Appendix 1: CBSA List

CBSA Code	CBSA Name	CBSA Code	CBSA Name
10580	Albany-Schenectady-Troy, NY	33340	Milwaukee-Waukesha-West Allis, WI
10740	Albuquerque, NM	33460	Minneapolis-St. Paul-Bloomington, MN-WI
10900	Allentown-Bethlehem-Easton, PA-NJ	33660	Mobile, AL
12060	Atlanta-Sandy Springs-Roswell, GA	34980	Nashville-Davidson--Murfreesboro--Franklin, TN
12420	Austin-Round Rock, TX	35300	New Haven-Milford, CT
12540	Bakersfield, CA	35380	New Orleans-Metairie, LA
12580	Baltimore-Columbia-Towson, MD	35620	New York-Newark-Jersey City, NY-NJ-PA
12940	Baton Rouge, LA	36420	Oklahoma City, OK
13820	Birmingham-Hoover, AL	36540	Omaha-Council Bluffs, NE-IA
14460	Boston-Cambridge-Newton, MA-NH	36740	Orlando-Kissimmee-Sanford, FL
14860	Bridgeport-Stamford-Norwalk, CT	37100	Oxnard-Thousand Oaks-Ventura, CA
15940	Canton-Massillon, OH	37900	Peoria, IL
16700	Charleston-North Charleston, SC	37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
16860	Chattanooga, TN-GA	38060	Phoenix-Mesa-Scottsdale, AZ
16980	Chicago-Naperville-Elgin, IL-IN-WI	38300	Pittsburgh, PA
17140	Cincinnati, OH-KY-IN	39300	Providence-Warwick, RI-MA
17460	Cleveland-Elyria, OH	39580	Raleigh, NC
17820	Colorado Springs, CO	40140	Riverside-San Bernardino-Ontario, CA
17900	Columbia, SC	40380	Rochester, NY
18140	Columbus, OH	40900	Sacramento--Roseville--Arden-Arcade, CA
19100	Dallas-Fort Worth-Arlington, TX	41620	Salt Lake City, UT
19340	Davenport-Moline-Rock Island, IA-IL	41700	San Antonio-New Braunfels, TX
19740	Denver-Aurora-Lakewood, CO	41740	San Diego-Carlsbad, CA
19820	Detroit-Warren-Dearborn, MI	41860	San Francisco-Oakland-Hayward, CA
21340	El Paso, TX	42540	Scranton--Wilkes-Barre--Hazleton, PA
22420	Flint, MI	42660	Seattle-Tacoma-Bellevue, WA
23420	Fresno, CA	43340	Shreveport-Bossier City, LA
24340	Grand Rapids-Wyoming, MI	44060	Spokane-Spokane Valley, WA
24660	Greensboro-High Point, NC	44140	Springfield, MA
26420	Houston-The Woodlands-Sugar Land, TX	45060	Syracuse, NY
26900	Indianapolis-Carmel-Anderson, IN	45300	Tampa-St. Petersburg-Clearwater, FL
27260	Jacksonville, FL	45780	Toledo, OH
28140	Kansas City, MO-KS	46060	Tucson, AZ
28940	Knoxville, TN	46140	Tulsa, OK
29820	Las Vegas-Henderson-Paradise, NV	46520	Urban Honolulu, HI
30460	Lexington-Fayette, KY	46700	Vallejo-Fairfield, CA
30780	Little Rock-North Little Rock-Conway, AR	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV
31080	Los Angeles-Long Beach-Anaheim, CA	48620	Wichita, KS
32820	Memphis, TN-MS-AR	49340	Worcester, MA-CT
33100	Miami-Fort Lauderdale-West Palm Beach, FL	49660	Youngstown-Warren-Boardman, OH-PA

Appendix 2: Imputing the Rise in Land Values for a 1985 Buyer in San Francisco

A number of assumptions have to be made to impute the capital gain on homes bought three decades ago in a market such as San Francisco. A given quality unit has to be defined as the starting point for such a calculation. For example, the unit underlying the median 1985 HP/MPPC value of 1.55 in San Francisco contained 1,300 square feet of living space and was reported to be worth $150,000 (in 1985 dollars; $324,000 in 2013 dollars given the 116% increase in the general urban price level between 1985-2013). Given our knowledge of construction costs and presuming a 17% gross builder's margin, we can impute a nominal raw land value of $66,284 for this unit ($143,279 in 2013 dollars) using equation (1) above. If we further presume that this owner kept the home and experienced the same 98% real increase reported for the median home in this market, the underlying land increased in value by just over $272,000 to about $416,000 (in 2013 dollars).

The details behind that calculation are as follows. The 98% real appreciation on the $324,000 value of the home in 2013 dollars yields a value of $641,520 in 2013. If we conservatively subtract the real value of construction costs times the builder's 17% gross margin, that leaves $486,416 in value. Presuming that 17% of that remainder somehow gets captured by a builder still leaves a land price of $415,742 in 2013. Subtracting off the $143,279 that the owner paid in 2013 dollars in 1985 yields the gain of $272,463. One could argue the gain is higher, as there is no 'builder' involved if the owner simply kept the property. One could argue over various assumptions and our point is not to provide a precise dollar figure. Rather, it is to show that a readily defensible, back-of-the-envelope calculation indicates that owners of modest properties in San Francisco in 1985 have seen more than a quarter million dollars of wealth come their way over the past three decades from land value appreciation that we believe is driven by binding land use restrictions. This is a near tripling of real land value for a long-term owner of a very modest house in San Francisco over the past three decades.

Appendix 3: Speculative Calculations of Welfare Losses from Land Use Restrictions

Our discussion of possible G.D.P. gains from eliminating land use controls assumes away construction cost differences across space, as well as congestion externalities and the like. We will also ignore amenity differences, so an absence of regulation means that housing costs will be equal and hence wages will also be equal across space.

The basic algebra of misallocation costs can be seen by assuming that wages reflect the marginal productivity of labor in each location i: $F_L^i(L_i)$. The output gain from reallocating Δ individuals from place B to place A, for any two locations is $\int_0^{\Delta} F_L^A(L_A+z)dz - \int_{-\Delta}^{0} F_L^B(L_A+z)dz$. If we use a linear approximation $F_L^i(L_i+z) = F_L^i(L_i)\left(1-\frac{\alpha z}{L_i}\right)$, then to equalize wages between B and A, there must be a change in population of $\Delta = \frac{L_A L_B\left(F_L^A(L_A)-F_L^B(L_B)\right)}{\alpha\left(F_L^A(L_A)L_B+F_L^B(L_B)L_A\right)}$. The total output impact of the change is $\frac{F_L^A(L_A)-F_L^B(L_B)}{2}\Delta$, or the traditional welfare triangle of 0.5 times the gap in wages times the predicted population movement to eliminate misallocation. Everything needed for this calculation is observable directly from the data, except for α, which represents the inverse elasticity of labor demand.

To understand just how big the possible range of welfare gains could be, assume that $F_L^A(L_A) = 1.5 \cdot F_L^B(L_B)$, and that $L_A = .5L_B$. In that case, Δ must equal $\frac{L_B}{8\alpha}$ and the welfare gains equals the current earnings in area B, times $\frac{1}{32\alpha}$. Consequently, if α equals one, then this benefit would equal no more than 1/32 of total payroll in the lower paying area, which is significant but not massive.

There are functional forms that would deliver far higher welfare gains. Following Hsieh and Moretti (2017), assume instead that $F_L^i(L_i+z) = F_L^i(L_i)\left(\frac{L_i+z}{L_i}\right)^{\frac{\gamma+\eta-1}{1-\eta}}$, where γ represents the share of labor in a Cobb-Douglas production function (assumed to be .65) and η represents the share of fungible capital (assumed to be .25), which will move in response to labor. In that case, a 50 percent initial wage gap can only be closed if 87 percent of the population of the less productive area moves to the more productive area. Assuming that output is $F_L^i(L_i)\left(\frac{L_i+z}{L_i}\right)^{\frac{\gamma+\eta-1}{1-\eta}}\frac{L_i+z}{\gamma}$, then the increase in output is 40 percent of output in the initially less productive place. This Cobb-Douglas formulation produces a value of $-\frac{\partial Log(Wage)}{\partial Log(Labor)}$ of 0.13, and if this were the value of α in our linear model, the welfare gains would rise to ¼ of payroll in the lower paying area.

The Cobb-Douglas structure with fungible capital implies that cities can grow enormously with only modest decreases in wages. Perhaps, this is true. Agglomeration economies would only further attenuate the downward impact of added population on earnings. Yet, as we will shortly discuss, the empirical literature on local labor demand tends to find that labor demand is far less responsive to wages than this Cobb-Douglas model would imply.

Before proceeding with our main calibration, it is worth stressing that any spatial allocation exercise must face the problem of omitted human capital. Any misallocation calculation will typically increase with the variance in perceived productivities, and the noise created by unobserved human capital heterogeneity will generally cause an overestimate of misallocation costs.

Housing costs can themselves be used to assess the heterogeneity in human-capital adjusted wages. If places with higher human capital-adjusted wages typically have lower amenities, because cities are more likely to form only if an area is either productive or nice or both, then these cost of living differences may underestimate the true heterogeneity of productivity. If more productive people live in places with more amenities, then housing differences will also overestimate true productivity heterogeneity.

For our exercise, we will treat differences in payroll per worker as the true differences in the marginal product of labor, but we recognize that this is likely to lead to an overestimate of the true gains from reallocating labor. Using our linear approximation, if have a large number of areas, with initial populations L_i and initial wage levels $F_L^i(L_i)$ and we move their populations to the point where their wages are equal to a constant $\widehat{w} = \sum_i L_i / \sum_i \left(L_i / F_L^i(L_i) \right)$, then the total gains from reallocation equal:

$$Gain\ from\ Reallocation = \frac{1}{2\alpha} \sum\nolimits_i L_i \left(F_L^i(L_i) - \widehat{w} \right)$$

Our linear approximation means that when labor moves from less productive places to more productive places of equal size, then the average wages will fall since the marginal product curve is steeper in the more productive place. Equalizing wages will generate a reduction in the total wage bill and the output gain from reallocation will be proportionate to this total wage bill reduction. This wage reduction is a feature of our approximation, not a general feature of reallocation models. Still, this calculation suggests that the elimination of land use barriers would primarily redistribute from land owners to employers (and ultimately to customers).

Using the 2014 *County Business Patterns*, we can gauge the magnitudes of this quantity if we treat annual payroll per workers as synonymous with wage. We restricted our analysis to the 266 metropolitan areas with more than 50,000 workers. Assuming that α is low enough so that all areas maintain a positive population, equalizing wages would involve a total movement of $\frac{1}{\alpha}$ times 8 million workers, or about $\frac{1}{\alpha}$ times 8 percent of the employees in that sample. The largest gainer would be New York City (an extra 2.2 million times $\frac{1}{\alpha}$ workers). The overwhelming majority of cities would lose population, because they have current wages that are below the equalizing wage of $49,000. Cities such as Orlando and Miami would lose particularly large numbers of workers, because they are large and relatively low wage. Since these areas may benefit from high amenities, this illustrates a shortcoming of our approach.

The total output gain would be $\frac{1}{\alpha}$ times 109 billion dollars, relative to a total payroll of 5.1 trillion in this sample. If we follow Hsieh and Moretti (2017) and assume that payroll is 65 percent of total output, this gain would represent $\frac{1}{\alpha}$ times 2.12 percent of total output. The obvious empirical necessity in this calculation is an estimate of α, the *inverse* elasticity of demand for labor.

The Cobb-Douglas formulation used by Hsieh and Moretti (2017) implies a value of $\frac{1}{\alpha}$ of 7.5. This produces in our calculations, as in theirs, a large misallocation effect. Our calculations suggests reallocation could increase total output by over 15 percent of G.D.P., but this would be reduced somewhat since some metropolitan areas would hit their lower bound of zero population.

Yet, the relatively large reaction of employment to wages implied by their Cobb-Douglas formulation is somewhat at odds with the empirical estimates of the link between wages and labor demand. For example, Beaudry, Green and Sand (2014) present city-level labor demand elasticities that seem matched to our needs. They find that a city-level labor elasticity of -0.3, which suggests that the overall impact is 0.7 percent of G.D.P. Their city-industry level estimates are larger (-1) and those would imply a misallocation cost equal to about 2 percent G.D.P. Past demand elasticities have typically ranged from -0.25 to -1.0, which suggests that two percent may be an upper bound on the gains from reallocation.

Labor demand elasticities are so important for these calculations because they determine how quickly an influx of labor into New York City would cause New York wages to fall to the national average. The Cobb-Douglas assumptions mean that an area with wages that are 50 percent above the national norm could see its employment increase 20 fold before wages fell to the national norm. In our formulation, if $\alpha = 1$, then a mere 1/3 increase in population will drop wages to the national norm.

We have nothing to add to discussions about labor demand elasticities at the local level. As 2 percent of G.D.P. is itself a large, we believe that these exercises illustrate that the benefits of reducing local land regulations may be sizable. If local labor demand is quite elastic, then Hsieh and Moretti (2017) may be right, and the output gains may be far larger.

Amenity differences and heterogeneity in building costs will tend to reduce this figure, but our calculations reflect only an estimate based on entirely static factors. It is quite possible that Silicon Valley is about creativity as well as high wages, and more Silicon Valley residents could also mean more technological innovation and faster productivity growth. Such hypotheses are quite speculative, but it is possible that the longer term costs of keeping people away from the most dynamic parts of the U.S. economy will prove higher than our short-term calculation.