“The Roots We Reap: The Legacy of Slavery and Contemporary Environmental Inequality”

Written by Margaret Doyle towards fulfillment of the Economics Distinguished Majors Program at the University of Virginia. Advised by Professor Jonathan Colmer.

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Acknowledgements

This was, in many different ways, the most difficult academic assignment I've ever completed. I don't think this paper is one that I'll ever feel "finished" with & it leaves me with much to think about. This current draft is the product of tremendous intellectual support from my peers in the Distinguished Majors Program and my advisor, Professor Jonathan Colmer. I am also grateful for all of my former teachers (namely Stephen Cushman, Bill Shobe, and Rob Dominguez) who inspired and informed this analysis by treating the topics discussed here with care, nuance, and attention. The history of the University of Virginia is inseparable from the history of enslavement in the United States, and I hope that the University's future students will continue to candidly reckon with this legacy in the same way that my peers and professors have.

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Abstract

This paper asks: how does the history of enslavement in a place influence environmental quality there today? In doing so, it looks to bridge two robust but previously-unconnected bodies of economic literature: (1) publications which investigate the impact of enslavement on contemporary economic outcomes and (2) publications which investigate the relationship between contemporary demographic variables and contemporary pollution exposures. Based on the literature surveyed, it proposes three channels through which past enslavement in a place could relate to environmental quality there today: these channels are grouped under categories of "race," "income," and "political inequality." In a preliminary, bivariate test, I find that a 10% increase in the percentage of county residents enslaved in 1860 was associated with a 5.60% higher Risk-Screening Environmental Index (RSEI) score but a .54% lower ambient $PM_{2.5}$ concentration in 2022. Restricting this analysis to just the southern U.S. states, I find that a 10% increase in the percentage of county residents enslaved in 1860 was associated with a 1.25% higher RSEI score but a .49% lower ambient $PM_{2.5}$ concentration in 2022. However, given the empirical limitations of this paper, I hazard away from a causal analysis of these results. Instead, I try to point out ways in which future authors may better test the channels which I propose.

Introduction

- "Slavery is the most important aspect of southern history." -Art Carden
- "Historians know that the past can never be erased and that the ugliest human actions cast the longest shadows." -William McFeely
- "We do not inherit the earth from our ancestors. We borrow it from our children." -Chief Seattle

Few issues loom larger on the American past than slavery. Few issues loom larger on the American future than sustainability & environmental justice. This paper asks: how does the history of enslavement in a place influence environmental quality there today? Subsequently, it looks to bridge two robust but previously-unconnected bodies of literature: (1) publications which investigate the impact of enslavement on contemporary economic outcomes and (2) publications which investigate the relationship between contemporary demographic variables— primarily race and income— on pollution exposures.

In the following literature review, I begin by orienting the economics papers about slavery within the broader "institutions versus geography" debate. I then survey a series of publications which quantify the place-based correlation between 19th-century chattel slavery and contemporary variables like income, educational attainment, and crime in the American South. I briefly touch on a growing series of papers which studies the contemporary, place-based impact of 20th-century lynchings in the postbellum South before turning to the literature on environmental inequality. I acknowledge the heterogeneity in recent environmental economic findings before touching on the "unit-hazard fallacy," which complicates the attempt to study the relationship between slavery in 1860 and environmental inequality in 2022.

Based on the literature surveyed, I propose 3 channels through which 19th-century enslavement— measured by the proportion of county residents enslaved in 1860— may relate to modern environmental quality today. I categorize these channels under "race, "income," and "political inequality." After proposing these relationships, I explore why they may not hold in theory, and then explore why they may not show up empirically, or why they cannot be properly tested with the available unit of analysis.

Despite the aforementioned empirical difficulties, I test for a preliminary correlation between the proportion of county residents enslaved in 1860 and two environmental quality indicators: (1) the EPA's Risk-Screening Environmental Indicators (RSEI) score and (2) ambient

$PM_{2.5}$ concentration. In a preliminary, bivariate test, I find that a 10% increase in the percentage of county residents enslaved in 1860 was associated with a 5.60% higher Risk-Screening Environmental Index (RSEI) score but a .54% lower ambient $PM_{2.5}$ concentration in 2022. Restricting this analysis to just the southern U.S. states, I find that a 10% increase in the percentage of county residents enslaved in 1860 was associated with a 1.25% higher RSEI score but a .49% lower ambient $PM_{2.5}$ concentration in 2022. After these initial tests, I further specify the regression to exclude major urban areas and to control for impactful 1860 observables, documenting these iterative changes in a series of Stata outputs included in the Appendix.

In the "Empirical Results" and "Conclusion" sections, I summarize some of the interpretive limitations of this paper. Reflecting on what this project feasibly could & could not accomplish, I identify key areas where future researchers could improve upon this initial analysis. I do not think of this paper as a definitive investigation into the relationship between enslavement & contemporary environmental inequality. Instead, I hope it's an invitation into future research and reflection.

Literature Review

A substantial body of economic literature works to understand how historical social institutions impact subsequent economic development. Daron Acemoglu, Simon Johnson, and James A. Robinson won the 2024 Nobel Prize in Economics for "studies of how institutions are formed and affect prosperity" (see: *Why Nations Fail*). Seminole works on "how institutions are formed and affect prosperity" converse with publications studying the economic impact of natural factor endowments (see: *Guns, Germs, and Steel*, *Salt: A World History*) and consider the potential endogeneity of economic institutions to the natural environment (see: Auty (2002), Engerman and Sokoloff (2002), Logan et al. (2021)).

Economists studying these types of relationships have coined the term "resource curse" to describe how places "with oil, mineral or other natural wealth, on average, have failed to show better economic performance than those without, often because of undesirable side effects" (Auty (2022), Frankel (2010)). This concept has been extended to study the origins & evolution of chattel slavery as an institution across New World economies. By the 18th century, European colonies rich in precious minerals & with climates suitable for growing large-scale cash crops (like those in the Caribbean and Southern United States) developed economies which depended on enslaved labor, even when more northern colonies (which became the Northern U.S. & Canada) held by the same European nations did not (Engerman and Sokoloff (2002)).

How does the legacy of slavery persist & transmit itself within a geographic location? Engerman and Sokoloff (2002) propose the following chronology: First, "differences in the extent of inequality across New World economies emerged early and were primarily due to factor endowments." The mineral wealth in Spanish America plus the cash crop suitability of the Caribbean and American South precipitated strictly hierarchical, slave-based economies. Meanwhile, the colder, grain-suitable climates of upper North America enabled "the great majority of adult men" to "operate as independent proprietors" such that "large landholdings unraveled because even men of rather ordinary means could set up independent farms when the land was cheap and scale economies were absent."

Then, in colonies where more extreme economic inequality emerged, the slaveholding elite could create the "basic legal framework to establish rules, laws, and other government policies" which "gave them greater access to economic opportunities… thereby contributing to the high degree of inequality." Meanwhile, in free labor economies, relative social homogeneity "led, over time, to more democratic political institutions, to more investment in public goods and infrastructure, and to institutions that offered relatively broad access to economic opportunities." Analyzing various historical moments, Engerman and Sokoloff (2002) demonstrate that these types of political and economic inequalities self-proliferate locally over hundreds of years. At one point, they posit that "if the early processes of early industrialization were based on broad participation in the commercial economy" then "economies with institutions that provided narrow access might have been less capable of realizing the potential of new technologies, markets, and other economic opportunities developed over the nineteenth century."

Nuun (2008) empirically tests the Engerman-Sokoloff Hypothesis across the New World and within the United States. He finds that a 1 standard deviation increase in the proportion of enslaved laborers to total colony population in 1750 was correlated with a 1.51 standard deviation decrease in per capita national income. O'Connell (2012) similarly finds that the proportion of enslaved laborers to total county residents in 1860 predicts 21st-century black-white inequality in American poverty rates even after controlling for contemporary demographics and modern racial threat. Considering multiple potential mechanisms, she posits that this relationship may exist because "local areas previously dependent on slavery continue to be dependent on exploitative economic systems."

Turning to examine political attitudes, Acharya et al. (2016) find that the proportion of enslaved laborers in a U.S. county in 1860 predicts the contemporary proportion of White Republicans, measures of racial resentment towards Black neighbors, and anti-Affirmative Action attitudes in that county today. Modern racial threat & demographic composition do not fully explain their results, leading them to predict that the "historical persistence of political attitudes" may help explain this relationship. They posit that "the sudden enfranchisement of blacks was politically threatening to whites" after the Civil War because "the emancipation of Southern slaves undermined whites' economic power." In combination with pre-existing racial animus, these changes "gave Southern Black Belt elites an incentive to further promote anti-black sentiment in their local communities by encouraging violence towards blacks and racist attitudes." In formerly-slaveholding southern counties, this "intensified radically conservative attitudes" such that counties "that were politically similar before the war" began to "diverge greatly in terms of both institutionalized and socially enforced racism around the time of the Civil War."

Related papers examine the relationship between enslavement and educational attainment today (see: Bertocchi and Dimico (2012), Bertocchi and Dimico (2014)), Reese and O'Connell (2015)). Related papers also examine the effect of enslavement on contemporary crime & punishment (see: Vandiver et al. (2006), Gottlieb and Flynn (2021), Gouda and Rigterink (2017)). In conversation with these papers is a second series of studies examining how postbellum lynchings in former slave states predict contemporary racial animosities there today. Benitez et al. (2024) study the relationship between postbellum lynchings and racial disparities in state Medicaid administration. Williams (2022) looks at contemporary Black voter registration and voter turnout. Gabriel and Tolnay (2017) study the relationship between postbellum lynchings and modern homicide, using physics' Ohm's Law to explain how southern political attitudes & cultures of violence have been passed down from generation to generation via localized memory and resistance.

Many of the aforementioned papers endorse place-based methods of studying the legacy of slavery, versus (or in addition to) an individual-level analysis. The effects of slavery on the individual may transmit from generation-to-generation within formerly-enslaved families, even if formerly-enslaved laborers migrated across the U.S. during population movements like the Great Migration (see: Logan 2022). However, despite migrational effects & demographic heterogeneity today, the above authors elucidate the importance of studying slavery at the geographical level. They maintain that "the continuous in-flow of new residents does not, by itself, negate the possibility that a social structure based on the assumption of black inferiority explains the relationship between slavery and contemporary racial inequality" since "historical conditions…have been imprinted on the social and legal traditions of states, or even areas within a state" (O'Connell (2012), Vandiver et al. (2006)). Based on the rationale outlined by these papers & the significance of their results, this paper continues to work at the county level to study the relationship between slavery & the physical environment.

Though no paper has studied the impact of historical enslavement on the physical environment, a substantial number of papers investigate the relationship between contemporary demographic variables and physical environmental conditions. For a more comprehensive review of recent environmental economic literature, see Cain et al. (2023) and Banzhaf et al. (2019)'s "Environmental Justice: The Economics of Race, Place, and Pollution."

The latter paper proposes four mechanisms through which race, income, and race-income interactions may determine individual pollution exposures: (1) "Disproportionate siting" by firms in low income and/or underrepresented minority neighborhoods. (2) Low income and/or underrepresented minorities "coming to the nuisance" by "sorting" into areas with lower property values, which internalize local pollution. (3) A market-like coordination of sorting & siting via Coasian bargaining between firms and residents. (4) Pure discrimination in politics and/or law enforcement, whereby the government intentionally incentivizes polluting firms to move into underprivileged neighborhoods, specifically historically-black neighborhoods (see: Mohai et al. (2009)). Looking at environmental racism specifically, Hamilton (1995) also proposes (5) "the propensity of communities to engage in collective action," citing how minority communities are less likely to overcome free rider problems and engage in collective action due to historical discrimination and disenfranchisement.

It is important to flag that there is significant heterogeneity & disagreement among the economic papers studying environmental inequality. For example, Fowlie et al. (2012), Bakkensen and Ma (2020), and Grainger and Ruangmas (2018) all observe income as a determinant of individuals' environmental exposures, primarily through mechanisms of sorting or siting. However, Colmer et al. (2024) found “almost no” relationship between personal income and air pollution exposures for both Black and White individuals in 2016. Empirical conclusions about the effect of income or race on pollution exposures often vary due to the unit of analysis and outcome variable selected (see: Banzhaf et al. (2019)).

It is also important to flag that environmental economics’ “unit-hazard fallacy” complicates the interpretations of this paper’s county-level results. The unit-hazard fallacy describes how cases of environmental injustice may exist within geographic pockets smaller than the available unit of observation. For example, polluting plants may disproportionately site in a county's historically-black neighborhoods (Mohai et al. (2009)). However, county-level environmental studies may average the net amount of pollution released by those firms across a county’s aggregate demographic makeup, obscuring the heterogeneity in exposures which exists within the unit of observation (McMaster et al. (2013), Mohai and Saha (2006)).

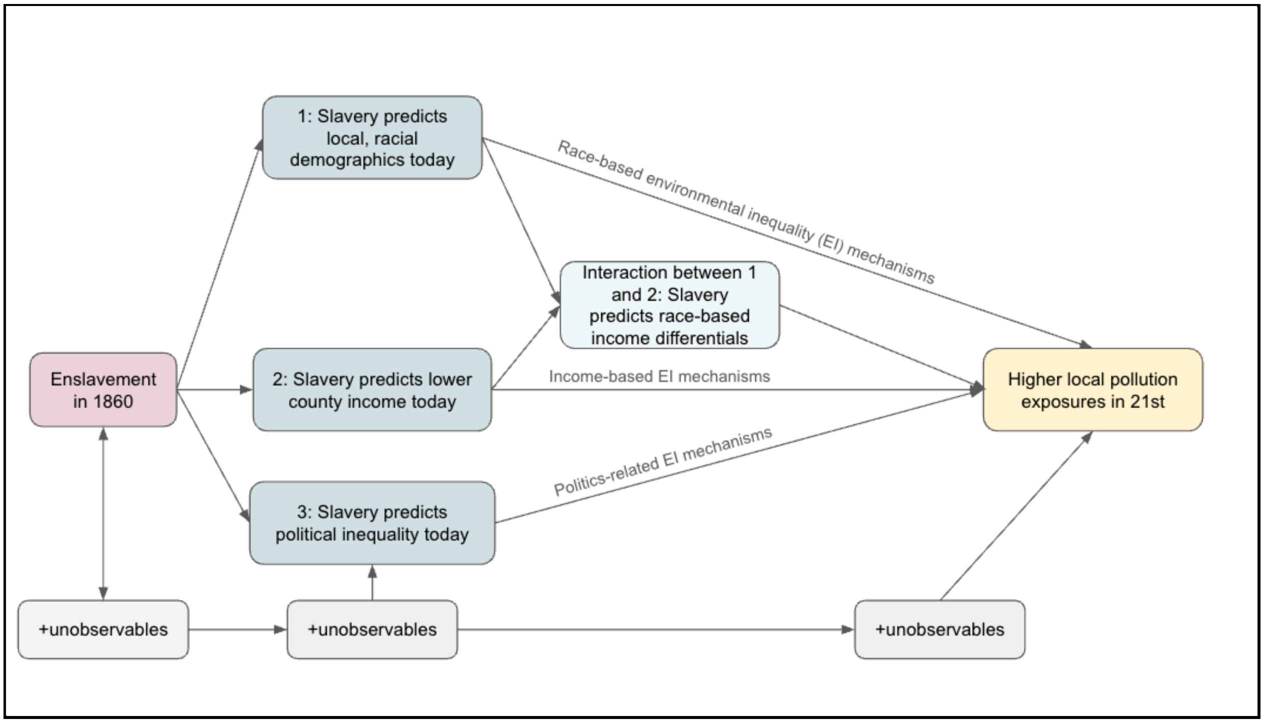
Channels

Based on a synthesis of the sources surveyed above, I propose three channels through which the legacy of slavery in a place may predict that place’s environmental condition today. I explore the *theoretical* limitations of each channel here, then explore some *empirical* limitations in the following “Confounders” section.

1. **Race:** The legacy of slavery in a place predicts county racial compositions there today. County racial compositions influence environmental exposures via mechanisms described by Banzhaf et al. (2019).
2. **Income:** The legacy of slavery in a place predicts lower average incomes for all people there today. Some environmental economists report a relationship between average personal income and environmental inequalities based on disproportionate siting, Tiebout-type sorting, or Coasian coordination between siting & sorting. Furthermore, the legacy of slavery is associated with greater black-white income inequality at the county level— this could amplify the aforementioned effects of race or income.
3. **Political Inequality:** There is a relationship between slavery in 1860 and the strength of local civic life and political participation in that place today. The ability of local communities to engage in collective bargaining & political activism may discourage toxic

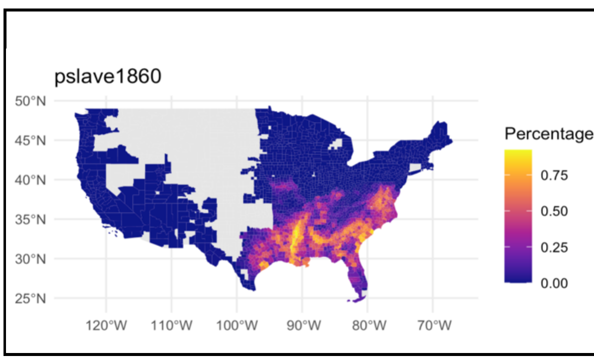
firms from siting in their community, subsequently determining local pollution exposures.

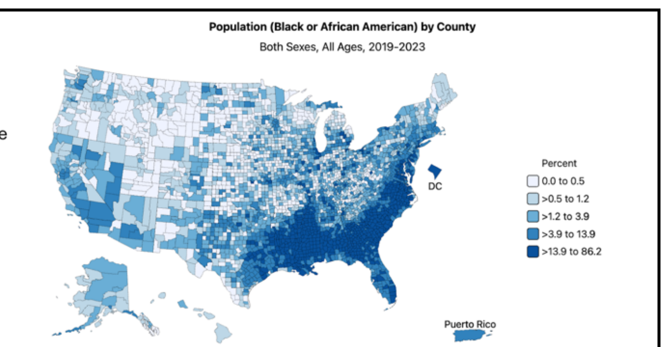
Image 1: Map of the proposed channels



Map 1: Percentage of total county population enslaved in 1860, U.S. Census.

Map 2: Average percent of total county population reporting as African American or Black from 2019-2023, according to the American Community Survey. [Accessed from the NIH](#).





1. Race: The legacy of slavery in a place predicts county racial compositions there today. County racial compositions influence environmental exposures via mechanisms described by Banzhaf et al. (2019).

Many counties which once relied on enslaved, Black labor in the South's agricultural "Black Belt" have remained majority-black into the 21st century. As an overview, formerly-confederate, slaveholding states represent ten of the twelve states with the highest reported percentage of Black residents from 2019-2023 (National Institutes of Health). More than half of all Black Americans live in the South (Pew 2025). Maps 1 and 2 help visualize correlation between the percentage of a county enslaved in 1860 & average Black population percentages in a county from 2019-2023. Brookings explains this correlation by observing that many Black Americans— including the descendants of formerly-enslaved people—left the South during the Great Migration. However, millions of Black Americans continued to raise families in the South during the late 18th and early 19th centuries. Furthermore, a significant number of Black Americans living outside of the South moved into the South in the 1960s & 1970s in pursuit of emerging economic opportunity, beginning the era of the "New South." These factors help explain the correlation between enslavement historically & demography in the U.S. today, though a complete analysis of Black population migration in American history is beyond the scope of this paper.

How might the relative size of the Black population in a county relate to environmental exposures there today? Banzhaf et al. (2019) summarize environmental inequality literatures to describe (1) "disproportionate siting" in underrepresented minority neighborhoods, (2) Black Americans feeling forced to "come to the nuisance," sorting into areas with lower property values due to local pollution, (3) a market-like coordination of the following two mechanisms via Coasian bargaining, and (4) pure, anti-black discrimination by the relevant regulatory agencies. Any of these mechanisms may connect the legacy of enslavement in a place to environmental inequality there today via the correlation between slavery and modern demographic patterns.

The relationship between race & environmental exposures today may also be intensified by the correlation between race today & slavery in 1860 via the "historical persistence of political attitudes" theory proposed by Acharya et al. (2016). Even after controlling for contemporary racial threat, they find that the proportion of people enslaved in a county in 1860 predicts contemporary measures of White racial resentment towards Black neighbors.

Subsequently, Acharya et al. (2016) posit that "the sudden enfranchisement of blacks was politically threatening to whites" after the Civil War because "the emancipation of Southern slaves undermined whites' economic power." In combination with "the massive pre-existing racial hostility throughout the South," this "gave Southern Black Belt elites an incentive to further promote anti-black sentiment in their local communities by encouraging violence towards blacks and racist attitudes." In slaveholding southern counties versus similar, non-slaveholding southern counties, this "intensified radically conservative attitudes" such that "even for counties that were politically similar before the war, partisan voting became more pronounced." Acharya et al. (2016) and Gabriel and Tolnay (2017) observe that these attitudes have been passed down & persist in the Black Belt via the strong correlation between parents' & childrens' political attitudes in the South.

What if this "historical persistence" of these anti-black attitudes motivates the individual, business, or government decision to pollute a local, predominantly-black neighborhood? More specifically, what if the persistence of postbellum racism towards Black people amplifies the effect of (1) disproportionate siting or (4) pure, anti-black discrimination? In this case, Black individuals living in counties in the Deep South that historically depended on enslaved labor may face higher pollution exposures than Black individuals (1) from counties in the same state which did not rely on enslaved labor or and (2) from counties with similar geographic profiles north of the Mason-Dixon line. However, this effect may also exist within individual counties in ways which aggregated, county-level analyses cannot detect. It feels feasible that the historical persistence of the attitudes driving environmental racism operates on the neighborhood-by-neighborhood level, with local non-black individuals, firms, and policymakers acting the most discriminatorily towards their immediate Black neighbors.

What issues might exist within this train of thought? First, the type of conservative, anti-black political attitudes identified by Acharya et al. (2016) might apply to policies like Affirmative Action, but not to southerners'— particularly White southerners'— attitudes about pollution and environmental quality. If this is true, then modern racial threat might entirely explain the disproportionate & discriminatory siting of pollution in Black communities. In other words, the legacy of slavery may have no influence on local environments beyond slavery's influence on modern demographic compositions. Second, anti-black attitudes fostered by slavery might apply to environmental issues, but the effect of said attitudes on actual environmental quality may be muddied by historic & ongoing migration. In this case, the in & out migration of both Black and White individuals to & from the Deep South could have diffused the otherwise-strong correlation in intergenerational, environmental attitudes.

2. Income: The legacy of slavery in a place predicts lower average incomes for all people there today. Some environmental economists report a relationship between average personal income and environmental inequalities based on disproportionate siting, Tiebout-type sorting, or Coasian coordination between siting & sorting. Furthermore, the legacy of slavery is associated with greater black-white income inequality at the county level— this could amplify the aforementioned effects of race or income.

On the county level, Lagerlöf (2005) finds a negative relationship between past enslavement, observed in 1850, and per capita income, observed in 1994. Nuun (2008) finds a negative & significant relationship between the proportion of county residents enslaved in 1860 and per capita county income in 2000. Nuun (2008) speculates that this net-negative county average is explained either by steep political inequality in slaveholding regions or local approaches to property rights there. Lagerlöf (2005) and Michener and McLean (2003) also point to subsequent differences in postbellum educational attainment & social institutions.

Lower-income tracts— county-sized or otherwise— may face higher pollution exposures (Hausman and Stolper (2021), Kalnins and Dowell (2017), Wang and Zhou 2021) for a number of reasons. First, polluting firms may choose to site in lower-income neighborhoods where rents are cheapest ("disproportionate siting" mechanism from Banzhaf et al. (2019)). Alternatively, low-income individuals may Tiebout sort (Banzhaf and Walsh (2008)) into areas where toxic emissions releases have been internalized into property values. The effect of pollution on costs of living can incentivize lower-income individuals to move into the now-cheaper, low-amenity neighborhood as higher-income individuals move out ("coming to the nuisance" from Banzhaf et al. (2019)). The combination of these mechanisms (siting and sorting) may create a spiraling, "chicken or egg" cycle (Mohai et al. (2009)). Furthermore, these two mechanisms may interact via a Coasian bargaining process if low-income neighborhoods exhibit the lowest marginal willingness to pay for environmental quality, or the highest marginal tolerance for pollution based on underlying wealth (Coase (1960), Banzhaf et al. (2019)).

Taken together, the links between [slavery → income] + [income → exposures] could imply that southern counties which relied more heavily on enslaved labor face higher exposures than (1) southern counties which relied less heavily on enslaved labor or (2) otherwise-similar counties north of the Mason-Dixon line. The independent effects of race (Channel 1) and income (Channel 2) may be amplified by the fact that slavery not only predicts lower average county income, but also higher black-white income inequality (O'Connell (2012)). For example, if firms choose to site based on both neighborhood income ("discriminatory siting") *and* racial motivations ("pure discrimination"), Black neighborhoods in previously-slaveholding counties may face especially high pollution exposures.

What issues might exist within this train of thought? The most prominent issue arises within the second link—the relationship between modern income & pollution exposures— given recent papers like Colmer et al. (2024)'s "Income, Wealth, and Environmental Inequality in the United States." Looking at air pollution specifically, they find a significant black-white inequality in ambient air pollution exposures but "almost no" relationship between personal income and air pollution exposures for both Black and White individuals in 2016. If there truly exists no relationship between income & certain pollution exposures, then the legacy of slavery may still predict lower local incomes (Lagerlöf (2005), Nuun (2008), Engerman and Sokoloff (2002)), but lower local incomes may not translate into worse local environmental outcomes.

3. Political Inequality: There is a relationship between slavery in 1860 and the strength of local civic life and political participation in that place today. The ability of local communities to engage in collective bargaining & political activism may discourage toxic firms from siting in their community, subsequently determining local pollution exposures.

Engerman and Sokoloff (2002) hypothesize that slave-based economies produced highly-asymmetric political systems whereby the slaveholding elites could "establish a basic legal framework to establish rules, laws, and other government policies" to benefit the aristocratic few. The slaveholding elite could also design local systems which "gave them greater access to economic opportunities… thereby contributing to the high degree of inequality." Engerman and Sokoloff (2002) describe how these localized political inequalities self-proliferate over time, while Nuun (2008) points out that political inequality may exist independent of economic inequality (hence this separate channel). Quantifying one dimension of persistent political inequality, Williams (2022) finds antebellum slavery predicts (1) lower contemporary Black voter registration and (2) racial differentials in voting rates in the American South.

How might the types of political inequalities precipitated by slavery translate into higher pollution exposures, either for entire counties or subgroups within a county? Hamilton (1995) posits that "the propensity of communities to engage in collective action" can predict local pollution exposures, such that communities with a more-participatory local governments are better able to organize to deter polluting firms from citing in their neighborhoods. Consequently, politically generated environmental inequalities may exist at the county-level for counties which relied heavily on enslavement given the link between enslavement & political inequalities like disenfranchisement. Depending on the precise nature of post-slavery political inequalities, this relationship may also exist within & across county lines in ways which county-level analyses cannot detect.

What issues might exist within this train of thought? With the [slavery → political inequality]: like with Channel 1, the political inequalities produced by slavery in the antebellum South may have partially dissipated, specifically due to the in & out migration of all race groups over the past 150 years. Furthermore, political inequalities predicted by slavery may still predict "the propensity of communities to engage in collective action" in the South, but only for levels of government which are less influential in discouraging polluting firms from site in an area (a process regulated by the federal government and influenced by local councils).

With the [political inequality → environmental inequality]: political inequalities which arose from slavery may predict "the propensity of communities to engage in collective action," but the "propensity of communities to engage in collective action" may not be a dominant determinant of local environmental quality. Though the rationale laid out by Hamilton (1995) feels compelling, I have yet to find an environmental economics paper which isolates the "propensity of communities to engage in collective action" theory empirically, or which compares the relative importance of "the propensity to engage in collective action" to the importance of other mechanisms.

Confounders

Above, I call out the key theoretical limitations for each proposed channel. However, this paper also faces several empirical confounders & limitations. I discuss three of these empirical issues— the unit-hazard fallacy, urban bias in environmental justice indices, and regional climatic differences— below.

1. Unit-Hazard Fallacy: The available unit of observation for data on enslavement exists at the county level from the 1860 U.S. Census. This means that many of the relationships described above could feasibly exist below the county level or across county lines in ways which I cannot test. For example, with Channel 1 (race), it feels feasible that the historical persistence of the attitudes driving environmental racism operates at the neighborhood-by-neighborhood level. In this case, averaging pollution exposures across a county's demography definitionally obscures the heterogeneity I attempt to test for. Unit-hazard coincidence also poses issues with Channel 2 (income), given that income inequality may exist among neighborhoods within one southern county, and with Channel 3 (political inequality), given that some town councils may exhibit a much stronger "propensity to engage in collective actions" than others within their county.

2. Population Density/Urban Biases: There is a strong correlation between urban population density & environmental exposures, particularly $PM_{2.5}$ air pollution (Wrightson et al. (2025), Borck and Schrauth (2021), Carozzi (2023)). However, the American South is one of the least-urban, least-densely populated regions of the entire county— 75.8% of people living in the Southeast live outside of urban areas (U.S. Census Bureau 2022). Subsequently, I regress on air pollution data based on the judgement of Colmer et al. (2024), but recognize this variable might not capture an effect which is otherwise-present in Southern water quality, soil quality, or biodiversity metrics. In an attempt to correct for this, I examine EPA RSEI scores, which I describe in the "Data & Model Section." However, this index may still obscure the lived experience of individuals in the rural Southeast based on its population weighting and traditional biases against rural & tribal communities in environmental justice data. For a more detailed analysis of how urban-biased environmental quality indexes may fail to capture the lived experiences of rural Americans, see Balakrishnan et al. (2022).

3. Climatic Factors & Cash Crop Suitability: In the United States, slavery existed & flourished in the geographic areas best suited for growing cash crops, like tobacco and then cotton. In the harsher climates of New England, Engerman and Sokoloff (2002) observe that the returns to farm labor favored individual proprietors over slave-owning planters, such that large, plantation-style landholdings tended to "unravel." The warm climate and fertile soil which attracted plantation-style may have also played a role in post-Civil War economic development, explaining (alongside institutional factors) why the South has been slow to industrialize away from its agrarian roots. What if the physical climate of southern counties still determines which types of industries dominate there today & whether toxin-releasing plants choose to site there? This could create issues of endogeneity within the model. Furthermore, even if physical climatic differences no longer determines how firms & industries site, different temperatures, humidity levels, and physical environmental factors change the way in which toxic chemicals behave (Wang et al. (2023)). This means that a southern & northern county could have an identical ambient $PM_{2.5}$ concentration, but that said ambient $PM_{2.5}$ concentration has a different real impact on population health in each county.

Data & Methods

Despite these empirical limitations, I attempt to test for a preliminary correlation between the legacy of enslavement in a county and environmental outcomes there today. These regressions begin to examine if the proposed relationship exists but does not conduct a mediation analysis of any one proposed channel.

Data: For the independent variable, I use U.S. Census data on the proportion of people in a county enslaved in 1860 (the last Census before the Civil War) provided by Acharya et al. (2016). I use the proportion of people enslaved rather than a binary indicator to capture variation within the local southern economies, including variation between the "Deep South" versus the "Upper South." While some southern counties relied more heavily on slave labor (with most of the residents being enslaved), other counties relied predominantly on free male labor from both White & Black free men, particularly counties which were geographically rocky or otherwise ill-suited to plantation-style returns to scale.

For the dependent variables, I use two different environmental indicators, selected based on the heuristics & background research done by Colmer et al. (2024). First, I use the EPA's Risk-Screening Environmental Indicators (RSEI) scores, which measures county-level exposures to toxic chemical waste. At the broadest level, the RSEI model weighs "the size of a chemical release, the fate and transport of a chemical within the environment, the size and location(s) of potentially exposed populations, and a chemical's relative toxicity." A higher RSEI score implies worse local pollution & toxicity exposures.

Second, I use air pollution data, specifically annual, satellite-derived measures of $PM_{2.5}$ concentration ($\mu g/m^3$) in 2022 made available by Shen et al. I average coordinate-level observations for 0.01° × 0.01° tracts into county means using R. A higher average $PM_{2.5}$ implies that local air contains more particles of chemicals like sulfates, nitrates, ammonium, and mineral dust. These components of $PM_{2.5}$ are all chemicals associated with negative health outcomes & shorter life expectancies (Dominici et al. (2016)).

After running the preliminary, bivariate regressions, I attempt to control for how urban areas may skew the coefficients by specifying the regression to exclude counties containing major U.S. cities. Subsequently, this new regression only looks at the county types which are most common in the American South (the key region of interest). I use the EPA's Environmental Quality Index data, where counties are rated 1 (most rural) through 4 (most urban) to exclude type 4 counties.

I then control for 1860 observables which may have been correlated with the presence of slavery and/or subsequent economic development patterns using replication data from Acharya et al. (2016). For example, I control for total county population in 1860 and 3 descriptors of county wealth in 1860: (1) the total number of improved county farm acres, (2) the total farm value per improved acre, and (3) Gini inequality in farmland holdings in 1860. These factors may predict the prevalence of slavery in a county by (1) describing the general, historical economic condition (i.e. inequality in land holdings) and (2) determining the return to farm labor (for example, returns to enslaved labor should be higher in counties with higher total farm value per improved acre). Still thinking about the returns to labor & the siting of plantation farms, I control for a county's climatic suitability for growing cotton using an index created by the UN Food and Agriculture Organization (FAO). I hope that this controls for some of the potential endogeneity explored in the "Confounders" section. Finally, I control for the commercial impact of access to rail & waterways for shipping, plus spatial effects using longitude and latitude.

After controlling for these 1860 observables, I *do not* control for 21st century county observables like demographic composition, income, or political party in power in 2022. Controlling for these variables would, in effect, "control away" the proposed channels through which pslave1860 could affect RSEI scores & $PM_{2.5}$ concentrations. However, future, more advanced studies could incorporate these 2024 observables into mediation analyses which test the relative validity of each of this paper's proposed channels.

Table 1: Variables & Variable Names

Variable	**Variable Name**
Proportion of county residents enslaved in 1860	pslave1860
County RSEI score in 2022	rseiscore
Satellite-observed ambient $PM_{2.5}$ concentration	pmsatelite
Urban-rural category from EPA EQI	ruralurbancategory
1860 county population	countypop1860
Number of improved farm acres in a county in 1860	improvedacres1860
Average farm value per improved acre in a county in 1860	farmvalueperacre1860
Gini-index of inequality in county landholdings in 1860	inequalitylandholding1860
UN FAO index of cotton suitability	cottonsuitability1860
Index of relative access to shipping by rail	railways1860
Index of relative access to shipping by water	waterways1860
Longitude	countylong
Latitude	countylat

Regressions: As described above, I run the ordinary least squares (OLS) tests for both the RSEI and $PM_{2.5}$ data:

- $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1\text{pslave1860}_i + \varepsilon_i$
- $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1\text{pslave1860}_i + FE_{\text{state}} + \varepsilon_i$
- $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1\text{pslave1860}_i + FE_{\text{state}} + \varepsilon_i \mid \text{category} =/= 4$
- $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1\text{pslave1860}_i + \beta_2\text{countypop1860} + \beta_3\text{improvedacres1860} + \beta_4\text{valueperacre1860}_i + \beta_5\text{landholding1860}_i + \beta_6\text{railways1860}_i + \beta_7\text{waterways1860}_i + \beta_8\text{countylong1860}_i + \beta_9\text{countylat}_i + \beta_{10}\text{cottonsuitability}_i + FE_{\text{state}} + \varepsilon_i \mid \text{category} =/= 4$

I then rerun each of these tests, this time excluding all states but those which seceded from the U.S. around 1861 (South Carolina, Mississippi, Florida, Alabama, Georgia, Louisiana, Texas, Virginia, Arkansas, Tennessee, and North Carolina). This restricts the analysis to states where slavery was legally permitted in 1860, removing the cluster of pslave1860 = 0 observations from states which had banned slavery by 1860. I do this to (1) eliminate some of the region-to-region variation in demography, physical climate, and political attitudes and (2) to specifically identify the correlation between pslave1860 & environmental quality in the primary geographic region of interest (the American South). Regressions 5-8 are modeled as:

- $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1\text{pslave1860}_i + \varepsilon_i$ | state = southern
- $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1\text{pslave1860}_i + FE_{\text{state}} + \varepsilon_i$ | state = southern
- $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1\text{pslave1860}_i + FE_{\text{state}} + \varepsilon_i$ | urban-rural category =/= 4 | state = southern
- $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1\text{pslave1860}_i + \beta_2\text{countypop1860} + \beta_3\text{improvedacres1860} + \beta_4\text{valueperacre1860}_i + \beta_5\text{landholding1860}_i + \beta_6\text{railways1860}_i + \beta_7\text{waterways1860}_i + \beta_8\text{countylong}_i + \beta_9\text{countylat}_i + \beta_{10}\text{cottonsuitability1860}_i + FE_{\text{state}} + \varepsilon_i$ | state = southern

Based on the theories categorized under "race," "income," and "political inequality," I hypothesize that β_1 will generally < 0. In other words, I predict that there should be a negative correlation between the presence of slavery in a county (measured by pslave1860) and contemporary environmental quality (measured by rseiscore and pmsatelite) there today.

Empirical Results

Before reporting the results of these regressions, I include summary statistics for pslave1860 and the 2 outcome variables alongside county-level heatmaps. Then, I report the coefficient on pslave1860 from Regressions 1-8 for RSEI and $PM_{2.5}$ data in Table 1. I include the full, corresponding Stata output table for each test in the Appendix, labeled there as described in each cell of Table 5.

Table 2: Summary Statistics for All U.S. States

. summarize pslave1860

Variable	Obs	Mean	Std. dev.	Min	Max
pslave1860	1,738	.1644795	.2173977	0	.9226992

. summarize rseiscore

Variable	Obs	Mean	Std. dev.	Min	Max
rseiscore	1,738	169725.3	1611537	0	5.50e+07

. summarize pmsatelite

Variable	Obs	Mean	Std. dev.	Min	Max
pmsatelite	1,738	8.008108	1.168546	3.173802	12.30519

Table 3: Summary Statistics for Southern States

. summarize pslave1860

Variable	Obs	Mean	Std. dev.	Min	Max
pslave1860	755	.3437492	.2103197	0	.9226992

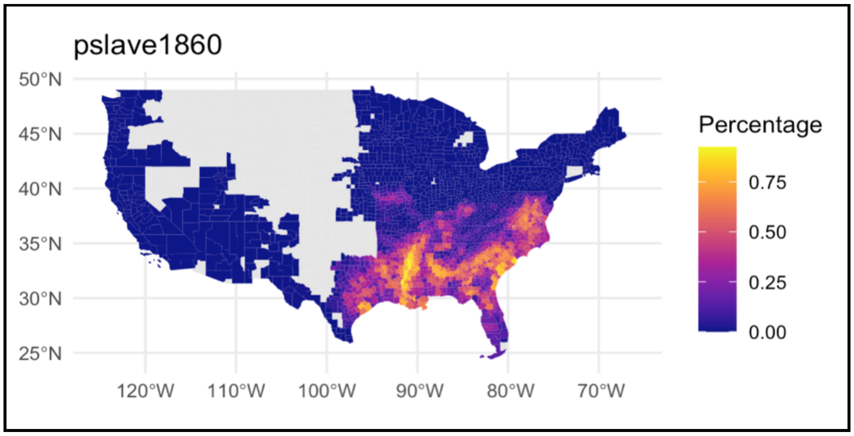
. summarize rseiscore

Variable	Obs	Mean	Std. dev.	Min	Max
rseiscore	755	197462.7	2159257	0	5.50e+07

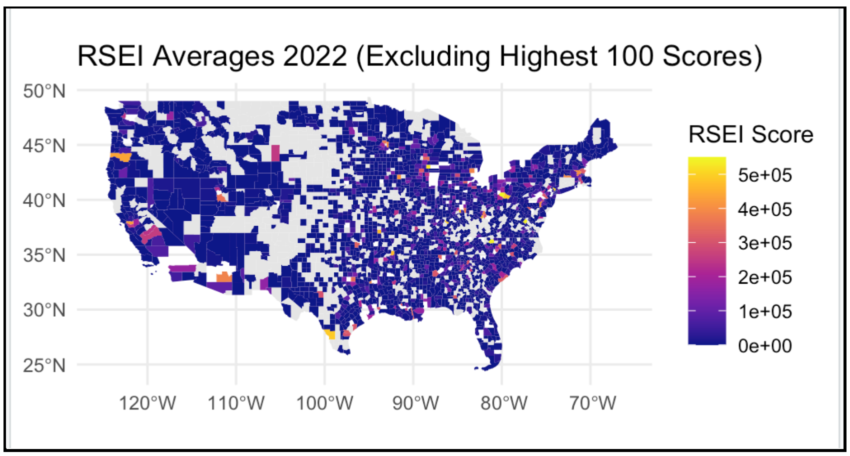
. summarize pmsatelite

Variable	Obs	Mean	Std. dev.	Min	Max
pmsatelite	755	7.870629	1.181902	5.385951	12.30519

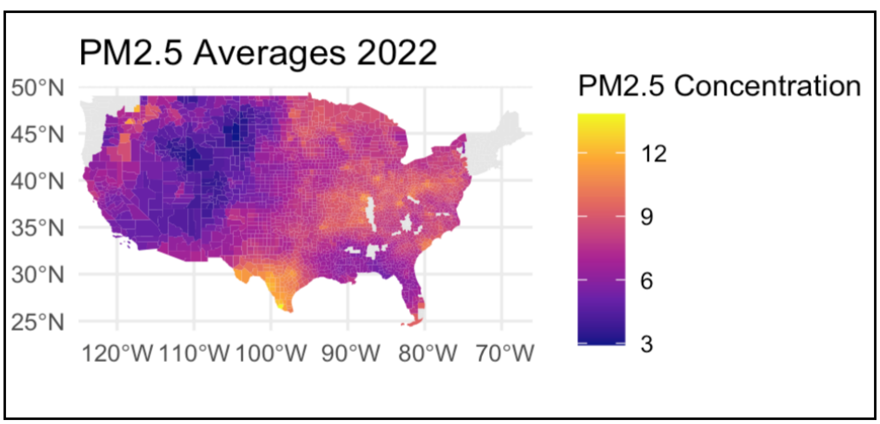
Map 3: Proportion of County Residents Enslaved in 1860



Map 4: 2022 County RSEI Scores (excluding highest 100 scores to visualize variation)



Map 5: 2022 County Mean $PM_{2.5}$



Summary of Regressions in Table 4

1. $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1 \text{pslave1860}_i + \varepsilon_i$
2. $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1 \text{pslave1860}_i + FE_{state} + \varepsilon_i$
3. $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1 \text{pslave1860}_i + FE_{state} + \varepsilon_i \mid \text{category} =/= 4$
4. $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1 \text{pslave1860}_i + \beta_2 \text{countypop1860} + \beta_3 \text{improvedacres1860} + \beta_4 \text{valueperacre1860}_i + \beta_5 \text{landholding1860}_i + \beta_6 \text{railways1860}_i + \beta_7 \text{waterways1860}_i + \beta_8 \text{countylong}_i + \beta_9 \text{countylat}_i + \beta_{10} \text{cottonsuitability1860}_i + FE_{state} + \varepsilon_i \mid \text{category} =/= 4$
5. $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1 \text{pslave1860}_i + \varepsilon_i \mid \text{state} = \text{southern}$
6. $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1 \text{pslave1860}_i + FE_{state} + \varepsilon_i \mid \text{state} = \text{southern}$
7. $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1 \text{pslave1860}_i + FE_{state} + \varepsilon_i \mid \text{urban-rural category} =/= 4 \mid \text{state} = \text{southern}$
8. $\log(\text{environmentalindicator}_i) = \beta_0 + \beta_1 \text{pslave1860}_i + \beta_2 \text{countypop1860} + \beta_3 \text{improvedacres1860} + \beta_4 \text{valueperacre1860}_i + \beta_5 \text{landholding1860}_i + \beta_6 \text{railways1860}_i + \beta_7 \text{waterways1860}_i + \beta_8 \text{countylong}_i + \beta_9 \text{countylat}_i + \beta_{10} \text{cottonsuitability1860}_i + FE_{state} + \varepsilon_i \mid \text{state} = \text{southern}$

Table 4: Regression Results

	Log of RSEI score	**Log of Ambient $PM_{2.5}$ Concentration**
Regression 1: Whole U.S.	$\beta_1 = -.6072617$ Appendix 1.1	$\beta_1 = -.0912683$ Appendix 1.2
Regression 2: Whole U.S. with State-Level Fixed Effects	$\boldsymbol{\beta_1 = .5599394}$ Appendix 2.1	$\boldsymbol{\beta_1 = -.0535569}$ Appendix 2.2
Regression 3: Whole U.S. with State-Level Fixed Effects, Excluding the Most Urban Counties	$\beta_1 = .3885193$ Appendix 3.1	$\beta_1 = -.0442538$ Appendix 3.2
Regression 4: Whole U.S. with State-Level Fixed Effects, Excluding the Most Urban Counties, Including 1860 Observables	$\beta_1 = -3.873868$ Appendix 4.1	$\beta_1 = - .0514166$ Appendix 4.2
Regression 5: Southern U.S.	$\beta_1 = -.1923264$	$\beta_1 = -.1777698$

	Appendix 5.1	Appendix 5.2
Regression 6: Southern U.S. with State-Level Fixed Effects	**β_1 = .1254003** Appendix 6.1	**β_1 = -.0493050** Appendix 6.2
Regression 7: Southern U.S. with State-Level Fixed Effects, Excluding the Most Urban Counties	β_1 = .1283972 Appendix 7.1	β_1 = -.0377646 Appendix 7.2
Regression 8: Southern U.S. with State-Level Fixed Effects, Excluding the Most Urban Counties, Including 1860 Observables	β_1 = -3.914407 Appendix 8.1	β_1 = .-.0524426 Appendix 8.2

In Regression 2, I look at every state which existed by 1860 while controlling for state-level fixed effects. I find that a 10% increase in the percentage of county residents enslaved in 1860 is correlated with a 5.60% higher RSEI score but a .54% lower $PM_{2.5}$ concentration. In Regression 6, I restrict Regression 2 to examine just the southern U.S. states. Here, I find that a 10% increase in the percentage of county residents enslaved in 1860 is correlated with a 1.25% higher RSEI score but a .49% lower $PM_{2.5}$ concentration. In other words, the estimates retain the same direction but become smaller in magnitude when I restrict the analysis to only former-confederate states, effectively erasing some inter-regional variation.

When I exclude category = 4 urban counties from Regression 2, the results retain the same direction but diminish in magnitude— now, 10% more residents having been enslaved in 1860 is correlated with a 3.9% higher county RSEI score and .44% lower $PM_{2.5}$ concentration. Alternatively, when I exclude the category 4 urban counties for just southern states from Regression 6, the RSEI coefficient becomes more pronounced in magnitude— the 1.25% higher RSEI score figure becomes 1.29%, while the .49% lower $PM_{2.5}$ figure shrinks .38%. Perhaps the RSEI coefficient increases from Regression 6 to 7 because the localized effects of slavery in a place are marginally more-intense for still-rural areas than now-urban ones. However, given the number of empirical limitations & relevant omitted variables here, I refrain from making a definitive causal interpretation like this.

Generally speaking, these RSEI coefficients follow the proposed theory: they describe a negative correlation between slavery in 1860 and environmental quality in a place today. Again, given the number of empirical limitations & relevant omitted variables here, I refrain from making a definitive causal interpretation. However, perhaps these coefficients do suggest that the history of slavery is a determinant of environmental quality in a place today. Based on the race channel, this could be because of the relationship between slavery & racial compositions today, plus the interaction between the historical persistence of anti-black attitudes & mechanisms like disproportionate siting. Based on the income channel, this could be because places which previously relied on slavery are poorer & exhibit higher black-white income inequality, given that income predicts environmental exposures in some cases (Hausman and Stolper (2021), Kalnins and Dowell (2017), Wang and Zhou 2021). Based on the political inequality channel, this could be because places which previously relied on slavery developed asymmetric, less-participatory local politics, which inhibit local communities— specifically minority communities— from resisting toxic siting via collective action. Further research is needed to confirm or deny the general effect of enslavement on toxic chemical exposures today, and then to test if any one specific theory of causality best explains the correlation.

Unlike the coefficients from the RSEI score regressions, the $PM_{2.5}$ coefficients do not follow the proposed theory— here, there is not a positive relationship between the presence of slavery in a county and ambient $PM_{2.5}$ concentration there today. Why might this be?

For one, the theories themselves may not hold. When it comes to slavery's effects via race, perhaps there is no additional, historical persistence of anti-black attitudes which explain disproportionate siting/discrimination beyond the explanatory power of contemporary racial threat. Furthermore, perhaps historical & ongoing migrational effects have diffused the potential effect of the "historical persistence of political attitudes" which could otherwise motivate environmental racism. When it comes to slavery's effect via income, perhaps there is no income-$PM_{2.5}$ exposure relationship at the county level, like what Colmer et al. (2024) finds at the individual level. When it comes to slavery's effect via political inequality, perhaps the effect of "the propensity of communities to engage in collective action" operates upon relatively-unimportant levels of government, or has diffused through in- and out- migration of individuals over generations.

Alternatively, perhaps these theories contain some truth, but this is obscured by limited data & analysis. For example, perhaps there are marked differences in $PM_{2.5}$ exposures *within* counties that this study misses based on its unit of observation. Alternatively, perhaps there is a relationship between slavery & air pollution exposures on the county level, but this is masked by the more-dominant relationship between air pollution exposures & some variable like contemporary population density.

Each of these theoretical & empirical issues may also help explain why the relationship between pslave1860 & both environmental variables is negative in the regressions which control for 1860 observables (Regressions 4 and 8). The results of Regression 4 and 8 are complex and, to be honest, I am not entirely confident in interpreting them. For example, I notice that the coefficients on pslave1860 are negative but the coefficients on inequality in farmland holding in 1860 tend to be both positive & large in magnitude. If inequality in landholding is an important descriptive variable here, then this makes me wonder— what if the effect of slavery today somehow depends on the historical, industrial organization of plantation operations in a place and not just the proportional measure of enslaved residents? Is using a proportional level for pslave1860 obscuring how the unique culture & violence of plantation-type slavery may have incubated greater hostility than small-farm-type slavery? This is one more possibility which I'd like to explore in future research.

Conclusion

In this paper, I've attempted to connect two interesting bodies of economics literature: (1) publications which investigate the impact of enslavement on contemporary economic outcomes and (2) publications which investigate the relationship between contemporary demographic variables— primarily race and income— and contemporary pollution exposures.

Based on these papers, I theorize three ways in which the history of enslavement in southern counties may relate to environmental exposures & inequalities in that place today.

First, I propose: the legacy of slavery in a place predicts county racial compositions there today. County racial compositions influence environmental exposures via mechanisms described by Banzhaf et al. (2019).

Second, I propose: the legacy of slavery in a place predicts lower average incomes for all people there today. Some environmental economists report a relationship between average personal income and environmental inequalities based on disproportionate siting, Tiebout-type sorting, or Coasian coordination between siting & sorting. Furthermore, the legacy of slavery is associated with greater black-white income inequality at the county level— this could amplify the effects of race or income.

Third, I propose: there is a relationship between slavery in 1860 and the strength of local civic life and political participation in that place today. The ability of local communities to engage in collective bargaining & political activism may discourage toxic firms from siting in their community, subsequently determining local pollution exposures.

Beyond the theoretical limitations identified under each of these theories in "Channels," I identify a few confounding empirical issues which make these potential relationships difficult to test for, including (1) unit-hazard coincidence, (2) urban bias in environmental justice metrics, and (3) the potential endogeneity of toxic firm siting based on regional climatic differences. In the regressions above, I attempt to control for some of these issues, like when I control for "cotton suitability" in Regressions 4 & 8. Nonetheless, I think that future research could improve upon this paper by (1) working at a smaller unit of analysis, (2) experimenting with different environmental justice indicators, and (3) testing to see if endogenous climatic conditions influenced both plantation siting in 1860 & pollution siting in 2025.

Future studies could also improve upon this paper's theoretical preliminaries. Other authors could conduct mediation analyses of the channels proposed here, or could suggest alternative channels through which the institution of slavery in the U.S. still influences environmental quality. For example, what if local economies which relied upon the exploitation of enslaved laborers somehow remain exploitative in ways not captured by the channels above, either in their treatment of workers or in their treatment in the physical landscape? Could this culture of exploitation have been passed down by the historical persistence of attitudes (Acharya et al. (2016)), and might this explain environmental inequalities today in ways not captured by descriptors like race and income? Testing a theory like this may require an analysis of southern plantation farming methods versus the methods used by farmers in colonial New England. It could also call for an analysis of the rate of contemporary environmental resource extraction in different regions of the country (inspired by Hotelling (1931)). Furthermore, It could call for an analysis of the types of industries which dominated the postbellum South versus the rest of the country & how these industries tended to treat their employees.

I realize that this paper yields more questions than answers. Consequently, I hope that future economists will study these proposed relationships in more detail than I could this semester. Identifying this potential relationship feels not just intellectually important, but also practically imperative— no issue looms larger on southern history than slavery, and no issue casts an uglier shadow. Understanding the potential impact of enslavement on environmental quality in the South feels key to remedying current environmental injustices & preventing future ones. As environmental crises loom large locally & globally, "the planet remains stirringly beautiful, and that beauty must be one of the things that moves us to act (Bill McKibben)."

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Appendix

Appendix 1.1

```
. regress logrseiscore pslave1860, robust

Linear regression                               Number of obs     =      1,731
                                                F(1, 1729)        =       1.49
                                                Prob > F          =     0.2226
                                                R-squared         =     0.0008
                                                Root MSE          =     4.5871

------------------------------------------------------------------------------
             |               Robust
logrseiscore | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |  -.6072617   .4976887    -1.22   0.223    -1.583397    .3688735
       _cons |   6.856659   .1426693    48.06   0.000     6.576836    7.136481
------------------------------------------------------------------------------
```

Appendix 1.2

```
. regress logpmsatelite pslave1860, robust

Linear regression                               Number of obs     =      1,738
                                                F(1, 1736)        =      30.92
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0162
                                                Root MSE          =     .15473

------------------------------------------------------------------------------
             |               Robust
logpmsatel~e | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |  -.0912683   .0164122    -5.56   0.000    -.1234581   -.0590786
       _cons |   2.083927   .0048539   429.33   0.000     2.074407    2.093447
------------------------------------------------------------------------------
```

Appendix 2.1

```
. xtreg logrseiscore pslave1860, fe robust

Fixed-effects (within) regression               Number of obs     =      1,731
Group variable: state_id                        Number of groups  =         38

R-squared:                                      Obs per group:
     Within  = 0.0002                                         min =          1
     Between = 0.0011                                         avg =       45.6
     Overall = 0.0008                                         max =        122

                                                F(1, 37)          =       0.27
corr(u_i, Xb) = -0.2204                         Prob > F          =     0.6032

                               (Std. err. adjusted for 38 clusters in state_id)
------------------------------------------------------------------------------
             |               Robust
logrseiscore | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |   .5599394   1.068021     0.52   0.603    -1.604077    2.723956
       _cons |   6.664298   .1760159    37.86   0.000     6.307656     7.02094
-------------+----------------------------------------------------------------
     sigma_u |  1.3449587
     sigma_e |  4.4957046
         rho |  .08214766   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 2.2

```
. xtreg logpmsatelite pslave1860, fe robust

Fixed-effects (within) regression               Number of obs     =      1,738
Group variable: state_id                        Number of groups  =         38

R-squared:                                      Obs per group:
     Within  = 0.0054                                         min =          1
     Between = 0.0431                                         avg =       45.7
     Overall = 0.0162                                         max =        122

                                                F(1, 37)          =       2.66
corr(u_i, Xb) = 0.0649                          Prob > F          =     0.1115

                               (Std. err. adjusted for 38 clusters in state_id)
------------------------------------------------------------------------------
             |               Robust
logpmsatel~e | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |  -.0535569   .0328494    -1.63   0.112    -.1201161    .0130023
       _cons |   2.077724   .0054031   384.55   0.000     2.066777    2.088672
-------------+----------------------------------------------------------------
     sigma_u |  .24124915
     sigma_e |  .09052795
         rho |  .87657009   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 3.1

```
. xtreg logrseiscore pslave1860, fe robust

Fixed-effects (within) regression               Number of obs     =      1,602
Group variable: state_id                        Number of groups  =         38

R-squared:                                      Obs per group:
     Within  = 0.0001                                         min =          1
     Between = 0.0001                                         avg =       42.2
     Overall = 0.0012                                         max =        115

                                                F(1, 37)          =       0.11
corr(u_i, Xb) = -0.2197                         Prob > F          =     0.7418

                              (Std. err. adjusted for 38 clusters in state_id)
------------------------------------------------------------------------------
             |               Robust
logrseiscore | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |   .3885193   1.170547     0.33   0.742    -1.983234    2.760272
       _cons |   7.014712   .1912259    36.68   0.000     6.627252    7.402172
-------------+----------------------------------------------------------------
     sigma_u |  1.3233112
     sigma_e |  4.3454586
         rho |  .08486667   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 3.2

```
. xtreg logpmsatelite pslave1860, fe robust

Fixed-effects (within) regression               Number of obs     =      1,608
Group variable: state_id                        Number of groups  =         38

R-squared:                                      Obs per group:
     Within  = 0.0036                                         min =          1
     Between = 0.0478                                         avg =       42.3
     Overall = 0.0104                                         max =        115

                                                F(1, 37)          =       1.93
corr(u_i, Xb) = 0.0499                          Prob > F          =     0.1726

                              (Std. err. adjusted for 38 clusters in state_id)
------------------------------------------------------------------------------
             |               Robust
logpmsatel~e | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |  -.0442538   .0318212    -1.39   0.173    -.1087296     .020222
       _cons |   2.076187   .0051907   399.98   0.000     2.065669    2.086704
-------------+----------------------------------------------------------------
     sigma_u |  .24249581
     sigma_e |  .09063586
         rho |  .87742506   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 4.1

```
. xtreg logrseiscore pslave1860 countypop1860 improvedacres1860 farmvalueperacre1860 inequalitylandholding1860 railways1860
>  waterways1860 countylong countylat cottonsuitability1860, fe robust

Fixed-effects (within) regression               Number of obs     =      1,076
Group variable: state_id                        Number of groups  =         24

R-squared:                                      Obs per group:
     Within  = 0.0738                                         min =          3
     Between = 0.3682                                         avg =       44.8
     Overall = 0.0392                                         max =        106

                                                F(10, 23)         =      11.91
corr(u_i, Xb) = -0.7215                         Prob > F          =     0.0000

                                        (Std. err. adjusted for 24 clusters in state_id)
------------------------------------------------------------------------------------------
                          |               Robust
             logrseiscore | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------------------+---------------------------------------------------------------
               pslave1860 |  -3.873868   1.285073    -3.01   0.006    -6.532244   -1.215492
            countypop1860 |   4.38e-06   .0000121     0.36   0.721    -.0000207    .0000295
        improvedacres1860 |   .0000115   4.03e-06     2.85   0.009     3.15e-06    .0000198
     farmvalueperacre1860 |   .0168532    .007649     2.20   0.038     .0010299    .0326765
inequalitylandholding1860 |   3.413442     1.2406     2.75   0.011      .847066    5.979818
             railways1860 |   1.178875   .4196601     2.81   0.010     .3107424    2.047009
            waterways1860 |   1.327036   .2681994     4.95   0.000     .7722234    1.881849
               countylong |   .1520541     .16672     0.91   0.371    -.1928325    .4969407
                countylat |   .0014736   .1531071     0.01   0.992    -.3152525    .3181997
    cottonsuitability1860 |  -.7495877    1.10495    -0.68   0.504    -3.035351    1.536176
                    _cons |    17.4154   14.62036     1.19   0.246    -12.82913    47.65992
--------------------------+---------------------------------------------------------------
                  sigma_u |  2.2080297
                  sigma_e |  4.1216855
                      rho |  .22299054   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Appendix 4.2

```
. xtreg logpmsatelite pslave1860 countypop1860 improvedacres1860 farmvalueperacre1860 inequalitylandholding1860 railways186
> 0 waterways1860 countylong countylat cottonsuitability1860, fe robust

Fixed-effects (within) regression               Number of obs     =      1,081
Group variable: state_id                        Number of groups  =         24

R-squared:                                      Obs per group:
     Within  = 0.0475                                         min =          3
     Between = 0.1949                                         avg =       45.0
     Overall = 0.0126                                         max =        106

                                                F(10, 23)         =       4.23
corr(u_i, Xb) = -0.5648                         Prob > F          =     0.0021

                                        (Std. err. adjusted for 24 clusters in state_id)
------------------------------------------------------------------------------------------
                          |               Robust
            logpmsatelite | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------------------+---------------------------------------------------------------
               pslave1860 |  -.0514166   .0364842    -1.41   0.172    -.1268899    .0240566
            countypop1860 |  -1.95e-07   1.75e-07    -1.11   0.278    -5.58e-07    1.68e-07
        improvedacres1860 |  -3.88e-08   1.45e-07    -0.27   0.792    -3.39e-07    2.62e-07
     farmvalueperacre1860 |   .0005913   .0002912     2.03   0.054     -.000011    .0011937
inequalitylandholding1860 |  -.0984722    .081296    -1.21   0.238    -.2666458    .0697013
             railways1860 |   .0167175   .0103979     1.61   0.122    -.0047922    .0382272
            waterways1860 |   .0066573   .0086475     0.77   0.449    -.0112315    .0245461
               countylong |  -.0072917   .0106883    -0.68   0.502    -.0294022    .0148187
                countylat |   .0019158   .0205027     0.09   0.926    -.0404973    .0443289
    cottonsuitability1860 |  -.0303354    .052234    -0.58   0.567    -.1383897    .0777188
                    _cons |   1.420344   .8194111     1.73   0.096    -.2747374    3.115425
--------------------------+---------------------------------------------------------------
                  sigma_u |  .17223002
                  sigma_e |  .08824084
                      rho |  .79208215   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Appendix 5.1

```
. regress logrseiscore pslave1860, robust

Linear regression                               Number of obs     =        754
                                                F(1, 752)         =       0.05
                                                Prob > F          =     0.8163
                                                R-squared         =     0.0001
                                                Root MSE          =     4.4768

------------------------------------------------------------------------------
             |               Robust
logrseiscore | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |  -.1923264   .8277305    -0.23   0.816    -1.817264    1.432611
       _cons |   6.709367   .3399803    19.73   0.000     6.041944    7.376791
------------------------------------------------------------------------------
```

Appendix 5.2

```
. regress logpmsatelite pslave1860, robust

Linear regression                               Number of obs     =        755
                                                F(1, 753)         =      52.03
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0634
                                                Root MSE          =     .14384

------------------------------------------------------------------------------
             |               Robust
logpmsatel~e | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |  -.1777698   .0246462    -7.21   0.000    -.2261533   -.1293863
       _cons |   2.113192   .0101696   207.80   0.000     2.093228    2.133156
------------------------------------------------------------------------------
```

Appendix 6.1

```
. xtreg logrseiscore pslave1860, fe robust

Fixed-effects (within) regression               Number of obs     =        754
Group variable: state_id                        Number of groups  =         11

R-squared:                                      Obs per group:
     Within  = 0.0000                                         min =         40
     Between = 0.0000                                         avg =       68.5
     Overall = 0.0001                                         max =        122

                                                F(1, 10)          =       0.01
corr(u_i, Xb) = -0.0888                         Prob > F          =     0.9180

                              (Std. err. adjusted for 11 clusters in state_id)
------------------------------------------------------------------------------
             |               Robust
logrseiscore | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |   .1254002   1.186963     0.11   0.918    -2.519318    2.770118
       _cons |   6.600238   .4076849    16.19   0.000     5.691859    7.508617
-------------+----------------------------------------------------------------
     sigma_u |  .81337133
     sigma_e |  4.4431617
         rho |  .03242487   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 6.2

```
. xtreg logpmsatelite pslave1860, fe robust

Fixed-effects (within) regression               Number of obs     =        755
Group variable: state_id                        Number of groups  =         11

R-squared:                                      Obs per group:
     Within  = 0.0072                                         min =         40
     Between = 0.1417                                         avg =       68.6
     Overall = 0.0634                                         max =        122

                                                F(1, 10)          =       1.76
corr(u_i, Xb) = 0.2628                          Prob > F          =     0.2138

                              (Std. err. adjusted for 11 clusters in state_id)
------------------------------------------------------------------------------
             |               Robust
logpmsatel~e | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |  -.0493058   .0371403    -1.33   0.214    -.1320596    .0334479
       _cons |   2.069032   .0127669   162.06   0.000     2.040586    2.097479
-------------+----------------------------------------------------------------
     sigma_u |  .11154545
     sigma_e |  .10478197
         rho |  .53123447   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 7.1

```
. xtreg logrseiscore pslave1860, fe robust

Fixed-effects (within) regression               Number of obs     =        695
Group variable: state_id                        Number of groups  =         11

R-squared:                                      Obs per group:
     Within  = 0.0000                                         min =         40
     Between = 0.0108                                         avg =       63.2
     Overall = 0.0002                                         max =        115

                                                F(1, 10)          =       0.01
corr(u_i, Xb) = -0.1145                         Prob > F          =     0.9253

                              (Std. err. adjusted for 11 clusters in state_id)
------------------------------------------------------------------------------
             |               Robust
logrseiscore | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |   .1283972   1.336076     0.10   0.925    -2.848565    3.105359
       _cons |   6.891855   .4584994    15.03   0.000     5.870255    7.913456
-------------+----------------------------------------------------------------
     sigma_u |  .78514389
     sigma_e |  4.3198088
         rho |  .03197824   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 7.2

```
. xtreg logpmsatelite pslave1860, fe robust

Fixed-effects (within) regression               Number of obs     =        696
Group variable: state_id                        Number of groups  =         11

R-squared:                                      Obs per group:
     Within  = 0.0041                                         min =         40
     Between = 0.1279                                         avg =       63.3
     Overall = 0.0530                                         max =        115

                                                F(1, 10)          =       1.09
corr(u_i, Xb) = 0.2544                          Prob > F          =     0.3203

                              (Std. err. adjusted for 11 clusters in state_id)
------------------------------------------------------------------------------
             |               Robust
logpmsatel~e | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
  pslave1860 |  -.0377646   .0361112    -1.05   0.320    -.1182255    .0426962
       _cons |   2.069074   .0124032   166.82   0.000     2.041438     2.09671
-------------+----------------------------------------------------------------
     sigma_u |  .11020871
     sigma_e |  .10497593
         rho |  .52430324   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 8.1

```
. xtreg logrseiscore pslave1860 countypop1860 improvedacres1860 farmvalueperacre1860 inequalitylandholding1860 railways1860
>  waterways1860 countylong countylat cottonsuitability1860, fe robust

Fixed-effects (within) regression               Number of obs     =        667
Group variable: state_id                        Number of groups  =         11

R-squared:                                      Obs per group:
     Within  = 0.0949                                         min =         40
     Between = 0.0015                                         avg =       60.6
     Overall = 0.0217                                         max =        106

                                                F(10, 10)         =      70.62
corr(u_i, Xb) = -0.7990                         Prob > F          =     0.0000

                                  (Std. err. adjusted for 11 clusters in state_id)
------------------------------------------------------------------------------------------
                          |               Robust
             logrseiscore | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------------------+---------------------------------------------------------------
               pslave1860 |  -3.914407   1.482346    -2.64   0.025    -7.217281   -.6115334
            countypop1860 |   .0001801   .0000363     4.96   0.001     .0000992     .000261
        improvedacres1860 |  -7.14e-06   4.47e-06    -1.60   0.141    -.0000171    2.82e-06
     farmvalueperacre1860 |   .0096578   .0075804     1.27   0.231    -.0072324     .026548
inequalitylandholding1860 |   .9786761   1.687255     0.58   0.575    -2.780763    4.738115
             railways1860 |   .9692859    .523129     1.85   0.094    -.1963182     2.13489
            waterways1860 |   1.081603   .2903273     3.73   0.004     .4347135    1.728493
               countylong |   .2905841   .1992587     1.46   0.175     -.153392    .7345603
                countylat |   .0058182   .1148444     0.05   0.961    -.2500711    .2617076
    cottonsuitability1860 |  -.3247056   2.027965    -0.16   0.876    -4.843293    4.193882
                    _cons |   30.71492   16.63413     1.85   0.095    -6.348238    67.77809
--------------------------+---------------------------------------------------------------
                  sigma_u |  2.1408512
                  sigma_e |  4.0612691
                      rho |  .21745082   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Appendix 8.2

```
. xtreg logpmsatelite pslave1860 countypop1860 improvedacres1860 farmvalueperacre1860 inequalitylandholding1860 railways186
> 0 waterways1860 countylong countylat cottonsuitability1860, fe robust

Fixed-effects (within) regression               Number of obs     =        668
Group variable: state_id                        Number of groups  =         11

R-squared:                                      Obs per group:
     Within  = 0.0835                                         min =         40
     Between = 0.0305                                         avg =       60.7
     Overall = 0.0804                                         max =        106

                                                F(10, 10)         =      56.33
corr(u_i, Xb) = -0.2929                         Prob > F          =     0.0000

                                  (Std. err. adjusted for 11 clusters in state_id)
------------------------------------------------------------------------------------------
                          |               Robust
            logpmsatelite | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
--------------------------+---------------------------------------------------------------
               pslave1860 |  -.0524426   .0458909    -1.14   0.280     -.154694    .0498088
            countypop1860 |  -8.74e-07   2.31e-06    -0.38   0.713    -6.02e-06    4.27e-06
        improvedacres1860 |   1.27e-07   3.61e-07     0.35   0.732    -6.78e-07    9.32e-07
     farmvalueperacre1860 |   .0009311    .000356     2.62   0.026     .0001378    .0017244
inequalitylandholding1860 |  -.1419135   .1056788    -1.34   0.209    -.3773806    .0935537
             railways1860 |   .0193275   .0139878     1.38   0.197    -.0118392    .0504943
            waterways1860 |   .0056499   .0153757     0.37   0.721    -.0286094    .0399092
               countylong |  -.0113817   .0135057    -0.84   0.419    -.0414743    .0187109
                countylat |   .0060243   .0282345     0.21   0.835    -.0568861    .0689348
    cottonsuitability1860 |  -.0410284   .1115362    -0.37   0.721    -.2895464    .2074897
                    _cons |   .9324824   1.062331     0.88   0.401    -1.434539    3.299503
--------------------------+---------------------------------------------------------------
                  sigma_u |  .12047063
                  sigma_e |  .09949144
                      rho |  .59451662   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```