

[8]The boundary value of p stays constant because it is anchored by the agricultural land rent via (1). Note that further analysis would be required to measure the welfare effect for a city with multiple income groups. The difficulty is that the change in welfare for a group that lives entirely in the interior of the city could not be gauged from the impact on the edge resident.

[9]The height contours in Figure 1 are drawn as straight lines for convenience. For a more-realistic figure based on numerical simulations, where the contours are convex, see BB.

[10]Computation of the **aginc** variable is based on the the sum of the output of agriculture, forestry, and fisheries in the district containing the city, which is then divided by the population of the entire district. Hence the **aginc** variable is per capita agricultural product based on the entire, not just rural, population of the district in which the city is located. An alternate variable computed using only the agricultural population of the district did not perform as well, and the reason may be that many urban residents partly rely on nearby rural resources (firewood from forests, fish from lakes) for consumption and perhaps income.

[11]Another specification would use the logs of both **area** on the left-hand side and **pop** on the right-hand side, recognizing that these variables exhibit large ranges in the sample. The suitability of this alternate specification can be checked using a Box-Cox routine, and the corresponding value of the Box-Cox transformation parameter (zero, applied to both **area** and **pop**) lies just inside the 95% confidence interval for that parameter, suggesting that the specification is appropriate. However, the resulting coefficient estimates are unsatisfactory and inconsistent with the theory, with the FAR coefficient being insignificant with the wrong positive sign. Given this outcome and the low reliability of the Box-Cox routine in small samples like the current one, the more-successful linear and semilog specifications are presented instead.

[12]The default region is not a state but a territory (of which India contains several): the National Capital Territory of Delhi.

[13]When **aginc** is included in this regression, its coefficient is counterintuitively positive and significant. Since the state dummies are preferred as a means of capturing agricultural productivity differences, this finding is not viewed as credible.

[14]Let the log of area before the increase in FAR be $logA_0 = k$, where k represents the RHS of the semilog regression evaluated at the starting level of FAR. With a unit increase in FAR,

log area falls to $logA_1 = k - 0.196$. The proportional change in area is then

$$\frac{A_1 - A_0}{A_0} = \frac{e^{k-0.196} - e^k}{e^k} = e^{-0.196} - 1 = -0.177$$

or an 18% area reduction.

[15]The initial radius of the city is $(81.65/\pi)^{1/2} = 5.10$ km. The final radius is $[(81.65 - 16.33)/\pi)^{1/2} = 4.56$ km, for a reduction of 0.54 km.

[16]It should be noted that the calculations in the appendix reflect the assumption that the speed of travel within the city remains constant as it becomes more compact. If higher residential densities reduce travel speed, then the calculations overstate the gain from relaxation of the FAR limit. We thank a referee for this observation.

[17]This calculation uses US median household income for 2011, equal to about $49,500, and a household size of 2.6. The welfare gain equals $\$49,500 \times .07 \times 750,000/2.6$.

[18]India's expert committee on urban infrastructure (2011) estimates the requirements of urban infrastructure over the 20-year period from 2012-13 to 2031-32 in eight sectors (covering water supply, sewerage, solid waste, urban roads, storm drains, urban transport, traffic-supporting infrastructure and street lights) to be Rs. 30,981.41 billion (or $619 billion). This number, of course, applies to all cities in the country and may include infrastructure improvements above and beyond those necessitated by higher FARs.