The Role of Urban Greenspace in Shaping Labor Market Outcomes

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September 8, 2025

Abstract

This paper examines how urban greenspace influences labor market outcomes, focusing on whether workers are willing to accept lower wages in exchange for greener environments. Using a panel dataset of 950 urban U.S. counties from 2011 to 2019, we apply the theory of compensating differentials within a spatial equilibrium framework. Greenspace is measured using the Normalized Difference Vegetation Index (NDVI), a remote sensing indicator derived from satellite imagery. To address endogeneity concerns, we employ an instrumental variables strategy that leverages historical land cover data from the 1970s-80s. Our findings show a significant negative relationship between NDVI and wages, suggesting that workers accept lower pay in greener counties due to the non-monetary benefits of greenspace. At the same time, we find that greener cities have higher employment and population levels, indicating broader economic appeal. Sector-level analysis further reveals that the strength of this wage effect varies by industrial composition, with more diversified economies exhibiting stronger compensating differentials. These results highlight the economic value of greenspace beyond environmental or aesthetic benefits. As an amenity that can be shaped through public policy, greenspace offers a tool for enhancing urban livability and attracting labor, making it a valuable component of sustainable urban development strategies.

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1 Introduction

Urban greenspace is often viewed as a desirable feature of sustainable cities, credited with improving public health (WHO, 2016), mitigating heat (Gunawardena et al., 2017), managing stormwater (Berland et al., 2017), and enhancing overall livability (Reyes-Riveros et al., 2021). However, in cities where land is scarce and development pressures are high, policymakers and planners frequently face trade-offs between allocating land for greenspace versus using it for higher-yielding commercial or residential purposes. In such contexts, greenspace is typically treated as a secondary amenity, valued in principle but de-prioritized in practice. This study offers a concrete economic rationale for investment in urban greenspaces. By showing that workers are willing to accept lower wages in exchange for access to greenspace, it quantifies a compensating differential that can help justify urban greening efforts not merely on environmental or aesthetic grounds, but as a strategy for enhancing a city's economic competitiveness and long-term appeal.

This study asks a simple but underexplored question: *do urban workers accept lower wages in exchange for living in greener areas?* In other words, is greenspace a local amenity that improves quality of life, leading people to accept lower incomes in return? According to the theory of compensating differentials (Roback, 1982; Rosen, 1979), equilibrium wages reflect not just productivity but also local amenity values. In equilibrium, utility is equalized across cities and if an amenity is utility enhancing, workers are willing to accept a lower wage as long as their overall utility remains constant. While such non-market valuation frameworks have been applied to value amenities like climate (Albouy et al., 2016), air quality (Chay and Greenstone, 2003; Currie et al., 2015), and crime (Gyourko and Tracy, 1991; Dentler and Rossi, 2024), the wage valuation of urban greenery remains largely unexplored in the economic literature.

We examine the utility value of greenspace using a panel dataset covering 950 urban counties in the United States from 2011 to 2019. Our measure of greenspace is the Normalized Difference Vegetation Index (NDVI), a widely used remote-sensing index derived from satellite imagery that captures the extent and density of green vegetation. NDVI offers high spatial and temporal resolution, allowing for consistent, comparable tracking of greenspace across counties over time. We combine this with county-level wage data from the U.S. Bureau of Labor Statistics (BLS) and a rich set of controls, including cost-of-living indices, employment structure, and socio-economic characteristics, to estimate the relationship between greenspace and wages. To address potential endogeniety concerns, we employ an Instrumental Variable (IV) strategy using historical land cover data from the 1970s-80s, leveraging the persistent nature of land use patterns to isolate exogenous variation in contemporary greenspace.

Our results indicate a robust and statistically significant negative relationship between greenspace and urban wages, consistent with the hypothesis that workers value greener environments and are willing to trade off earnings to access them. In our preferred model specification, a 1 standard deviation increase in NDVI is associated with a **3.6%** decrease in average annual wages, holding other factors constant. We also find that greener cities have higher population growth and more employment, factors important to city growth, compared to their less green counterparts.

By documenting the wage-amenity tradeoff associated with urban greenspace, this paper makes several contributions to the literature. First, it extends the compensating differentials framework to a widely recognized but understudied amenity. While most prior studies on greenspace rely on perceived measures derived from qualitative surveys (Lafortezza et al., 2009; Kabisch, 2015), we take a revealed preference approach, using wage variation as an implicit valuation mechanism. Second, while much of the environmental economics literature focuses on housing prices as the primary outcome (Cho et al., 2008; Geoghegan, 2002; Zambrano-Monserrate et al., 2021; Zhang et al., 2020), our wage-based estimates provide an independent and theoretically consistent measure of how greenspace enters the utility function and influences labor market dynamics.

In addition, to the best of our knowledge, this is the first paper to take a causal approach to estimating the value of greenspace using a compensating differentials framework. By leveraging historical land cover as an instrument for contemporary greenspace, we address endogeneity concerns such as reverse causality and omitted variable bias, issues that often limit interpretation in this area. Finally, unlike many natural amenities such as coastline or elevation, greenspace is malleable through policy. Urban tree planting, park creation, and land use regulations can significantly alter greenspace availability within relatively short time frames, as opposed to the availability of a coastline or a river. As such, our findings offer actionable insights for planners and policymakers seeking to improve urban livability and attract or retain labor through environmental interventions.

The remainder of this paper proceeds as follows. The *Background* section discusses the previous work done in this context and explores the role of natural amenities like greenspace. The *Data* section gives an overview of the data used in the analysis. The *Methodology* section describes the theoretical background, the empirical formulation of the hypothesis and details the identification strategy. The *Results* section discusses the empirical findings, and finally the paper ends with the *Conclusion* section.

2 Previous Literature

Urban greenspace has traditionally been examined in the literature in terms of its impact on environmental quality, public health, and property valuation, yet its influence on labor markets and wages remains relatively underexplored. This paper adds to the expanding interdisciplinary literature at the intersection of urban economics, environmental economics, and regional science by evaluating the economic value associated with improvements in quality of life.

The conceptual foundation of this study lies in the theory of compensating differentials, which posits that workers will accept lower wages in locations that offer higher non-monetary utility, such as better climate, lower pollution, or more amenities (Roback, 1982; Rosen, 1979). In equilibrium, wages and rents adjust to equalize utility across space, making it possible to infer the value of local amenities from labor and housing market outcomes. The model has been extensively used in explaining regional differences in many sectors, including housing and real estate (Anenberg and Kung, 2020; Harris, 2024; Glaeser et al., 2014; Bischoff, 2012) and other areas of economics (Kahn and Tracy, 2024). Recent work in the context of natural resources by Weinstein et al. (2023) Clay et al. (2023) and Albouy et al. (2016) uses this framework to show natural factors like weather, proximity to water and access to natural resources can have significant impact in explaining regional differences.

The idea of city providing certain amenities as an area of study emerged during the 1970s (Polinsky and Shavell, 1976; Yinger, 1976). Urban amenities are often understood as bundles of desirable goods that attract individuals to urban areas, shaping the way cities are consumed (Glaeser et al., 2001), explaining how quality of life influences both economic performance and urban expansion in inter-city comparisons. With improvements in transportation and communication technologies, the primary function of cities has evolved from minimizing commuting distance to offering a wide array of consumption-based amenities. The demand for urban living is increasingly driven by access to cultural institutions, diverse dining options, entertainment, high-performing schools, and safer neighborhoods (Glaeser and Gottlieb, 2006).

Natural amenities such as greenspace have been widely linked to improvements in both physical and mental health, contributing to a higher overall quality of life for urban residents (Carrus et al., 2015; Wolf et al., 2020; Donovan and Gatziolis, 2019; Weichenthal et al., 2016; Gu et al., 2022). Parks, green corridors, and lakes also serve as vital "third spaces," fostering social interaction, reducing isolation, and strengthening community ties (Kabisch, 2015). These amenity-driven improvements in well-being make cities more attractive places to live and work. In turn, natural amenities have been shown to support urban growth by enhancing a city's ability to attract both firms and skilled workers (Rickman and Wang, 2017; Weinstein et al., 2023; Stephens and Partridge, 2015; Hausman et al., 2025), making them a critical component of urban development strategies. These differences in amenities can explain the wage differntials between regions (Roback, 1982; Rosen, 1979; Albouy et al., 2016; Beeson and Eberts, 1989).

In the Roback spatial equilibrium framework, amenities influence equilibrium outcomes in both the labor and housing markets by shifting the utility of a location. Urban greenspace, such as parks, tree-lined streets, and gardens, is typically classified as a natural consumption amenity, meaning it enhances residents' utility without directly affecting firm level improvements. Unlike amenities such as transportation infrastructure or proximity to industrial hubs, greenspace does not contribute to the production function in most urban contexts. Its value lies in non-market benefits such as psychological well-being, recreational opportunities, and aesthetic pleasure Carrus et al. (2015); Lafortezza et al. (2009). Therefore, the compensating differential induced by greenspace is expected to appear primarily through wage adjustments rather than productivity-linked earnings increases (Chen and Wang, 2013; Roback, 1982). Workers may accept lower wages in greener areas because the utility gained from living near greenspace offsets the monetary trade-off, while firms operating in those areas do not necessarily realize cost-savings or productivity enhancements that would drive wages upward. This distinction reinforces the interpretation of greenspace as a pure utility-shifting amenity in line with Roback's theoretical predictions (Roback, 1988).

While the amenity value of greenspace is increasingly recognized in urban research, most existing studies focus on its capitalization into housing prices (Siriwardena et al., 2025; Pandit et al., 2014) or its broader cost–benefit implications (Soares et al., 2011), with far less attention to its effects on labor market outcomes. This study addresses that gap by examining whether access to urban greenspace influences worker wages across a diverse panel of U.S. counties. Unlike prior work that often relies on subjective measures of quality of life, we use wages as an objective indicator to capture workers' revealed preferences for environmental amenities. To strengthen causal inference, we adopt an IV strategy using historical land cover data, controlling for cost of living, allowing us to isolate the utility channel through which greenspace operates within the Roback framework. Moreover, our focus on greenspace is particularly policy-relevant, as it represents a feature of the urban environment that can be directly influenced through public planning, unlike many other natural amenities that depend on natural endowment. By linking greenspace to labor market behavior, this paper highlights its economic relevance beyond aesthetics or property valuation and provides tangible guidance for urban policy design.

3 Data

The academic literature has defined greenspaces in various ways. A systematic review of the academic literature across multiple disciplines was conducted by Taylor and Hochuli (2017) and finds two major definitions of greenspace. For purposes of this study, we focus specifically on urban vegetation, encompassing features such as trees, parks, gardens and yards typically referring to vegetated forms of open space within urban environments (Chong et al., 2013; Bastian et al., 2012). This is also consistent with the definition from the U.S. Environmental Protection Agency (EPA) defines greenspace as urban land that is partly or completely covered with grass, trees, shrubs, or other vegetation (EPA, 2023).

To measure greenspace, we use NDVI, collected from the National Oceanic and Atmospheric Administration (NOAA). The Advanced Very High Resolution Radiometer (AVHRR) dataset from NOAA is a cross-tracking scanning system with five spectral bands which takes high resolution images from the satellite twice a day at a resolution of 1.1 km. This is then coupled with the Visible Infrared Imaging Radiometer Suite (VIIRS) to produce NDVI values on a daily basis with a 0.05° by 0.05° grid. *Figure 1* shows a visual representation of what NDVI identifies as greenspace, highlighted in red, from the satellite image of Point State Park in Pittsburgh, Pennsylvania.

Although there are many vegetation indexes, the NDVI enables for comparison across spatial and temporal spectrums (Huang et al., 2021) and has been widely used in analyzing

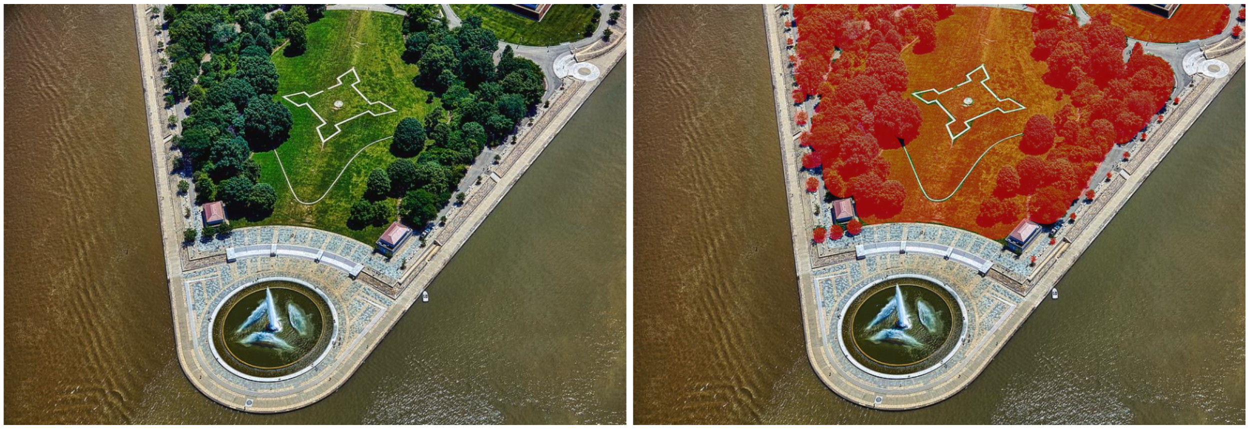

Figure 1: NDVI Vision

greenspaces in other settings (Donovan and Gatziolis, 2019; Huang et al., 2021; Lei et al., 2021). The NDVI uses the Near Infra-Red band and the red band spectrums of satellite images to calculate an index value with a range of -1 to +1, with the higher the value, the higher the greenspace, values below 0 are associated with non-greenspaces, *equation 1* shows the calculation formula. The satellite images were read into a GIS software, and were superimposed on a county shapefile. Using a raster extractor, the NDVI values were extracted as a mean of the all the NDVI value grids within a county shape polygon. *Figure 2* shows the NDVI values across the counties for the year 2000 and 2022, with more green areas representing a higher NDVI value, thus, a higher greenspace. It is also evident from the maps that greenspace has had a distinct change over the years.

The previous literature shows that NDVI values can fluctuate seasonally, however, it is the highest during the summer (Jia et al., 2004; Kulenbekov et al., 2021). At the same time, satellite images can be often compromised by cloud covers, making a one-off assessment faulty. As a result, to create our annual measures of greenspace, we used the bi-weekly satellite images for the months of June and July for each year, to extract the NDVI values for each county from 2011 to 2019.

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - R}{\mathrm{NIR} + R} \tag{1}$$

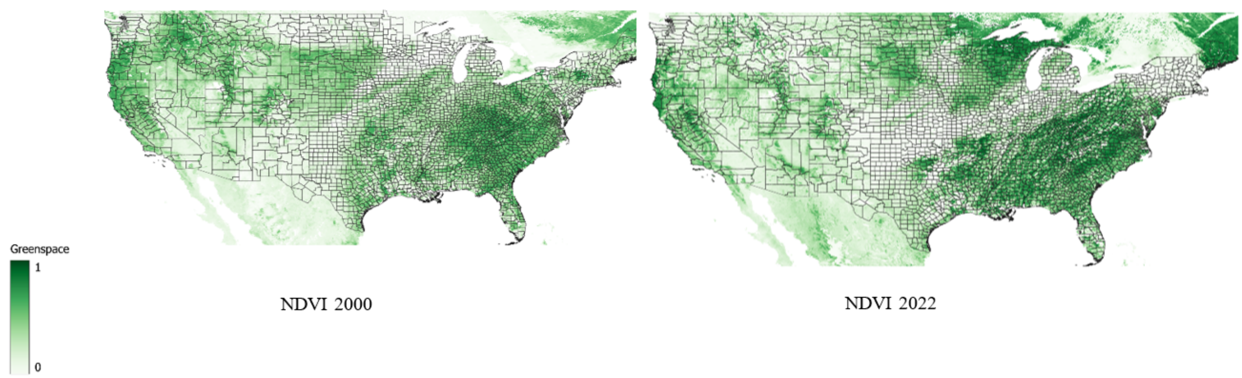

Figure 2: NDVI distribution across counties 2000 and 2022

Previous studies have investigated the efficacy of NDVI and has concluded that it demonstrates substantial reliability (Huang et al., 2021). Our analysis exclusively considered values exceeding 0 when extracting data from the raster files. NOAA provides two distinct NDVI measurements for each day: the daily mean and the daily maximum. To annualize these values, we computed the yearly mean using data from June and July. Our sample analysis reveals that the mean daily average NDVI value is 0.343 per county per annum, while the mean daily maximum value is 0.848 per county per annum, as depicted in *table 1*.

The primary dependent variable in our analysis is county-level wages, obtained from BLS. To examine broader labor market dynamics, we also analyze two additional outcomes: total population, sourced from the U.S. Census Bureau, to evaluate whether greenspace attracts more residents; and total employment levels, also from BLS, to assess whether greener areas exhibit higher employment. *Table 1* presents descriptive statistics for all variables included in the model. On average, counties report annual wages of approximately $42,000.

The paper uses 950 urban counties in the contiguous United States with data for the years 2011 - 2019. For classification of urban and rural, we rely on the identification provided by the U.S. Census (Census, 2024). In our model specification, we also incorporate a comprehensive set of county-level characteristics as control variables to account for potential confounding factors. The control variables encompass geographic and environmental attributes, including the county's land area, proximity to the nearest Metropolitan Statistical Area (MSA), annual

Variable	N	Mean	SD	Min	Max
Average Annual Wage	10,750	41,721	10,339	20,968	138,273
Annual average of daily mean NDVI	10,750	0.343	0.142	0.00481	0.848
Annual average precipitation	10,750	0.111	0.0387	0.00250	0.282
Annual High Temperature days	10,750	30.66	16.97	0	105
% of people employed	10,750	57.41	6.92	21.40	77.60
Median HH income (in 2010 USD)	10,750	54,582	14,000	22,083	142,299
% of population with Highschool Degree	10,750	62.16	8.038	19	81.20
% of population with Bachelors Degree	10,750	15.84	5.955	2.600	38
% of population with Graduate Degree	10,750	8.986	4.755	0.400	40.30
% of population less than HS	10,750	13.01	5.812	1.300	49.50
Total Population	10,750	238,739	516,492	709	1.011e+07
% of people White	10,750	82.14	14.41	12.60	99.80
% of people Black	10,750	9.949	12.59	0	78.50
% of people American Indian/Alaskan	10,750	0.798	3.191	0	83.90
% of people Asian	10,750	2.161	3.263	0	36.50
% of people Hawaii/Pacific	10,750	0.0752	0.179	0	2.300
% of people other race	10,750	2.495	3.624	0	38.40
% of people multiracial	10,750	2.374	1.399	0	18.80
% of people working in-county	10,750	59.64	19.94	11	98.50
Miles to nearest MSA	10,750	15.79	12.70	0	62.15
Median Rent	10,750	916.46	266.15	497	3269
House Price Index (HPI-86 base prices)	10,539	363.41	240.56	79.36	2575
County land area (sq km)	10,750	2.194e+09	3.438e+09	5.868e+07	5.195e+10

Table 1: Descriptive statistics of key variables.

high temperature days and annual precipitation data obtained from the NOAA.

Furthermore, we incorporate economic indicators such as median household income, educational attainment levels, and percentage of people working in the county. Demographic factors are also considered, including total county population and racial composition, derived from the American Community Survey (ACS) 5-year estimates. The income data was collected from the U.S. Bureau of Economic Analysis (BEA). To account for the economic structure of each county, we include variables representing the industrial composition based on North American Industry Classification System (NAICS) categories from BLS. These variables are expressed as proportional shares of each industry within the county's economic landscape. We also control for historical industrial composition from the 1970s-80s in our IV specifications.

Our analysis focuses exclusively on urban counties, effectively comparing conditions across urbanized areas. A key challenge in this context is that many U.S. urban counties encompass significant rural land, such as forests, farmland, or undeveloped areas, that may be detected by NDVI as greenspace. However, these areas are often not directly accessible or enjoyed by the urban population, potentially biasing our measure of greenspace. To address this concern, we include present-day land cover as a control variable in our model. This allows us to account for the influence of non-urban vegetation and isolate the effect of greenspace that is more likely to be experienced within the urban environment. Finally, the Roback model considers the dynamic between wages and rents. As such, we control for the median rent using the Fair Market Rents (FMR) collected from the U.S. Department of Housing and Urban Development. The FMR provides median rents across different size of housing, which we averaged for each county per year.

4 Methodology

4.1 Theoretical Foundations

This paper builds on the spatial equilibrium framework introduced by Roback (1982) to examine how urban greenspace influences labor market outcomes. In this framework, workers are assumed to be fully mobile and choose among locations by comparing bundles of wages, housing, and local amenities. Because utility must be equalized across space in equilibrium, differences in local quality of life are offset by adjustments in either wages or rents.

Urban greenspace enters this setup as a local amenity that improves individual well-being but does not directly affect productivity. The implication is straightforward: workers may be willing to accept lower wages in greener locations, since the utility they derive from the amenity compensates for the reduction in income. In other words, locations with greater greenspace can sustain lower wages while still attracting workers.

This perspective generates a clear empirical prediction. If greenspace enhances quality of life, then equilibrium wages should be lower in counties with more greenspace, holding productivity constant. The size of this compensating wage differential reflects the implicit value workers place on greenspace in their location decisions.

Our empirical analysis draws on this logic by estimating how wages vary with urban greenspace across 950 U.S. urban counties. By focusing on settings where variation in land prices can be abstracted away, we isolate the wage component of the equilibrium adjustment, providing direct evidence on how workers value environmental amenities.

4.2 Empirical Model

Using equation (2), we examine the relationship between urban greenspace and wages across counties in the United States from 2011 to 2019.

$$\log(\text{wage}_{ct}) = \beta_0 + \beta_1 \log(\text{NDVI}_{ct}) + \boldsymbol{\gamma}_i \text{Controls}_{ct} + \theta_c + \tau_t + \varepsilon_{ct} \tag{2}$$

The dependent variable of the model is the logarithm of annual wages for county c in year t, measured in USD. We also estimate alternative specifications, varying the dependent variable. We use the average annual employment level in county c in year t, to measure the impact of greenspace on overall employment level in the county. In addition, we also employ total population as another dependent variable to see the overall growth of the county. Greenspace is represented by the NDVI value for county c in year t, ranging from 0 to 1, and serves as the primary variable of interest, making β_1 the coefficient of concern. Controls_{ct} is a vector of control variables, including geographic characteristics, socio-economic indicators, and industry composition, as discussed above. θ_c represents state-level fixed effects, while τ_t captures year fixed effects.

4.3 Identification

One of the primary concerns with identifying the impact of greenspace on wages is that places with higher wages may invest in more greenspace resulting in possible reverse causality. Greenspace may also be correlated with unobserved factors resulting in endogenity.

Furthermore, there can be simultaneous effects on wages and greenspace due to factors like government zoning policies, etc. which might make our estimators biased. To address the potential endogeneity concerns inherent in our model, we employ an IV approach utilizing historical land cover data. Specifically, we leverage land cover data from the 1970s-1980s, sourced from the United States Geological Survey (USGS), which predates our study period by approximately three decades. This temporal distance is crucial for our identification strategy.

$$\log(\widehat{\text{NDVI}_{ct}}) = \alpha_0 + \alpha_1 \text{HistLC}_{ct} + \alpha_2 \text{HistIC}_{ct} + \boldsymbol{\gamma}_i \text{Controls}_{ct} + \theta_c + \tau_t + \varepsilon_{ct} \tag{3}$$

Equation (6) specifies the first stage of an IV approach, where the dependent variable is the predicted log of NDVI, denoted as $\log(\widehat{\text{NDVI}_{ct}})$, for county c in year t. This formulation leverages historical variables to isolate exogenous variation in urban greenspace, inspired from previous work (Stephens and Partridge, 2011). The term HistLC_{ct} represents historical land cover characteristics, such as forest or shrub density, which shape current greenspace levels but are plausibly uncorrelated with contemporary labor market shocks. HistIC_{ct} captures the historical industry composition of the county, reflecting long-run economic patterns that may influence the development and preservation of greenspace. Controls_{ct} includes additional observable county-level controls such as demographic, climatic, or spatial characteristics similar to the primary specification. The fixed effects θ_c and τ_t account for unobserved county-specific heterogeneity and common temporal shocks, respectively, and ε_{ct} is the error term. This first-stage regression generates exogenous variation in NDVI used in the second-stage wage equation to identify the causal effect of greenspace on labor market outcomes.

The selection of this instrument is predicated on two key assumptions of IV estimation. First, regarding relevance, we see a strong correlation between historic land cover patterns and contemporary NDVI values. This relationship is expected to persist due to the long-term nature of land use changes and environmental characteristics. Second, concerning the exclusion restriction, we find that land cover from three decades prior is unlikely to exert a direct influence on current wage levels, except through its impact on present-day greenspace as measured by NDVI, when controlling for histrocial industrial composition. Results of these individual relevance and exclusion regressions are given in *Appendix 1*.

This IV strategy aims to mitigate potential bias arising from reverse causality, omitted variables, or simultaneous determination of greenspace and productivity. By utilizing historically determined land cover patterns, we seek to isolate the exogenous variation in current greenspace, thereby enabling a more robust estimation of its causal effect on worker wages. The first stage regression results show that this is a very efficient instrument in controlling endogeneity.

5 Results

5.1 Primary Results

The results in *table 2* provide empirical support for the hypothesized relationship between urban greenspace and labor market outcomes. Detailed regression results are provided in *Appendix 2*. *Column (1)* reports a simple OLS estimate, suggesting a positive but statistically insignificant association between log NDVI and wages. This likely reflects the influence of omitted variables or measurement error in the greenspace measure. Once we address endogeneity using an IV approach in *column (2)*, we find a statistically significant and negative relationship between greenspace and wages. Specifically, a 1% increase in NDVI is associated with a 0.064% decrease in wages, holding other factors constant. This aligns with predictions from the Roback model, where workers accept lower wages in exchange for higher amenity value from greenspace.

Column (3) extends the analysis by including the squared term of NDVI to test for potential nonlinearities. Both the linear and squared terms are statistically significant and negative, indicating diminishing returns to greenspace in terms of wage compensation. This suggests that while moderate increases in greenery may be highly valued by workers, the

Table 2: Regression Results

VARIABLES	OLS	IV-Annual Avg Wage	IV-Squared Wage	IV-Avg Emp Level	IV-Population
Log Greenspace (NDVI)	0.000781	-0.0642***	-0.197***	17,481***	222,009***
	(0.000689)	(0.0143)	(0.0423)	(4,572)	(33,593)
Log Squared Greenspace (NDVI)			-0.052***		
			(0.0112)		
Observations	9,355	9,355	9,355	9,355	9,355
R-squared	0.900	0.868	0.864	0.986	0.916
Number of Counties	950	950	950	950	950
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
First Stage:		NDVI	NDVI	NDVI	NDVI
Historic Land Cover		0.090***	0.090***	0.090***	0.090***
		(0.0065)	(0.0065)	(0.0065)	(0.0065)
CD Wald F-Stat		183.02	183.02	183.02	183.02

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

marginal value declines at higher levels of greenspace, possibly due to trade-offs with urban density or accessibility.

Beyond wages, we also examine broader economic effects. *Column (4)* shows that greater greenspace is associated with higher average employment levels, with a 1% increase in NDVI linked to approximately 17,500 more employed individuals. This is consistent with economic theory, where a lower wage would lead to cheaper cost of labor hiring and as a result, more workers will be employed. *Similarly, column (5)* reports a strong positive association with total population, suggesting that greener counties attract more residents. These findings imply that greenspace not only influences individual preferences as captured by wages but may also contribute to local economic vitality by increasing labor supply and population.

The first-stage F-statistics well exceed the conventional threshold, supporting the strength of the instrument (historic land cover) used to isolate exogenous variation in greenspace. Present NDVI is highly correlated with past land cover patterns of greenery, when controlling for present and historical industrial composition. The detailed first stage regressions are provided in the *Appendix*.

5.2 Heterogeneity in Effect

6 Conclusion

This study provides compelling evidence that urban greenspace plays a critical role in shaping labor market outcomes through the lens of compensating differentials. By applying a spatial equilibrium framework and using NDVI as a proxy for greenspace across 950 urban U.S. counties from 2011 to 2019, the analysis shows that increased greenspace is associated with lower wages. This negative relationship, confirmed through an IV approach using historical land cover data, suggests that workers accept lower pay in exchange for the non-monetary benefits provided by greener environments. This tradeoff underscores the utility-enhancing role of greenspace in urban areas, consistent with the theoretical predictions of Roback (1982).

Importantly, the wage effects of greenspace are not uniform across regions. Our sectoral heterogeneity analysis reveals that the magnitude of compensating wage differentials depends on local economic structures. Counties with diverse employment bases experience more pronounced wage reductions in greener environments, whereas specialized counties see weaker effects. At the same time, greater greenspace is positively associated with employment levels and population growth, indicating that while workers may earn less, greener cities attract more people and support greater labor demand. This signals that greenspace contributes to local economic vitality, not stagnation.

These findings offer both theoretical and practical contributions. Theoretically, the study expands the compensating differentials literature by introducing a causal framework for valuing urban greenery using wage data, a departure from the housing-price focus seen in earlier work. Practically, the results have significant policy relevance: unlike fixed amenities such as coastline or climate, greenspace is malleable and can be shaped through urban planning. Investments in tree planting, park development, and green infrastructure can enhance city livability, attract talent, and foster economic growth, even in the absence of direct productivity gains.

As urban populations continue to grow and climate-related stressors intensify, prioritizing greenspace should be viewed not merely as an environmental or aesthetic goal, but as a viable economic development strategy. By recognizing the compensatory value of greenery in wage setting and labor dynamics, policymakers can justify and design greenspace interventions that support inclusive, resilient urban economies. Future research could further unpack how the quality, accessibility, and spatial distribution of greenspace mediate these labor market effects, particularly across different socio-economic groups.

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Appendix

Appendix 1: IV testing regression

Table 1: NDVI regressed with Historical Landcover

VARIABLES	ln_NDVI	ln_wage
hist_landcover	0.0898***	0.000768
	(0.00876)	(0.000723)
miles to nearest MSA	0.000550	-0.00147***
	(0.000729)	(0.000260)
present_landcover	7.12e-08***	-8.27e-09**
	(9.94e-09)	(3.74e-09)
HPI	0.000242***	7.87e-05***
	(5.50e-05)	(6.24e-06)
% working in-county	-0.00131**	0.00121***
	(0.000592)	(0.000141)
% High School Degree	-0.00326	0.00180***
	(0.00238)	(0.000316)
% Bachelors Degree	-0.00514	0.00423***
	(0.00342)	(0.000446)
% Graduate Degree	0.00154	0.00265***
	(0.00406)	(0.000555)
% Employed	0.00133	5.81e-05
	(0.00193)	(0.000264)
Median HH income (2010 USD)	1.32e-06	1.56e-06***
	(1.13e-06)	(1.68e-07)
Total Population	-7.74e-08*	-5.02e-08***
	(4.56e-08)	(1.27e-08)
% Black	0.00155*	0.00233***
	(0.000840)	(0.000281)
% American Indian/Alaskan	0.00773*	0.00167
	(0.00436)	(0.00105)
% Asian	-0.00591*	0.00550***
	(0.00348)	(0.000861)
% Hawaii/Pacific	0.0850**	0.00583
	(0.0433)	(0.00402)
% Other race	-0.00381	-5.35e-05
	(0.00269)	(0.000271)
% Multiracial	0.0215***	0.000558
	(0.00662)	(0.000692)
Annual avg precipitation	0.00417	0.0206
	(0.200)	(0.0138)
NAICS - Mine, Oil, Gas	0.000813	0.0162***
	(0.00384)	(0.000487)
NAICS - Utilities	0.00150	0.0121***
	(0.00717)	(0.00129)

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Table 3 – continued from previous page

VARIABLES	ln_NDVI	ln_wage
NAICS - Construction	0.00799**	0.00907***
	(0.00323)	(0.000406)
NAICS - Manufacturing 1	-0.000303	0.00300***
	(0.00206)	(0.000368)
NAICS - Manufacturing 2	0.00270	0.00626***
	(0.00236)	(0.000399)
NAICS - Manufacturing 3	0.000394	0.00612***
	(0.00151)	(0.000300)
NAICS - Wholesale	-0.00198	0.00390***
	(0.00464)	(0.000630)
NAICS - Retail 1	0.00413	-0.00306***
	(0.00563)	(0.000728)
NAICS - Retail 2	0.00463	-0.00293***
	(0.00378)	(0.000548)
NAICS - Transport 1	-0.00169	0.00431***
	(0.00389)	(0.000723)
NAICS - Transport 2	-0.00522	-0.00106**
	(0.00436)	(0.000506)
NAICS - Information	-0.00239	0.0148***
	(0.00884)	(0.00117)
NAICS - Finance, Insurance	0.00244	0.0111***
	(0.00329)	(0.000607)
NAICS - Real Estate	-0.00571	-0.000235
	(0.0132)	(0.00153)
NAICS - Prof Science Tech	-0.00169	0.0108***
	(0.00387)	(0.000610)
NAICS - Management	0.00940*	0.00824***
	(0.00512)	(0.000631)
NAICS - Admin, Waste	-0.00696**	0.000119
	(0.00352)	(0.000415)
NAICS - Education	0.00371	0.00111*
	(0.00307)	(0.000604)
NAICS - Healthcare	0.00385**	6.77e-05
	(0.00184)	(0.000340)
NAICS - Arts, Entertainment	0.00613*	-0.00122*
	(0.00366)	(0.000736)
NAICS - Accommodation, Food	-0.00560*	-0.00673***
	(0.00295)	(0.000520)
NAICS - Other Services	-0.00933*	-0.000795
	(0.00489)	(0.000544)
20 hist_ind_value_70	5.26e-06***	1.49e-06**
	(1.88e-06)	(7.13e-07)
40 hist_ind_value_70	1.06e-05***	1.99e-06
	(3.73e-06)	(1.43e-06)
50 hist_ind_value_70	2.14e-05	-2.22e-05***
	(1.81e-05)	(7.17e-06)
70 hist_ind_value_70	7.15e-06	7.12e-07
	(1.03e-05)	(4.02e-06)

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Table 3 – continued from previous page

VARIABLES	ln_NDVI	ln_wage
90 hist_ind_value_70	-6.21e-06***	-1.56e-06*
	(2.38e-06)	(9.13e-07)
100 hist_ind_value_70	-4.86e-05**	1.15e-05
	(2.43e-05)	(9.71e-06)
200 hist_ind_value_70	8.80e-06	-2.47e-06
	(6.18e-06)	(2.41e-06)
300 hist_ind_value_70	1.91e-07	1.52e-05***
	(4.85e-06)	(1.82e-06)
400 hist_ind_value_70	3.07e-06*	5.99e-07
	(1.76e-06)	(6.88e-07)
500 hist_ind_value_70	-1.56e-05***	3.42e-06**
	(4.54e-06)	(1.73e-06)
610 hist_ind_value_70	1.49e-05***	-3.86e-06**
	(4.09e-06)	(1.60e-06)
620 hist_ind_value_70	-1.78e-06	-4.59e-06***
	(3.94e-06)	(1.56e-06)
700 hist_ind_value_70	-5.12e-06	-4.19e-07
	(3.75e-06)	(1.48e-06)
910 hist_ind_value_70	-6.57e-06**	2.86e-06**
	(3.02e-06)	(1.18e-06)
920 hist_ind_value_70	-4.51e-06**	-1.62e-06**
	(2.10e-06)	(8.12e-07)
Constant	-1.631***	9.978***
	(0.207)	(0.0387)
present_NDVI		-0.0146***
		(0.00331)
Observations	8,419	
Number of geoid	936	

Standard errors in parentheses.
**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Appendix 2: Primary Regressions

VARIABLES	(1) OLS	(2) Wage	(3) Empl	(4) Pop	(5) Square
ln_yndvi	0.000781	-0.0642***	17,481***	222,009***	-0.197***
	(0.000689)	(0.0143)	(4,643)	(33,593)	(0.0423)
ln_yndvi_sq					-0.0521***
					(0.0112)
miles to nearest MSA	-0.00155***	-0.000394***	132.7***	799.3***	-0.000441***
	(0.000256)	(0.000106)	(34.65)	(176.8)	(0.000106)
present_landcover	-1.15e-08***	-3.73e-09**	0.00209***	-0.0452***	-7.76e-09***
	(3.56e-09)	(1.69e-09)	(0.000677)	(0.00605)	(1.15e-09)
HPI	7.23e-05***	9.95e-05***	42.67***	-134.2***	8.58e-05***
	(6.15e-06)	(9.53e-06)	(4.987)	(21.97)	(9.45e-06)
rent	2.75e-05***	5.24e-05***	-19.52***	26.08	5.99e-05***
	(4.71e-06)	(8.14e-06)	(3.649)	(17.55)	(8.22e-06)
Value	-3.49e-05	0.000130*	1.825	-359.4**	-5.13e-05
	(2.20e-05)	(7.64e-05)	(28.33)	(162.4)	(6.46e-05)
% of people working in-county	0.00115***	0.00147***	412.6***	-1,078***	0.00155***
	(0.000135)	(8.83e-05)	(30.80)	(147.1)	(8.99e-05)
County land area (sq km)	0**	-0	-1.61e-06***	2.49e-05***	0**
	(0)	(0)	(2.80e-07)	(2.18e-06)	(0)
% of population with Highschool Degree	0.00180***	0.00103***	-1,041***	632.3	0.000615
	(0.000299)	(0.000393)	(145.1)	(805.5)	(0.000431)
% of population with Bachelors Degree	0.00456***	0.00131**	-1,066***	12,630***	0.00136**
	(0.000423)	(0.000600)	(217.4)	(1,036)	(0.000610)
% of population with Graduate Degree	0.00277***	0.00557***	-1,404***	-12,547***	0.00494***
	(0.000524)	(0.000714)	(280.2)	(1,278)	(0.000740)
% of people employed	0.000110	-0.000170	701.6***	811.1	-0.000361

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VARIABLES	(1) OLS	(2) Wage	(3) Empl	(4) Pop	(5) Square
	(0.000250)	(0.000305)	(103.0)	(541.2)	(0.000315)
Median HH income (in 2010 USD)	1.09e-06***	2.78e-06***	-0.338***	-1.044***	2.68e-06***
	(1.63e-07)	(1.84e-07)	(0.0734)	(0.400)	(1.83e-07)
Total Population	-5.81e-08***	-2.12e-08***	0.389***		-1.21e-08**
	(1.19e-08)	(5.30e-09)	(0.00681)		(5.87e-09)
% of people Black	0.00229***	0.00281***	-227.5***	-2,355***	0.00261***
	(0.000271)	(0.000122)	(50.44)	(235.8)	(0.000126)
% of people American Indian/Alaskan	0.00207**	0.00172***	315.6*	-6,348***	0.000652
	(0.00100)	(0.000571)	(180.2)	(1,633)	(0.000563)
% of people Asian	0.00469***	0.00346***	3,153***	13,578***	0.00375***
	(0.000811)	(0.000605)	(363.7)	(1,281)	(0.000607)
% of people Hawaii/Pacific	0.00569	0.0386***	-9,478***	51,386***	0.0390***
	(0.00382)	(0.00835)	(3,003)	(12,984)	(0.00844)
% of people other race	-6.22e-05	0.00197***	-1,619***	2,427**	0.00221***
	(0.000252)	(0.000410)	(207.5)	(1,158)	(0.000419)
% of people multiracial	0.000888	0.00830***	-1,104***	-4,053**	0.00775***
	(0.000648)	(0.00144)	(378.2)	(1,903)	(0.00141)
Annual average precipitation	-0.00568	0.168***	-14,019	15,583	0.160***
	(0.0148)	(0.0419)	(15,148)	(88,104)	(0.0422)
NAICS - Mine,Oil,Gas	0.0155***	0.0151***	-71.57	-4,716***	0.0152***
	(0.000462)	(0.000562)	(181.8)	(1,249)	(0.000575)
NAICS - Utilities	0.0119***	0.0269***	557.3***	163.7	0.0269***
	(0.00124)	(0.000983)	(192.6)	(1,197)	(0.00102)
NAICS - Construction	0.00886***	0.00389***	-709.4***	-1,197	0.00396***
	(0.000385)	(0.000702)	(152.3)	(885.3)	(0.000713)
NAICS - Manufacturing 1	0.00306***	0.00137***	18.92	313.3	0.00134***
	(0.000345)	(0.000301)	(71.46)	(442.7)	(0.000301)
NAICS - Manufacturing 2	0.00627***	0.0102***	-176.7**	1,005**	0.0102***

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VARIABLES	(1) OLS	(2) Wage	(3) Empl	(4) Pop	(5) Square
	(0.000375)	(0.000394)	(75.22)	(478.3)	(0.000399)
NAICS - Manufacturing 3	0.00607***	0.00838***	118.4*	1,747***	0.00846***
	(0.000284)	(0.000329)	(61.53)	(366.7)	(0.000345)
NAICS - Wholesale	0.00414***	0.00315***	416.0**	3,585***	0.00357***
	(0.000594)	(0.000751)	(210.6)	(1,213)	(0.000746)
NAICS - Retail 1	-0.00302***	-0.00644***	-3,439***	9,610***	-0.00656***
	(0.000685)	(0.000949)	(249.1)	(1,277)	(0.000951)
NAICS - Retail 2	-0.00306***	-0.00303***	-1,014***	551.4	-0.00274***
	(0.000519)	(0.000723)	(167.8)	(889.0)	(0.000730)
NAICS - Transport 1	0.00420***	0.00757***	374.4**	5,193***	0.00740***
	(0.000692)	(0.000525)	(149.8)	(834.0)	(0.000547)
NAICS - Transport 2	-0.00122***	0.00201***	110.0	2,348***	0.00202***
	(0.000465)	(0.000551)	(149.2)	(905.7)	(0.000568)
NAICS - Information	0.0152***	0.0130***	6,997***	12,891***	0.0124***
	(0.00110)	(0.00183)	(813.4)	(2,536)	(0.00181)
NAICS - Finance, Insurance	0.0113***	0.00967***	417.2***	-391.5	0.00957***
	(0.000578)	(0.000655)	(161.4)	(798.4)	(0.000675)
NAICS - Real Estate	-0.00139	0.00556***	884.4*	-3,802	0.00437**
	(0.00144)	(0.00205)	(532.7)	(3,290)	(0.00211)
NAICS - Prof Science Tech	0.0103***	0.0198***	2,859***	-206.0	0.0197***
	(0.000582)	(0.000640)	(302.4)	(921.0)	(0.000646)
NAICS - Management	0.00837***	0.0245***	1,717***	-4,219***	0.0244***
	(0.000606)	(0.00118)	(283.2)	(1,540)	(0.00121)
NAICS - Admin, Waste	0.000212	0.00149**	-1.866	8,723***	0.00188***
	(0.000391)	(0.000609)	(161.3)	(880.2)	(0.000606)
NAICS - Education	0.000900	0.000538	-401.9***	2,080**	0.000328
	(0.000571)	(0.000349)	(137.1)	(829.1)	(0.000346)
NAICS - Healthcare	-0.000150	0.00223***	-1,026***	683.5	0.00210***
	(0.000319)	(0.000358)	(93.85)	(502.0)	(0.000357)

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VARIABLES	(1) OLS	(2) Wage	(3) Empl	(4) Pop	(5) Square
NAICS - Arts, Entertainment	-0.000948	-0.00154**	360.0**	899.6	-0.00147**
	(0.000706)	(0.000671)	(180.7)	(808.9)	(0.000647)
NAICS - Accommodation,Food	-0.00708***	-0.00483***	-156.5	4,571***	-0.00482***
	(0.000491)	(0.000490)	(118.0)	(839.4)	(0.000488)
NAICS - Other Services	-0.000599	-0.0121***	-229.9	-6,383***	-0.0118***
	(0.000511)	(0.000942)	(240.6)	(1,266)	(0.000934)
20 value_70	1.80e-06***	9.09e-07***	-0.167	5.695***	5.34e-07**
	(5.86e-07)	(2.55e-07)	(0.193)	(0.770)	(2.55e-07)
40 value_70	9.53e-07	-3.95e-07	-1.597***	13.18***	-1.05e-06*
	(1.31e-06)	(5.83e-07)	(0.396)	(1.586)	(5.72e-07)
50 value_70	-1.26e-05*	-5.84e-06***	-5.198***	-8.180	-7.83e-06***
	(6.74e-06)	(2.19e-06)	(0.988)	(7.315)	(2.23e-06)
70 value_70	-3.13e-06	-3.44e-06***	2.388***	0.754	-3.63e-06***
	(3.77e-06)	(1.27e-06)	(0.729)	(4.615)	(1.25e-06)
90 value_70	-1.62e-06*	-3.37e-07	-0.798***	-4.298***	3.29e-07
	(8.74e-07)	(3.23e-07)	(0.281)	(1.084)	(3.41e-07)
100 value_70	1.76e-05**	1.49e-05***	-4.768***	67.53***	1.36e-05***
	(8.89e-06)	(3.04e-06)	(1.723)	(13.16)	(3.08e-06)
200 value_70	-2.39e-06	2.34e-06***	1.427**	19.04***	-6.98e-07
	(2.37e-06)	(7.13e-07)	(0.651)	(3.743)	(8.97e-07)
300 value_70	1.63e-05***	5.86e-06***	9.800***	31.70***	6.44e-06***
	(1.76e-06)	(5.97e-07)	(0.687)	(2.675)	(6.77e-07)
400 value_70	3.76e-07	1.66e-07	0.164	-2.916***	-3.32e-07
	(6.54e-07)	(2.26e-07)	(0.259)	(0.989)	(2.50e-07)
500 value_70	1.99e-06	1.54e-07	-3.033***	-10.09***	1.81e-06**
	(1.24e-06)	(7.35e-07)	(0.528)	(2.055)	(7.34e-07)
610 value_70	-4.13e-06***	-1.08e-06**	6.350***	-9.733***	-3.00e-06***
	(1.55e-06)	(5.25e-07)	(0.572)	(2.340)	(5.90e-07)
620 value_70	-4.84e-06***	-4.14e-06***	0.786	1.738	-4.55e-06***

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VARIABLES	(1) OLS	(2) Wage	(3) Empl	(4) Pop	(5) Square
	(1.29e-06)	(5.09e-07)	(0.550)	(2.315)	(5.44e-07)
700 value_70	-8.81e-08	-8.54e-07*	4.619***	1.543	-9.35e-07*
	(1.36e-06)	(4.90e-07)	(0.612)	(2.315)	(5.47e-07)
910 value_70	3.02e-06***	1.51e-06***	-1.344***	-7.166***	1.91e-06***
	(1.00e-06)	(3.85e-07)	(0.254)	(1.142)	(3.81e-07)
920 value_70	-2.07e-06***	-1.30e-06***	0.520**	-0.537	-1.13e-06***
	(7.40e-07)	(2.69e-07)	(0.205)	(0.771)	(2.69e-07)
Constant	9.948***	9.757***	94,221***	166,818**	9.729***
	(0.0354)	(0.0395)	(13,280)	(78,741)	(0.0440)
Observations	9,412	9,355	9,355	9,355	9,355
R-squared		0.870	0.986	0.911	0.867
Number of geoid	942				
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.