Three Essays on Urban Economics: Wage Inequality, Urban Sprawl, and Labor Productivity

A Thesis Submitted to the College of

Graduate Studies and Research

in Partial Fulfillment of the Requirements

for the Degree of Doctor of Philosophy

in the Department of Bioresource Policy, Business, and Economics

University of Saskatchewan

Saskatoon

By: Belal N Fallah

PERMISSION TO USE

DISCLAIMER

ABSTRACT

The thesis consists of three essays on urban economies. The first essay investigates the relationship between proximity to larger markets and wage distribution within local labor markets. In this essay I derive a theoretical spatial skill demand equation that positively links skill premiums to market access. Using data from U.S. metropolitan areas, I provide evidence that while average wages are higher in metropolitan areas with higher market access, as suggested in the existing literature, the wage differential is unequally distributed across the metropolitan workers. That is, greater access to markets is linked to relatively weaker outcomes for those at the bottom of the wage distribution.

The second essay examines the extent of urban sprawl with respect to the volatility of local economies. Specifically, it investigates how uncertainty over future land rents explains changes in the extent of urban sprawl. To theoretically study this relationship, I develop a theoretical model that links sprawl to shocks to changes in land development rent, among other factors. The econometric analysis draws upon panel data from U.S. metropolitan areas over the 1980-2000 censuses. To measure urban sprawl, I construct a distinctive measure that better captures the distribution of population density within metropolitan areas. Using suitable proxy that accounts for uncertainty over future land rents, I provide robust evidence confirming the theoretical prediction. That is, metropolitan areas with higher levels of uncertainty have a lower level of sprawl.

Finally, the third essay uses theories from urban production economics to empirically investigate the relationship between the economic performance of U.S. metropolitan areas and their respective amounts of sprawl. Specifically, this essay provides a comprehensive empirical analysis on the impact of urban sprawl on labor productivity. The main finding suggests that higher levels of urban sprawl are negatively associated with average labor productivity. Interestingly, this negative association is even stronger in smaller metropolitan areas. Still, there is evidence that the significance of the negative impact of sprawl is not homogenous across major industries.

ACKNOWLEDGEMENTS

I would like to thank my supervisor Mark Partridge for his time and guidance. Also, I would like to thank Rose Olfert for her encouragement. I am grateful to her as she was always willing to spend time and effort when needed. I would also like to thank my committee members for their cooperation. A special thanks to my friends (Simona, Crina, Menghis, and Dimitris) for their patience and support. Finally, I would like to acknowledge that I am indebt to my family for their unconditional support. It was their love and prayers that help me accomplish this thesis. Therefore, this work is dedicated to them.

TABLE OF CONTENTS

ABSTRACT ii
ACKNOWLEDGEMENTS iii
TABLE OF CONTENTS iv
LIST OF TABLES vi
Introduction 1
Essay 1: The effect of Market Access on the Wage Distribution of U.S. Metropolitan Workers. 4
1. Introduction 4
2. Theoretical Model 8
2.1 Consumer behavior 8
2.2 Producer Behavior 9
2.3 Profit maximization 10
3. Empirical Specifications 12
3.1 Measuring Market potential 12
3.2 Empirical Model 13
3.2 Data 17
4. Base Model Empirical Results 18
5. Sensitivity Analysis 21
6. Conclusion 23
Appendix I 25
References 33
Essay 2: Urban Sprawl: Evidence from a Stochastic Urban Growth Approach. 37
1. Introduction 37
2 Theoretical model 40
2.1 Household Problem 40
2.2 Developer problem. 41
2.3 Density and land value 43
3. Empirical Model and Data 44
3.1 Measuring Urban Sprawl 44
3.2 Empirical Model 48
4. Empirical Results 51
5. Sensitivity Analysis. 52
6. Conclusion 54
Appendix II 56
References 62
Essay 3: Urban Sprawl and Productivity 66
1. Introduction 66
2. Theoretical Framework 69
3. Empirical Model 70
3.1 Measuring Urban Sprawl 70
3.2 Empirical Specification 73
4. Empirical Results – Base Model 76
4.1 Productivity: Linkages Across Metropolitan Size and Industries 78

5. Sensitivity analysis.. 80
6. Conclusion 83
Appendix III... 85
Appendix IV... 91
References.. 96

LIST OF TABLES

Table A: Descriptive Statistics.......... 25
Table 1.1: Wage inequality-Market Access Base model.......... 27
Table 1.2: Higher Education-Market Access Cross Sectional model.......... 28
Table 1.3: Wage Inequality-Market Access Parsimonious Model (Market Potential IV Estimates).. 29
Table 1.4: Wage Inequality-Market Access Parsimonious Model (No Industry Shares).......... 30
Table 1.5: Wage Inequality-Market Access Parsimonious Model (Only Market Potential and State Dummies).......... 31
Table 1.6: Wage Inequality-Market Access Parsimonious Model (No State Dummies) 32
Table 2.1: Region of U.S. Metropolitan Areas and Extent of Sprawl Over Time.......... 47
Table 2.2: Size of U.S. Metropolitan Areas and Extent of Sprawl Over Time.......... 47
Table B: Descriptive Statistics. 56
Table 2.3: Uncertainty–Sprawl Fixed Effects Model 57
Table 2.4: Uncertainty-Sprawl Fixed Effects Model (Excluding *avepop*).......... 58
Table 2.5: Uncertainty–Sprawl Fixed Effects Model (25th Percentile Cut-Off Density) 59
Table 2.6: Uncertainty-Sprawl Fixed Effects Model (Overall Population Density) 60
Table 2.7: Uncertainty-Sprawl Random Effects Model 61
Table 3.1: Metropolitan Sprawl-Average Labor Productivity (Different Functional Forms).......... 85
Table 3.2: Metropolitan Sprawl-Metropolitan Higher Education 86
Table 3.3: Urban Sprawl-Labor Productivity: Linkages Across Metropolitan Size 87
Table 3.4: Urban Sprawl-Labor Productivity: Linkages Across Industries 88
Table 3.5: Urban Sprawl-Labor Productivity: Different Sprawl Measures.......... 89
Table 3.6: Urban Sprawl-Labor Productivity: Global Models (Pooled regression) 90
Table C: Descriptive Statistics.......... 91
Table D: Urban Sprawl-Labor Productivity: Linkages Across Industries 92

Introduction

The first essay examines the relationship between proximity to larger markets and wage distribution within local labor markets. This essay is a natural extension of the new economic geography (NEG) literature, initially pioneered by the seminal work of Krugman (1991). The main theme of NEG emphasizes the underlying forces behind the spatial concentration of economic activities in limited number of sites. One of the most distinctive derivations of NEG models is the wage equation, developed by Fujita et al. (1999). The wage equation predicts that wages are higher in areas near larger markets. An extensive research has been devoted to empirically test this prediction. Absent from this empirical literature is any consideration to the skill compositions of labor markets.

The objective of this essay is to fill this gap. More specifically, it investigates the distributional aspects of NEG-based agglomeration. That is, while average wages are higher in areas with greater market access, how is this gain distributed across the wage distribution? Following existing NEG literature, I derive a spatial skill demand equation that identifies the maximum skilled and unskilled wage at which firms in a given region break even given the income, relative prices, and transportation costs across all regions. The wage equation predicts that the *relative* wages of skilled workers are higher in areas with higher market access.

To test the above prediction, I use cross sectional data from U.S. metropolitan areas to compare wages between different skill groups ranging from the most to the least skilled, measured at the 90^{th}, 50^{th}, and 10^{th} percentile of the wage distribution. Due to data limitations, the price indices are assumed constant across metropolitan areas. This reduces the market access, specified in the wage equation, to Harris's (1954), which I use to conduct the econometric analysis. I provide robust evidence that greater access to markets is associated with a greater wage gap between the most and least skilled, and also between average and the least skilled. On the other hand, the results show that, in most specifications, greater market access is not significantly associated with the wage gap between the most and average skilled. The findings of this essay have a significant implication regarding redistribution policies that target workers at the bottom of the wage distribution. Policies that encourage higher education, such as tax cuts and student loans, would prove effective to reduce inequality.

The second essay studies the extent of urban sprawl in volatile local economies. The growing trend of urban sprawl in North America has spurred a mounting literature aimed at understanding its underlying causes. In doing so, urban economists have traditionally used the theory of monocentric city model, which suggests that in equilibrium lower land rent at the urban fringe offsets the commuting cost to the central business district (CBD). The declining rent gradient leads to a decline in the density gradient as distance increases from CBD to the urban fringe.

Yet, when modeling the spatial structure of urban areas, it is usually assumed that a risk-neutral developer will choose to invest when the present value of expected cash flows exceeds the cost of development. However, if the future cash flow is uncertain and the investment is durable and irreversible, as in land development, the latter assumption is no longer valid. For example, consider an open urban area experiencing shocks in labor demand, the follow-on shocks in population growth and housing demand result in an uncertain future land/housing rents. The aim of this essay is to investigate how uncertainty over future rents of land development explains changes in the extent of U.S. urban sprawl. In this essay I utilize the work of Capozza and Helsley (1990) and Capozza and Li (1994) to develop a theoretical expression that negatively links urban sprawl to shocks in future rents of land development, among other factors.

The econometric analysis of this essay draws upon panel data from U.S. metropolitan areas over the 1980-2000 censuses. Consistent with the theoretical model, I construct a distinctive measure for urban sprawl that better captures the distribution of population density within a metropolitan area. To do so, I use sufficiently disaggregated scale data to ensure that differences in the distribution of population can be identified. Using a suitable proxy that accounts for uncertainty over future land rent, I provide robust evidence confirming the theoretical prediction. That is, metropolitan areas with higher level of uncertainty have lower levels of sprawl. This conclusion implies that failing to address the volatility of local economies could produce policies that may not be effective in improving the livability of urban environment, intra-city-commuting relationships, and efficient provision of physical infrastructure, such as roads; schools; sewers; and other public facilities.

The last essay provides a comprehensive analysis onto the economic performance of sprawling U.S. metropolitan areas. Anti-sprawl activists suggest that higher levels of urban sprawl might come at the cost of reducing the productivity gains from agglomeration in urban density. Yet, proponents of urban sprawl argue that the rapid advances in communication technology and information processing is likely to diminish this productivity gain as face to face interaction becomes obsolete. They also suggest that the construction of highways has further diminished tranport cost savings within agglomerated areas, leading to more dispersion of both people and firms. In the light of these contradicting schemes, the effect of urban sprawl on labor productivity can only be determined by empirical research, which constitutes the objective of the third essay.

Following productivity literature I model differences in labor productivity using an aggregate production function. This approach assumes that all firms are perfectly competitive and that spatial labor productivity differences are generated due to externalities related to site specific characteristics. The empirical analysis utilizes cross sectional data from U.S. metropolitan statistical areas of the 1990s. To quantify urban sprawl, I use the sprawl index I developed in the second essay. Measuring labor productivity as metropolitan gross domestic products (GDP) per worker, I provide robust evidence that a higher level of sprawl is associated with lower metropolitan average labor productivity.

Yet, when examining the sprawl-labor productivity link across metropolitan size, the negative effect of urban sprawl is greater in smaller MSAs. This indicates that lower levels of urbanization economies in smaller MSAs magnify the negative impact of sprawl. Furthermore, when conducting the analysis across major industries, the negative relationship between sprawl and labor productivity is significant for the following industries: manufacturing; construction; finance and insurance; real estate and rental and leasing; information; professional and technical services; government; and health care and social assistance.

Essay 1: The effect of Market Access on the Wage Distribution of U.S. Metropolitan Workers.

1. Introduction

Over the last two decades, economic geography has been reinvented. The seminal work of Krugman (1991) and other NEG theorists (Krugman and Venables 1995; Fujita et al. 1999) have significantly contributed to our understanding of the formation of agglomeration economies[1] and the emergence of the core-periphery pattern. Possibly, one of the most successful derivations of NEG is the wage equation, which posits a positive association between wages and market access (Fujita et al. 1999). A mounting literature has been devoted to link NEG to spatial wage disparity (e.g. Hanson 2005 and Redding and Venables 2004). Yet, not enough attention has been given to the distributional aspects of market access effects in local labor markets.

The foundation of NEG theory is the interaction between economies of scale at the firm level and transportation costs. While economies of scale drive firms to concentrate in a limited number of locations i.e. cities, minimizing transportation costs implies that preferred locations would be those with greater access to large markets (backward linkage) and input factors (forward linkage). On the labor side, forward linkages influence workers' location decisions favoring areas that offer a good access to a wide range of commodities produced at a lower transportation cost (Head and Mayer 2004). This cumulative process of forward and backward linkages encourages households and firms to concentrate and regions to diverge.[2]

The idea of market access dates back to Harris' (1954) influential market potential index. Harris suggests that the spatial concentration of production depends on access to markets, with access measured as the sum of purchasing power of all locations weighted inversely by transportation cost. In its early form, market potential lacked a theoretical foundation. Fujita et al. (1999) derived market potential from a general equilibrium model, and show that it can be regarded as a

1

2 Congestion effects (limited supply of local goods and greater firm competition) serve as a dispersion force that (partially) offsets the spatial agglomeration of economic activities (Hanson 2001).

spatial labor demand function. That is nominal wages are positively associated with proximity to consumer demand.

Recently, the theoretical inferences from NEG have been the object of intensive empirical research. A major strand of the NEG empirical literature has focused on assessing whether greater access to market demand in given regions influences firms' location decision as suggested by Krugman (1991) and Krugman's (1980) home market effect. Assuming that firms choose locations with the highest expected profits, production tends to concentrate near large national or regional markets (Davis and Weinstein 1999, 2003; Head and Reis 2001; Hanson and Xiang 2004). Another strand of literature emphasizes the effect of access to markets on migration choices of workers through spatial wage differentials and good access to supply sources (Crozet 2004; Pons et al. 2007).

Closer to the focus of this study, other empirical research has examined whether wage/income is higher in regions or countries that have greater access to markets, as would be consistent with predictions related to backward linkages. At the international level, Redding and Venables (2004) estimate a structural wage model derived from Fujita et al. (1999). Utilizing data from bilateral trade flows to provide measures of market and supply access, they show that countries that are remote to markets and sources of supply suffer a penalty in terms of their income.[3]

At a regional level, Hanson (2005) utilizes the work of Helpman (1998) and Krugman (1991) to estimate a non-linear model of an augmented market potential function using data from U.S. counties. Specifically, Hanson interacts Harris's (1954) index with housing stock and wages in the surrounding counties. Consistent with the findings of Redding and Venables, Hanson shows that the average nominal wages are higher the greater is the access to markets. Moreover, the structural estimates of his augmented market potential model reflect the magnitude of scale economies and transportation cost as predicted by NEG theories, and also show that the agglomeration forces are spatially limited.[4]

[3] At the U.S. level, Knapp (2006) employs Redding and Venables' (2004) estimation framework and finds that the explanatory power of their access variables is weak and can not explain income variation across states. Knapp justifies his finding arguing that the U.S. economy is largely dominated by a few large states and that their wage level cannot be explained by their access to neighboring states.

[4] Partridge et al. (2008) investigate how market potential contributes to differences in household earnings and housing costs across U.S. counties. They provide evidence that while market potential is consistent with agglomeration spillovers, its effect is smaller and less pervasive than the urban hierarchy distance effects.

Following from the above, NEG theories rests on explaining the spatial concentration of both firms and workers as a result of the interaction between backward and forward linkages. Backward linkages imply that firms locate in areas with large demand for their products; greater access to markets ensures higher profit to local firms, and thus higher wages. On the other hand, forward linkages imply that workers are attracted to areas where production is concentrated to benefit from wage differentials and access to consuming various goods at lower prices. While most of the NEG literature has been dedicated to testing these propositions, to my knowledge, no empirical research has addressed the distributional aspects of NEG-based agglomeration. In this paper, I investigate how market access affects the wage *distribution* in U.S. metropolitan areas.

The wage distribution in agglomerated areas (urban areas) has been the subject of several studies. Yet, in most cases, the agglomeration economy-inequality linkage has been established based on non-pecuniary externalities. Examples include knowledge spillovers (Bruinshoofd et al. 1999) and urbanization economy effects (Black and Henderson 1999; Korpi 2007; Garofalo and Fogarty 1979). Yet, the main contribution of this essay is highlighting the importance of pecuniary externalities (inter-metropolitan demand linkages) as a new insight on the mechanism driving urban wage inequality, a matter that is central to the interest of researchers and policy analysts. Thus, the natural evolution of the urban system may be another cause of changes in income inequality, which has not been explored in past research.

The only theoretical study, I am aware of, that deals with market access and wage inequality is by Redding and Schott (2003). Based on existing NEG literature (Fujita et al. 1999; Krugman 1999; Redding and Venables 2004), they develop a theoretical model to investigate the effect of remoteness from global economic activities on a country's human capital accumulation. Allowing for endogenous investment in education, they show that skill wage premiums are higher in countries that have higher access to markets and suppliers. As a result, skill premiums enhance the incentives for human capital accumulation. This conclusion applies if skill intensive sectors have higher trade cost, and pervasive input-output linkages.

Yet, to establish a structural relationship between country's location and its human capital incentives, Redding and Schott derive a theoretical wage equation that determines the maximum skilled and unskilled wage a firm, in a given country, can pay as a function of Redding and Venables' (2004) market and supply access. Since measuring those access variables requires bilateral trade data, which is not available at U.S. metropolitan level, I cannot use Redding and Schott's wage equation as a base for my empirical estimation.

In this essay, I modify Redding and Schott's theoretical work by discarding the discussion of input-output linkages. Instead, I focus on the demand for final goods. Doing so, I derive a wage equation as a function of market access. The latter is defined as Fujita et al's (1999) market potential. My theoretical framework emphasizes the importance of the interaction between returns to scale, transportation cost, and the share of skilled and unskilled labor on one hand, and skill premiums on the other hand. The theoretical wage equation predicts that in areas that are characterized by skill-intensive sectors, a greater market access[5] increases the demand for skilled workers relative to unskilled labor. Therefore, market access is expected to increase the *relative* wage of skilled workers. Though the outcome is similar to traditional international trade models, the mechanism through which this outcome is obtained is very different.

As derived below, the asymmetric effect of market access on the wage distribution forms the basis to empirically investigate the effect of market access on wage inequality in U.S. metropolitan areas. However, while the theoretical model classifies workers into only skilled and unskilled, the data allows us to finely distinguish various skill levels. Therefore, in the empirical models, I compare wages between skill groups ranging from the most to the least skilled as measured by the 90th, 50th, and 10th percentiles of the wage distribution.

The results suggest that at the same time as average wages are higher in metropolitan areas with a greater market access, as suggested in the past literature (Hanson 2005), the wage gain is disproportionately distributed. Specifically, greater access to markets is associated with a greater wage gap between the most and least skilled, and also between average and the least skilled. On the other hand, I find that in most specifications, greater market access is not significantly associated with the wage gap between the most and average skilled. Thus, greater market access is linked to relatively weaker outcomes for those at the bottom of the wage distribution.

In what follows, section 2 outlines the theoretical relationship between access to market and skill premiums. Section 3 discusses the empirical specification and data sources. Section 4 presents the empirical results with sensitivity analysis following in section 5. Section 6 presents the conclusion and policy implications.

[5] The remaining of this essay uses market potential and market access interchangeably unless stated otherwise.

2. Theoretical Model

2.1 Consumer behavior

Consider an economy that consists of a finite set of regions (*R*). Following Fujita et al. (1999) and Krugman (1991), each region has two sectors, manufacturing and agriculture. The agriculture sector is perfectly competitive,[6] and produces a single homogenous product (*A*), whereas, the manufacturing sector is monopolistically competitive and produces a variety of differentiated goods (*M*).

All consumers have identical preferences, which are defined over consuming *A* and *M*. The utility function takes the form of Cobb-Douglas function:

$$U = M^{\mu} A^{1-\mu} \qquad 0 < \mu < 1 \tag{1}$$

where the constant μ represents the expenditure share of *M*. The consumption index of *M* is defined according to the following CES function:

$$M = \left[\int_0^n m(i)^{(\sigma-1)/\sigma} di \right]^{\sigma/(\sigma-1)} \tag{2}$$

where *n* is the number of available varieties, *m(i)* denotes each consumed variety, and $\sigma > 1$ is the elasticity of substitution between varieties.

The agriculture good is chosen as numeraire by assumption, and thus the price of the agricultural good is normalized to 1 (P^A=1) across all regions. Nonetheless, while both agriculture and manufacturing goods can be shipped between regions, only the latter incurs transportation costs in shipment (Krugman 1991). Conventionally, the transportation costs are assumed to take the iceberg form. That is when shipping one unit of manufacturing variety from region *r* to region *s*, only T_{rs}<1 unit arrives. Hence, the price of a manufacturing variety produced in region *r* and shipped to region *s* is $P_{rs}=P^M{}_r T^M{}_{rs}$. Assuming that all varieties produced in one region have the same price, the manufacturing price index for region *s* can be written as:

$$G_s = \left(\sum_{r=1}^{R} n_r (P_r{}^M T_{rs}{}^M)^{1-\sigma} \right)^{1/(1-\sigma)} \qquad , s = 1 \ldots R \tag{3}$$

[6] The label Agriculture should not be interpreted literally. It refers to an industry that operates under perfect competition, which is a counterpart to other monopolistic competitive industries.

From the utility function (equation 1), and the budget constraint: $GM+P^A A=Y$, the consumption demand in region s for a manufacturing variety produced in region r can be expressed as $\mu Ys(P_r^M T_{rs}^M)^{-\sigma} G^{(\sigma-1)}$. To supply this level of consumption, $T_{rs}>1$ times this amount should be shipped. Summing the consumption demand across all regions in which the product is sold yields the total sales[7] (demand), q_r^m, such that:

$$q^m{}_r = \mu \sum_{s=1}^{R} Y_s P_r^{-\sigma} G_s^{\sigma-1} T_{rs}^{1-\sigma} \tag{4}$$

where Y_s is the income at region s.

2.2 Producer Behavior

The homogenous agricultural product is produced under perfect competition with the following CRS Cobb-Douglas function:

$$f_r^A = \theta_r (L_r^{AK})^{\varphi} (L_r^{AU})^{1-\varphi} \qquad 0 < \varphi < 1 \tag{5}$$

Equation (5) assumes that the agriculture product is produced using only skilled L^K, and unskilled labor, L^U. Land endowment and other productivity factors are captured in the productivity shifter, θ_r.

The differentiated manufacturing products are produced with increasing returns to scale technology, which is the same for all varieties and all regions. Like the agricultural sector, the input factors are skilled and unskilled workers. The technology involves fixed input (F), and marginal input requirement (c^m). Because of increasing returns to scale and consumers' preference for varieties, it is assumed that each variety is produced in a single region by a single specialized firm. For a representative firm in region r, the profit maximization function can be written as:

$$\Pi_r = P_r^m q_r^m - (w_r^k)^{\alpha} (w_r^u)^{B} [F + c^m q_r{}^m] \tag{6}$$

where q_r^m is given by equation (4), w_r^k is the wage of skilled workers with input share $\alpha > 0$, and w_r^u is the wage for unskilled worker with input share $\beta > 0$,[8] such that $\alpha + \beta = 1$. The magnitude of α and B reflects the relative demand of each type of labor, that is If $\alpha > \beta$, then the manufacturing industry is skill intensive.

[7] A detailed derivation of the demand of a given manufacturing variety is available at Fujita el (1999), page 47-48.
[8] Setting $\alpha > 0$ and $\beta > 0$ indicates that regions under study are not perfectly specialized.

2.3 Profit maximization

Before discussing the profit maximizing conditions, it is important to clarify that the theoretical framework depicted in this section does not represent a full general equilibrium model that determines endogenous variables, such as, the equilibrium spatial distribution of production, input factors, equilibrium prices, and real wages. However, the purpose is to establish a structural relationship between skill premiums and access to markets *given* the location of economic activities (including the spatial location of input factors i.e. skilled and unskilled workers).[9]

Maximizing profit of agricultural sector implies that price of the agricultural product equals its unit cost of production, such that:

$$P_r^A = \frac{1}{\theta}(w_r^k)^{\varphi}(w_r^u)^{1-\varphi} = 1 \tag{7}$$

The profit maximization of a representative manufacturing firm in region r implies:

$$P_r^m = \frac{\sigma c^m}{(\sigma - 1)}(w_r^k)^{\alpha}(w_r^u)^{B} \tag{8}$$

Equation (8) reveals that the price of a differentiated variety is a constant mark-up over its marginal cost. Moreover, under monopolistic competition assumption, free entry and exit, as response to the firms' profits and losses, entail a zero profit for all firms in equilibrium. This implies that, given the price ruling of equation (8), the representative firm breaks even at the following constant output:

$$q^* = \frac{F(\sigma - 1)}{c^m} \tag{9}$$

The price needed to sell the above constant output can be determined by the firm's demand function (equation 4), such that:

$$P_r^m = \frac{(\sigma - 1)}{\sigma c^m}\left[\frac{\mu}{q^*}\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}\right]^{1/\sigma} \tag{10}$$

Combining equation (8) and (10), the wage equation of skilled and unskilled can be expressed as:

$$(w_r^k)^{\alpha}(w_r^u)^{B} = \frac{(\sigma - 1)}{\sigma c^m}\left[\frac{\mu}{q_r^m}\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}\right]^{1/\sigma} \tag{11}$$

[9] The determination of the equilibrium spatial distribution of economic activities using NEG models has been addressed in previous literature (see Fujita et al (1999) and Krugman (1991). However, in our case, solving for general equilibrium with different types of skill labor would come at the expense of huge complexity, mostly arises from factor mobility, without adding much to the main purpose of this paper. Though, I leave this issue for a future research.

The wage equation can be further simplified by applying normalization assumptions as specified by Fujita et al. (1999), page 54-55, such that:

$$(w_r^k)^{\alpha}(w_r^u)^{B} = \left[\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}\right]^{1/\sigma} \tag{12}$$

Similar to Fujita et al.'s (1999), equation (12) equates wages to the firm's market potential. Specifically, it identifies the maximum skilled and unskilled wage at which a firm in region ***r*** breaks even, given: income, Y_s, price index G_s in all regions, which reflects the level of competitiveness,[10] and transportation costs, T_{rs}, to those regions. Nonetheless, the major difference between the wage equation (equation 12) and Fujita et al's is that the former split wages into skilled and unskilled, whereas the latter defines a wage as an average of all skill types. Therefore, equation (12) can be regarded as a *spatial skill demand equation*.

To determine the equilibrium wage of skilled and that of unskilled workers, I incorporate the zero profit conditions of the manufacturing and agricultural sector, equation (12) and (7), respectively. Taking the logarithm and total differentiation of each zero profit conditions yields:

$$0 = \varphi \frac{dw_r^k}{w_r^k} + (1-\varphi)\frac{dw_r^u}{w_r^u} \tag{13}$$

$$\frac{\alpha dw_r^k}{w_r^k} + \frac{\beta dw_r^u}{w_r^u} = \frac{1}{\sigma}\left[\begin{array}{l} \dfrac{\sum_{s=1}^{R} G_s^{\sigma-1} T_{rs}^{1-\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dY_s + \dfrac{(\sigma-1)\sum_{s=1}^{R} Y_s G_s^{\sigma-2} T_{rs}^{1-\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dG_s + \\ \dfrac{(1-\sigma)\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{\sigma}}{\sum_{s=1}^{R} Y_s G_s^{\sigma-1} T_{rs}^{1-\sigma}} dT_{rs} \end{array}\right] \tag{14}$$

Equation (13) can be expressed as:

$$\frac{dw_r^u}{w_r^u} = -\frac{\varphi}{1-\varphi}\frac{dw_r^k}{w_r^k} \tag{15}$$

Substituting equation (15) into (14) yields:

[10] Note that price index is decreasing in the number of varieties sold.

$$\frac{dw_r^k}{w_r^k}=(\alpha-\frac{\beta\varphi}{1-\varphi})^{-1}\frac{1}{\sigma}\left[\begin{array}{l}\frac{\sum_{s=1}^{R}G_s{}^{\sigma-1}T_{rs}{}^{1-\sigma}}{\sum_{s=1}^{R}Y_sG_s{}^{\sigma-1}T_{rs}{}^{1-\sigma}}dY_s+\frac{(\sigma-1)\sum_{s=1}^{R}Y_sG_s{}^{\sigma-2}T_{rs}{}^{1-\sigma}}{\sum_{s=1}^{R}Y_sG_s{}^{\sigma-1}T_{rs}{}^{1-\sigma}}dG_s+\\ \frac{(1-\sigma)\sum_{s=1}^{R}Y_sG_s{}^{\sigma-1}T_{rs}{}^{\sigma}}{\sum_{s=1}^{R}Y_sG_s{}^{\sigma-1}T_{rs}{}^{1-\sigma}}dT_{rs}\end{array}\right] \tag{16}$$

The zero profit conditions of the agricultural and manufacturing sectors do not constitute a full economic model. Therefore, there is no enough information to determine the sign of dY_s, $dG_{s,}$ and dT_{rs}. Nevertheless, since the RHS of equation (16) is the total differentiation of market potential of a manufacturing firm in region *r*, the net sign of the terms between brackets is positive if region *r* experiences an increase in the level of its market potential, i.e., a higher level of income, less competition in all regions, and a lower transportation cost to those regions. Therefore, for regions that gain a higher level of market potential, the new equilibrium implies that the relative wage for skilled workers is higher (the sign of dw^k_r/w^k_r is positive), if the share of manufacturing skilled workers is higher relative to that of the agricultural sector, such that:

$$\frac{\alpha}{\beta} > \frac{\varphi}{1-\varphi} \tag{17}$$

Intuitively, an increase in the level of market potential would violate the manufacturing zero profit condition at the initial equilibrium factor price, and would result in an expansion of the manufacturing sector. The expansion of the manufacturing sector implies a higher demand for skilled labor than what the agricultural sector can release at the initial equilibrium factor prices. Therefore, in the new equilibrium, the nominal wage of skilled workers is higher, and the nominal wage of unskilled workers is lower (to satisfy the agricultural zero profit condition, equation 13). This implies that the relative wage of skilled workers is higher.

3. Empirical Specifications

3.1 Measuring Market potential

The wage equation, derived in the previous section, equates the maximum skilled and unskilled wage a firm in a given region can pay with the firm's market potential. The market potential is a function of income and price indices in all regions, and transportation cost to those regions. However, since price indices, G_s, are not available at the U.S. metropolitan level, I assume that G_s is constant across metropolitan areas. Doing so reduces the above market potential function (the RHS of equation 12) to that of Harris' (1954). This amounts to saying that the wage of skilled relative to unskilled workers is positively related to incomes in all regions deflated by transportation cost.

If the objective of this paper were to estimate the magnitude of scale economies and transportation cost parameters as in Hanson (2005), then using Harris' reduced form would certainly be unacceptable. However, the goal of this essay is to provide a measure of agglomeration stemming from economic geography and evaluate its impact on the wage distribution. Thus, I believe that using Harris' market potential serves this purpose. Giving credibility to Harris' market potential, Head and Mayer (2005) compare several measures of market potential and find that the former produces results that are similar to other complex measures in terms of predictive power and magnitude. In addition, Harris's index is easier to construct and has proven to be influential in assessing the effect of backward linkages across and within countries (Hanson 1997; Ottavano and Pinelli 2006).

3.2 Empirical Model

To examine the effect of market access on the metropolitan wage distribution, I use cross sectional reduced form models, where the unit of observation is the Metropolitan Statistical Area (MSA) and Primary Metropolitan Statistical Area (PMSA). In specifying the empirical models, I undertake the following measures: First, all the explanatory variables are measured at the beginning of the period (1990) to mitigates any direct endogeneity between the dependent and independent variables.

Second, I include a broad range of control variables such as human capital accumulation, industry shares, supplies of exogenous amenities, and other economic and demographic variables. This diminishes the possibility of market potential confounding other effects. However, including a multitude of control variables might come at the expense of introducing multicollinearity. Therefore, to check the robustness of the base model results, in the sensitivity analysis section, I conduct robustness checks with respect to more parsimonious models (Perotti 1996; Panizza 2002).

Yet, the empirical model does not explicitly control for some metropolitan-specific factors that vary little over time and possibly correlated with agglomerated areas. Examples of those factors are welfare policies, access to highways and railroads, and availability of agricultural land. Given the data availability, I am limited to use cross sectional estimation rather than fixed effects or first differencing estimation that would control for such fixed factors.[11] However, since many of those factors are determined at a state level, state dummies are included to pick up common factors within the same state.[12] Because some metropolitan areas extend across state boundaries, each of these metropolitan areas is assigned to the state in which the majority of the metropolitan population resides.

For simplicity, the above theoretical model classifies wages into that of skilled and unskilled workers. However, to explore how market access affects different parts of the wage distribution, in the empirical models below, I compare wages between workers that are conventionally concentrated in the top (the most skilled), middle (average skilled), and lowest part of the wage distribution (the least skilled).[13] Particularly, the analysis pivots around three empirical models in which the respective dependent variables are specified as the difference of the logarithmic wage between: (1) the most skilled (measured by the 90^{th} percentile of the wage distribution) and the least skilled (measured by the 10^{th} percentile of the wage distribution); (2) The most skilled and average skilled (measured by the 50^{th} percentile of the wage distribution); and (3) average skilled and the least skilled.[14] Using gaps between different wage percentiles is more instructive in measuring inequality, since it allows for detecting structural changes within the wage distribution. The wage percentiles are measured for the year 2001.

The cross sectional model is expressed as follows:

[11] First differencing approach assumes that the regression coefficients are the same each period. This could be problematic when considering 10 year differencing. Nonetheless, although fixed effects estimation controls for omitted time-invariant factors, the estimates might not be robust if the explanatory variables are measured with error (Hauk and Wacziarg, 2004).

[12] When controlling for state fixed effects, the coefficients of the other explanatory variables reflect the within-state variation of those explanatory variables on the dependent variables.

[13] Generally, using wages to measure inequality rather than income is informative to policy analysts since it reflects more precisely on the market price for human capital elements (Juhn et al. 1993)

[14] These measures of wage inequality are familiar in the literature, see Juhn et al. (1993), Wheeler (2004), and Garofalo and Fogary (1979).

$$\log(w^{z}_{i,2001}) - \log(w^{S}_{i,2001}) = B_0 + B_1 MP_{i,1990} + B_2 totpop_{i,1990} + B_3 \%\Delta emp_{i(1980-1990)} + B_4 indust_{i,1990} + B_5 educ_{i,1990} + B_6 Natural\_Amenity_i + B_7 totpop^2_{i,1990} + B_9 immigrants_{i,1987-1990} + B_{10} race_{i,1990} + state_i + e_i \quad (18)$$

Where *z* and *s* in the left hand side term denotes wage percentiles as noted above. Market access is specified as Harris' (1954) market potential index (MP_i):

$$MP_i = \sum_{i \neq k}^{k} \frac{Y_k}{D_k} \quad (19)$$

In our case, *Y* is total personal income[15] in metropolitan area *k*, and *D* is the distance, measured in kilometers, from the centroid of metropolitan area *i* to the centroid of metropolitan area *k*, where $i \neq k$, and *k* includes all the metropolitan areas[16] in the sample. By convention, I use distance to proxy for transportation costs.

Total metropolitan population ($totpop_i$) is included to control for city-size effect. Nevertheless, previous studies differ on the impact of the latter on income (wage) inequality. For example, Garofalo and Fogarty (1979) argue that productivity-agglomeration effects in larger cities increase the productivity of skilled labor more than that of unskilled. This would imply that income inequality rises as we move up the urban hierarchy (see also Mathur 1970; Farbman 1975). However, other researchers contend that greater city size is a source of more equality (Danziger 1969; Bums 1976). The latter view is shared in a more recent paper (Levernier et al. 1998), where it is argued that the negative relationship between inequality and city size might be due to higher rate of job match in larger cities favoring less skilled and less mobile labor. Therefore, the net effect of city size is ambiguous.

Among other factors that affect the wage distribution and have interested researchers and policy analysts is employment growth ($\%\Delta emp_{i,(1980\text{-}1990)}$), which is measured between 1980 and 1990. How employment growth affects inequality is not clear and depends on the geographical scope of

[15] According to the Bureau of Economic Analysis (BEA) personal income is "Income received by persons from all sources. It includes income received from participation in production as well as from government and business transfer payments. It is the sum of compensation of employees (received), supplements to wages and salaries, proprietors' income with inventory valuation adjustment (IVA) and capital consumption adjustment (CCAdj), rental income of persons with CCAdj, personal income receipts on assets, and personal current transfer receipts, less contributions for government social insurance. See http://www.census.gov.

[16] To avoid direct endogeneity, income of the metropolitan area under study is not included when calculating its market potential index.

the study[17] (national versus regional). Closer to this essay, Bartik (1994) uses pooled time-series cross-section data for U.S. metropolitan areas and finds that the average income of the poorest increases by a greater percentage than that of the average family. Rather than using mean family income for different quintiles, as in Bartik (1994), I investigate how employment growth affects the wage gap between different wage percentiles, which is more informative in terms of the change of the size of wage distribution.

Industry employment share ($indust_i$) might also have a differential effect on wage distribution. Previous studies show that wages differ significantly across industries with similar observed skills (Katz and Summer 1989; Bartik 1996). For example, the downsizing of the U.S. manufacturing sector has contributed to a decline in wages for modest and low skill labor (Kasadra 1985; Wilson 1987). To capture inter-industry wage differences, as well as any related effects such as unionization, I include the employment shares of 15 major industries, $indust_i$, of which the agriculture industry is the omitted category.

Human capital, $educ_i$, is measured by the share of population above 25 years old that have: (1) high school degree; (2) some college with no degree; (3) associate degree; and (4) at least a bachelor degree. The estimates of these categories are compared to the omitted high school drop outs. The effect of the human capital stock on wage inequality is not clear *a priori*. An increase in the relative demand of skilled labor would raise the return to education, and thus, cities with higher levels of education tend to have more wage inequality (Bound and Johnson 1992; Katz and Murphy 1992; Juhn et al. 1993). On the other hand, if high and low skilled workers are imperfect substitutes, enhancing human capital accumulation would produce just the opposite effect (Moretti 2004).

To control for location specific externalities that could affect the spatial distribution of both workers and firms, two control variables are included: supply of exogenous amenities measured

[17] Using U.S. national data, Blank (1993) finds that, for the period 1983 to 1989 the reduction in the U.S. male unemployment rate appeared to increase income inequality. At the regional level, Blank and Card (1993) find that the decrease in regional unemployment has no effect on income distribution and a minimal effect on poverty. On the other hand, other studies contradict those findings and suggest that increase in regional labor demand do indeed have a progressive effect on income distribution (e.g. Freeman 1991 and 1991; Topel 1986). However, Bartik (1996) argues that, unlike metropolitan areas, using regions as units of observation is problematic since the latter do not accord to the definition of local labor markets and that the results are biased due to change in local population composition as migrants enter the region.

by natural amenity index (*Natural_amenity*$_i$),[18] and congestion measured as the squared-term of total metropolitan population ($totpop^2_i$). To control for the effects of recent immigrants on wage inequality, I add the share of population that immigrated to the U.S. in the prior three years (1987-1990). Finally, racial effects are controlled for by including the population shares of African American; Native American; Asian American; and other minorities.[19]

3.2 Data

The units of observation are MSAs and PMSAs.[20] The U.S. office of Management and Budget (OMB) updates the list and boundaries of the metropolitan areas periodically according to changes in population and other factors.[21] In order to conduct the analysis on consistent metropolitan boundaries across time, I use the 2000 census definition, producing a total sample of 307 metropolitan areas.

Wage percentile data is from the U.S. Department of Labor's Occupational Employment Statistics (OES) program. The OES survey produces wages and percentile estimates for about 800 occupations for all industries. In this study, I use the *annual* total industry wage percentile estimates for the year 2001[22] as provided by the Bureau of labor statistics website, (http://www.bls.gov/oes/oes_dl.htm).

Total personal income data (used to calculate the market potential index) and employment data are collected from the U.S. Department of Commerce's BEA Regional Economic Information system (REIS). The data on the natural amenity index is derived from the U.S Department of Agriculture (USDA). However, since REIS and USDA produce data at a county level, I aggregate total personal income and total employment and calculate the average of the natural amenity indices over all counties that belong to the same metropolitan area. Finally, the data source of the

[18] The amenity index ranges from 1 to 7, which combines six measures of natural amenities: warm winter, winter sun, temperate summer, low summer humidity, topographic variation, and water area. A higher value reflects more natural amenities.
[19] All variables are listed in the descriptive statistics table (table A) in appendix I.
[20] The general concept underlying metropolitan area is that of a large population nucleus, together with adjacent counties that have close economic and social ties to the nucleus. MSAs are metropolitan areas that are not closely associated with other metropolitan areas, typically, those that are surrounded by rural areas. PMSAs are individual metropolitan areas centered on a large central city or several closely related center cities. More information on metropolitan definition can be found at http://www.census.gov/geo/www/cob/ma_metadata.html.
[21] For more discussion on this issue, go to http://www.census.gov/population/www/estimates/pastmetro.html.
[22] Total industry wage estimates are not available prior to 2001.

rest of the explanatory variables are from the Geolytics Census data base, which provides consistent census metropolitan data for 1980 and 1990 using 2000 census boundaries.

4. Base Model Empirical Results

The following empirical discussion focuses mainly on the market potential/wage inequality relationship; though some other notable results will be pointed out. Table (1.1) reports the results of the base model, which is more fully specified to control for human capital, location-specific externalities, and other economic and demographic characteristics, as specified in equation (18).

One potential problem with our cross sectional models is that the residuals could be spatially correlated, which would negatively bias the standard errors. To correct for this problem, I estimate the empirical model using GLS estimation, in which the residuals are assumed to be correlated within particular geographical clusters, but uncorrelated across clusters.[23] The advantage of using the clustering approach is that it does not impose restrictions on the cross sectional correlation of the residuals within clusters. This is unlike other spatial econometric models that use more restrictive assumptions, such as, distance or adjacency weight matrix. Still, to check if the estimates are not driven by the clustering approach, in the sensitivity analysis section, I use a different technique that corrects of spatial heteroskedasticity.

Before thoroughly discussing the impact of market potential and other factors on the metropolitan wage distribution, it is informative to check if Hanson's (2005) findings are consistent when estimating a linear reduced form model using metropolitan areas instead of U.S. counties. To do so, I estimate the same model as specified in equation (18), but with the dependent variable measured as the logarithm of average annual wages.[24] As reported in column (1) in Table (1.1),[25] the results confirm Hanson's (2005) prediction, i.e., the demand linkages between metropolitan areas are strong and contribute to spatial agglomeration. The coefficient of market potential is positive and statistically significant at the 5% level. This implies that increasing the market

---

[23] The clusters used are BEA economic areas, which consist of one or more economic nodes that reflect regional centers of economic activities. In the sample, there is 156 BEA economic areas. Stata cluster command is used for the estimation. The definition of BEA economic area is available at http://www.bea.gov/regional/docs/econlist.cfm.
[24] Data on average annual wages are also produced by OES.
[25] All the tables are reported in the Appendix I.

potential by one standard deviation increases the logarithm of average wages by 9.7 percentage points, *ceteris paribus*.[26]

While the previous result suggests that wages are higher in metropolitan areas with a greater market potential, it does not elucidate the latter's influence on the *distribution* of wages. Therefore, the following analysis examines the effect of market potential on the wage gap between: (1) the most and least skilled ($log(w^{90th})-log(w^{10th})$); (2) the most and average skilled ($log(w^{90th})-log(w^{50th})$); and (3) average and the least skilled ($log(w^{50th})-log(w^{10th})$), as reported in Column (2), (3), and (4), respectively in Table (1.1).

Starting with the model reported in column (2), the results reveal that greater market potential increases the wage gap between the most and least skilled workers; the coefficient of market potential is positive and highly significant at the 5% level. The same result is obtained when comparing the wage gap between average and the least skilled; column (4) shows that the coefficient of market potential is positive and also highly significant at the 5% level. These estimates suggest that increasing market potential by one standard deviation implies a 10.5 percentage point increase in the logarithmic wage gap between the most and the least skilled, and 11 percentage point increase in the logarithmic wage gap between average and least skilled. However, the picture is considerably different when considering the wage gap between the most and average skilled, column (3). The coefficient of market potential is positive but statistically insignificant, suggesting no significant impact of market potential on the earning gap between the latter skill groups.

The above findings suggest that relative to the wage of the least skilled, the wage increase resulting from a greater market potential is disproportionately allocated to those with at least average skill levels. This conclusion is affirmed when directly assessing the impact of a greater market access on the lowest, middle, and top percentile of the wage distribution, respectively. I estimate three regressions, in which the explanatory variables are the same as in the base model (equation 18), but the dependent variables are now specified as $log(w^{90th})$, $log(w^{50th})$, and $log(w^{10th})$. The results, not reported, reveal that the coefficient of market potential is positive and statistically significant at the 1% and 10% level for the $log(w^{90th})$ and $log(w^{50th})$ models,

[26] Since the major focus of this essay is to examine the distributional effect of market potential, the remaining discussion excludes any discussion on the *Log(w)* model.

respectively. Conversely, the market potential coefficient is statistically insignificant for the $log(w^{10th})$ model.[27]

Though the main focus is on the wage inequality-market potential relationship, some other results are noteworthy. However, unless specified, the discussion will be limited to the $log(w^{90th})$-$log(w^{10th})$ and $log(w^{50th})$-$log(w^{10th})$ models for brevity purposes. First, employment growth has a greater positive impact on workers at the bottom of wage distribution, *ceteris paribus*. Increasing employment growth by one standard deviation implies a 20 percentage point decrease in the logarithmic wage gap between the most and least skilled and a 17 percentage point decrease in the logarithmic wage gap between the average and the least skilled.[28]

Consistent with Garofalo and Fogarty (1979), Mathur (1970), and Farbman (1975), the agglomeration effects in larger metropolitan areas favor more skilled labor. The coefficient of total metropolitan population is positive and statistically significant only for ($log(w^{90th})$-$log(w^{10th})$ and $log(w^{50th})$-$log(w^{10th})$) models. In addition, consistent with human capital models and previous inequality literature (Lemieux 2006; Bound and Johnson 1992; Katz and Murphy 1992; and others) returns to skills are found to increase the wage gap between the most and the least skilled and between average and the least skilled. The coefficients of the population share with associate degree and at least a bachelor degree, reported in column (2) and (4) in Table (1.1), are positive and statistically significant at least at the1% level.

So far, the estimates of the above empirical models support the prediction of the spatial skill demand equation (equation 12), which implicitly states that an increase in the demand for skilled workers in areas with greater market potential yields an increase in the relative wage of those workers. For this to happen, the above theoretical model requires that areas with greater market potential should be characterized by skill intensive sectors. So, what left to find is whether the empirical findings are consistent with the latter condition. This would apply if we find a positive relationship between areas with greater access to markets and the level of skilled workers in those areas.

---

[27] The results of this model and any unreported model in this paper are available on request.

[28] The coefficient of employment growth in the $log(w^{90th})$-$log(w^{50th})$model is negative and significant at 10% level, as reported in column (3), table (1.1). Yet, I re-estimated the latter model using different specifications (see column (2), table (1.3), (1.4), and (1.6)), the employment growth coefficient is negative but insignificant in most specifications.

To achieve this purpose, I employ an empirical framework similar to that of Redding and Scott (2003). Particularly, I estimate a cross sectional model in which the 2000 share of population that have at least a bachelor degree (as a proxy for skilled workers) is regressed on the 2000 market potential. Since the share of higher education is bounded between 0 and 1, I employ a logistic specification:

$$Log\left(\frac{Higher\_educ_{i,2000}}{1-Higher\_educ_{i,2000}}\right) = \alpha_0 + \alpha_1 LogMP_{i,2000} + v_i + \varepsilon_i \quad (20)$$

Where v_i is state dummies included to control for fixed factors that are common among metropolitan areas within the same state. Examples of fixed factors include taxes and expenditure on infrastructure and other public goods.

Column (1) in table (1.2) reports the results of the above bivariate model. The coefficient of market potential is positive and statistically significant at the 1% level, suggesting that metropolitan areas with a greater market potential are associated with a greater share of educated workers. This finding is robust even when including other variables that could attract skilled workers, namely, 1990-2000 employment growth, 1990-2000 per capita growth, and natural amenity index as reported in column (2) in Table (1.2).

5. Sensitivity Analysis

The evidence from the base model shows that while metropolitan areas with a greater market potential tend to have higher average wages, the wage increase is tilted to workers with at least average skills.

In this section, I assess the extent to which the aforementioned findings are driven by the specification of the base models. But firstly I address the possible simultaneity issue between the lagged market potential and the subsequent wage inequality measures. The simultaneity effect would be a concern if, for example, metropolitan areas with higher level of wage inequality tend to attract firms to benefit from the wide distribution of skills. Nevertheless, if there is a persistence serial correlation, then it is possible that shocks and events happened decades before could induce simultaneity between the lagged market potential and the subsequent wage inequality. To deal with this issue, I instrument the lagged market potential ($MP_{i,1990}$) with its lag from earlier decades, specifically, the market potential of 1970. The 2SLS results appear in table (1.3). As previously reported, the effect of market potential is robust.

Secondly, in the previous section I corrected for the potential spatial autocorrelation by assuming that the residuals are clustered in BEA areas. In this section, I employ general method of moments (GMM) as an alternative approach to check if the standard errors of the base model estimates are just a product of the clustering approach. The GMM approach assumes a general form of the spatial correlation that declines with distance from the metropolitan area of interest.[29] Not reported, the GMM results are similar to those of the base model (Conley 1999).

As noted earlier, the base model accounts for a multitude of factors that affect the wage distribution and might be correlated with market potential. Including these variables would avoid omitted variables bias, but might introduce multicollinearity. To test if multicollinearity affects the results, I next estimate more parsimonious models (Perotti 1996; Panizza 2002). The parsimonious model implicitly assumes that market potential and/or few other control variables are the causal forces behind other factors (Partridge 2005). First, Table (1.4) omits the industry employment shares inasmuch there maybe a correlation between skill demand shifts in those sectors and market potential.[30] Regardless, the market potential-wage inequality findings remain the same.

Second, the models reported in Table (1.5), include only the market potential variable and state dummies. Moreover, table (1.6) omits only state dummies to test if the explanatory variables in the base model are adequate to explain changes in the wage distribution and that omitted fixed effects do not have an impact on the reported estimates. The results show a robust impact of market potential on the wage gap between the least skilled and those with at least average skills.[31] Yet, the only difference is that the effect of market potential has now a significant positive impact on the wage gap between the most and average skilled.

[29] The cut off distance we undertake is 400 km, in which it is assumed that the error terms are not correlated beyond this distance. In separate regressions, the GMM modes are estimated using different cut off distances (200 km and 600 km). The results are similar.

[30] The base models include industry employment share to control for wage differentials across industries, among other factors. Yet, I re-estimate the based model including 12 major non-agricultural occupations to ensure that market potential does not confound the effects of skill demand differences across different occupations. Not reported, the effect of market potential remains the same.

[31] In one sensitivity analysis I excluded location-specific externalities (natural amenity index and the squared term of total population). In other robustness check, I excluded the education attainment variables to tests if the reported market potential effect is a by product of its correlation with human capital accumulation. Not reported, the results are similar to those of the base models.

To summarize the sensitivity analysis, the positive effect of market potential on the wage gap between workers with at least average skills and those with the least skills is robust to various specification changes. Therefore, the findings do not appear to be an artifact of model specifications. Yet, since the sample of this essay includes only metropolitan areas, the measure of market potential ignores access to non-metropolitan areas. Therefore, the results should be interpreted within the framework of demand linkages among U.S. metropolitan areas.

6. Conclusion

NEG theories explain the spatial concentration of economic activities as a result of the interaction between backward and forward linkages. Backward linkages imply that firms locate in areas with large demand for their products and that higher access to markets ensures higher profit to local firms and thus higher wages. On the other hand, forward linkages indicate that workers are attracted to areas with high industrial production to take advantage of spatial wage differentials and access to consuming various goods at a lower price. Most of the NEG literature has been dedicated to providing evidence to test these propositions. This essay sheds light on a different aspect of NEG. Specifically; it considers questions pertaining to the income distribution effects. That is, while the average wages are higher in areas with a greater market potential (as consistent with past literature) how does market potential affect the *distribution* of wages (wage inequality) across U.S. metropolitan workers?

To provide a theoretical foundation of the empirical analysis, I modify the work of Redding and Schott (2003) and derive a spatial skill demand equation. The latter defines the maximum skilled and unskilled wages that a firm in a given region can pay given the market access of that region, with market access defined as the market potential devised by Fujita et al. (1999). The major implication of the spatial skill demand equation is that in regions with skill intensive sectors, a greater access to markets increases demand for skilled workers and thus increase their relative wages.

I use data from U.S. metropolitan areas to compare wages between different skill groups ranging from the most to the least skilled, measured at the 90^{th}, 50^{th}, and 10^{th} percentile of the wage distribution. Due to data limitations, the price indices are assumed constant across metropolitan areas. This reduces the market potential specifications to Harris's (1954), which I use to conduct the econometric estimation. I provide robust evidences that greater access to markets is associated with a greater wage gap between the most and least skilled, and also between average and the least skilled. On the other hand, the results show that, in most specifications, greater market access is not significantly associated with the wage gap between the most and average skilled.

This essay is unique since it directly emphasizes the importance of considering various skill compositions within local labor markets when empirically testing the influence of market location on nominal wages. Inasmuch as average wages are higher in areas with greater market access, the overreaching conclusion suggests that the resulting proximity to markets does not raise all boats; rather it is tilted to more skilled labor. These results are consistent with Fallah and Partridge's (2007) hypotheses regarding how inequality and agglomeration economies interact. Moreover, the conclusion of this essay is also consistent with other inequality research that emphasizes the role of skill premiums and increasing demand for skills in explaining wage inequality (Bound and Johnson 1992; Katz and Murphy 1992; Juhn et al. 1993; Lemieux 2006).

In this setting, this essay has a significant implication regarding redistribution policies that target workers at the bottom of the wage distribution (The least skilled). Expanding subsidized training programs (Job Training Partnership Act, the Comprehensive Employment and Training Act, and the Job Corps program for disadvantaged youth) would be imperative in reducing wage inequalities. Moreover, since the gap between skilled and skilled earnings, in parts, reflects returns to education (Lemieux 2006), a widening of that gap signals the need for policies aimed at increasing the supply of more skilled workers. A policy recommendation to achieve that is improving the access to student loan and post graduate tax cut. Given the demand for skilled workers, this would be instrumental in upgrading the local labor force and reducing wage gap.

Appendix I

Table A: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Log(w)	307	10.35	0.117	10.11	10.80
$log(w^{90th})-log(w^{10th})$	307	1.39	0.105	1.129	1.79
$log(w^{90th})-log(w^{50th})$	307	0.792	0.063	0.603	0.968
$log(w^{50th})-log(w^{10th})$	307	0.604	0.075	0.385	0.858
$log(w75^{th})-log(w^{10th})$	307	1.03	0.092	0.811	1.36
$log(w^{90th})$	307	10.93	0.143	10.65	11.51
$log(w75^{th})$	307	10.56	0.133	10.29	11.10
$log(w50^{th})$	307	10.14	0.127	9.79	10.59
$log(w10^{th})$	307	9.54	0.071	9.40	9.76
1970 Market potential	307	831201	485773	318951	4572003
1990 Market potential	307	4694477	2336789	1963108	2.26E+07
1990 Total population	307	624312.7	1057593	56735	8862513
(1980-1990) Employment growth	307	0.203	0.182	-0.227	1.13
(1990-2000) Employment rowth	307	0.149	0.118	-0.059	0.707
Natural amenity scale	307	3.82	1.28	1	7
1990 Total populaion-squared	307	1.50E+12	7.22E+12	3.22E+09	7.85E+13
1990 share of high school	307	0.307	0.055	0.165	0.488
1990 share of some college, no degree	307	0.195	0.039	0.095	0.302
1990 share of associate degree	307	0.064	0.016	0.024	0.117
1990 share of at least bachelor degree	307	0.198	0.063	0.095	0.44
2000 log share of at least bachelor degree	307	-1.22	0.397	-2.09	0.096
2000 percapita income growth	307	0.522	0.078	0.278	0.729
1990 share of African American	307	0.103	0.102	0.0007	0.457
1990 share of Native American	307	0.008	0.018	0.0003	0.279
1990 share of Asian American	307	0.018	0.024	0.001	0.205
1990 share of other minorities	307	0.029	0.0501	0.0005	0.291
Recent immigrants 1987-1990	307	0.008	0.01	0.0001	0.063
1990 shares of industry employment:					
Mining industry	307	0.006	0.014	0.0002	0.139
Construction industry	307	0.062	0.015	0.036	0.124
Transportation industry	307	0.04	0.012	0.021	0.097
Communication and utility industry	307	0.027	0.008	0.01	0.07
whole sale industry	307	0.042	0.012	0.017	0.116
Retail industry	307	0.18	0.02	0.126	0.26
Business & repair industry	307	0.044	0.009	0.024	0.07
Personal service industry	307	0.032	0.013	0.018	0.177
Entertainment industry	307	0.014	0.01	0.005	0.114
Other professional & related services	307	0.063	0.016	0.036	0.196

Continue in the next page

Table A: Descriptive Statistics con't

Variable	Obs	Mean	Std. Dev.	Min	Max
Public administration industry	307	0.046	0.029	0.017	0.195
FIRE industry	307	0.061	0.019	0.027	0.163
Manufacturing industry	307	0.17	0.072	0.043	0.463
Educational service industry	307	0.094	0.037	0.046	0.296
1990 shares of occupational employment:					
Executive, Administrative, and Managerial Occupations	307	0.114	0.02	0.072	0.196
Prof. speciality	307	0.141	0.027	0.085	0.247
Technicians and related support	307	0.038	0.009	0.021	0.097
Sales	307	0.121	0.014	0.086	0.163
Administrative support, including clerical	307	0.157	0.018	0.117	0.228
Service, private household	307	0.004	0.002	0.001	0.012
Service, protective service	307	0.017	0.005	0.009	0.041
Service, except protective and household	307	0.118	0.019	0.07	0.226
Farming, forestry, and fishing	307	0.024	0.02	0.004	0.169
Precision production, craft and repair	307	0.115	0.019	0.063	0.181
Machine operator, assemblers, and inspectors	307	0.067	0.031	0.021	0.24
Transportation and material moving	307	0.042	0.009	0.021	0.092
Handlers, equipment cleaners, helpers, and laborers.	307	0.041	0.008	0.022	0.072

Table 1.1: Wage inequality-Market Access Base model.

Variables	*Log(w)*	*log(w^90th)-log(w^10th)*	*log(w^90th)-log(w^50th)*	*log(w^50th)-log(w^10th)*
	(1)	**(2)**	**(3)**	**(4)**
1990 market potential	4.90E-09	4.76E-09	1.44E-09	3.61E-09
	(2.19)	(2.45)	(0.82)	(2.44)
1990 total metropolitan population	1.67E-08	1.73E-08	4.09E-09	1.32E-08
	(2.2)	(2.06)	(0.66)	(1.83)
(1980-1990) Employment Growth	-0.011	-0.114	-0.041	-0.073
	(-0.5)	(-4.03)	(-1.84)	(-2.73)
Natural amenity scale	-5.35E-03	-1.03E-02	-6.93E-03	-3.66E-03
	(-1.04)	(-1.69)	(-1.31)	(-0.69)
1990 total population_squared	-1.29E-15	-1.49E-15	-2.44E-16	-1.14E-15
	(-1.24)	(-1.22)	(-0.33)	(-1.23_
1990 share of high school	0.122	0.139	-0.188	0.387
	(1.00)	(0.88)	(-1.22)	(2.9)
1990 share of some college, no degree	-0.348	-0.336	-0.293	0.006
	(-2.11)	(-1.57)	(-1.52)	(0.03)
1990 share of associate degree	1.033	1.324	0.438	0.872
	(2.84)	(3.01)	(1.34)	(2.65)
1990 share of at least bachelor degree	0.898	0.75	0.258	0.533
	(8.22)	(4.75)	(1.84)	(5.48)
1990 share of African American	-1.584	0.209	0.063	0.145
	(-2.03)	(2.87)	(1.14)	(3.21)
1990 share of Native American	-0.182	-0.326	-0.298	0.001
	(-2.01)	(-1.9)	(-1.75)	(0.02)
1990 share of Asian	0.472	0.314	-0.109	0.449
	(2.74)	(2.02)	(-0.72)	(3.23)
1990 share of other race	0.161	0.392	0.223	0.084
	(1.66)	(3.5)	(1.36)	(0.86)
Share of recent immigrants 1987-1990	0.081	0.05	0.04	0.007
	(1.77)	(0.1)	(0.08)	(0.01)
1990 shares of Industrial Employment	Y	Y	Y	Y
State dummies	Y	Y	Y	Y
constant	10.031	0.8	0.621	0.182
	(79.2)	(5.1)	(4.04)	(1.49)
R-square	0.93	0.86	0.74	0.81
N	307	307	307	307

* Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.

Table 1.2: Higher Education-Market Access Cross Sectional model

Variable†	I	II
2000 Market potential	0.488	0.508
	(2.78)*	(2.97)
(1990-2000) Employment Growth		0.725
		(2.07)
(1990-2000) Per capita income Growth		1.395
		(2.05)
Natural Amenity		0.051
		(0.94)
State dummies	Y**	Y
Constant	-8.213	-9.464
	(-2.93)	(-3.35)
R-square	0.24	0.31
N	307	307

† The dependent variable is the logarithm of the 2000 share of population with at least a bachelor degree.

* Robust (spatially clustered) t-statistics are in parenthesis. Like the base model (table 1.1), the clusters are formed based on BEA economic areas.

** Because some metropolitan areas run across state boundaries, each of these metropolitan areas is assigned to the state in which the majority of the metropolitan population resides.

Table 1.3: Wage Inequality-Market Access Parsimonious Model (Market Potential IV Estimates)

Variables	***log(w^90th)-log(w^10th)*** **(1)**	***log(w^90th)-log(w^50th)*** **(2)**	***log(w^50th)-log(w^10th)*** **(3)**
1990 Market potential	4.90E-09	1.62E-09	3.28E-09
	(2.61)	(1.03)	(2.3)
1990 total metropolitan population	1.74E-08	4.40E-09	1.30E-08
	(2.09)	(0.72)	(1.82)
(1980-1990) Employment Growth	-0.114	-0.041	-0.073
	(-4.03)	(-1.87)	(-2.73)
Natural amenity scale	-0.01	-0.007	-0.004
	(-1.69)	(-1.28)	(-0.69)
1990 total population_squared	-1.50E-15	-3.81E-16	-1.12E-15
	(-1.23)	(-0.55)	(-1.21)
1990 share of high school	0.139	-0.249	0.387
	(0.88)	(-1.62)	(2.9)
1990 some college, no degree	-0.338	-0.347	0.009
	(-1.57)	(-1.66)	(0.05)
1990 share of associate degree	1.328	0.466	0.862
	(3.02)	(1.42)	(2.63)
1990 share of at least bachelor degree	0.75	0.217	0.533
	(4.75)	(1.55)	(5.48)
1990 share of African American	0.209	0.064	0.145
	(2.87)	(1.13)	(3.22)
1990 share of Native American	-0.326	-0.328	0.002
	(-1.9)	(-1.84)	(0.02)
1990 share of Asian	0.314	-0.137	0.451
	(2.02)	(-0.98)	(3.28)
1990 share of other race	0.392	0.309	0.083
	(3.5)	(3.02)	(0.85)
Share of recent immigrants (1987-1990)	0.04	0.016	0.26
	(0.09)	(0.03)	(0.05)
1990 shares of Industrial Employment	Y	Y	Y
State dummies	Y	Y	Y
constant	0.85	0.74	0.81
	(5.1)	(4.04)	(1.51)
R-square	0.78	0.68	0.72
N	307	307	307

Table 1.4: Wage Inequality-Market Access Parsimonious Model (No Industry Shares)

Variables	***log(w^{90th})-log(w^{10th})*** **(1)**	***log(w^{90th})-log(w^{50th})*** **(2)**	***log(w^{50th})-log(w^{10th})*** **(3)**
1990 Market potential	9.69E-09	-5.99E-10	1.03E-08
	(4.29)	(-0.26)	(4.52)
1990 total metropolitan population	5.13E-08	1.15E-08	3.98E-08
	(6.36)	(2.38)	(5.17)
(1980-1990) Employment Growth	-0.093	-0.027	-0.066
	(-2.76)	(-1.24)	(-2.24)
Natural amenity scale	-0.003	-0.004	-0.00001
	-0.45	-0.64	(0.00)
1990 total population_square	-4.00E-15	-8.84E-16	-3.11E-15
	(-2.89)	(-1.35)	(-2.71)
1990 share of high school	0.173	-0.227	0.4
	(0.97)	(-1.35)	(2.58)
1990 share of some college, no degree	0.092	0.063	0.029
	(0.42)	(0.37)	(0.14)
1990 share of associate degree	1.05	-0.033	1.082
	(2.44)	(-0.1)	(3.02)
1990 share of at least bachelor degree	0.762	0.274	0.488
	(6.21)	(2.78)	(5.78)
1990 share of African American	0.175	0.018	0.156
	(2.87)	(0.4)	(3.33)
1990 share of Native American	-0.27	-0.209	-0.061
	(-1.5)	(-1.34)	(-0.56)
1990 share of Asian	0.479	-0.2	0.679
	(1.99)	(-1.57)	(2.95)
1990 share of other race	0.419	0.3	0.12
	(2.88)	(3.31)	(0.89)
Share of recent immigrants (1987-1990)	-0.879	0.426	-1.302
	(-1.23)	(0.73)	(-1.49)
1990 shares of Industrial Employment	N	N	N
State dummies	Y	Y	Y
Constant	0.99	0.8	0.19
	(10.26)	(8.67)	(2.09)
R-square	0.78	0.68	0.72
N	307	307	307

Table 1.5: Wage Inequality-Market Access Parsimonious Model (Only Market Potential and State Dummies)

Variables	***log(w^90th)-log(w^10th)*** **(1)**	***log(w^90th)-log(w^50th)*** **(2)**	***log(w^50th)-log(w^10th)*** **(3)**
1990 market potential	1.77E-08	3.63E-09	1.41E-08
	(5.95)	(1.74)	(3.61)
1990 total metropolitan population	N	N	N
(1980-1990) Employment Growth	N	N	N
Natural amenity scale	N	N	N
1990 total population_squared	N	N	N
1990 share of high school	N	N	N
1990 share of some college with no degree	N	N	N
1990 share of associate degree	N	N	N
1990 share of at least bachelor degree	N	N	N
1990 share of African American	N	N	N
1990 share of Native American	N	N	N
1990 share of Asian	N	N	N
1990 share of other race	N	N	N
Share of recent immigrants (1987-1990)			
1990 shares of Industrial Employment	N	N	N
State dummies	Y	Y	Y
constant	1.45	0.83	0.62
	(95.92)	(78.52)	(31.19)
Number of Observations	307	307	307
R-square	0.44	0.49	0.45

Table 1.6: Wage Inequality-Market Access Parsimonious Model (No State Dummies)

Variables	***log(w^{90th})-log(w^{10th})*** **(1)**	***log(w^{90th})-log(w^{50th})*** **(2)**	***log(w^{50th})-log(w^{10th})*** **(3)**
1990 market potential	1.17E-08	2.67E-09	9.03E-09
	(5.85)	(2.92)	(4.91)
1990 total metropolitan population	3.00E-08	3.47E-09	2.66E-08
	(3.51)	(0.68)	(3.89)
(1980-1990) Employment Growth	-0.092	-0.03	-0.061
	(-3.1)	(-1.47)	(-2.52)
Natural amenity scale	-0.003	0.003	-0.006
	(-0.52)	(0.84)	(-1.39)
1990 total population_square	-2.46E-15	-1.66E-16	-2.30E-15
	(-2.19)	(-0.26)	(-2.72)
1990 share of high school	0.254	-0.22	0.474
	(1.76)	(-1.85)	(4.35)
1990 share of some college, no degree	-0.181	-0.469	0.288
	(-1.07)	(-3.85)	(1.85)
1990 share of associate degree	1.033	0.227	0.806
	(3.46)	(1.2)	(3.95)
1990 share of at least bachelor degree	0.414	0.058	0.356
	(2.72)	(0.53)	(3.51)
1990 share of African American	0.144	0.068	0.076
	(2.29)	(1.63)	(1.84)
1990 share of Native American	-0.251	-0.259	0.008
	(-0.97)	(-1.83)	(0.05)
1990 share of Asian	0.626	0.064	0.562
	(3.32)	(0.61)	(2.9)
1990 share of other race	0.419	0.349	0.07
	(3.67)	(4.04)	(0.69)
Share of recent immigrants 1987-1990	-0.136	-0.332	0.195
	(-0.17)	(-0.79)	(0.26)
1990 shares of Industrial Employment	Y	Y	Y
State dummies	N	N	N
constant	0.883	0.621	0.262
	(5.74)	(4.77)	(2.15)
R-square	0.73	0.6	0.7
N	307	307	307

References

Bartik TJ (1996) The distributional effects of local labor demand and Industrial Mix: Estimates using individual panel data. *Journal of Urban Economics*, 40: 379-407.

Bartik TJ (1994) The effects of metropolitan job growth on the size distribution of family Income. *Journal of Regional Science*, 34: 483-501.

Bartik TJ (1993) Who benefits from local job growth: Migrants or the original residents? *Regional Studies*, 27: 297-311.

Becker GS, Chiswick BR (1966) Education and the distribution of earnings. *American Economic Review*, Papers and Proceedings, 56: 358-369.

Black D, Henderson V (1999) A theory of urban growth. *The Journal of Political Economy*, 107: 252-284.

Blank RM, Card D (1993) Poverty, income distribution, and growth: Are they still connected? Brookings Papers on Economic Activity, 2: 285-339.

Bound J, Johnson G (1992) Changes in the structure of wages in the 1980's: An evaluation of alternative explanations. *American Economic Review*, 82:371-392.

Bruinshoofd A, Hollanders H, Weel BT (1999) Knowledge spillovers and wage inequality: An empirical investigation of knowledge-skill complementarity, MERIT Research Memorandum 99-008 (MERIT, Maastricht).

Bums LS (1976) The urban income distribution: a Human capital explanation. *Regional Science and Urban Economics*, 5: 465-482.

Conley TG (1999) GMM estimation with cross-sectional dependence. *Journal of Econometrics*, 92: 1-45.

Crozet M (2004) Do migrants Follow Market Potentials? An estimation of a new economic geography model. *Journal of Economic Geography*, 4: 439–458.

Danziger S (1969) Determinants of the level and distribution of family income in metropolitan areas, 1969. *Land Economics*, 52: 467-478.

Davis DR, Weinstein DE (1999) Economic geography and regional production structure: An empirical investigation. *European Economic Review*, 43: 379–407.

Davis DR, Weinstein, DE (2003) Market Access, economic geography and comparative advantage: an empirical assessment. *Journal of International Economics* 59: 1 – 24.

Deschênes O (2001) Unobserved ability, comparative advantage and the rising return to education in the United States: A cohort-based approach. Princeton University Industrial Relations Section, Working Paper No. 465.

Fallah BN, Partridge MD (2007) The elusive inequality-economic growth relationship: are there differences between cities and the countryside? *Annals of Regional Science* 41: 375-400.

Farbman M (1974) Income concentration in the southern United States. *The Review of Economics and Statistics*, 56: 333-340.

Freeman RB (1991) Employment and earnings of disadvantaged young men in a labor shortage economy, in ‘‘The Urban Underclass’’. Jencks and P. E. Peterson, Eds, The Brookings Institution, Washington, DC.

Freeman RB (1991) Labor market tightness and the mismatch between demand and supply of less-educated young men in the United States in the 1980s, in ‘‘Mismatch and Labor Mobility’’ F. P. Schioppa, Ed.., Cambridge Univ. Press, New York.

Fujita M, Krugman P, Venables A. (1999) The spatial economy: cities, Regions, and international trade. MIT Press, Cambridge.

Garofalo G, Fogarty M S (1979) Urban inequality and city size: An examination of alternative hypotheses for large and small cities. *Review of Economics and Statistics*, 61: 381-388.

Giordano M, Paolo N (2005) Urbanization externalities, market potential and spatial sorting of skills and firms. CEPR Discussion Papers 5172.

Hanson G (2005) Market potential, increasing returns, and geographic concentration. *Journal of International Economics*, 67: 1–24.

Hanson G, Xiang C (2004) The home-market effect and bilateral trade patterns. *American Economic Review*, 94: 1108–1129.

Hanson G. (2001) Scale economies and the geographic concentration of industry. *Journal of Economic Geography*, 1:255–276.

Hanson G (1997) Increasing returns, trade, and the regional structure of wages. *Economic Journal*, 107: 113– 133.

Harris CD (1954) The market as a factor in the localization of industry in the United States. *Annals of the Association of American Geographers*, 44: 315– 348.

Hauk WR, Wacziarg R (2004) A Monte Carlo study of growth regressions. Technical working paper 296, National Bureau of Economic Research.

Head K, Ries J (2001) Increasing returns versus national product differentiation as an explanation for the Patterns of U.S. Canada Trade. *American Economic Review*, 91: 858–876.

Head K, Mayer T (2005) Regional wage and employment responses to market potential in the EU. University of Paris I, mimeo.

Head K, Mayer T (2003) The empirics of agglomeration and trade. *Handbook of Regional and Urban Economics*, 4: 2609-2669.

Helpman E (1998) The size of regions. In: Pines, D., Sadka, E., Zilcha, I. (Eds.), Topics in Public Economics. Cambridge University Press, Cambridge, pp. 33– 54.

Juhn C, Murphy KM, Pierce B (1993) Wage inequality and the rise in returns to skill. *Journal of Political Economy*, 101: 410-42.

Kasarda JD (1985) Urban change and minority opportunities, in ‘‘The New Urban Reality” (P. E. Peterson, Ed), The Brookings Institution, Washington, DC.

Katz LF, Summers LH (1989) Industry rents: Evidence and implications, Brookings Papers on Economic Activity- Microeconomics, 1989: 209-290.

Katz F, Murphy KM (1992) Changes in relative wages, 1963-1987: Supply and demand factors. *Quarterly Journal of Economics*, 107: pp.35-78.

Knaap T (2006) Trade, location and wages in the United States. *Regional Science and Urban Economics*, 36: 595–612.

Knight JB, Sabot RH (1983) Educational expansion and the Kuznets effect. *American Economic Review*, 73:1132-1136.

Korpi M (2007) Does size of local labour markets affect wage inequality? A rank-size rule of income distribution. *Journal of Economic Geography*, 24: 1-27

Krugman P, Venables A (1995) Globalization and the inequality of nations. *Quarterly Journal of Economics*, 110: 857–80.

Krugman P (1992) A Dynamic spatial model. National Bureau of Economic Research, Working paper, number 4219.

Krugman P (1991) Increasing returns and economic geography. *Journal of Political Economy*, 99: 483–499.

Krugman P (1980) Scale economies, product differentiation, and the pattern of trade. *American Economic Review*, 70: 950– 959.

Lemieux T (2006) Postsecondary education and increasing wage Inequality. *American Economic Review* (Papers and Proceedings), 96: 195-199.

Levernier W, Partridge M, Rickman D (1998) Differences in metropolitan and non-metropolitan U.S. family income inequality: A cross-country comparison. *Journal of Urban Economics*, 44: 272–290.

Mathur VK (1970) Occupational composition and its determinants: An intercity size class analysis. *Journal of Regional Science*, 10: 81-91.

Mincer J (1997) Changes in wage inequality, 1970-1990. *Research in Labor Economics*, 16: 1-18.

Moretti E (2004) Estimating the social return to higher education: Evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics*, 121: 175-212.

Moro A (2003) The Effect of statistical discrimination on black-white wage inequality: Estimating a Model with multiple equilibria. *International Economic Review*, 44: 467–500.

Ottaviano GIP, Pinelli D (2006) Market potential and productivity: Evidence from Finnish regions. *Regional Science and Urban Economics*, 36: 636–657.

Partridge MD, Rickman DS, Ali K, Olfert MR (2008) Agglomeration spillovers and wage and housing cost gradients across the urban hierarchy. Under review.

Partridge MD (2005) Does income distribution affect U.S. state economic growth? *Journal of Regional Science*, 45: 363-394.

Panizza U (2002) Income inequality and economic growth: Evidence from American data. *Journal of Economic Growth*, 7: 25–41.

Perotti R (1996) Growth, income distribution, and democracy: What the data say. *Journal of Economic Growth*, 2: 149–187.

Pons J, Paluzie E, Tirado DA, Silvestre J (2007) Testing the new economic geography, migrations and industrial agglomerations in Spain. *Journal of Regional Science*, 47: 289-313.

Redding S, Venables A (2004) Economic geography and international inequality. *Journal of International Economics*, 62: 53–82.

Redding S, Schott P K (2003) Distance, skill deepening and development: Will peripheral countries ever get rich? *Journal of Development Economics*, 72: 515- 541.

Teulings CN, Thijs van Rens (2003) Education, growth inequality. CEPR DP 3863 or Tinbergen Institute DP 02-001/3.

Topel RH (1986) Local labor markets. *Journal of Political Economy*, 94, S111-S143 40:150-178.

Wheeler CH (2004) On the distributional aspects of urban growth. *Journal of Urban Economics*, Elsevier, 55: 371-397.

Wilson WJ (1987) The truly disadvantaged: The inner city, the underclass, and public policy. Chicago: University of Chicago Press.

Essay 2: Urban Sprawl: Evidence from a Stochastic Urban Growth Approach.

1. Introduction

The phenomenon of urban sprawl in North America, emerging since the middle of the last century, has spurred a mounting urban economic literature aimed at understanding its underlying causes. Urban sprawl represents an important shift in population distribution and land-use as it reshapes the rural-urban interface, pushing development well out into what were historically rural communities, changing the distribution of economic activities across the urban areas (Glaeser and Khan 2004), and potentially creating environmental degradation.

Urban economists have traditionally used the theory of the static monocentric city to explain the underlying forces behind urban sprawl and the related decrease in population density farther from the central business district (CBD). Specifically, the expansion of urban structure hinges on the trade off between land rent and commuting cost. In equilibrium, this requires lower land rent at the urban fringe to offset the commuting cost to the CBD. The declining rent gradient leads to a decline in the density gradient (often modeled as a constant decline) as distance increases from CBD to the urban fringe (Alonso 1964; Muth 1969; Mills 1967).[1]

Despite its success in reproducing general aspects of urban spatial structure, implications of static models have been criticized by many urban economists. For example, Anas (1978) suggests that the monotonic decline of density away from the CBD occurs only under special conditions such as rising income levels. Moreover, in dynamic models with durable housing and myopic landowners, Anas (1978), Harrison and Kain (1974), and McFarlane (1999) argue that residential

[1] Other research offers a major insight with respect to the rising income (Margo 1992) and declining transportation cost (Glaeser and Khan 2004) and development of infrastructure, such as highways (Baum-Snow 2007) in explaining urban sprawl.

development around the employment center is an incremental process and that density depends on the economic conditions at the time of development.

Yet, generally in dynamic models, it has been conventionally assumed that a risk-neutral developer will choose to invest when the present value of expected cash flows exceeds the cost of development. However, if the future cash flow is uncertain and the investment is durable and irreversible, as in land development, the latter rule of thumb is no longer valid. For example, consider an open urban area experiencing shocks in labor demand, the resulted shocks in population growth and housing demand lead to an uncertain future land/housing rent. Titman (1985), McDonald and Siegel (1986, 1985), and others[2] suggest that under the uncertainty assumption and illiquid durable investment, developers might choose to delay investment. The ability to delay investment (or not to invest at all) has economic value, referred to real options[3].

Cappoza and Helsely (1990) are among the first to explore the relationship between urban spatial structure and uncertainty. Assuming that future rent follows a stochastic pattern, they find that in cities with higher level of uncertainty, developers should delay land development until the rent (usually referred to reservation or hurdle rent) of the built-up land compensates not only for the agricultural land value and conversion cost, as in the case of certain future, but also for the real option value. In their model, the real option value reflects the ability to delay land development awaiting more information on future land prices. As a result of the development delay, Cappoza and Helsely (1990) suggest that the expected city size decreases.

To be able to examine the effect of uncertainty on city size, Capozza and Helsley (1990) assume that the lot size is fixed across urban areas. Capozza and Li (1994) extend the latter work by investigating the interaction between uncertainty and the ability to vary residential capital intensity. Assuming that developers choose the optimum capital intensity and time of development, they find that, under the uncertainty assumption, the ability to vary capital intensity raises the reservation rent and delay the development decision. An important aspect of Capozza and Li's (1994) model is that it is site-specific, and therefore, their model explains the irregular profile of urban density, rather than the typical smooth or exponential pattern as predicted by other static models.

---

[2] See Pindyck (1991) for an extensive review on investment under uncertainty.
[3] Real options are similar to financial options, which give the investor the right but not the obligation to invest at a future point in time contingent on new information.

To this date, urban economists have done little to empirically test the implications of models that relate uncertainty about future land rent to urban spatial structure.[4] The objective of this essay is to address this gap. Specifically, it investigates how uncertainty over future rent explains changes in the extent of U.S. metropolitan sprawl. The importance of this quest derives from the need to understand how urban sprawl responds to an expanding and volatile urban economy. This pursuit is directly related to the livability of urban environment, residence-work commute relationships, and delivering physical infrastructure (roads, schools, sewers, and other public facilities), factors that are central to policy makers and urban planners.

The empirical analysis of this essay is based on a theoretical model that is originally developed by Capozza and Helsley (1990) and Capozza and Li (1994). However, since I seek a theory consistent measure of sprawl that links metropolitan population density to uncertainty, the theoretical model in the following section differs from the latter's work mainly in two ways. First, the model does not include structural capital. Instead, the variation in the overall density (sprawl) across urban areas arises from the variation in lot size. Second, unlike Capozza and Li (1994), I assume that a representative household chooses the optimal lot size through utility maximization behavior. In addition, a representative developer takes the optimal lot size as given and chooses the optimal time of converting the agricultural land to a residential use.

Assuming that the future rent of a developed land evolves in a stochastic fashion and solving for optimal lot size and optimal conversion time, I derive an expression that positively links population density to reservation land rent. As in Capozza and Helsely (1990), the reservation rent is a function of shocks to changes in future rent of developed land, among other factors, reflecting the real option value arises from the ability of delaying land development due to uncertainty. A higher level of uncertainty raises the reservation rent in order to cover the real option value. Since land is a normal good, the increase in the (reservation) land rent would eventually reduce land consumption relative to other goods or services. A reduction in land consumption means that households would, among other things, choose a smaller lot (Skaburskis 2001). Therefore, the theoretical model predicts that urban areas with higher level of uncertainty are expected to be denser (less sprawl).

[4] Most of the related literature on uncertainty (real options) has focused on capital investment (e.g, Caballero and Pindyck 1996; Paddock et al. 1988; Moel and Tufano 2002). Fewer studies have explored linkages between uncertainty and real estate. For example, Holland et al. (2000) examined the effect of price uncertainty on net change on property size.

The econometric analysis of this paper draws upon panel data from U.S. metropolitan areas over 1980-2000 censuses. Consistent with the theoretical model, I construct a distinctive measure for urban sprawl that better captures the over all density and population distribution. Mainly, this sprawl index measures the share of the population that lives in low density block groups within a metropolitan area.[5] Using suitable proxy that account for uncertainty over future land rent, I provide robust evidence confirming the theoretical prediction.

The only empirical study that has tackled the issue of uncertainty and sprawl, I am aware of, is one by Burchfield et al. (2006). Unlike my approach, they define sprawl as the amount of undeveloped land surrounding an average urban dwelling, they find that uncertainty is positively associated with this type of sprawl. Despite the sophisticated GIS technology they use in quantifying the separation of urban land use, their findings are based on using remote sensing data, which is inappropriate to measuring low residential land use (Irwin et al. 2006). A related study is by Cunningham (2006) in which he tests the implication of real options for vacant land price. His findings are consistent with real option theories; a higher level of uncertainty delays the timing of development and increase land prices.

In what follows, Section 2 presents the theoretical model. Section 3, presents the sprawl measure, followed by the empirical model and empirical results in section 4. Section 5 presents sensitivity analysis. Finally, section 6 concludes with some emphasis on some policy implications.

2 Theoretical model

2.1 Household Problem

The theoretical model is consistent with an open city model, where the economic activities are concentrated in its central business district (CBD), a point to which household commute daily. Residential locations are indexed by their distance, z, from the CBD. The cost of commuting is normalized to \$1 per kilometer. Households are identical in terms of taste and income, y, which is assumed, for now, to be exogenous to the size of the city population. Households in each period derive their utility from consuming land (lot) denoted by q, and numéraire non-land goods,

[5] Yet, the sensitivity analysis section of this essay uses different measures of sprawl (also based on population density) to ensure that the uncertainty-sprawl findings are not subject to the specific measure of sprawl developed in this essay.

denoted by m. The price of m is normalized to \$1. The budget constraint of households is given by $m + Rq = y - z$, where R is land rent.

Following Anas (1978), the mobility of urban households, across urban areas, is assumed costless and that an urban area will attain competitive short run equilibrium at every point in time (t), such that:

$$u(m,q,t_1)= u(m,q,t_2)= u(m,q,t_3)=\ldots u(m,q,t_n)= v \tag{1}$$

From the budget constraint the bid rent function can be obtained, which is the maximum rent per lot size that a household can pay for residing at distance z while enjoying a fixed utility level (v). The utility function takes the following Cobb Douglas form: $u = m^a q^b$, where $a > 0$, $b > 0$, and $a+b=1$. The bid rent function at time t is given by:

$$R(z,t) = \max_{q,m}\left[\frac{y(t) - z - m}{q}\right] \tag{2}$$

Subject to:

$$m^a q^b = v \tag{3}$$

The objective of the representative household is to choose the optimal bundle of q^* and m^*, which can be achieved by differentiating equation (2) subject to the utility constrain (equation 3), such that:

$$q^*(t,z) = \phi[y(t) - z]^{\frac{-a}{b}} \tag{4}$$

where the constant $\phi = v^{\frac{1}{b}} a^{\frac{-a}{b}}$, and

$$m^*(t,z) = a[y(t) - z] \tag{5}$$

Substituting q^* and m^* into the bid rent function (equation 2) yields:

$$R^*(t,z) = \theta[y(t) - z]^{\frac{1}{b}} \tag{6}$$

where the constant $\theta=(1-a)/ø$. As explained below, equation (6) is crucial in determining the expected city boundary.

2.2 Developer problem

At the edge of the urban area, agricultural land earns a constant net return R^A. A representative developer considers converting the agricultural land into residential use. The cost of development is c, which by assumption does not depreciate over time. The optimal time of development is t^*, which is specified as $t^*=t+s$ (also known as first hitting time), where s is the stopping time. The development of the agricultural land is irreversible due to prohibitive cost, and once developed the land earns an urban rent ($R(s, z)$). Therefore, the following is the price of agricultural land at location z, conditional on current information at time t is:

$$P^A(t,s,z) = E\{ \int_t^{t^*} R^A(s,z)e^{-r(s-t)}ds + \int_{t^*}^{\infty} R(s,z)e^{-r(s-t)}ds - (R^A - C)e^{-r(t^*-t)} \big| R(t,z)\} \qquad (7)$$

The first term in equation (7) is the net return to agricultural land up to the date of development (t^*). The second term is the net return to the developed land from the date of development. I assume that the representative developer is risk neutral and the discount rate (r) is assumed to be constant across urban areas. Equation (7) is specified under the assumption that the lot size is exogenous to the developer.

Following Capozza and Helsely (1990), the urban rent, R, takes a stochastic pattern. Specifically, it follows a Brownian motion process with a drift g > 0 and variance σ^2, such that at time $t+s$ developed land rent becomes:

$$R(t+s,z) = R(t,z) + gs + \sigma B(s) \qquad (8)$$

Equation (8) implies that the distribution of rent after s periods is equivalent to current time (t) rent plus a drift and a random component evaluated at time s. Substituting equation (8) into equation (7) and integrating by parts, the expected value of the agricultural land is:

$$P_t^A(t,s,z) = \frac{R^A}{r} + E\left\{\left[\frac{R\ (t^*,z)}{r} + \frac{g}{r^2} - \frac{R^A}{r} - C\right]e^{-r(t^*-t)} \big| R(t,z)\right\} \qquad (9)$$

The developer chooses the optimal time t^* of converting the agricultural land into residential use. This occurs when the land development rent (R) reaches the optimal reservation rent R^*. The conversion time t^* is defined as:

$$t^* = \min_S\left[t+s \geq t \big| R(t+s,z) \geq R^*\right] \qquad (10)$$

Form Karlin and Taylor (1975, pp. 361-362), the expected value of the Laplace transformation of t^*, conditional on the initial value of development rent (R) and R^*, is given by:

$$E\left[e^{-r(t^*-t)} \big| R(t,z), R^*\right] = e^{-\alpha[R^*-R(t,z)]} \qquad (11)$$

where $\alpha = [(g^2 + 2\sigma^2 r)^{\frac{1}{2}} - g]/\sigma^2$. Substituting equation (11) into (9) yields:

$$P^A(t,s,z) = \frac{R^A}{r} + E\left\{\left[\frac{R^*}{r} + \frac{g}{r^2} - \frac{R^A}{r} - C\right]e^{-\alpha(R^*-R\ (t,z))} \big| R(t,z)\right\} \qquad (12)$$

The developer chooses R^* that maximizes the land value.[6] Differentiating equation (12) with respect to R^* yields:

$$R^* = R^A + rC + (r - \alpha g)/\alpha r \tag{13}$$

where $(r\text{-}\alpha g) \geq 0$. Equation (13) reveals that the optimal reservation rent is a function of returns to agricultural land (R^A), cost of conversion (c), rate of change in development rent (g), and shocks to change in development rent (σ). The latter is subsumed in the uncertainty term $(r\text{-}\alpha g)/\alpha r$, which, as discussed earlier, reflects the option value arise from delaying the land development due to future rent uncertainty.

2.3 Density and land value

The expected average population density at time t can be written as:

$$D^*(t) = \left[\frac{N(t)^*}{L(z^*)}\right] \tag{14}$$

where $L(z^*)$ is the expected city size and z^* is the expected boundary of the city. N^* is the expected total population, which is given by:

$$N^*(t) = \int_{z=0}^{z=z^*} \frac{L(z)}{q^*(y - z)} \tag{15}$$

Equation (15) states that all households should fit inside the city boundary. The only unknown variable in the density function (equation 15), is z^*. From equation (13), z^* occurs where $R = R^*$. Using equation (6), the expected urban boundary can be written as:

$$z^*(t) = y(t) - \left(\frac{R^*}{\theta}\right)^b \tag{16}$$

Substituting equation (16) and equation (4) into equation (15) and solving for the integral, the expected population density (equation 14) becomes:

$$D^*(t) = \phi^{a-1}\left(\frac{1}{1-a}\right)^a (R^*)^a \tag{17}$$

Substituting the reservation rent function (equation 13), into equation (17) yields:

$$D^*(t) = \phi^{a-1}\left(\frac{1}{1-a}\right)^a \left(R^A + rC + (r - \alpha g)/\alpha r\right)^a \tag{18}$$

Equation (18) states that the expected population density is a function of the equilibrium reservation rent, which is, as mentioned above, a function of returns to agricultural land (R^A), cost

[6] All land within the urban boundary is assumed to be developed. In other words, Agricultural land does not separate residential lots.

of conversion (c), rate of change in land development rent (g), and shocks to changes in land development rent (σ).

Undertaking a comparative static analysis of equation (18) reveals that the expected population density is increasing in the reservation rent components (R^*). As in static models, all else equal, an increase in the agricultural rent or an increase in the conversion cost raises the reservation rent. An increase in the value of σ delays developing the agricultural land, leading to a higher option value and thus increasing the reservation rent. Moreover, an increase in the value of g also implies a higher future returns to developed land, thus increasing reservation rent.[7] However, the lot size is the mechanism through which an increase in the reservation rent leads to a higher population density. Consistent with normal goods theory, households would react to increases in land rent by reducing land consumption in the form of smaller lot size (Skaburskis 2001). This can be seen mathematically by substituting the equilibrium boundary expression (equation 16) into the optimum lot size (equation 4), such that:

$$q^*(t,z) = \phi\left[\frac{R^*}{\theta}\right]^{-a} \tag{19}$$

$$\frac{\partial q^*}{\partial R^*} < 0 \tag{20}$$

Undoubtedly, a higher density corresponds to a lower sprawl. Therefore, a higher values R^A, C, σ, and g are expected to impact sprawl negatively. Testing this prediction is conducted in the empirical analysis below.

3. Empirical Model and Data

3.1 Measuring Urban Sprawl

Urban sprawl can take different forms. It may involve low density development, clustering of population and economic activities at the urban fringe (edge cities), separation of land use, also known as leapfrog development (Nechyba and Walsh 2004). Although there have been several attempts to develop measures of sprawl,[8] researchers have mainly focused on population density as a measure of sprawl. Density has been used widely because of its intuitive appeal and the

[7] A thorough discussion on the derivation of σ and g, is available from Capozza and Helsely (1990) and Capozza and Li (1994)

[8] Using Geographic Information Systems (GIS) and field surveys, Galster et al. (2000) devise eight measures that capture many dimensions of sprawl: density; continuity; concentration; compactness; centrality; nuclearity; diversity; and proximity.

difficulty and cost burden of obtaining data on alterative measures that require high technology such as geographical information system (GIS)[9] (Lopez and Hynes 2003). Moreover, higher density development is seen, by many sprawl critics, as an antidote to many unwanted aspects of U.S. urban structure that accompany sprawl, such as infill land, loss of open space and rural agriculture.

Typically, metropolitan population density has been defined as the total metropolitan population divided by total metropolitan land. A major drawback of this measure is that large areas of counties contained the metropolitan areas are rural. This leads to an upward bias in measuring sprawl (Lang 2003). Alternatively, other researchers (e.g. Fulton et al. 2001) use smaller geographic bases, namely, the census urbanized areas.[10] However, the latter measure excludes a relatively large area of 'developed' land at the urban fringe leading to a downward bias in the sprawl measure (Cutsinger et al. 2005). Moreover, measuring population density using urbanized areas can not be used in the panel setting of this essay since the boundaries of the urbanized areas are not consistent over time.[11]

Another important concern of using such aggregate measures of sprawl is that they do not incorporate the distribution aspect of population within an urban area. That is there is no distinction between metropolitan areas where population is scattered or evenly distributed and those with population highly concentrated.[12] In this essay I construct a sprawl index that incorporates both density and concentration aspect of the metropolitan sprawl using a sufficiently disaggregated scale, specifically, census block groups. Census block group is an area comprising a group of co-located census blocks that contain between 600 and 3,000 people, with an optimum size of 1,500 people. Using block groups ensures that fine differences in the distribution of population density can be identified.

Metropolitan sprawl is measured as:

$$Sprawl = (((L\% - H\%) + 1)) * 0.5 \tag{21}$$

[9] Example of studies that used GIS technology is: Burchfield et al. (2006) and Irwin et al. (2006).
[10] Census urbanized area is densely settled territory that consist of core census block groups or blocks that have a population density of at least 1,000 people per square mile and surrounding census blocks that have an overall density of at least 500 people per square mile. See below the definition of census block group.
[11] For a thorough discussion on differences between 1990 and 2000 census urbanized areas see http://www.census.gov/geo/www/ua/uac2k_90.html.
[12] Consider two identical MSAs in terms of area and population, the one with concentrated population sprawls less than that with scattered population.

L% is the share of metropolitan population living in a block group with density *below* the overall U.S. metropolitan median.
H% is the share of metropolitan population living in a block group with density *above* the overall U.S. metropolitan median.

The sprawl measure, equation (21) is an index, which ranges between 0 and 1. Closer to 1 represents a greater sprawl. The population density of each census block is calculated by dividing its population by its land, measured in square mile. For each metropolitan area, block groups are sorted and aggregated into high density (above the U.S. metropolitan block group median) and low density (below the U.S. metropolitan block group median). A metropolitan area with high percentage of its population living in block groups with density below the median suggests more low-density-sprawl compared to those with density above median.[13]

To account for rural clusters in metropolitan areas, I exclude all block groups with density below 200 persons per square mile. This cut-off corresponds to one residential unit per eight acres—about the lowest residential density of many new exurban housing developments. The source of census block group data is from Geolytics Census data base (www.geolytics.com), which provides consistent census block group data for 1980, 1990, and 2000 using 2000 census boundaries.[14]

Lopez and Hynes (2003) use similar measure of sprawl, but use fixed density cut offs (high density corresponds to greater than 3,500 persons per square mile, while low density lies between 3,500 and 200 persons per square mile). A concern with their choice of high and low density cut off is that it is relatively random and does not base on a solid reference, and thus can not be used for international comparisons.

Using the sprawl index (equation 21), the remaining of this section provides a descriptive analysis of sprawl across U.S. metropolitan areas between 1980-2000 censuses. Column (1) in table (2.1) reports the median sprawl index across all metropolitan areas included in the sample. The results

[13] In measuring the degree of sprawl, Glaeser and Khan (2001) consider the density at which average city citizen live. The correlation between the sprawl index (equation 21) and Glaeser and Khan's is -0.60, -0.61, and -0.60 for the 1980, 1990, and 2000 Censuses, respectively. The later measure is specified as: $\sum(N_i/N)/(N_i/A_i)$, where N_i and A_i are the total population and area of a metropolitan block group. Moreover, the correlation between the sprawl index and population density is -0.66, -0.7, and -0.69 for the same censuses, respectively.
[14] Due to data limitation, I use 2000 census boundary definition instead of 1990 or 1980's definitions. An advantage of using the former definition is that I am able to consider the entire settlement patterns up to 2000.

reveal that by 1980, the sprawl index for a median metropolitan area is 0.665 indicating that two third of the metropolitan population lived in a block group density below the median.[15] Consistent with previous research (e.g. Nechyba and Walsh 2004) sprawl continues to grow over time. That is between 1980 and 2000, sprawl for a median metropolitan area has expanded by 8 percent.[16]

Table 2.1: Region of U.S. Metropolitan Areas and Extent of Sprawl Over Time

Year	Whole Metropolitan U.S. (1)	Northeast (2)	Midwest (3)	South (4)	West (5)
1980	0.665	0.653*	0.611*	0.785*	0.595*
1990	0.684	0.677	0.644	0.826	0.532
2000	0.720	0.705	0.694	0.861	0.539
# of MAs	328	57	80	126	65

* indicates the median sprawl index of the respective regions.

Focusing only on the median sprawl might mask substantial spatial sprawl differences. Indeed, as shown in columns (2)-(5), the spatial distribution of sprawl is not uniform. Southern metropolitan areas sprawled the most, while those in the west sprawled the least. Over time, the level of sprawl has risen for all regions except in the west, which experienced a decreasing sprawl over the 1980s but relatively stabled over the 1990s. Interestingly, the size of metropolitan areas is greatly associated with the degree of Sprawl. Column (2)-(4) in table (2.3) divide metropolitan areas into: small (population less than 350,000), medium (population between 350,000 and 1,000,000), and large (population larger than 1,000,000), respectively. The results show that sprawl decreases as we move up the urban hierarchy. In sum, the results show that while the median metropolitan area is sprawling over time, there is a significant variation over size and regions.

Table 2.2: Size of U.S. Metropolitan Areas and Extent of Sprawl Over Time

Year	Whole U.S. -1-	Small -2-	Medium -3-	Large -4-
1980	0.665	0.716**	0.578**	0.437**
1990	0.684	0.738	0.615	0.429
2000	0.720	0.777	0.663	0.467

** indicates the median sprawl index of the respective metropolitan sizes.

[15] For the censuses 1980, 1990, and 2000, the median U.S. density for metropolitan block group is 4161, 4358, and 4367, respectively.

[16] This finding contradicts that of Burchfield et al. (2006) who argue that the amount of residential sprawl remained constant between 1976 and1992. As referred earlier, their results are based on remote sensor data, which is inappropriate for measuring low density development (Irwin et al. 2006).

3.2 Empirical Model

The sections below discuss the empirical estimation of the density expression[17] (equation 18), which, as derived above, is a function of return to agricultural land (R^A), cost of conversion (c), rate of change in land development rent (g), and shocks to change in land development rent (σ). However, before thoroughly discussing the empirical model, I shed light on several empirical issues.

The first one relates to the estimation method. This essay directly addresses an important policy question; how changes in the expectation of economic activities (future uncertainty) within a given metropolitan area affect changes in the extent of urban sprawl of that metropolitan area. To directly estimate this relationship, I use fixed effects panel estimation (FE). Another important aspect of FE model is that it controls for differences in time-invariant metropolitan characteristics that are likely to affect sprawl, but assumed fixed across metropolitan areas in the theoretical model. Examples of such fixed characteristics are topographical and other geographical characteristics[18] (Burchfield et al. 2006), zoning policies (Fischel 1985), and natural amenity (JunJie 2001; Brueckner et al. 1999). Therefore, any bias resulting from the correlation of those characteristics and the urban sprawl will be removed.

The second estimation issue concerns the conversion cost. I am not aware of any data that estimate the cost of converting agricultural land into residential use at a metropolitan level. However, since conversion cost is associated with the land topography and other city specific factors, such as soil quality (Irwin and Bockstael 2004), differences in conversion costs across metropolitan areas will be controlled for in the FE model.

Thirdly, in the empirical model, I control for other time variant economic and social variables that are not addressed in the theoretical model but other research has shown to be influential in explaining urban sprawl. Doing so would ensure that the uncertainty measure does not confound other effects. Yet, this might come at the expense of introducing multicollinearity. Therefore, the

[17] Although previous section discusses the differences of urban sprawl across space and size, explaining such differences is beyond the scope of this paper and left for future research.
[18] Burchfield et al. (2006) provide evidence that physical geography (natural barriers, ground water, terrain ruggedness) and climate explain 23.5 percent of the variation of sparse development across U.S metropolitan areas.

sensitivity analysis section undertakes robustness checks in which estimates of more parsimonious models are reported (Perotti 1996; Panizza 2002). Finally, to mitigate any direct endogeneity, the explanatory variables are measured at a period prior to that of the dependent variable.[19]

The empirical model is specified as follows:

$$\begin{aligned} sprawl_{it} &= \beta_1 avepop_{it-1} + \beta_2 stdpop_{it-1} + \beta_3 \log Income_{it-1} + \beta_4 Gini_{it-1} \\ &+ B_5 Blackcentral_{it-1} + \beta_6 Povertycentral_{it-1} + B_7 undevelopedland_{it-1} + \varphi_i + \mu_{t+} e_{it} \end{aligned} \qquad (23)$$

The unit of observation is the Metropolitan Statistical Area (MSA) and Primary Metropolitan Statistical Area (PMSA). In order to conduct the analysis on consistent boundaries, all variables are aggregated using 2000 census definition. The dependent variable is measured as specified in equation (21) for 1980, 1990, and 2000.

To assign suitable proxies for the rate of changes and shocks to changes in future land development rent (g_i and σ_i), respectively), land developers are assumed to form their expectations regarding future development rent based on *past* changes. Moreover, we need to account for differences in the expectation of development rent across metropolitan areas. Many of these differences are subsumed in the expected population growth. Therefore, the *average annual change of MA population* ($avepop_{it-1}$) is used to proxy for g_i, measured between 1969-1975, 1969-1985, and 1969-1995. Moreover, the *standard deviation of annual change*[20] *of MA population* ($stdpop_{it-1}$) is used to proxy for σ_i for the same periods.

Urban population is endogenously determined in the theoretical model. Empirically, I assume that past population changes is associated with future development rent. However, lagging ($avepop_{it-1}$) and ($stdpop_{it-1}$) five years[21] would ensure that any direct endogeneity is mitigated. The data on population changes are constructed from the U.S. Department of Commerce's Regional Economic Information System (REIS).[22]

[19] Unless specified, the explanatory variables are measured at the initial period (1970, 1980, and 1990).
[20] In constructing the proxies for g_i and σ_i Plantinga et al. (2002) use changes in population density. I can not use their proxies due to simultaneity problem.
[21] The earliest data on estimated annual population is 1969. In order to utilize as much historical data, $avepop_{it-1}$ and $stdpop_{it-1}$ are lagged for only 5 years.
[22]Since REIS produces data at a county level, all REIS data used in this essay are aggregated over all counties that belong to the same metropolitan area using 2000 census definition. The same thing holds for other explanatory variables derived from County Data Book.

Regarding the control variables, $logincome_{it-1}$ is added to control for the income effect. Previous literature has emphasized the effect of income level on the extent of sprawl and urban structure (e.g. Margo 1992; Brueckner and Fansler 1983; Anas 1978; Ottensmann, 1977). A higher level of income makes it affordable for people to buy more space, and thus richer metropolitan areas are expected to have a higher level of sprawl. However, the effect of income might not be as clear since higher income is positively correlated with land value which leads to a higher density (less sprawl). Further more, Gini coefficient ($Gini_{it-1}$) is included to control for income inequality effects. The source of income data is from County Data Book.

Many urban economists suggest that urban sprawl is affected by other factors including ethnic segregation, crime rate and other local public finance considerations (Tiebout 1956).[23] Although Tiebout's theory has gained a theoretical ground, evidence of the relative importance of social city problems in explaining urban sprawl is mixed. For example, Sigleman and Heing (2001) suggest that rising crime rates contribute significantly to the depopulation of inner cities. Yet, Mills and Price (1984) conclude that among the inner city social problems, only racial tension contributed to the decline of population and employment density gradient. Yet, Cutler et al. (1999) find no evidence of the link between racial segregation and density. The aforementioned mixed results suggest that further research is needed before we fully understand the relationship between inner city problems and urban sprawl.

To control for racial segregation, the share of black in central cities $centralBlack_{it-1}$ is included. Also, central city poverty rate ($centralpoverty_{it-1}$) is added to control for inner city socioeconomic conditions. A higher poverty rate in central cities over-burdens city government, leading to high taxes and/or deterioration of inner city public service, which might encourage flight to low dense suburbs (Jordan et al. 1998). The source of data on poverty and share of black in central cities are derived from the County Data Book.

Panel data on agricultural rent is not readily available at a metropolitan level. As a proxy I use the ratio of undeveloped to developed land,[24] $undevelopedland_{it-1}$. *Ceteris paribus,* a metropolitan area with a higher supply of undeveloped land is expected to have a lower price of agricultural

[23] Tiebout's theory (1956) suggests that people may sort themselves into different local jurisdiction based on their willing to pay for provision of public goods and their taste of local public amenities.
[24] Descriptive statistics of all variables are listed in table B in appendix II.

land (lower agricultural rent)[25] and thus is expected to sprawl more. Data on developed/undeveloped land, measured in 1982, 1987, and 1997, is derived from National Resource Inventory (NRI).[26] Finally, φ_i controls for metropolitan fixed effects. μ_t is period dummies, which control for time-varying effects that are not captured by the explanatory variables included in the FE model. Examples of such time-varying effects are changes in mortgage rates and national spending on public infrastructure.[27]

4. Empirical Results

Most of the empirical discussion will be focused on the sprawl-uncertainty relationship, though other notable results are pointed out. A potential estimation concern is that the residuals could be spatially correlated, which would negatively bias the standard errors. To correct for this problem, the empirical model is estimated assuming that the residuals are correlated within a particular geographical cluster, but uncorrelated across clusters.[28] The advantage of using the clustering approach is that it does not impose restrictions on the spatial correlation of the residuals within clusters. This is unlike other spatial econometric models that use more restrictive assumptions, such as, distance or adjacency weight matrix.

Column (1) in table (2.3) presents the estimates of the base model,[29] which is more fully specified to account for uncertainty and other economic and demographic variables. Confirming the prediction of the theoretical model, the results reveal that metropolitan areas with higher level of uncertainty sprawl less. The coefficient of $stdpop_{it\text{-}1}$ is negative and highly significant at the 1% level. This finding suggests that increasing the standard deviation of population change by one standard deviation decreases the extent of sprawl by 9.5 percentage points. The same result is obtained with regard to the expectation of annual change of metropolitan population. The

---

[25] I assume that all undeveloped land is agricultural. However, rent (price) of agricultural land might be affected by other factors, such as, the topography and the type of soil. These factors are controlled for in the FE model.

[26] According to NRI definition developed land is "A combination of land cover/use categories, Large urban and built-up areas, Small built-up areas*, and* Rural transportation land". Undeveloped land includes: crop land cultivated, crop land non-cultivated, pasture land, range land, forest land, minor land cover use rural transportation (roads and railways),. http://www.nrcs.usda.gov/TECHNICAL/NRI/2002/glossary.html. Like REIS data, NRI produces data at a county level. Therefore, developed and undeveloped land data is aggregated over all counties that belong to the same metropolitan area.

[27] Baum (2007) provides evidence that construction of new limited access highways has significantly contributed to suburbanization; a cross central city highway reduces the core city's population by 20 percent.

[28] The clusters used in the empirical model are BEA economic areas, which consist of one or more economic nodes that reflect regional centers of economic activities. The sample consists of 157 BEA economic areas. I used Stata cluster command for the estimation. For more information on the definition of BEA economic area visit http://www.bea.gov/regional/docs/econlist.cfm.

[29] All tables are reported in appendix II.

coefficient of *avepop*$_{it-1}$ is negative and highly significant at the 5% level. Increasing the average of population change by one standard deviation, decrease the extent of sprawl by 8.5 percentage points. Also, as predicted, a lower agricultural rent (measured using the share of undeveloped land) is positively associated with urban sprawl; the coefficient of *undeveloped*$_{it-1}$ is positive and highly significant at the 1% level.

With regard to the results of the other variables, consistent with Mills and Price (1984), racial segregation is found to have a large impact on urban sprawl. One standard deviation increase in *blackcentral*$_{it-1}$ is associated with 20 percentage point increase in the level of urban sprawl. In addition, richer metropolitan areas are likely to sprawl more (Brueckner and Fansler 1982; Margo 1992). T he coefficient of *logpercapita*$_{it-1}$ is positive and highly significant at the 5% level. In addition, the Gini coefficient is positive and significant at the 1% level. This suggests that as income dispersion increases, the rich are more likely to segregate and locate in a rich and low density areas leading to greater extent of sprawl.

The poverty rate in central cities is not influential in explaining urban sprawl. The coefficient of *centralpoverty*$_{it-1}$ is positive but not significant. To check if the insignificance of *centralpoverty*$_{it-1}$ is a product of a possible collinearity with other social or economic variables, I undertake several sensitivity analyses. For example, I estimate the base model excluding *blackcentral*$_{it-1}$. In another specification, I include only *centralpoverty*$_{it-1}$. Regardless, the latter effect is insignificant.

5. Sensitivity Analysis.

This section assesses whether the negative relationship between uncertainty and urban sprawl reported in the previous section is robust. To save space, the sensitivity analysis discussion will mostly be limited to uncertainty (*stdpop*$_{it-1}$) results. The first sensitivity analysis concerns the extent to which the results are driven by the specification of the base model. Therefore, I report estimates of more parsimonious models to check if collinearity is a driving factor. The second concerns the measurement of sprawl. Specifically, I investigate whether the results obtained are specific to the measure of sprawl proposed above. The last sensitivity analysis estimates the base and other parsimonious models using random effects as alternative panel estimation.

The results of the following parsimonious models are reported in table (2.3), column (2)-(4). First, column (2) includes only *avepop*$_{it-1}$, *stdpop*$_{it-1}$, and period dummies. Second, column (3) includes the base model omitting the soci-economic variables, $blackcentral_{it\text{-}1}$ and $centralpoverty_{it\text{-}1}$. Fourth, column (4) reports the base model omitting the other economic variables, $logpercapi_{it\text{-}1}$ and $Gini_{it\text{-}1}$. Regardless, the findings are robust; the coefficient of $stdpop_{it\text{-}1}$ is positive and significant at least at the 5% level across all the specifications. The other robustness check is related to the collinearity between $avepop_{it\text{-}1}$ and $stdpop_{it\text{-}1}$. One might argue that metropolitan areas with higher rate of population change are more likely to have a greater variation of population change (greater standard deviation). Indeed, the collinearity between $avepop_{it\text{-}1}$ and $stdpop_{it\text{-}1}$ is 0.5. To investigate if this is a real concern, I re-estimate the same models reported in table (2.3) excluding $avepop_{it\text{-}1}$. Reported in table (2.4), the results show that the negative uncertainty-sprawl relationship is robust.[30]

Measuring sprawl using the sprawl index (equation 21) is superior to other measures that use aggregate population density. That is because, as explained earlier, the former controls for overall density and intra-metropolitan distribution of population, using cut off density extrapolated from the data sample. However, to check if the uncertainty/sprawl relationship is not a produce of the specifications of this sprawl index, I undertake two sensitivity checks. Firstly, I use a more conservative cut off density than the median. Specifically, I use the 25th percentile of the overall metropolitan block group density[31]. Table (2.5) reports the results where the base model along with the other parsimonious models (reported in table 2.3) are re-estimated using the latter measure of sprawl as the dependent variable. The results show that the uncertainty-sprawl relationship is robust[32]; the coefficient of $stdpop_{it\text{-}1}$ is negative and statistically significant at least at the 10 % level across all specifications. The same results are also obtained with regard to the expectations of the annual change of metropolitan population, $avepop_{it\text{-}1}$.

Secondly, I use a different measure of sprawl, calculated as metropolitan population over metropolitan land, as initially specified in the theoretical model. Like the above sprawl index, I correct for rural clusters within metropolitan areas. Since density is negatively correlated with sprawl, the former is expected to be higher in metropolitan areas with higher level of uncertainty.

---

[30] I re-estimated the models reported in table (2.3) without including $stdpop_{it\text{-}1}$. Unreported, the $avepop_{it\text{-}1}$ estimate is robust.

[31] This implies that a metropolitan area with high percentage of its population living in block groups with density below the 25th percentile would have more low-density sprawl compared to those with block group density above the 25th percentile. For the censuses 1980, 1990, and 2000, the 25th percentile of the overall metropolitan block groups is 1641, 1835, and 1931, respectively.

[32] Unreported, the uncertainty-sprawl relationship is also robust when excluding $avepop_{it\text{-}1}$.

Indeed, as reported in table (2.6), the coefficient of $stdpop_{it\text{-}1}$ is positive and significant at least at the 10% level across all specifications.[33]

The final sensitivity test in this section is estimating the empirical models using alternative panel estimation, specifically, random effects. The major difference between random and fixed effects is in the information utilized in estimating the coefficients. While fixed effects estimates reflects within metropolitan changes over time, random effects is more efficient since it incorporates information across metropolitan areas and over time (Forbes 2000). Yet, the major assumption of random effects is that the estimates are consistent only if metropolitan-fixed effects are uncorrelated with other explanatory variables. As reported in table (2.7), the coefficient of $stdpop_{it\text{-}1}$ is highly significant at the 1% level. The main difference between the results of random effects model and those of the FE models is that in the former, the effects of income and income inequality are statistically insignificant.

6. Conclusion

This paper investigates how urban sprawl responds to an expanding and volatile urban economy. In doing so, I modify the theoretical work of Capozza and Helsley (1990) and Capozza and Li (1994). Specifically, I assume that changes in population density across urban areas are due to changes in the lot size. Secondly, I assume that households choose the optimal lot size, while developers take lot size as given and choose the optimal time of land development. I derive a theoretical expression that links population density (sprawl) to uncertainty over future land development rent, among other factors. The major prediction of the theoretical model is that an urban area with higher levels of uncertainty is expected to have higher density (less sprawl).

The empirical analysis draws upon panel data from U.S. metropolitan areas over 1980-2000 censuses. Consistent with the theoretical model, I construct a distinctive sprawl index that better captures the overall density and population distribution. In constructing the index I use a sufficiently disaggregated scale data, so that fine differences in the distribution of population density can be identified. Moreover, the sprawl index uses a cut off density extrapolated from the data sample, distinguishing between high and low dense areas. Particularly, I utilize the median of the overall U.S. metropolitan block group density. A metropolitan area with high percentage of

[33] In unreported model, I also estimate the density models with $avepop_{it\text{-}1}$ excluded; the coefficient of $stdpop_{it\text{-}1}$ is positive and highly significant at 1% level.

it population living in block groups with density below the median is designated to have a greater sprawl than those with density above the median.

This essay shows that urban sprawl can be affected by factors other than those derived from static and dynamic models with prefect future foresight. Consistent with the theoretical prediction, I provide evidence that the extent of metropolitan low density-sprawl is negatively influenced by uncertainty regarding land development rent. As a proxy for uncertainty, I use the standard deviation of past annual metropolitan population change.

An important implication of this essay is that it would be inappropriate to address urban planning policies in isolation from the underlying economic volatility of urban areas. That is, consider two identical urban areas, the one with greater uncertainty sprawls less and therefore requires different urban planning package. For urban planners and policy makers, appropriate recognition of the role of uncertainty regarding economic growth will improve their ability to deliver efficient growth management of urban areas and reduce costs of servicing residential development. Failing to recognize the role of uncertainty is likely to result an inefficient provision of physical infrastructure, including roads, schools, sewers, and other public facilities. This will, in turn compromise the livability of urban environment and residence-work commute relationship.

Appendix II

Table B: Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
2000					
Sprawl index (median cut of density)	328	0.703	0.196	0.028	1
Sprawl index (25th percentile cut of density)	328	0.419	0.184	0.017	1
Overall density (population/area)	328	1473.72	1219.72	276.84	16156.12
Avepop	320	6484.75	11967.13	-10664	80734.8
Stdpop	319	4792.51	7704.54	298.40	70922.49
log per capita income	319	9.79	0.175	9.14	10.34
Gini	318	0.407	0.029	0.336	0.508
Black share in central cities	316	0.108	0.106	0.000	0.502
share of undeveloped land	316	16.05	46.94	0.415	778.34
poverty rate in central cities	316	0.131	0.049	0.000	0.411
1990					
Sprawl index (median cut of density)	328	0.676	0.194	0.030	1
Sprawl index (25th percentile cut of density)	328	0.380	0.174	0.013	1
Overall density (population/area)	328	1513.37	1128.88	280.23	14657.04
Avepop	320	5696.56	11307.40	-33287.10	83314
Stdpop	319	4417.35	6961.41	313.56	73959.45
log per capita income	317	9.15	0.240	6.95	9.70
Gini	318	0.442263	0.039	0.370	0.637
Black share in central cities	316	0.10235	0.103	0.000	0.439
share of undeveloped land	316	19.67	65.71	0.483	1120.05
poverty rate in central cities	316	0.118453	0.041621	0.000	0.346
1980					
Sprawl index (median cut of density)	328	0.669	0.181	0.031	1
Sprawl index (25th percentile cut of density)	328	0.348	0.168	0.011	1
Overall density (population/area)	328	1517.00	1175.59	340.21	16410.04
Avepop	320	5586.01	10243.11	-56457.20	65251.67
Stdpop	319	4461.50	6801.22	215.58	76681.16
log per capita income	319	8.23	0.170	7.57	8.73
Gini	317	0.324	0.030	0.257	0.459
Black share in central cities	316	0.094	0.098	0.000	0.415
share of undeveloped land	316	28.277	108.052	0.5	1798.21
poverty rate in central cities	316	0.135	0.061	0.000	0.486

Table 2.3: Uncertainty–Sprawl Fixed Effects Model

	Base Model	Parsimonious Models		
Variable	**-1-**	**-2-**	**-3-**	**-4-**
Stdpop	-5.44E-06	-4.99E-06	-5.05E-06	-5.10E-06
	(-5.75)*	(-5.67)	(-5.69)	(-5.52)
Avepop	-1.03E-06	-1.00E-06	-1.00E-06	-1.10E-06
	(-1.86)	(-1.91)	(-1.87)	(-2.04)
log percapita income	-0.04		-0.016	
	(-1.09)		(-1.19)	
Gini	0.033		0.035	
	(0.36)		(0.41)	
Black share in central cities	0.47			0.46
	(4.09)			(3.81)
poverty rate in central cities	-0.08			-0.026
	(-0.85)			(-0.31)
share of undeveloped land	0.00011		0.00012	0.00011
	(3.59)		(3.81)	(3.55)
period dummies	Y	Y	Y	Y
Constant	(0.97)	0.69	0.80	0.65
	3.13	(47.65)	(7.31)	(31.95)
N	939	957	945	939

***** Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.

****** The number of observations varies across the different models due to missing data for some explanatory variables.

Table 2.4: Uncertainty-Sprawl Fixed Effects Model (Excluding *avepop*)

Variable	**-1-**	**-2-**	**-3-**	**-4-**
Stdpop	-3.79E-06	-3.98E-06	-3.90E-06	-3.77E-06
	(-4.94)*	(-4.96)	(-5.04)	(-4.38)
log per capita income	0.07		0.02	
	(2.18)		(1.12)	
Gini	0.21		0.16	
	(2.38)		1.88	
Black share in central cities	0.38			0.36
	(2.44)			(2.13)
poverty rate in central cities	0.04			-0.07
	(0.36)			(-0.77)
share of undeveloped land	(0.00012)		0.00014	0.00012
	(3.39)		(3.6)	(3.29)
period dummies	Y	Y	Y	Y
Constant	-0.019	0.68	0.50	0.65
	(-0.07)	(116.15)	(4.43)	)38.5)
N**	939	957	945	939

***** Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.

****** The number of observations varies across the different models due to missing data for some explanatory variables.

Table 2.5: Uncertainty–Sprawl Fixed Effects Model (25th Percentile Cut-Off Density)

	Base Model	Parsimonious Models		
Variable†	**-1-**	**-2-**	**-3-**	**-4-**
Stdpop	-9.34E-07	-1.61E-06	-1.23E-06	-9.88E-07
	(-1.94)*	(-3.41)	(-2.69)	(-1.95)
Avepop	-1.67E-06	-1.28E-06	-1.51E-06	-1.59E-06
	(-3.16)	(-2.82)	(-3.27)	(-3.12)
log per capita income	0.04		0.03	
	(1.04)		(1.67)	
Gini	0.31		0.26	
	(3.22)		(2.58)	
Black share in central cities	0.41			0.38
	(2.43)			(2.06)
poverty rate in central cities	-0.18			-0.24
	(-1.25)			(-2.14)
share of undeveloped land	7.46E-05		9.31E-05	7.14E-05
	(3.08)		(4.49)	(2.3)
period dummies	Y	Y	Y	Y
constant	-0.10	0.35	0.048	0.34
	(-0.31)	(111.85)	(0.36)	(17.84)
N**	939	957	945	939

† Sprawl index is measured using 25th percentile of the overall metropolitan block group density.
***** Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.
****** The number of observations varies across the different models due to missing data for some explanatory variables.

Table 2.6: Uncertainty-Sprawl Fixed Effects Model (Overall Population Density)

	Base Model	Parsimonious Models		
Variable†	**-1-**	**-2-**	**-3-**	**-4-**
Stdpop	0.005	0.0076	0.0063	0.0055
	(1.77)*	(2.45)	(2.23)	(1.72)
Avepop	0.007	0.0055	0.0064	0.0067
	(3.71)	(2.63)	(3.68)	(3.75)
log percapita income	-105.08		-50.34	
	(-0.58)		(-0.9)	
Gini	-1436.56		-1238.9	
	(-2.96)		(-2.48)	
Black share in central cities	-1448			-1280.15
	(-3.85)			(-3.1)
poverty rate in central cities	168.8			332.3
	(0.32)			(0.74)
share of undeveloped land	-0.16		-0.22	-0.14
	(-1.19)		(-1.71)	(-0.81)
period dummies	Y	Y	Y	Y
Constant	2926.5	1478.9	2295.8	1559.8
	(1.98)	(86.46)	(4.8)	(26.12)
N	939	957	945	939

† Dependent variable is measured as an over all metropolitan density.
***** Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.
****** The number of observations varies across the different models due to missing data for some explanatory variables.

Table 2.7: Uncertainty-Sprawl Random Effects Model

	Base Model	Parsimonious Models		
Variable	**-1-**	**-2-**	**-3-**	**-4-**
Stdpop	-5.44E-06	-4.99E-06	-5.05E-06	-5.10E-06
	(-5.75)*	(-5.67)	(-5.69)	(-5.52)
Avepop	-1.03E-06	-1.00E-06	-1.00E-06	-1.10E-06
	(-1.86)	(-1.91)	(-1.87)	(-2.04)
log per capita income	-0.04		-0.016	
	(-1.09)		(-1.19)	
Gini	0.03		0.03	
	(0.36)		(0.41)	
Black share in central cities	0.47			0.46
	(4.09)			(3.81)
poverty rate in central cities	-0.08			(-0.02)
	(-0.85)			(-0.31)
share of undeveloped land	0.00012		0.00012	0.00011
	(3.59)		(3.81)	(3.55)
period dummies	Y	Y	Y	Y
Constant	0.97	0.69	0.80	0.65
	(3.13)	(47.65)	(7.31)	(31.95)
N**	939	957	945	939

***** Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.

****** The number of observations varies across the different models due to missing data for some explanatory variables.

References

Alonso W (1964) Location and land use. Cambridge. Harvard University Press.

Anas A (1978) Dynamics of urban residential growth. *Journal of Urban Economics*, 5: 66 -87.

Anselin L (1988) Spatial Econometrics: Methods and Models (Studies in Operational Regional Science). Kluwer Academic Publishers.

Baum-Snow N (2007) Did highways cause suburbanization? *Quarterly Journal of Economics*, 122: 775-805.

Burchfield M, Overman H, Puga, D, Turner M. (2006) Causes of sprawl: A portrait from space. *Quarterly Journal of Economics*, 121: 587-633.

Brueckner JK, Fansler DA (1983) The Economics of urban sprawl: Theory and evidence on the spatial size of cities. *The Review of Economics and Statistics*, 65: 479-482.

Brueckner JK, Thisse JF, Zenou Y (1999) Why is central Paris rich and downtown Detroit poor?: An amenity-based theory. *European Economic Review*, Elsevier, 43: 91-107.

Caballero RJ, Pindyck RS (1996) Uncertainty, investment, and industry evolution, *International Economic Review*, 37: 641–662.

Capozza DR, Helsley RW (1989) The Fundamentals of land prices and urban growth. *Journal of Urban Economics*, 26: 295-206,

Capozza DR and Helsley RW (1990) The stochastic city. *Journal of Urban Economics*, 28: 187-203.

Capozza DR, Yuming Li. (1994) The intensity and timing of investment: The case of land. *American Economic Review*, 84: 889-904.

Cunningham CR (2006) House price uncertainty, timing of development, and vacant land prices: Evidence for real options in Seattle. Journal of Urban Economics, Elsevier, 59: 1-31

Cutler DM, Glaeser EL, Jacob LV (1999) The rise and decline of the American ghetto. *Journal of Political Economy*, 107: 455-506.

Cutsinger J, George G, Wolman H, Hanson R, Towns D (2005) Verifying the multi-dimensional nature of metropolitan land use: Advancing the understanding and measurement of sprawl. *Journal of Urban Affairs*, 27: 235–259.

Downing PB, Gustely RD (1977). The Public service costs of alternative development patterns: A review of the evidence. In local service pricing policies and their effect on urban spatial structure, ed. Paul B. Downing, pp. 63-86. Vancouver: University of British Columbia Press for the British Columbia Institute for Economic Policy Analysis.

Fischel WA (1985) The economics of zoning laws: A property rights approach to American land use controls. Baltimore, md: Johns Hopkins University Press.

Forbes KJ (2000) A reassessment of the relationship between inequality and growth. American Economic Review, 90:869–887

Fulton WR, Pendall MN, Harrison A (2001) Who sprawls most? How growth patterns differ across the U.S. Washington, DC: Brookings Institution.

Galster GR, Hanson HW, Coleman S, Friebage J (2000). Wrestling sprawl to the ground: Defining and measuring an elusive concept. Washington, DC: Fannie Mae.

Glaeser EL, Khan ME (2001) Decentralized employment and transformation of the American city, Brookings-Wharton Papers on Urban Affairs.

Glaser EL, Khan ME (2004) Sprawl and urban growth. *Handbook of Regional and Urban Economics*, 4:2481-2527.

Harrison D, Kain J (1974) Cumulative urban growth and urban density functions. *Journal of Urban Economics* 1: 61-98.

Heikkila EJ, Peiser RB (1992) Urban sprawl, density, and accessibility. *Papers in Regional Science*, 71: 127-138.

Holland AS, Ott SH, Riddiough TJ (2000) The role of uncertainty in investment: An examination of competing investment models using commercial real estate data. *Real Estate Economics*, 28: 33–64.

Irwin EG, Bockstael NE (2004) Land use externalities, open space preservation, and urban sprawl. *Regional Science and Urban Economics*, 34: 705-725

Irwin EG, Bockstael NE, Jin Cho HJ (2006) Measuring and modeling urban sprawl: Data, scale and spatial dependencies. Invited paper presented at the Urban Economics Sessions, 53rd Regional Science Association International Annual Meeting, Toronto, November 16-18.

Jordan S, Ross JP, Usowski KG (1998) . U.S. suburbanization in the 1980s. *Regional Science and Urban Economics*, 28: 611-627(17)

JunJie W (2001) Environmental amenities and the spatial pattern of urban sprawl. *American Journal of Agricultural Economics*, 83: 691–697.

Karlin H, Tyalor M (1975) A first course in stochastic processes, Academic Press, New York.

Kolko J (1999) Can I get some service here? Service industries and urban density. Harvard University Mineography.

Lang R (2003) Open spaces, bounded places: Does the American west's arid landscape yield dense metropolitan growth? *Housing Policy Debate*, 13, 755–778.

Lopez R and Hynes H (2003) Sprawl in the 1990s: measurement, distribution, and trends. *Urban Affairs Review*, 38: 325–355.

Margo RA (1992) Explaining the postwar suburbanization of population in the United States: The role of income. *Journal of Urban Economics*, 31: 301-310.

McDonald R, Siegel D (1986) The value of waiting to invest, *Quarterly Journal of Economics*, 101: 707–727.

McDonald R, Siegel D (1985) Investment and the valuation of firms when there is an option to shut down. *International Economic Review*, 26: 331–349.

McFarlane A (1999) Taxes, fees, and urban development. *Journal of Urban Economics*, 46: 416-436.

Mills ES (1967) An aggregative model of resource allocation in metropolitan area. *American Economic Review*, 197: 197-210.

Mills, ES, Price R (1984) Metropolitan suburbanization and central city problems. *Journal of Urban Economics*, 15: 1-17.

Moel A and Tufano P (2002) When are real options exercised? An empirical study of mine closings. *Review of Financial Studies*, 15: 35–64.

Muth R F (1969) Cities and housing: the spatial pattern of urban residential land use. Chicago, IL: University of Chicago Press.

Nechyba T, Walsh R (2004) Urban sprawl, *Journal of Economic Perspectives*, 18:177-200.

Ogawa H, Fujita M (1989) Nonmonocentric urban configurations in a two-dimensional space. *Environment and Planning* A, 21: 363–74.

Ohls JC, Pines D (1975) Discontinuous urban development and economics efficiency. *Land Economics*, 51: 224–34.

Ottensmann JR (1977) Urban sprawl, land values and the density of development. *Land Economics*, 53: 389-400.

Paddock JL, Siegel D, Smith JL (1988) Option valuation of claims on real assets: The case of offshore petroleum leases, *Quarterly Journal of Economics*, 103: 479–508.

Panizza U (2002) Income inequality and economic growth: Evidence from American data. *Journal of Economic Growth*, 7: 25–41.

Peiser, RB (1989) Density and urban sprawl. *Land Economics*, 65: 193-204.

Perotti R (1996) Growth, income distribution, and democracy: What the data say. *Journal of Economic Growth*, 2: 149–187.

Pindyck R (1991) Irreversibility, uncertainty, and investment. *Journal of Economic Literature*, 29: 1110-48.

Plantinga AJ, Lubowski RN, Stavins RN (2002) The effects of potential land development on agricultural land prices. *Journal of Urban Economics*, 52: 561-581.

Schmid AA (1968) Converting land from rural to urban users. Baltimore: The Johns Hopkins Press for Resources for the Future, Inc.

Sigelman L, Heing J (2001) Crossing the great divide – race and preferences for living in the city versus the suburbs. *Urban Affairs Review*, 37: 3–18.

Skaburskis A (2001) Housing prices and housing density: Do higher prices make more compact cities. *Canadian Journal of Regional Science*, XXIII: 3: 455-480.

Tiebout CM (1956) A pure theory of local expenditure. *Journal of Political Economy*, 64: 416-24.

Titman S (1985) Urban land prices under uncertainty. *American Economic Review*, 75: 505–514.

Tsai YH (2005) Quantifying urban form: compactness versus sprawl. *Urban Studies*, 42: 141-161.

Essay 3: Urban Sprawl and Productivity

1. Introduction

The emergence of urban sprawl[1] during the past century has ignited a growing debate regarding its costs and benefits. Opponents of urban sprawl suggest that the increasing trend of urban sprawl continues to generate adverse socio-economic outcomes. The continuing flight of high income people to low density suburban areas is believed to increase the concentration of poor households in low-income neighborhoods i.e. central cities, which may suffer from high crime or low-employment rates, etc. Consequently, a higher concentration of poverty reduces tax revenue (Power 2001; Glaeser and Sacerdote 1999) leading to a deteriorated provision of public goods and services in central cities (Jordan et al. 1998). In addition, Putnam (2000) shows that sprawling cities are associated with social isolation and deteriorating urban social capital.[2]

Several observers have also argued that sprawling cities are inefficient in terms of providing infrastructure and other public services. In particular, low density and expansion of city spatial structure lead to a greater per unit cost of development (e.g. roadways, sewage, and electricity) (Carruthers 2002; Knaap and Nelson 1992).[3] Furthermore, urban sprawl represents an important shift in land-use as it is greatly altering agricultural patterns, potentially creating environmental degradation, and changing the residence-work relationship through longer commutes and traffic congestion. These potential negative impacts of urban sprawl place great pressures on regional

[1] A mounting urban literature has been devoted to understand the underlying forces behind the increasing trend of urban sprawl. Urban economists have mainly highlighted the rule of declining transportation cost and rising income as conventionally postulated by the monocentric model (Alonso 1964; Muth 1969; Mills 1967; Margo 1992). In the same vein the advent of automobile (Glaeser and Khan 2003) and construction of highways (Baum-Snow 2007) have been found a primary catalyst of the urban sprawl phenomenon. Others point out that urban sprawl is an outcome of bad governmental policies including property taxes (Brueckner and Kim 2003), political fragmentation (Carruthers 2003), and to some extent crime and racial tension in central cities.

[2] Brueckner and Largey (2006) provide empirical evidence contesting the negative association between social interaction and urban sprawl.

[3] Most notably, Real Estate Research Corporation (RERC 1974) has estimated the direct cost of serving alternative development patterns and find that sprawl-type development costs twice as much to serve as high density development. Yet, the relationship between urban form and cost of public service remains controversial as other researchers find less supportive results. For a detailed discussion on this issue see Carruthers and Ulfarsson (2003).

planners and local government to curb urban sprawl and alternatively promote compact cities (also known as smart growth of development pattern[4]).

Yet, the negative perception of urban sprawl has not gone unchallenged. Proponents of urban sprawl suggest that it is determined by market process fueled by individual preferences rather than bad urban planning. Brueckner (2001), however, argues that the operation of this process is distorted by failing to internalize particular negative externalities.[5] Gordon and Richardson (1997) contend that urban sprawl is a natural product of growing cities and that the arguments against urban sprawl do not support promoting compact cities. After all, urban sprawl has been credited for creating opportunities for people to enjoy consumption of land and housing at lower prices (Brueckner and Fansler 1983; Glaeser and Khan 2004) and through self-sorting, a preferred level of local public services in the sprawling areas (Ellickson 1971; Mills and Oates 1975).

While most of the related literature has focused on the social and equity aspects, surprisingly, little empirical research has explored the economic performance of sprawling U.S. cities. The aim of this essay is to provide an empirical examination of this issue. Specifically, it investigates the effect of urban sprawl on U.S. metropolitan labor productivity. Doing so sheds light on whether urban sprawl is a real concern and whether compact cities better serve the economic performance of its citizens.

The underlying question becomes how urban form (compact versus sprawling city) affects labor productivity. Several scholars stress that the productivity premium of denser environment emanates from lower transportation costs of delivering goods and services. For example, Ciccone and Hall (1996) argue that if production technologies exhibit constant returns to scale, but the marginal cost of transporting intermediate goods rises with distance, then the ratio of output to input (productivity) rises with density.[6] Moreover, Wheeler (2001) draws upon theories from spatial mismatch hypothesis, suggesting that lower rates of commuting and searching cost

[4] Muro and Puentes (2004) define smart growth as a set of planning goals and policies that limit outward expansion and encourage higher density development by concentrating housing and employment.
[5] Brueckner (2001) attributes the source of distortions to: 1) failure to account for the benefit of open space; 2) failure to account for the social cost of congestion; and 3) failure to account for the infrastructure cost of sprawling areas.
[6] Ciccone and Hall (1996) empirically investigate the role of density on productivity across U.S. states. Using a density index that aggregates data at a county level, they estimate that doubling county density translates into a 6 percent increase in labor productivity. Yet, despite their rigorous work, the findings of Ciccone and Hall can not be generalized to draw a conclusion on the economic performance of sprawling cities. That is simply because sprawl is an urban phenomenon and can not be explored using data at state level. This is despite the fact that Ciccone and Hall carefully give more weight to more populated counties when calculating their state density index. Still, urban areas comprise a small fraction of a state's area.

associated with dense settings is likely to enhance labor productivity via more productive matching between firms and workers.

Theories from endogenous growth models emphasize the importance of dynamic externalities, particularly knowledge spillover, in enhancing productivity (Jacob 1969; Marshal 1890; Romer 1986; Lucas 1988; Glaeser 1998). The concentration of individuals and firms along with higher frequency of face to face communication provide an environment in which learning is more efficient and ideas are exchanged quickly. In this regard, knowledge spillovers imply that improvements and innovations in one firm or industry are expected to increase the productivity of other firms. If so, then we would expect that closer geographical proximity (lower level of sprawl) significantly facilitates this process. Jaffe et al. (1991) use patent data to confirm that knowledge spreads slowly and diminishes over distance, making geographical concentration important to firms. In a more recent paper, Carlino et al. (2007) find that the rate of patenting is positively associated with employment density in U.S. urbanized areas; doubling urban density leads to a 20 to 30 percent increase in the rate of patenting.

As a result, one might conclude that policies which excessively encourage urban sprawl would diminish productivity gains from agglomeration economies of urban density. However, the latter conclusion is contested among several researchers. The rapid advances in communication technology and information processing may make the need for face to face communication obsolete, reducing the need for a dense environment to generate productivity gains (see Gordon and Richardson 1997). Also, lower transportation costs due to the construction of improved highways have further diminished the cost-saving of agglomerated areas and may have been a significant force toward more sprawling cities (see Glaser and Khan 2004; Baum-Snow 2007). In the same vein, Glaeser and Khan (2004) have cast some doubt on the negative relationship between sprawl and productivity. They argue that well functioning sprawling cities (e.g., Silicon Valley and Route 128) maybe conducive to productivity.

In sum, the relationship between urban sprawl and labor productivity is ambiguous. We might expect that less-sprawling cities enhance productivity through knowledge spillovers, labor matching, and saving on transportation cost. But other factors, such as massive advancement of communication and construction of highways make the latter prediction uncertain. Thus, urban sprawl effect on labor productivity can only be determined by empirical research.

The empirical analysis of this paper draws upon cross sectional data from U.S. metropolitan statistical areas (MSAs) of the 1990s. To measure urban sprawl, I use data at a disaggregate level to construct a distinctive index that, unlike many existing measures, carefully addresses the distribution of population density within a given metropolitan area. Measuring labor productivity as metropolitan gross domestic products (GDP) per worker, this essay provides robust evidence that a higher level of metropolitan sprawl is associated with lower metropolitan average labor productivity. Interestingly, when examining the sprawl-labor productivity link across metropolitan size, the negative effect of sprawl is higher in smaller MSAs. Yet, the statistical significance of the sprawl effect varies when undertaking the analysis across major industries.

The rest of the paper is organized as follows: section 2 outlines the theoretical framework. Section 3 discusses the empirical models and the measure of urban sprawl. Section 4 presents the empirical results with sensitivity analysis following in section 5. Section 6 presents the conclusion.

2. Theoretical Framework

The theoretical approach of this essay draws from previous literature on spatial differences in productivity (e.g., Moomaw 1983; Sveilkauskas 1975; Carlino and Voith 1992). Differences in productivity are modeled using an aggregate production function. This approach assumes that all firms are perfectly competitive and that the production factors are characterized by constant returns to scale across MSAs. Metropolitan productivity differences are generated due to externalities related to differences in site specific characteristics, which are embedded in the Hicks-neutral multiplier (A_i). The aggregate production function in a given metropolitan area is assumed to take a Cobb Douglas form, such that:

$$Q_i = A_i \left(K_i^{\alpha} L_i^{1-\alpha} \right) \tag{1}$$

Where Q_i is out put in MSA i. α and 1-α are the share of the metropolitan capital stock (K_i) and labor (L_i), respectively. Since data on capital stock is hard to obtain at a metropolitan level, I overcome this issue assuming that the rental price of capital, r, is equalized across all areas.[7] Differentiating output with respect to capital stock, the marginal product of capital (*MPK*) can be equated with rental price of capital, such that:

[7]This assumption is fairly realistic since the large open economy of U.S. is associated with less regional variation in terms of capital rental price.

$$MPK_i = \partial Q_i / \partial K_i = A_i \alpha K_i^{\alpha-1} L_i^{1-\alpha} = r \tag{2}$$

Dividing (2) by $Q_i = A_i\left(K_i^{\alpha} L_i^{1-\alpha}\right)$ yields:

$$K_i = \frac{\alpha Q_i}{r} \tag{3}$$

Substituting (3) into (1) and collecting Q_i terms yields:[8]

$$Q_i = A_i^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} L \tag{4}$$

The labor productivity expression can be obtained by dividing equation (4) by L_i, such that:

$$\frac{Q_i}{L_i} = A_i^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} \tag{5}$$

Early literature that has investigated labor productivity differences across metropolitan areas tended to make the production shifter (A_i) exclusively a function of metropolitan population size (Moomaw 1983). However, Carlino and Voith (1992) generalize this approach to include other metropolitan characteristics related to productivity, such as: industry mix, labor force characteristics, and other location-specific characteristics. Consistent with Carlino and Voith, A_i is expressed as:

$$A_i = \exp\left[\varphi_0 + \sum_{k=1}^{k} \varphi_k x_{ki}\right] \tag{6}$$

Substituting equation (6) into equation (5) and taking the logarithmic transformation yields the labor productivity expression that is used as the basis for the empirical analysis of this essay, such that:

$$\log\left(\frac{Q_i}{L_i}\right) = B_0 + \sum_{k=1}^{k} B_k x_{ki} \tag{7}$$

Where $B_0 = [\alpha/1- \alpha] log(\alpha/r) + 1/(1- \alpha)\varphi_0$ and $B_k = 1/(1- \alpha)\, \varphi_k$. As discussed below, x_{ki}, denotes the metropolitan characteristics, including sprawl, the main variable of interest.

3. Empirical Model

3.1 Measuring Urban Sprawl

[8]Alternatively, Sveikauskas (1975) assume seperability between A_i and $f(K_i,L_i)$, so that A_i can be estimated independently, avoiding the need to use data on capital. Since A_i is not observed, Sveikauskas substitutes it with labor productivity and regressed it on city size, among other factors.

Urban sprawl can take different forms. It may involve low density development, clustering of population and economic activities at the urban fringe (edge cities), and separation of land use, also known as leapfrog development (Nechyba and Walsh 2004). Although there have been several attempts to develop measures of sprawl,[9] researchers have mainly focused on population density as a measure of sprawl. Density has been used widely because of its intuitive appeal and the difficulty and cost burden of obtaining data on alterative measures that require high technology such as geographical information system (GIS)[10] (Lopez and Hynes 2003). Moreover, higher-density development is seen, by many sprawl critics, as an antidote to many unwanted aspects of U.S. urban structure that accompany sprawl, such as infill land, loss of open space, and less rural agriculture.

Typically, metropolitan population density has been defined as the total metropolitan population divided by total metropolitan land. A major drawback of this measure is that large areas of counties that contained in the metropolitan areas are rural. This leads to an upward bias in measuring sprawl (Lang 2003). Alternatively, other researchers (e.g. Fulton et al. 2001) use smaller geographic bases, namely, census urbanized areas.[11] Yet, the latter measure excludes a relatively large area of 'developed' land at the urban fringe, leading to a downward bias in the sprawl measure (Cutsinger et al. 2005).

Another important concern of using such aggregated measures of sprawl is that they do not incorporate the distribution aspect of metropolitan population. That is, there is no distinction between metropolitan areas where population is scattered or evenly distributed and those with population highly concentrated[12] (Lopez and Hynes 2003). In this paper, I develop a sprawl index that incorporates both the density and concentration aspect of sprawl using data at a sufficiently disaggregated scale, specifically, census block groups. Block group is an area comprising a group of co-located census blocks that contain between 600 and 3,000 people, with a typical size of

---

[9] Using Geographic Information Systems (GIS) and field surveys, Galster et al. (2000) devise eight measures that capture many dimensions of sprawl; density, continuity, concentration, compactness, centrality, nuclearity, diversity, and proximity.

[10] Examples of studies that used GIS technology are: Burchfield et al. (2006) and Irwin et al. (2006).

[11] Census urbanized area is densely settled territory that consist of core census block groups or blocks that have a population density of at least 1,000 people per square mile and surrounding census blocks that have an overall density of at least 500 people per square mile. See below for the definition of census block group.

[12] Consider two identical MSAs in terms of area and population, the one with concentrated population sprawls less than that with scattered population.

1,500 people. Using block groups ensures that fine differences in the distribution of population density within metropolitan areas can be identified.

Sprawl is measured as:

$$Sprawl = ((L\% - H\%) + 1) * 0.5 \tag{8}$$

Where:

L% is the share of metropolitan population living in a block group with density *below* the overall U.S. metropolitan block group median.

H% is the share of metropolitan population living in a block group with density *above* the overall U.S. metropolitan block group median.

The sprawl measure in equation (8) is an index that ranges between 0 and 1. Values closer to 1 represents greater sprawl. The population density of each census block is calculated by dividing its population by its land, measured in square miles. For each metropolitan area, block groups are sorted and aggregated into high density (above the U.S. metropolitan block group median) and low density (below the U.S. metropolitan block group median). A metropolitan area with high percentage of its population living in block groups with density below the median suggests more low-density sprawl compared to those with density above the median. To account for 'rural clusters' in metropolitan areas, I exclude all block groups with density below 200 persons per square mile. This cut off corresponds to one residential unit per eight acres—about the lowest residential density of many new exurban housing developments. The source of census block group data is from Geolytics data base (www.geolytics.com).

Lopez and Hynes (2003) use similar measure of sprawl, but employ fixed density cut offs (high density corresponds to greater than 3,500 persons per square mile, while low density lies between 3,500 and 200 persons per square mile). The main concern of their choice of high and low density cut off is that it is relatively random and is not based on a widely recognized benchmark.

Due to data availability, I do not use data on metropolitan employment distribution. Yet, the sprawl index (equation 8) captures, to a great extent, the intra-metropolitan distribution of economic activities (people and firms). Evidently, Glaser and Khan (2004) provide evidence that job and population sprawl in U.S. metropolitan areas go hand in hand. Measuring sprawl using distance from central cities for the major 150 metropolitan areas, they find that the correlation between the distance, in miles, from central cities for median person and median worker is 0.89. Moreover, when measuring urban sprawl using density, they find that the correlation between metropolitan average population density and average employment density is 0.77.

3.2 Empirical Specification

To examine the effect of urban sprawl on labor productivity, I employ cross-sectional reduced-form models. The unit of observation is Metropolitan Statistical Areas[13] (MSAs), producing a total sample of 357 MSAs.[14] An advantage of using a reduced-form model is that it reveals the bottom-line effect of the empirical estimates, which is often at the central interest of policymakers. On the other hand, the weakness of using such a model is that it does not allow direct inference about the underlying structural model, which to some extent constrains interpreting the underlying causal linkages. Yet, this issue is addressed in the following section.

In specifying the empirical model, the following estimation issues are addressed. First, all the explanatory variables are measured at the beginning of the period (1990). This mitigates any direct simultaneity between the dependent and independent variables. Yet, in the sensitivity analysis section, I further explore the potential endogeneity of the lagged metropolitan sprawl. Second, the base model adds a number of control variables, including city size, supplies of exogenous amenities, and other economic variables. This would reduce the problem of omitted-variable bias and also ensure that we are not confounding other productivity effects with the influence of urban sprawl.

The stochastic version of equation (7) can then be written as:

$$Ln\left(\frac{Q_i}{L_i}\right)_{i,2001} = \beta_0 + \beta_1 metropolitan\_sprawl_{i,1990} + \beta_2 pop_{i,1990} + \beta_3 pop^2_{i,1990} + \beta_4 educ_{i,1990} + \beta_5 Natural\_amenity_i + \beta_6 indust\_share_{i1990} + v_i + e_i \quad (9)$$

---

[13] MSAs are geographic entities defined by U.S. Office of Management and Budget (OMB). An MSA includes one or more counties, which consist of a core urban area of at least 50,000 population, as well as any adjacent counties that have a high degree of social and economic integration with the urban core. OMB updates the standard for defining MSAs periodically to reflect most recent census bureau population estimates. The MSAs used in this essay are defined in June 2003, which are based on the 2000 standards and census data. The list of MSAs and their county components can be accessed from: http://www.census.gov/population/estimates/metro-city/03msa.txt. For more discussion on MSA definition see www.census.gov.

[14] Due to missing data, the number of observation varies across some regression analysis. All the regression estimates along with the number of observations are included in appendix III.

The dependent variable (labor productivity) is the logarithmic transformation of metropolitan gross domestic product (GDP) divided by total metropolitan employment, measured for the year 2001.[15] GDP is measured as the market value of final goods and services originating in industries located in the metropolitan area. The GDP data is newly released by the Bureau of Economic Analysis, U.S. Department of Commerce.[16] Total metropolitan employment includes both full and part time employment, which are obtained from the U.S. Department of Commerce's BEA Regional Economic Information system (REIS).

The use of GDP to measure labor productivity in this essay is superior to other measures of output that use the concept of value added or total value of production (see Rigby and Essletzbichler 2002; Bernard and Jones 1996; Moomaw 1985; Sveikauskas 1975). Cicconi and Hall (1996) argue that the findings of such studies "are seriously flawed by their reliance on unsatisfactory measures of output from the Census of Manufactures".[17] Nonetheless, other studies measure labor productivity using average wages on the basis that higher labor productivity should be reflected in higher wages (Glaeser and Mare 1994; Wheaton and Lewis 2002; Carlino and Voith 1992). In the sensitivity analysis section, the base model is re-estimated with labor productivity measured using data on average metropolitan wages. This procedure better ensures that sprawl-labor productivity relationship is not a product of a specific productivity measure.

$Metropolitan\_sprawl_i$, is specified as in expression (8). As for the other explanatory variables, consistent with agglomeration literature, total metropolitan population (pop_i), is included to control for urbanization economy effects. Larger cities are expected to have higher labor productivity through factors such as labor pooling and the availability of intermediate goods and services (Glaeser 1998; Quigley 1998). Yet, surpassing a specific metropolitan threshold size might raise congestion costs, which at some point might overwhelm the favorable agglomeration effects. This is particularly true when excessive increases of metropolitan size cannot be supported by the existing level of public goods, including infrastructure and accessible transportation networks. The squared-term of total metropolitan population (pop^2_i) is added to control for the congestion cost.

A related literature links productivity to the accumulation of knowledge and skills (e.g., Romer 1986; Lucas 1988). A larger stock of human capital would raise labor productivity by exposing

[15] GDP estimates are not available prior to 2001.
[16] See http://www.bea.gov.
[17] For more discussion on this issue, see Cicconi and Hall (1996) pp. 60.

workers to more information and allowing them to learn and exchange ideas more quickly. Lucas (1988) suggests that the clustering of human capital is a driving factor behind productivity gains in urban areas. Likewise, Black and Henderson (1999) suggest that workers are more productive when locating in areas with high levels of human capital. Human capital accumulation is captured by including the share of metropolitan population above 25 year old that have: (1) high school degree; (2) some college with no degree: (3) associate degree; (4) bachelor degree; and (5) graduate degree. The estimates of these categories are compared to the omitted category: those who did not complete high school. Education attainment data is derived from the Geolytics data base.

Metropolitan industry size could have an impact on the average labor productivity. That is, if a metropolitan area is relatively specialized, then its average labor productivity might be driven by the size of the dominating industry/industries. The industry size effect is captured by including the employment shares of 15 major industries ($Indust\_share_i$) of which agriculture is the omitted industry. Data on industry shares are collected from REIS. I also control for exogenous externalities, which is captured by including $natural\_amenity_i$ index.[18] Natural amenities would enhance labor productivity if they are associated with attracting high-skilled or high productivity firms. The data on the natural amenity index[19] is derived from the U.S Department of Agriculture (USDA). However, because some metropolitan areas extend across state boundaries, each of these metropolitan areas is assigned to the state where the majority of the metropolitan population resides.

Still, differences in metropolitan labor productivity might reflect differences in characteristics that vary little over time. Examples are access to railroad, highways, and the presence of universities. If any of those factors are correlated with urban sprawl, then the sprawl estimate may be biased. Due to data limitations, I could not use panel estimation or first differencing to remove metropolitan fixed effects. However, since many of the aforementioned factors are determined at the state level, state dummies are included to pick up effects that are common across all metropolitan areas within the same state.[20] In addition, differences in labor productivity might

[18] The amenity index ranges from 1 to 7, which combines six measures of natural amenities: warm winter, winter sun, temperate summer, low summer humidity, topographic variation, and water area. A higher value reflects more natural amenities

[19] Since USDA produces the natural amenity data at a county level, I calculate the average of the natural amenity indices over all counties that belong to the same MSA.

[20] When controlling for state fixed effects, the coefficients of the other explanatory variables reflect the within state variation of those explanatory variables on the dependent variable.

also reflect industry specific characteristics, including industry-labor skill type and investment in R&D. Again, bias could result if such factors are correlated with urban sprawl. This issue is further considered in the sensitivity analysis section.

4. Empirical Results – Base Model

This section discusses the base model (equation 9) results with main emphasis on the relationship between metropolitan sprawl and average labor productivity. One potential concern is that the error terms could be spatially correlated, which would negatively bias the standard errors. To correct for this possible bias, the base model is estimated assuming that the residuals are correlated within geographical clusters (BEA economic areas[21]), but uncorrelated across clusters. The advantage of using the clustering approach is that it does not impose restrictions on the spatial correlation of the residuals within clusters. This is unlike other spatial econometric models that use more restrictive assumptions, such as, distance or adjacency weight matrices. Section 5 conducts sensitivity analysis to test the robustness of the base model results.

As noted earlier, a main concern of employing a reduced form model is that it does not infer the mechanism through which sprawl influences labor productivity. Still, this section explores this issue using additional auxiliary regression analysis. Furthermore, the next section considers the following two issues: (1) the effect of metropolitan size on the sprawl-productivity relationship; and (2) the effect of metropolitan sprawl on cross industry labor productivity.

Starting with the base model, the results reported in column (1), table (3.1), reveal that, *ceteris paribus*, a higher level of urban sprawl is associated with lower metropolitan average labor productivity. The coefficient of $metropolitan\_sprawl_i$ is negative and highly significant at the 1% level. This finding suggests that increasing the level of metropolitan sprawl by one standard deviation is linked to a 14.5 percentage point decrease in labor productivity. The negative effect of metropolitan sprawl is consistent with previous work that more generally highlights a productivity premium in denser areas (Cicconi and Hall 1996).

[21] The BEA economic areas consist of one or more economic nodes that reflect regional centers of economic activities. In the sample there are 161 BEA economic areas. The Stata Cluster command is used for the estimation. For more information on the definition of BEA economic area visit http://www.bea.gov/regional/docs/econlist.cfm.

Though I emphasize the sprawl-productivity results, some other results are worth noting. First, the coefficient of pop_i is positive and highly significant at the 1% level. This result confirms previous literature (Glaser et al. 1992; Sveikauskas 1975; Moomaw 1981, 1985), which suggests that the productivity enhancing effects of urbanization economies are positively associated with the metropolitan size. Yet, the coefficient of pop^2_i is negative and highly significant at the 1% level, suggesting adverse congestion effects on productivity. Finally, as expected, the average labor productivity is higher in metropolitan areas with higher share of population with high school degree, bachelor degree, and graduate degree. The coefficients of the respective variables are highly significant at the 1% level. As explained earlier, the latter results are interpreted with respect to those who did not complete high school.

Yet, a remaining question is why metropolitan sprawl is associated with lower metropolitan labor productivity? The following analysis shed lights on this issue. As noted earlier, there has been a serious effort to explain cross metropolitan variation in labor productivity, highlighting the advantage of spatial agglomeration (dense settings) on the production side. Particularly, better access to ideas and technology across firms, lower transportation costs of delivering goods and services, and faster flow of ideas and knowledge spillovers across workers. This essay takes a different path, focusing on the consumption side.

A growing stream of literature (Adamson et al. 2004; Lloyed 2000; Lloyed and Clark 2001; Costa and Khan 2000) suggests that people's location decision is not only associated with economic opportunities, but also enhanced by the level of urban amenities, including: entertainment, diversity and life style, better access to goods and services,[22] and higher level of social capital;[23] characteristics that are extensively found in denser urban areas (Glaeser et al. 2001). This applies particularly to more skilled and talented workers who are more economically mobile. Evidently, Florida (2002) finds that talented workers (those with at least a bachelor degree) are attracted to areas that are characterized by diverse ethnicity and cultural amenity. Accordingly, we would expect that higher (lower) levels of urban amenities in compact (sprawling) MSAs enhance (reduce) labor productivity through attracting (repelling) more skilled workers.

[22] The economies of scale and transportation costs in denser cities create benefits for household in terms of higher access to consuming a wide range of commodities produced at a lower cost (Head and Mayor 2004).
[23] Glaeser and Sacerdote (1999) find that individuals living in denser buildings and bigger cities are more likely to socialize with their neighbors.

To explore this possible explanation, an auxiliary cross sectional model is estimated in which the 2000 share of MSA population above 25 year old that have at least a bachelor degree (as a proxy for skilled workers) is regressed on 1990 metropolitan sprawl and other control variables, including: 1990 total metropolitan population; 1980-1990 employment growth; 1980-1990 per capita income growth;[24] squared-term of total metropolitan population; natural amenity index; and state dummies. Consistent with the above prediction, the results, reported in table (3.2), show that metropolitan areas with higher level of sprawl are negatively associated with the subsequent share of highly educated workers. The coefficient of $metropolitan\_sprawl_i$ is negative and statistically significant at the 1% level.[25]

4.1 Productivity: Linkages Across Metropolitan Size and Industries

As pointed out earlier, the size of metropolitan areas plays an important role in explaining spatial differences in labor productivity. That is labor productivity tends to be higher in larger metropolitan areas due to higher level of urbanization economies. To investigate how metropolitan size shapes the impact of sprawl on labor productivity, the sample is divided into smaller MSAs; those that are below the 1990 median metropolitan size,[26] and larger MSAs; those that are above the 1990 median metropolitan size. The empirical model for both samples is specified as follows:

$$Ln\left(\frac{Q_i}{L_i}\right)_{i,2001} = \beta_0 + \beta_1 metropolitan\_sprawl_{i,1990} + \beta_2 indust\_share_{i,1990} + \beta_3 educ_{i,1990} + \beta_4 Natural\,amenity_i + v_i + e_i \qquad (10)$$

The results reported in table (3.3) reveal that the negative relationship between metropolitan sprawl and labor productivity holds in both samples. Yet, it turns out that a higher level of metropolitan sprawl is associated with much lower labor productivity in smaller MSAs compared to larger[27] MSAs. The estimates suggest that increasing the level of metropolitan sprawl by one standard deviation is associated with 25 percentage point lower labor productivity in smaller

[24] Employment and income growth variables are included to control for the economic conditions of sprawling MSAs.
[25] As a sensitivity analysis, a number of robustness checks are considered. For example, the model is re-estimated using a log-log form instead of linear one. In another separate regression, employment and income growth variables are excluded to check if collinearity problem is a driving factor. Regardless, the negative effect of metropolitan sprawl on the share of higher education is robust. All unreported results are available on request.
[26] The median MSA population in 1990 is 190,352.
[27] The sprawl coefficient in the smaller MSA sample is statistically different from that of the larger MSA sample at the 1% level.

MSAs and 16 percentage point lower in larger MSAs. This finding indicates that lower level of urbanization economies in smaller MSAs magnifies the negative impact of metropolitan sprawl.

Next, I investigate whether the negative impact of metropolitan sprawl is maintained when considering labor productivity across major industries. To explore this possibility, a separate regression is estimated for each of the main 20 industries,[28] such that:

$$Ln\left(\frac{Q}{L}\right)_{ij,2001} = \beta_0 + \beta_1 metropolitan\,sprawl_{i,1990} + \beta_2 pop_{i,1990} + \beta_3 pop^2_{i,1990} + \beta_4 educ_{i,1990} + \beta_5 Naturalamenity_i + v_i + e_i \quad (11)$$

Where $(Q/L)_{ij}$ is GDP per worker in industry[29] j located in MSA i. The results reported in table[30] (3.4) reveal that there are drastic differences across industries. However, in the following discussion, I do not attempt to explore causal linkages behind the differential effect of metropolitan sprawl across industries. Still, it is important to highlight some interesting findings. Metropolitan sprawl is associated with lower labor productivity in industries that use considerable information and face to face interaction such as finance and insurance. This is likely to happen since the level of agglomeration economies needed for spillovers to operate across firms and workers for such industries is lower in sprawling MSAs.

I also find evidence that higher level of sprawl lowers labor productivity in information industry (that specialized in data processing and computer programming). This particular result contests the argument that recent advances in information technology have made the productivity premium of the compact city obsolete (Gordon and Richardson 1997). In total, the coefficient of urban sprawl is negative and statistically significant at least at the 10 % level for the following industries[31]: manufacturing; construction; finance and insurance; real estate and rental and leasing; information; professional and technical services; government; and health care and social assistance.

[28] This list of the 20 industries is shown in the descriptive statistic (table C) in appendix IV.

[29] It is worth noting that it would have been ideal to have data that sort industries according to their level of skilled labor intensity, transportation cost, or land use. Therefore, I would be able to draw a connection between urban sprawl and industries' input factors. However, to my knowledge, such data does not exist. The cross industry data used in this section is aggregated at the first digit industry level, which is classified according to the type of goods and service produced. Therefore, the cross industry sprawl-productivity investigation is more of a descriptive analysis that aims at examining whether urban sprawl has homogenous effect on labor productivity across different industries.

[30] Table (3.4) only reports the metropolitan sprawl coefficient estimates. Those of the other explanatory variables are reported in table (D) in appendix IV.

[31] As reported in table (D), appendix IV; a number of industries have considerably lower number of observations. Specifically: transportation; mining; agriculture; utilities; and management of companies and enterprises. Therefore, the estimates of these industries should be interpreted cautiously.

5. Sensitivity analysis

The previous section assesses the impact of urban sprawl on metropolitan labor productivity. The main finding is that metropolitan areas with higher level of sprawl tend to experience lower average labor productivity. In this section the robustness of this finding is further investigated. The focus of the sensitivity analysis is limited to the discussion on the metropolitan average labor productivity, emphasizing the following issues: (1) simultaneity between metropolitan sprawl and labor productivity; (2) the functional form of the empirical base model; (3) the spatial correlation of the error terms; (4) measurement of metropolitan sprawl, (5) omitted industry-fixed effects; and (6) alternative productivity measure.

First: *simultaneity between urban sprawl and labor productivity*. To mitigate the direct simultaneity between metropolitan sprawl and labor productivity, the former is measured at the initial period (1990). The simultaneity effect would be a concern if, for example, the productivity gain from spatial agglomeration drives firms and people to spatially concentrate in urban areas. However, if there is a persistent serial correlation in the error terms, then it is possible that shocks and events that happened decades before might still induce simultaneity between the lagged sprawl measure (1990) and the subsequent labor productivity. To deal with this possible scenario, I instrument the metropolitan sprawl of 1990 with its lag from 1980, the 1970 metropolitan population density,[32] and the 1969 share of metropolitan people below low income level.[33]

To assure the validity of the instrumental variables (IV), two tests are performed. Specifically, a weak instrument test based on the critical values provided by Stock and Yogo (2005) and Sargan's overidentification test. The results, unreported, show that the Cragg-Donald Wald F-statistic exceeds Stock and Yogo (2005) critical values for bias reduction no more than 5% of the OLS estimates and also exceeds the critical value for 10% maximal IV size distortion, indicating that the instruments are strong. Moreover, Sargan statistic is insignificant at the conventional level, indicating that the instrumental variables can be treated as exogenous.[34]

[32] The 1970 sprawl index could not be constructed since geographically consistent census block group data for all MSAs is not available prior to 1980.
[33] Data on 1970 metropolitan population and share of metropolitan people below low income level are derived from 1972 county data book, U.S. Bureau of the Census [1972].
[34] Due to software limitations, the IV validity tests could not be performed using the cluster command. To consider whether this limitation affects the results, the standard errors of the IV estimates are compared to those of the OLS, the results shows no significant changes.

Reported in column (2), table (3.1), the 2SLS results of the base model, show that the negative impact of urban sprawl on metropolitan labor productivity is robust.

Second: *the functional form of the empirical base model*. In the previous section the empirical base model is estimated using a log-linear functional form. To test if using different functional forms alters the estimates; the base model is re-estimated using both linear and log-log forms, respectively. The results reported in column (3) and (4), table (3.1) show that the negative relationship between metropolitan sprawl and average labor productivity is not an outcome of a specific functional form. The coefficient of metropolitan sprawl is negative and remains highly significant in both alternative forms.

Third: *the spatial correlation of the error terms*. The base model corrects for the spatial correlation of the error terms assuming that they are clustered in BEA areas. As a robustness check, general method of moments (GMM) is employed alternatively. GMM assumes a general form of spatial correlation that declines with distance from the metropolitan area of interest (Conley, 1999).[35] Not reported, the GMM results are similar to those of the base model.

Fourth: *measurement of urban sprawl*. To ensure that the findings are not particular to the specification of the sprawl index (equation 8), I change the cut-off density that distinguishes between high and low-density block groups. That is, instead of the median, the 25th percentile of the overall metropolitan block group density is now used. This implies that a metropolitan area with high percentage of its population living in block groups with density below the 25th percentile would have more low-density sprawl compared to those with density above the latter threshold. Reported in column (1), table (3.5); the results demonstrate that the negative impact of metropolitan sprawl on labor productivity is robust. Moreover, as a further robustness check, I measure metropolitan sprawl using population density, which, despite its weaknesses, has been widely used in the urban sprawl literature.[36] Since density is inversely related to sprawl, labor productivity is expected to be greater in denser metropolitan areas. The results reported in column (2), table (3.5) confirm this expectation.

---

[35] The cut off distance used is 400 km, in which it is assumed that the error terms are not correlated beyond this distance. In separate regressions, the GMM model is re-estimated using different cut off distances, 200 km and 600 km. Still, the results are similar.

[36] Like the sprawl index, rural clusters within metropolitan areas are excluded.

Fifth: *omitted industry-fixed effects*. Underlying the measure of average labor productivity is the implicit assumption that all industries equally contribute to the average metropolitan productivity. However, looking at the productivity level across the main 20 industries[37] reveals large differences. For example, finance and insurance industry is among the highly productive industries with average productivity of $71,703 per worker compare to retail industry with $34,028 per worker. Such variation might reflect factors that are industry specific, which are not accounted for in the base model, such as R&D (innovation) intensity or skilled-labor intensity (Nagi and Samaniego 2008; Klenow 1996). If the latter are correlated with metropolitan sprawl, then the negative relationship between average labor productivity and metropolitan sprawl is spurious, reflecting omitted variables. To address this issue, I estimate a global model by pooling data for the main 20 industries. This allows to include industry dummies that pick up all industry-fixed effects as well as potential industry size effects, such that:

$$Ln\left(\frac{Q}{L}\right)_{ij,2001} = \beta_0 + \beta_1 metropolitan\_sprawl_{i,1990} + \beta_2 pop_{i,1990} + \beta_3 pop^2_{i,1990} + \beta_4 educ_{i,1990}$$

$$\beta_5 Naturalamenity_i + \mu_j + v_i + e_i \qquad (12)$$

Where $(Q/L)_{ij}$ is GDP per worker in industry j located in MSA i and μ_j is industry dummy. The other explanatory variables are specified as in the base model and are the same across all the pooled industries. In estimating the global model, the error terms are assumed to cluster across industries (Moulton 1986). This reflects the possibility that workers within the same industry share common characteristics. The results reported in column (1), table (3.6) reveal that the negative relationship between metropolitan sprawl and labor productivity is robust.

Finally: *alternative productivity measure*. A significant branch of the empirical agglomeration literature has used average wages to study labor productivity differences across regions. Wheaton and Lewis (2002) hypothesize that "if workers are more productive, then it is wages which should reflect this gain." Consistent with the latter literature, the following analysis re-investigates the relationship between average labor productivity and metropolitan sprawl using data on average metropolitan wages. The wage data is measured in 2001, which is obtained from the U.S. Department of Labor's Occupational Employment Statistics program (http://www.bls.gov/oes/oes_dl.htm).

[37] See the descriptive statistics (table C).

The wage-metropolitan sprawl model is estimated using a global model, which pools data for the major 22 occupations.[38] The main advantage of using global model is that inter-occupation wage differentials are controlled for by including occupation dummies. The explanatory variables included are the same as those in the base model[39] (equation 9). The results reported in column (2), table (3.6) are consistent with the findings in the previous section.[40] Wages are lower in metropolitan areas with a greater level of sprawl. The coefficient of $metropolitan\_sprawl_i$ is negative and highly significant at the 1% level.

6. Conclusion

The costs and benefits of urban sprawl have been the focus of a voluminous economic literature. Proponents of compact city policies suggest that the growing level of urban sprawl is associated with deteriorating socieconomic outcomes, inefficient provision of public goods, and environment degradation. On the other hand, a growing literature argues that there is slim evidence that supports the ill consequences of sprawl. In contrast, urban sprawl is perceived as a product of individual preferences and growing cities rather than a symptom of economic system gone awry.

Surprisingly, while most of the related empirical literature has focused on the efficiency of public service provision and socio-economic aspects, little empirical research has been done on the economic performance of sprawling cities. This paper addresses this vacuum by investigating the impact of urban sprawl on labor productivity. One distinctive aspect of this study is the measure of sprawl, which is constructed using data at a geographic disaggregated level. This carefully addresses the fine differences in the intra-metropolitan population distribution, which has been generally ignored in previous literature.

Using metropolitan GDP per worker to measure labor productivity, I find that sprawling metropolitan areas are associated with lower average labor productivity. This result implies that anti-sprawl policies serve better the economic performance of metropolitan citizens. The

[38] The units of observation are MSAs and PMSAs using 2000 census definition, see www.census.gov. The number of observation slightly varies across industries. Descriptive statistics on the 22 occupations are available on request.

[39] Other variables that might affect wage differences are unionization and public infrastructure. However, unionization rates greatly vary due to state labor laws. Large public infrastructure investments are mostly determined at the state level. Those effects are captured by the state dummies.

[40] Like in equation 12, a cross-occupation global model is estimated assuming that the error terms are clustered across occupations.

significance of the higher levels of urban amenity in compact cities proves instrumental in attracting more skilled and educated people, leading ultimately to higher metropolitan productivity and better economic conditions.

This essay also points out to the importance of exploring the metropolitan characteristics that shape the relationship between labor productivity and sprawl. Conducting the sprawl-labor productivity link across metropolitan size shows interesting results. That is, the negative effect of urban sprawl is found to be higher in smaller MSAs. This implies that that lower level of urbanization economies in smaller MSAs magnifies the negative impact of sprawl. Furthermore, this essay provides auxiliary analysis on how sprawl-labor productivity relationship is shaped when conducting the analysis across the main industries. The results reveal that the negative effect of sprawl is significant for the following industries: manufacturing; construction; finance and insurance; real estate and rental and leasing; information; professional and technical services; government; and health care and social assistance. Yet future research is needed to explore the direct linkages for the differential effects of metropolitan sprawl across industries.

The differential effect of sprawl across industries and different urban sizes implies that one size policy does not fit all. Mainly, urban planner should consider the characteristics of urban areas in terms of size and industrial specialization when setting anti-sprawl policies. Further, to the extent that sprawl occurs, knowledge of industry specific characteristics may assist in targeting support or amelioration for those sectors most affected.

Appendix III

Table 3.1: Metropolitan Sprawl-Average Labor Productivity (Different Functional Forms)

Variables	*Log-Linear*	*Log-Linear (2SLS)*	*Log-Log*	*linear*
	-1-	**-2-**	**-3-**	**-4-**
1990 metropolitan sprawl	-0.199	-0.17	-0.133	-0.010
	(-3.03)*	(-2.42)	(-4.49)	(-2.46)
1990 total metropolitan population	4.26E-08	4.22E-08	2.88E-02	2.55E-09
	(3.71)	(4.43)	(3.06)	(3.3)
1990 total population_squared	-2.51E-15	-2.47E-15	-3.75E-16	-1.32E-16
	(-3.41)	(-3.86)	(-1.68)	(-2.57)
Natural amenity scale	-0.018	-0.02	-6.66E-02	-1.20E-03
	(-1.68)	(-2.41)	(-1.86)	(-1.79)
1990 share of graduate degree	2.804	2.74	0.111	0.176
	(4.59)	(4.03)	(2.52)	(4.54)
1990 share of bachelor degree	1.523	1.428	0.181	0.085
	(3.32)	(3.26)	(3.56)	(3.44)
1990 share of associate degree	-0.402	-0.375	-0.001	-0.034
	(-0.76)	(-0.72)	(-0.04)	(-1.12)
1990 share of some degree	0.224	0.11	-0.018	0.001
	(0.93)	(0.49)	(-0.34)	(0.06)
1990 share of high school	0.596	0.505	0.103	0.032
	(2.89)	(2.6)	(1.5)	(2.76)
1990 shares of Industrial Employment	Y	Y	Y	Y
State dummies**	Y	Y	Y	Y
constant	-3.309	-3.22	-3.121	0.033
	(11.54)	(-13.24)	(-7.56)	(2.19)
R-square	0.83	0.84	0.82	0.83
N	357	357	357	357

* Robust (spatially clustered) t-statistics are in parenthesis. In calculating the robust t-statistics, the clusters are formed based on BEA economic areas, which are defined as the relevant regional markets surrounding metropolitan or micropolitan statistical areas. See: http://www.bea.doc.gov/bea/regional/docs/econlist.cfm.
** Because some metropolitan areas run across state boundaries, each of these metropolitan areas is assigned to the state in which the majority of the metropolitan population resides.

Table 3.2: Metropolitan Sprawl-Metropolitan Higher Education

Variables†	**-I-**
1990 metropolitan sprawl	-0.125
	(-2.81)*
1990 total metropolitan population	1.60E-08
	(2.40)
1990 total population_squared	-1.02E-15
	(-2.52)
Natural amenity scale	-0.006
	(-0.83)
1980 - 1990 Employment Growth	0.111
	(2.7)
1980 - 1990 Per Capita Income Growth	0.217
	(5.16)
State dummies	Y
constant	0.159
	(2.94)
R-square	0.53
N	356

† The dependent variable is the 2000 share of population with at least a bachelor degree..

* Robust (spatially clustered) t-statistics are in parenthesis.

Table 3.3: Urban Sprawl-Labor Productivity: Linkages Across Metropolitan Size

Variables	***Smaller MSAs‡*** **-1-**	***Larger MSAs*** **-2-**
1990 metropolitan sprawl	-0.314	-0.203
	(-2.96)*	(-2.00)
Natural amenity scale	-0.043	0.003
	(-2.4)	(0.15)
1990 share of graduate degree	2.053	1.949
	(1.4)	(1.31)
1990 share of bachelor degree	1.555	2.540
	(1.93)	(2.95)
1990 share of associate degree	1.329	-0.272
	(1.19)	(-0.28)
1990 share of some degree	0.421	-0.437
	(0.78)	(-0.92)
1990 share of high school	0.681	0.563
	(2.03)	(1.25)
1990 shares of Industrial Employment	Y	Y
State dummies	Y	Y
constant	-3.23	-3.71
	(-7.58)	(-6.97)
R-square	0.73	0.88
N	179	180

* Robust (spatially clustered) t-statistics are in parenthesis.

‡ Smaller MSAs are those below the median metropolitan size, with median equal to 190,352 population. Similarly, larger MSAs are those above the median.

Table 3.4: Urban Sprawl-Labor Productivity: Linkages Across Industries

Industry	**Metropolitan Sprawl**
Construction	-0.262
	(-2.52)*
Manufacturing	-0.383
	(-2.36)
Finance & insurance	-0.34
	(-2.36)
Real estate & rental & leasing	-0.502
	(-1.77)
Information	-0.388
	(-1.72)
Professional and technical services	-0.39
	(-2.79)
Government	-0.163
	(-2.52)
Health care & social assistance	-1.333
	(-2.09)
Administrative & waste services	-0.216
	(-1.4)
Art, entertainment & recreation	-0.164
	(-0.62)
Educational services	-0.371
	(-1.23)
Accommodation & food services	-0.043
	(-0.44)
Whole sale	-0.125
	(-0.96)
Retail	0.018
	-0.21
Transportation	-0.066
	(-0.39)
Mining	-0.587
	(-0.99)
Agriculture (forestry, fishing, hunting)	0.427
	(-0.51)
Utilities	-0.117
	(-0.38)
Management of companies & enterprises	-0.483
	(-1.3)
Other services	-0.104
	(-1.34)

* Robust (spatially clustered) t-statistics are in parenthesis.

Table 3.5: Urban Sprawl-Labor Productivity: Different Sprawl Measures

Variables	**(1)**	**(2)**
Metropolitan Sprawl (25thPercentile cut-off)		-0.129
		(-2.64)
Population density	2.82E-05	
	(2.05)*	
1990 total metropolitan population	4.53E-08	4.71E-08
	(3.77)	(4.23)
1990 total population_squared	-2.75E-15	-2.61E-15
	(-3.59)	(-3.65)
Natural amenity scale	-0.016	-0.015
	(-1.47)	(-1.41)
1990 share of graduate degree	2.83	2.962
	(4.53)	(4.55)
1990 share of bachelor degree	1.394	1.334
	(3.03)	(2.8)
1990 share of associate degree	-0.424	-0.478
	(-0.79)	(-0.9)
1990 share of some degree	0.193	0.133
	(0.79)	(0.55)
1990 share of high school	0.53	0.51
	(2.52)	(2.26)
1990 shares of Industrial Employment	Y	Y
State dummies	Y	Y
constant	-3.26	-3.2
	(-12.11)	(-11.91)
R-square	0.83	0.834
N	357	357

* Robust (spatially clustered) t-statistics are in parenthesis.

Table 3.6: Urban Sprawl-Labor Productivity: Global Models (Pooled regression)

Variables	GDP/L [a] (1)	Wage (2)
1990 metropolitan sprawl	-0.198	-0.035
	(-5.08)*	(-3.77)
1990 total metropolitan population	9.09E-08	4.83E-08
	(7.18)	(6.45)
1990 total population_squared	-5.42E-15	-0.00013
	(-7.14)	(-0.06)
Natural amenity scale	0.011	-3.81E-15
	(0.96)	(-4.95)
1990 share of graduate degree	-1.374	-0.54
	(-2.38)	(-2.85)
1990 share of bachelor degree	3.2	1.429
	(7.16)	(7.73)
1990 share of associate degree	1.53	0.319
	(3.16)	(2.08)
1990 share of some degree	-1.126	-0.066
	(-6.34)	(-0.75)
1990 share of high school	0.314	0.2
	(2.1)	(2.11)
Stare dummies	Y	Y
Industry dummies	Y	
Occupation dummies		Y
constant	-2.75	9.84
	(-54.67)	(191.29)
R-square	0.78	0.94
N	5006	6656

* Robust t-statistics are in parenthesis. The error terms are clustered across industries.

[a] Robust standard errors are calculated assuming that the error terms are clustered with industries (for the estimates in column 1) and within occupations (for the estimates in column 2).

Appendix IV.

Table C: Descriptive Statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
GDP/L	359	51163.3	9777	32954.20	110281
1990 metropolitan sprawl	360	0.639	0.128	0.163	0.950
1990 total metropolitan population	358	568658	1345379	40714	16900000
1990 total population_squared	358	2.13E+12	1.71E+13	1.66E+09	2.85E+14
Natural amenity scale	360	3.81	1.235	1.5	7
1990 share of graduate degree	360	0.056	0.023	0.021	0.161
1990 share of bachelor degree	360	0.112	0.033	0.054	0.232
1990 share of associate degree	360	0.061	0.016	0.024	0.123
1990 share of some degree	360	0.219	0.046	0.105	0.399
1990 share of high school	360	0.311	0.055	0.172	0.485
2001 Labor Productivity across industries:					
Administrative and waste services	241	24659	6039	12797	54865
Art, Entertainment & Recreation	280	20933	11567	8415	135839
Health Care & Social Assistance	221	40137	4535	24586	53233
Accommodation and food Services	283	20543	4862	13158	54319
Other services	330	24318	3582	17669	41519
Whole sale	249	77996	18465	40816	175332
Construction	326	41453	8174	21795	71420
Manufacturing	334	73754	19843	39967	161788
Retail	351	34019	5301	21144	58360
Finance & insurance	323	71703.3	29431.6	38572.8	346820.3
Real estate & rental & leasing	316	170585.6	73976	42049.9	485252.6
Information	291	81498	25354	40495	220434
Professional & technical services	231	46493	13405	25499	109980
Management of Companies & Enterprises	200	71025	32252	18692	275600
Mining	134	67020.95	2101751	6369.4	647115.8
Utilities	149	209512.9	1470521	93750.34	948114.5
Government	358	47523.07	1127666	33538.88	78567.28
Agriculture (forestry, fishing, & hunting)	114	78813.58	1981315	10928.95	388889.5
Transportation	187	46657.57	1230179	22774.36	127380.1
1990 shares of industry employment					
Public administration	360	0.050	0.031	0.017	0.218
Other professional & related services	360	0.060	0.015	0.030	0.154
Educational service	360	0.094	0.039	0.046	0.383
Health	360	0.086	0.020	0.043	0.221
Entertainment	360	0.014	0.011	0.005	0.140
Personal service	360	0.032	0.014	0.018	0.188
Business & repair	360	0.042	0.009	0.024	0.067
FIRE	360	0.057	0.018	0.026	0.163
Retail	360	0.180	0.021	0.124	0.260
whole sale industry	360	0.040	0.012	0.014	0.107
Communication and utility	360	0.026	0.008	0.010	0.074
Transportation	360	0.039	0.011	0.018	0.097
Manufacturing	360	0.179	0.079	0.043	0.484
Construction	360	0.064	0.016	0.036	0.129
Mining industry	360	0.007	0.017	0.000	0.175

Table D: Urban Sprawl-Labor Productivity: Linkages Across Industries

Variable	Construction	Manufacturing	Finance & Insurance	Real Estate & Rental & Leasing	Information
1990 metropolitan sprawl	-0.262	-0.383	-0.340	-0.502	-0.388
	(-2.52)	(-2.38)	(-2.36)	(-1.77)	(-1.72)
1990 total metropolitan population	1.17E-07	9.04E-08	1.11E-07	2.06E-07	1.08E-07
	(6.37)	(3.12)	(4.33)	(4.7)	(2.68)
1990 total population_squared	-1.02E-14	-9.29E-15	-5.05E-15	-1.71E-14	-5.49E-15
	(-5.39)	(-3.69)	(-3.48)	(-4.6)	(-2.44)
Natural amenity scale	-0.004	-0.009	-0.021	0.005	-0.004
	(-0.28)	(-0.43)	(-0.95)	(0.14)	(-0.15)
1990 share of graduate degree	-0.144	0.773	-3.242	-3.782	-3.300
	(-0.14)	(0.6)	(-2.23)	(-1.89)	(-2.32)
1990 share of bachelor degree	2.214	2.541	4.915	6.580	6.003
	(3.27)	(2.85)	(5.5)	(4.03)	(4.77)
1990 share of associate degree	0.476	0.476	-0.646	-2.128	2.401
	(0.44)	(0.42)	(-0.55)	(-1.04)	(1.23)
1990 share of some degree	-0.589	-0.333	-1.387	-0.048	-0.974
	(-1.47)	(-0.88)	(-3.64)	(-0.08)	(-1.74)
1990 share of high school	0.562	1.526	-0.337	-0.692	0.328
	(1.16)	(3.03)	(-0.87)	(-1.06)	(0.63)
State dummies	Y	Y	Y	Y	Y
constant	-3.363	-3.462	-2.279	-2.118	-2.902
	(-13.75)	9-14.19)	(-8.610	(-6.91)	(-11.32)
R-square	0.62	0.47	0.75	0.6	0.52
N	324	332	318	312	290

Table D: Urban Sprawl-Labor Productivity: Linkages Across Industries con't

Variable	Professional & Technical Services	Government	Health Care & Social Assistance	Administrative & Waste Services	Art, Entertainment & Recreation
1990 metropolitan sprawl	-0.390	-0.163	-1.333	-0.216	-0.164
	(-2.79)	(-2.52)	(-2.09)	(-1.4)	(-0.62)
1990 total metropolitan population	1.03E-07	4.86E-08	2.18E-07	1.00E-07	2.22E-07
	(3.62)	(4.82)	(2.93)	(3.68)	(6.23)
1990 total population_squared	-5.55E-15	-3.00E-15	-1.48E-14	-8.61E-15	-1.34E-14
	(-3.49)	(-5.18)	(-2.71)	(-3.54)	(-6.26)
Natural amenity scale	-0.007	-0.012	0.100	-0.009	0.119
	(-0.3)	(-1.32)	(1.44)	(-0.43)	(2.98)
1990 share of graduate degree	-1.888	0.329	5.326	-1.567	-5.425
	(-1.27)	(0.47)	(0.67)	(-1.48)	(-2.41)
1990 share of bachelor degree	6.019	1.410	8.650	4.691	4.302
	(5.87)	(3.22)	(2.17)	(4.69)	(2.75)
1990 share of associate degree	1.983	0.732	17.751	0.355	0.834
	(0.94)	(1.07)	(2.66)	(0.25)	(0.35)
1990 share of some degree	-2.004	0.173	-5.605	-1.352	-2.389
	(-4.55)	(0.78)	(-3.41)	(-3.08)	(-3.88)
1990 share of high school	0.461	0.963	1.290	0.155	-0.139
	(1.08)	(4.75)	(0.75)	(0.27)	(-0.2)
State dummies	Y	Y	Y	Y	Y
constant	-3.371	-3.466	-6.876	-4.227	-4.120
	(-17.29)	(-28.33)	(-8.38)	(-16.98)	(-11.07)
R-square	0.7	0.6	0.5714	0.63	0.54
N	229	358	222	240	278

Table D: Urban Sprawl-Labor Productivity: Linkages Across Industries con't

Variable	Educational Services	Accommodation & Food Services	Other Services	Whole Sale	Retail
1990 metropolitan sprawl	-0.371	-0.043	-0.104	-0.125	0.018
	(-1.23)	(-0.44)	(-1.34)	(-0.96)	(0.21)
1990 total metropolitan population	1.30E-07	5.76E-08	4.93E-08	1.33E-07	5.69E-08
	(3.53)	(4.25)	(4.01)	(6.09)	(5.5)
1990 total population_squared	-8.25E-15	-3.33E-15	-3.10E-15	-1.18E-14	-2.95E-15
	(-3.63)	(-3.65)	(-3.92)	(-6.01)	(-4.2)
Natural amenity scale	0.019	0.036	-0.005	-0.002	0.001
	(0.55)	(2.04)	(-0.45)	(-0.12)	(0.06)
1990 share of graduate degree	1.495	-0.358	-0.323	-0.884	-1.455
	(0.53)	(-0.36)	(-0.52)	(-0.91)	(-2.48)
1990 share of bachelor degree	2.594	3.348	2.161	5.020	2.553
	(1.72)	(4.7)	(4.81)	(6.15)	(5.67)
1990 share of associate degree	10.006	0.435	0.220	0.135	-0.759
	(3.26)	(0.48)	(0.39)	(0.13)	(-1.12)
1990 share of some degree	-3.097	-1.005	-0.514	-1.981	-0.661
	(-4.25)	(-3.24)	(-2.37)	(-4.61)	(-3.17)
1990 share of high school	0.605	0.217	-0.035	0.395	0.017
	(0.85)	(0.74)	(-0.12)	(0.8)	(0.07)
State dummies	Y	Y	Y	Y	Y
constant	-4.152	-4.284	-3.674	-2.911	-3.469
	(-11.00)	(-32.11)	(-25.81)	(-10.64)	(-31.46)
R-square	0.55	0.68	0.66	0.68	0.75
N	222	281	328	247	349

Table D: Urban Sprawl-Labor Productivity: Linkages Across Industries con't

Variable	Transportation	Mining	Agriculture (Forestry, Fishing, & Hunting)	Utilities	Management of Companies & Enterprises
1990 metropolitan sprawl	-0.066	-0.587	0.427	-0.117	-0.483
	(-0.39)	(-0.99)	(0.51)	(-0.38)	(-1.3)
1990 total metropolitan population	1.19E-07	3.70E-08	1.33E-07	2.18E-07	1.47E-07
	(2.82)	(0.3)	(0.93)	(2.39)	(1.68)
1990 total population_squared	-9.21E-15	-1.13E-15	-6.98E-15	-1.31E-14	-1.30E-14
	(-2.72)	(-0.11)	(-0.65)	(-1.72)	(-2.02)
Natural amenity scale	-0.033	-0.064	0.097	-0.040	0.020
	(-1.3)	(-0.65)	(0.85)	(-0.92)	(0.37)
1990 share of graduate degree	0.032	8.360	-14.810	3.799	-8.568
	(0.02)	(1.3)	(-1.89)	(0.94)	(-3.2)
1990 share of bachelor degree	0.078	-0.353	4.366	0.821	7.784
	(0.08)	(-0.08)	(1.05)	(0.44)	(3.67)
1990 share of associate degree	3.339	10.541	9.709	1.688	3.489
	(2.25)	(2.1)	(0.87)	(0.76)	(1.00)
1990 share of some degree	-1.222	-2.110	0.956	-1.094	-1.957
	(-2.58)	(-1.09)	(0.23)	(-1.38)	(-2.04)
1990 share of high school	-0.642	3.554	-4.887	0.498	-1.574
	(-0.98)	(1.55)	(-1.53)	(0.46)	(-1.15)
State dummies	Y	Y	Y	Y	Y
constant	-2.467	-3.548	-0.690	-1.231	-2.737
	(-8.38)	(-3.57)	(-0.48)	(-3.14)	(-3.97)
R-square	0.57	0.74	0.48	0.66	0.5
N	168	134	114	149	199

References

Adamson DW, Clark DE, Partridge MD (2004) Do urban agglomeration effects and household amenities have a skill bias? *Journal of Regional Science*, 44: 201-224.

Alonso W (1964) Location and land use. Cambridge. Harvard University Press.

Baum-Snow N (2007) Did highways cause suburbanization? *Quarterly Journal of Economics*, 122: 775-805.

Beeson PE (1987) Total factor productivity growth and agglomeration economies in manufacturing, 1959-1973. *Journal of Regional Science*, 72:183-99.

Beeson PE, De Jong DN, Troesken W (2001) Population growth in U.S. counties, 1840-1990. *Regional Science and Urban Economics*, 31: 669-699.

Bernard AB, Jones CI (1996) Comparing apples to oranges: productivity convergence and measurement across industries and countries. *American Economic Review*, 86: 1216-38.

Black D, Henderson V (1999) The theory of urban growth. *Journal of Political Economy*, 107: 252– 284.

Brueckner JK, Kim HA (2003) Urban sprawl and the property tax. *International Tax and Public Finance*, 10: 5–23.

Brueckner JK, Largey AG (2006) Social interaction and urban sprawl. CESifo Working paper Series No. 1843

Brueckner JK (2000) Urban sprawl: Diagnosis and remedies, *International Regional Science Review*, 23: 160–171.

Brueckner JK, Fansler DA (1983) The Economics of urban sprawl: Theory and evidence on the spatial size of cities. *The Review of Economics and Statistics*, 65: 479-482.

Burchfield M, Overman H, Puga, D, Turner M. (2006) Causes of sprawl: A portrait from space. *Quarterly Journal of Economics*, 121: 587-633.

Carlino A, Voith R (1992) Accounting for differences in aggregate state productivity. *Regional Science and Urban Economics* 22: 597–617

Carlino G, Chatterjee S (2002) Employment deconcentration: A new perspective on America's postwar urban evolution. *Journal of Regional Science*, 42: 455-75.

Carlino GA, Chatterjee S, Hunt R (2007) Urban density and the rate of invention. *Journal of Urban Economics*, 61: 389-419.

Carruthers J (2003) Growth at the fringe: The influence of political fragmentation in United States metropolitan areas. *Economics of Governance*, 82: 475-499.

Carruthers J (2002) Evaluating the effectiveness of regulatory growth management programs: an analytical framework. *Journal of Planning Education and Research*, 21: 406-420

Carruthers J, Ulfarsson G (2003) Urban sprawl and the cost of public services, *Environment and Planning B: Planning and Design,* 30: 503-522.

Cervero R (1986) Jobs-housing balancing and regional mobility. *Journal of the American Planning Association*, 55:136–150.

Ciccone A, Hall RE (1996) Productivity and the density of economic activity. *American Economic Review*, 86: 54-70.

Combes, PP (2000) Economic structure and local growth: France, 1984-1993. *Journal of Urban Economics*, 47: 329-355.

Conley TG (1999) GMM estimation with cross-sectional dependence. *Journal of Econometrics*, 92: 1-45.

Costa D, Khan M (2000) Power couples: Changes in the location choice of college educated: 1940-1990. *Quarterly Journal of Economics*, 115: 1287-1315.

Duranton G, Puga, D (2004) Micro-foundations of urban agglomeration economies. In: Henderson, V., Thisse, F. (Eds.), *Handbook of Regional and Urban Economics*, North-Holland, Amsterdam, 4: 2063–2117.

Ellickson B (1971) Jurisdictional fragmentation and residential choice, *American Economic Review*, 61: 334-339.

Florida R (2002) The economic geography of talent. *Annals of the Association of American Geographers*, 92: 743-755.

Fogarty MS, Garofalo GA (1988) Urban spatial structure and productivity growth in the manufacturing sector of cities. *Journal of Urban* Economics, 23: 60-70.

Fulton W, Pendall R, Nguyen M, Harrison A (2001) Who sprawls most? How growth patterns differ across the U.S. Washington, DC: Brookings Institution.

Galster G, Hanson R, Woman W, Coleman S, Friebage J (2000) Wrestling sprawl to the ground: Defining and measuring an elusive concept. Washington, DC: Fannie Mae.

Garreau J (1991) Edge city: Life on the new frontier. New York: Doubleday.

Gerald A, Carlino A, Voith R (1992) Accounting for differences in aggregate state productivity. *Regional Science and Urban Economics*, 22: 597 -617.

Glaeser EL, Kallal H, Scheinkman J, Shleifer A (1992) Growth in cities. *Journal of Political Economy*, 100: 1126-1152.

Glaeser EL, Mare DC (1994) Cities and Skills. *Journal of Labor Economics*, 19: 316 - 342.

Glaeser EL (1998) Are Cities Dying? *Journal of Economic Perspectives*, 12: 139-160.

Glaeser EL, Kahn M (2001) Decentralization and the transformation of the American city. NBER, Working Paper # 8117.

Glaeser EL, Kolko J. Saiz A (2001) Consumer city. *Journal of Economic Geography*, 1: 27-50.

Glaser EL, Khan ME (2004) Sprawl and urban growth. *Handbook of Regional and Urban Economics*, 4:2481-2527.

Glaeser EL, Sacerdote B (2000) The social consequences of housing. *Journal of Housing Economics*, 9: 1-23.

Glaeser EL, Sacerdote B (1999) Why is there more crime in cities? *Journal of Political Economy*, 107: 225-258.

Gordon P, Richardson HW (1997) Are compact cities a desirable planning goal? *Journal of the American Planning Association*, 63: 95-105.

Hanson GH (2005) Market potential, increasing returns, and geographic concentration. *Journal of International Economics*, 67: 1-24.

Head K, Mayer T (2003) The empirics of agglomeration and trade. *Handbook of Regional and Urban Economics*, 4: 2609-2669

Henderson JV, Kuncoro A, Turner M (1995) Industrial development in cities. *Journal of Political Economy*, 103: 1067-1085.

Henderson JV (1986) Efficiency of resource usage and city size. *Journal of Urban Economics*, 19: 47-70.

Ihlanfeldt KR, Sjoquist DL (1998). The spatial mismatch hypothesis: a review of recent studies and their implications for welfare reform. *Housing Policy*, 9: 849–892.

Irwin EG, Bockstael NE, Jin Cho HJ (2006) Measuring and modeling urban sprawl: Data, scale and spatial dependencies. Invited paper presented at the Urban Economics Sessions, 53rd Regional Science Association International Annual Meeting, Toronto, November 16-18.

Jackson K (1985) Crabgrass frontier: The suburbanization of the United States. Oxford University Press.

Jacobs J (1969) The economy of Cities. New York, NY: Random House.

Jaffe A, Trajtenberg M, Henderson R (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108: 577-598.

Jordan S, Ross JP, and Usowski KG (1998) U.S. suburbanization in the 1980s. *Regional Science and Urban Economics*, 28: 611-627.

Knaap G, Nelson A (1992) The Regulated landscape: lessons on state land use planning from Oregon, Lincoln Institute of Land Policy, Cambridge, MA.

Klenow PJ (1996) Industry innovation: Where and why, Carnegie-Rochester Conference Series on Public Policy 44: 125-150.

Lloyd R (2001) Digital bohemia: New media enterprise in Chicago's Wicker Park. Paper presented at the annual meeting of the American sociology Association, Anaheim, CA.

Lloyd R, Clark TN (2000) The city as entertainment machine. Chicago: University of Chicago.

Lopez R, Hynes H (2003) Sprawl in the 1990s: measurement, distribution, and trends. *Urban Affairs Review*, 38: 325–355.

Lucas RE, Rossi-Hansberg E (2002) On the internal structure of cities. *Econometrica*, 70: 1445-1476.

Lucas R. (1988): On the mechanics of economic development. *Journal of Monetary Economics*, 22: 3-42.

Marshal A (1890) Principles of Economics, Macmillan, London.

Margo RA (1992) Explaining the postwar suburbanization of population in the United States: The role of income. *Journal of Urban Economics*, 31: 301-310.

Moretti E (2004) Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of Econometric*, 121: 175–212.

Mieszkowski P, Mills ES (1993) The causes of metropolitan suburbanization. *Journal of Economic Perspectives*, 7: 135-147.

Mills ES (1967) An aggregative model of resource allocation in metropolitan area. *American Economic Review*, 197: 197-210.

Mills ES, Luan SL (1997) Inner cities. *Journal of Economic Literature*, 35: 727-756.

Mills ES, Oates WE (1975) Fiscal zoning and land use, D.C. Heath, Lexington MA.

Moomaw R (1981) Productivity and city size: A critique of the evidence. *Quarterly Journal of Economics*, 96: 675-688.

Moomaw R (1983) Spatial productivity variations in manufacturing: A critical survey of cross sectional analysis. *International Regional Science Review*, 8: l-11.

Moomaw R (1985) Firm Location and city size: Reduced productivity advantage as a factor in the decline of manufacturing in urban Areas. *Journal of Urban Economics*, 17: 73-89.

Moulton B (1986) Random group effects and the precision of regression estimates, *Journal of Econometrics*, 32: 385-397

Muro M, Puentes R (2004) Investing in a better future: A Review of the fiscal and competitive advantages of smarter growth development patterns, The Brookings Institution Center on Urban and Metropolitan Policy.

Muth RF (1969) Cities and housing: the spatial pattern of urban residential land use. Chicago, IL: University of Chicago Press.

Nakamura R (1985) Agglomeration economies in urban manufacturing industries: A case of Japanese cities. *Journal of Urban Economics*, 17: 108-124.

Nechyba T, Walsh R (2004) Urban sprawl. *Journal of Economic Perspectives*, 18:177-200.

Ngai LR, Samaniego RM (2008) Research and productivity growth across industries. Working Paper.

Power A (2001) Social exclusion and urban sprawl: Is the rescue of cities possible? *Regional Studies*, 35: 731-742.

Putnam RD (2000) Bowling alone, Simon and Schuster, New York.

Quigley JM. (1998) Urban diversity and economic growth. *Journal of Economic Perspectives*, 12:127-138

Rauch J (1993) Productivity gains from geographic concentration of human capital: Evidence from the cities. *Journal of Urban Economics*, 34: 380-400.

Real Estate Research Corporation (RERC) (1974) The costs of sprawl: Environmental and economic costs of alternative residential development patterns at the urban fringe. Vol. 1, Executive Summary; Vol. 2, Detailed Cost Analysis; Vol. 3, Literature Review and Bibliography. Washington, D.C.: U.S. Government Printing Office.

Rigby DL, Essletzbichler J (2002) Agglomeration economies and productivity differences in U.S. cities. *Journal of Economic Geography*, 2: 407-432.

Romer PM (1986) Increasing Returns and Long-Run Growth. *Journal of Political Economy*, 94:1002-1037.

Segal D (1976) Are there returns to scale in city Size? *The Review of Economics and Statistics*, 58: 339-350.

Sigelman L, Heing J (2001) Crossing the great divide – race and preferences for living in the city versus the suburbs. *Urban Affairs Review*, 37: 3–18.

Stock JH, Yogo M (2005) Testing for weak instruments in linear IV regression. In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, ed. D.W. Andrews and J.H. Stock, 80-108. Cambridge University Press.

Sveikauskas L (1975) The productivity of cities. *Quarterly Journal of Economics*, 89: 393-413.

Tabuchi T (1998) Urban agglomeration and dispersion: a synthesis of Alonso and Krugman. *Journal of Urban Economics*, 44: 333–351

Wheeler CH (2001) Search, Sorting, and Urban Agglomeration. *Journal of Labor Economics*, 19: 879-899.

Wheaton W, M Lewis. (2002) Urban wages and labor market agglomeration. *Journal of Urban Economics*, 51:542-562.