The Road to Equality

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Abstract

I show federal highway grants reduce the growth rate of the state-level Gini coefficients in the United States using a dynamic spatial Durbin model using a panel of the contiguous United States from 1956 to 2013. Grants reduce the growth rate of income inequality both in the recipient state as well as neighboring states. I find that federal highway grants reduce incoming inequality primarily by raising income of the lower three quintiles of the income distribution, while leaving the upper two essentially unaffected. I show that heterogeneity in educational attainment and industry of work help explain plausible mechanisms driving the results. My results suggest highway grants can be a powerful tool for policymakers concerned with reducing income inequality.

1 Introduction

Income inequality has been on the rise for the past half century. In 1956 the average share of the top 10% of state income earners received 32% of total income. By 2013 they earned nearly 45%. As of 2014, the average person in the top 10% of the income distribution makes nearly nine times more than the average person in the bottom 90%, a 50% increase over the first half of the 20^{th} century. The *maximum* state level of inequality as measured by the Gini coefficient in 1970 was lower than the *minimum* state level of inequality in 2010.[1] Figures 1 and 2 show rising inequality has occurred in every state of the United States since the 1950's. U.S. income inequality ranks 4th out of 34 OECD countries.[2] There is little indication that the trend is reversing. In 1980 income growth for the bottom quintile of income earners outpaced the top 1%. By 2014 income growth of the lowest quintile had slowed down to a meager one tenth of the income growth rate of the top .0001% of income earners.[3]

Figure 3 illustrates how voters preferences appear to have responded to rising income inequality. In 1985 voters overwhelmingly expressed a distaste for government redistribution of income (39% supporting to 61% opposing). By 2016, the majority of voters supported some form of redistribution of income (56% supporting to 44% opposing). Consequently, a variety of policy proposals aimed at combating inequality have emerged. Some emphasize access to education, as a direct response to skill-biased technical change (e.g. Acemoglu (1998); Goldin and Katz (2018)). Meanwhile, Piketty (2017) suggests that reducing the return on capital or increasing growth is the only long run way to reduce inequality.[4] Others have suggested explicit fiscal policy responses such as raising capital taxes, a more progressive income tax system, expanded public access to credit, guaranteed basic income, or raising limits on means tested programs.[5] While the existing literature has primarily focused on policies that explicitly aim to reduce income inequality, I add to it by exploring the effects of a policy with no explicit re-distributive goals: federal infrastructure investment.

[1] Idaho had the maximum level of inequality in 1970 with a pre-tax Gini coefficient of .506 while West Virginia had the minimum level of inequality in 1990 with a pre-tax Gini coefficient of .543. The Gini coefficient is defined by the area between the Lorenz curve and an equal (egalitarian) distribution of income. A Gini coefficient of 0 implies an egalitarian distribution of income and a Gini coefficient of 1 implies absolute income inequality.

[2] Post-taxes and transfers for 2014. Costa Rica, Mexico and Turkey had the top levels of inequality. See `https://stats.oecd.org/Index.aspx?DataSetCode=IDD` for more.

[3] https://www.nytimes.com/interactive/2017/08/07/opinion/leonhardt-income-inequality.html

[4] Consistent with this idea, (Dollar and Kraay, 2002) found that higher income growth tends to reduce income inequality and (Apergis, Dincer and Payne, 2010; Gupta, Davoodi and Alonso-Terme, 2002; Jong-Sung and Khagram, 2005) find reducing corruption can achieve the same ends.

[5] See Piketty (2014) for a more thorough list of policies that have been considered.

This paper analyzes the effect of federal infrastructure grants on income inequality. Using a long panel of US states from 1956 to 2013 I show that federal infrastructure grants reduce the growth rate of state-level income inequality. My empirical specification is able to capture both spatial spillover effects and temporal dynamics. I find that federal infrastructure grants reduce the growth rate of income inequality of the recipient state, and the effect spills over into neighboring states.[6] I find that these effects are larger in the short run, but persist into the long run.

Figure 4 shows a breakdown of federal physical investment in transportation and water infrastructure between 1956 and 2014. Highway investment represents the bulk of federal infrastructure outlays in each year. As Figure 5 shows, grants play a critical role in federal transportation infrastructure expenses. In 2012, 85% of all federal highway investment was expended via grants. Consequently, I focus on federal highway grants to proxy for federal infrastructure investment.

Bradford and Oates (1971*b*) show changes in grants do not necessarily imply changes in spending. Federal transportation infrastructure grants may crowd out local investment. Therefore, federal grants may not increase total spending on the program, just who pays for it. In Section 4, I find evidence of flypaper effect - the phenomenon that donor government grants do not fully crowd out recipient government spending. That is, I present evidence that changes in transportation grants *do* increase total highway spending.

I focus on federal transportation grants for several reasons. First, federal transportation investment is plausibly large enough to generate a significant change in a state's income distribution. In 2014, the federal government devoted just under $100 billion (equivalent to about 3.2% of the federal budget or about .5% of GDP) on physical infrastructure, much of which was devoted to highways. Additionally, federal transportation grants are large enough to be allocated to each state in the Union, which allows for a panel data analysis that can control for state fixed effects and national changes.

Second, federal infrastructure grants are plausibly predetermined. Congress apportions grants to states using formulas. Disbursements from these formulas use three year lagged data. Consequently, apportionments are not contemporaneously correlated with key economic factors. As a result, estimates in this analysis are less prone to concerns about endogeneity than, for example, education spending (e.g. Klasen, 2002). I return to institutional details of federal infrastructure expenditures in Section 3 and Appendix A.2.

[6] Throughout the text I refer to the spillovers occurring in neighboring states. My empirical model is less restrictive, in that spill over effects can reach higher ordered neighbors (neighbors of neighbors) - referred to as global spillover effects. I outline the empirical model in Section 5.

Finally, policymakers and economists may prefer public infrastructure spending over alternative approaches to reducing income inequality. Whereas oft-proposed policy prescriptions to income inequality may be unproductive or distortionary (Piketty and Saez, 2013; Albouy, 2012), highway spending has generally been found to be productive - increasing average income and lowering transportation costs (Aschauer, 1989; Bom and Ligthart, 2014; Leduc and Wilson, 2013*a*).[7]

Following Aschauer (1989), many studies have focused on the *average* effects of public physical capital investment, but few have examined the *distributional* effects thereof. In Sections 6 and 7, I show federal highway grants increase average income, as found by previous literature. However, this paper contributes to the literature by exploring the distributional effects of infrastructure spending. In section 6 I show that the majority of the benefits of federal highway grants are concentrated among the three lower income quintiles. In Section 7 I show that the gains are primarily captured by low-skilled workers and those working in low skilled industries.

This study relates to other studies that have examined the relationship between public physical investment and income inequality. Chatterjee and Turnovsky (2012) develop a model where infrastructure can affect both the growth rate and the distribution of income. They find that the sign of public investment's impact on income inequality is ambiguous, with many financing schemes resulting in short run declines in income inequality that are reversed in the long run.[8] Meanwhile, the macroeconomics literature has stressed the importance of the substitutability or complementarity between private and public capital in determining the sign of the effect of public infrastructure on income inequality (Getachew and Turnovsky, 2015).

The empirical literature appears mixed. Several studies find no negative (Khandker, Bakht and Koolwal, 2009), or even positive (Banerjee and Somanathan, 2007) effects of infrastructure programs on income inequality. However, others have found a strong negative relationship between the two. Studies examining the effect of infrastructure from Latin America (De Ferranti, 2004; Calderón and Chong, 2004) to rural China (Shenggen and Zhang, 2004), and Mexico (Gibson and Rioja, 2017) find that income inequality falls in response to changes in infrastructure or infrastructure spending. My empirical results are more aligned with the latter of these since I find federal transportation grants reduce income inequality. However, my analysis extends the current literature in two important

[7]Of course, some studies have found that highways are not very productive (Fernald, 1999; Chandra and Thompson, 2000), but even these studies typically do not find highways to be as unproductive as other forms of government spending, just not as productive as implied by e.g. Aschauer (1989)

[8]My approach largely sidesteps the question of source of financing since I use pre-tax data and because federal financing is largely constant across states. In section 8.3 I explicitly include state measures of implicit federal tax rates.

ways. First, I demonstrate the importance of accounting for spatial spillover effects. Second, I focus on the United States, whereas the existing literature has primarily focused on developing countries, which may react very differently to changes in infrastructure.

Little explicit attention has been given to the relationship between income inequality and public infrastructure spending in the United States, but several studies have done so indirectly by finding evidence of heterogeneous effects of infrastructure on industries (Fernald, 1999; Nadiri and Mamuneas, 1991; Mamuneas and Nadiri, 1996; Melo, Graham and Brage-Ardao, 2013). Though each of these studies analyze the heterogeneous effects of changes in transportation infrastructure differently, they all find that industries such as manufacturing, transportation, and construction benefit relatively more than industries in the service sector. Although these insights highlight the heterogeneous nature of public capital investment's impact on output and cost structures of industries and firms, they do not directly address its effect on the distribution of income as I do. Therefore, I expand on the current literature by exploring another dimension of the heterogeneous effects of changes in public infrastructure.

The rest of the paper is organized as follows. Section 2 provides a simple theoretical framework. Section 3 describes the data, and Section 4 links grants to spending. Section 5 motivates and presents my empirical specification. Section 6 presents the main results, and Section 7 tests for possible mechanisms driving those results. Section 8 provides robustness checks, extensions, and falsification tests. Section 9 discusses and concludes.

2 Motivating Theory

This section presents a straightforward example of how infrastructure spending can reduce income inequality. Since the relationship between income inequality and public infrastructure is not highly researched, the model builds intuition behind the empirical results.

2.1 Single Economy

Drawing from the labor economics literature, which has emphasized the importance of skill and education in accounting for the rapid increase in income inequality, I construct a competitive market model in which output (Y) is a function of public capital (K) and two types of labor - high-skilled (L_h) and low-skilled (L_l). Each type of worker supplies their labor exogenously and inelastically. Workers are exogenously assigned skill, and cannot switch skill-levels. High skilled workers are more productive; they earn a skill premium of

$A > 1$.[9] In this basic set-up, labor is perfectly immobile, but this assumption is relaxed in the next section. The production function is additively separable such that:

$$Y = L_l^{\alpha_l} K^{\theta} + A L_h^{\alpha_h} \tag{1}$$

Each sector exhibits diminishing returns to private inputs, $\alpha_h, \alpha_l < 1$. Public capital is exogenously determined, and affects the productivity of the low skilled sector and the elasticity of output the public capital for the low skilled sector is given by θ. Public capital is a complement in production with low-skilled labor, $\theta > 0$.[10] Public capital does not impact output in the high skilled sector.[11]

Since markets are competitive, labor in both sectors earn their marginal productivity,

$$\frac{\partial Y}{\partial L_l} = \alpha_l L_l^{\alpha_l - 1} K^{\theta_l} = w_l \tag{2}$$

$$\frac{\partial Y}{\partial L_h} = \alpha_h A L_h^{\alpha_h - 1} = w_h \tag{3}$$

Note that equilibrium wage, w_l and w_h, only depends on public capital for low skilled workers. Consequently, the response of wages to public capital in each sector is

$$\frac{\partial w_l}{\partial K} = \theta_l L_l^{\alpha_l - 1} K^{\theta - 1} > 0$$

$$\frac{\partial w_h}{\partial K} = 0$$

Wages increase for low skilled workers (since $\theta > 0$), but are unchanged for high skilled workers. Since there are only two types of workers, inequality can be summarized by the relative wage of high-skilled and low-skilled workers, $w_r = \frac{w_h}{w_l}$, with higher levels implying greater income inequality.[12] Since wages for high skilled labor remain the same,

[9] Alternatively, one could model this as a two goods two sector economy. However, this distinction does not meaningfully impact the analysis. Further, such an approach would require specifying the relative price of goods made by high skilled workers compared to the price of goods made by low skilled workers. In contrast, I implicitly normalize all prices to one in this model.

[10] Empirical estimates of the elasticity of output to public capital in the low skilled sectors are positive and usually large. See Nadiri and Mamuneas (1991); Fernald (1999).

[11] The assumption that public capital does not affect the high skilled sector is potentially overly restrictive, and could be generalized by allowing both sectors to depend on public capital. The results hold so long as the elasticity of output in the low skilled sector is sufficiently higher than the high skilled sector. This seems plausible, as estimates for the high skilled sector are typically small. Some estimates even find negative elasticities (implying public capital is a substitute in production), which would suggest the results in this model underestimate the effects of infrastructure investment on income inequality. See Mamuneas and Nadiri (1996) for more.

[12] Total income inequality measures like the Gini coefficient used later in this paper will also depend on the ratio of high to low skilled labor, but in this model the quantity of labor is constant.

and wages for low-skilled labor increase, public capital increase reduce the relative wage ($\frac{\partial w_r}{\partial K} < 0$), and thereby income inequality.

2.2 Spillovers

An important contribution of this paper is that I find empirical support for the effect of federal infrastructure grants spilling over into neighboring states. In this section I expand the previous model to account for spatial spillover effects. Consider now two neighboring states, i and j, each with identical production functions like the one above,

$$Y_s = L_{sl}^{\alpha_l} K_s^{\theta} + A L_{sh}^{\alpha_h} \tag{4}$$

where $s = i, j$. States i and j differ only in their endowments of public capital and labor, but have the same elasticity of output to capital (θ) and skill premium (A). Capital is exogenously given to each state. The demand for labor is similar to the precious section, with,

$$\frac{\partial Y_s}{\partial L_{sl}} = \alpha_l L_{sh}^{\alpha_l - 1} K_{sl}^{\theta} = w_{sl} \tag{5}$$

$$\frac{\partial Y_s}{\partial L_{sh}} = \alpha_h A L_{sh}^{\alpha_h - 1} = w_{sh} \tag{6}$$

for $s = i, j$. In each sector, labor is mobile, but total sectoral-labor is fixed; $\bar{L}_l = L_{il} + L_{jl}$ and $\bar{L}_h = L_{ih} + L_{jh}$. Equilibrium is therefore defined by:

$$\alpha_l L_{il}^{\alpha_l - 1} K_{il}^{\theta} = w_{il} \tag{7}$$

$$\alpha_l L_{jl}^{\alpha_l - 1} K_{jl}^{\theta} = w_{jl} \tag{8}$$

$$\bar{L}_l = L_{il} + L_{jl} \tag{9}$$

$$w_{il} = w_{jl} \tag{10}$$

$$\alpha_h A L_{ih}^{\alpha_h - 1} = w_{ih} \tag{11}$$

$$\alpha_h A L_{jh}^{\alpha_h - 1} = w_{jh} \tag{12}$$

$$\bar{L}_h = L_{ih} + L_{jh} \tag{13}$$

$$w_{ih} = w_{jh} \tag{14}$$

$$\tag{15}$$

Equations (7) to (10) describe equilibrium for the low skilled sector and Equations (11) to (14) describe the equilibrium for the low-skilled sector.

Equating (7) and (8) through (10) and substituting in (9) and differentiating leads to,

$$\frac{dw_{il}}{dK_i} = \frac{\partial w_{il}}{\partial K_i}\frac{dL_{il}}{dK_i} + \frac{\partial w_{il}}{\partial K_i} > 0 \tag{16}$$

since

$$\frac{\partial w_{il}}{\partial K_i} = \alpha(\alpha-1)L^{\alpha-2}K_i^{\theta} + [\alpha(\alpha-1)K_j^{\theta}(\bar{L}_l - L_{il})^{\alpha-2}] < 0$$
$$\frac{dL_{il}}{dK_i} = -w_{il}(\alpha\theta K_i^{\theta})^{-1} < 0$$
$$\frac{\partial w_{il}}{\partial K_i} = \theta\alpha L_i^{\alpha-1}K_i^{\theta-1} > 0$$

Wages equilibrate via mobility of labor. Since public capital and low skilled labor are complements in production, an increase in public capital for state i raises the marginal productivity of labor (MPL) of state i. Markets are competitive, so an increase in the MPL raises wages in state i, inducing workers from neighboring state j to migrate to state i. This migration puts downward pressure on wages in state i (since demand is downward sloping). At the same time, migration out of state j raises the MPL of it's low skilled sector. In equilibrium, just enough people migrate from state j to state i such that Equation 10 is met.

Therefore, an increase in public capital increases wages in the low-skilled sector of the home state i. In contrast, since the high-skilled sector is not a function of public capital, $\frac{dw_{ih}}{dK_i}$=0. Consequently, the relative wage falls in the home state in response to increases in public capital.

Since labor is perfectly mobile (Equation (10)), wages in each sector of neighboring state i change proportionately with changes in the wage of state i.[13] As a result, the effect of an increase of increasing public capital on the relative wage spills over into in state j as well.

In the basic model, labor in each state was constant, thus the relative wage was isomorphic to income inequality. However, in this context equilibrium is achieved by movement of labor, implying the number of people in each sector does not remain constant. Since wages for low-skilled workers increased in state j at the same time that the number of low-skilled laborers in state j decreased, there is an unambiguously negative effect on income inequality. However, in state i the influx of workers from state j leads

[13]The perfect mobility of labor is convenient, but not necessary. Labor does not have to be perfectly mobile for the basic result of this section to hold. One could introduce imperfect mobility by adjusting the model to include convex (in the number of people moving) cost of moving, reflecting heterogeneous attachment to home. Including such a movement cost would generate wage wedges, but not change the basic results. Note that perfect mobility does not create a corner solution in this case because the MPL tends to wards infinity as labor gets arbitrarily close to zero in either state, due to the diminishing returns on labor ($\alpha < 1$).

to an offsetting effect on total income inequality, as the share of low skilled workers is now lower than before. Consequently, the effect public capital expenditures on income inequality measures such as the Gini coefficient is ambiguous for state i, but unambiguously negative for state j. In the main results, I resolve this theoretical ambiguity and robustly find increases public capital reduces income inequality both in the recipient state and neighboring states.

The extended model highlights several important features that inform my later empirical specification. First, it implies low skilled workers or workers in the low skilled sector should see benefits from public capital expenditures. Second, it suggests there should be limited effect of changes in public capital on high skilled workers or workers working in the high skilled sector.[14] Third, it suggests an important role for spillover effects of public capital investment. Last, it suggests the direct effect (ie in the recipient state) of public capital investment on income inequality are attenuated by the presence of neighboring states, implying a non-spatial model may over estimate the effect of public capital investment on the home state.

3 Data

To empirically test the relationship between public infrastructure and income inequality, I use annual data spanning the years between 1956 and 2013 for the contiguous 48 United States.[15]

I use annual state-level Gini coefficients to measure total income inequality. I focus on the Gini coefficient because of it's historical ubiquity (Atkinson, 1975; Sen, Foster et al., 1973; Deininger and Squire, 1996) and contemporary relevance in both policy decisions and academia (Piketty, 2015). The source of these data is Frank (2014), who in turn derives estimates from the Statistics of Income (SOI) series that are annually published by the Internal Revenue Service (IRS). The SOI provides detailed tabulations of pre-tax aggregate income by state. More information on the SOI series is provided in Appendix A.1.

As mentioned in the introduction, I use federal highway transportation grants to states as a proxy for public infrastructure investment. Grants are distributed to states via congressionally mandated programs. To reduce redundancy, most programs that distribute grants relating to highways have been placed under the Federal-Aid Highway

[14] I test, and find empirical support, for each of these implications in section 7.

[15] I exclude Alaska and Hawaii because they share no border with other states. I exclude the District of Columbia because I am not able to control for political influence using political controls that will be defined later in this section.

Program (hereafter FAHP), which is administered by the Federal Highway Administration (hereafter FHWA).

Data regarding these grants are sourced from the FHWA's annual *Highway Statistics* report through its Office of Highway Policy Information.[16] The *Highway Statistics* series contains detailed statistics on federal spending and grants, including all FAHP activities. I use total apportionments of FAHP grants across all programs from the *Highway Statistics* series to measure federal highway transportation grants.

FAHP apportionments denote the distribution of funds by FAHP to states according to statutory formulas. Apportionments are the first step in the political process of FAHP funds being expended, so they better capture the anticipation effects and implementation lags commonly associated with fiscal policy (see, e.g., Ramey, 2011).[17]

Factors underlying the FAHP apportionment formulas vary by program, but they areall calculated using three year lagged data, due to the historical difficulty in obtaining accurate highway usage data in a timely fashion. Table 1 illustrates the factors underlying the apportionments for several major FAHP programs, and the weight assigned to each factor for the period spanning between 2010 and 2012. The formulaic nature of FAHP apportionments mitigates the potential endogeneity of FAHP grants to political manipulation, and the three year lagged formula factors greatly diminish the contemporaneous correlation between grants and key economic variables. Thus, FAHP grants are plausibly predetermined. Appendix A.2 expands on institutional detail and advantages of FAHP apportionments over other measures of infrastructure.

To further control for potential political influence, I include three covariates that capture a state's congressional power. The first two covariates indicate if the chairperson of the appropriations committee of either chamber of Congress represent their state. The third covariate measures each states' percent of total membership on the House of Representatives' Committee on Appropriations. Data for these covariates are sourced from the Government Publishing Office, Congressional profiles, and various documents available via the Library of Congress and official websites of each chamber of Congress (see the Data Glossary for more).[18]

[16]Data prior to 1994 were digitized from photocopied manuscripts. The photocopies have very poor quality (or are simply missing) for years prior for 1954. Thus I start my analysis at 1956 even though the *Highway Statistics* report nominally dates back to 1946. I know of no other paper that has digitized the *Highway Statistics* data as far back as I have.

[17]Funds are distributed either by apportionments or allocation. Allocated funds are not subject to formulas, and therefore more subject to political influence. I exclude all allocated funds from my sample. See Appendix A.2 for details on each of the stages of FAHP grants.

[18]Appendix A.2 elaborate on why these three controls are the most appropriate measures of congressional power.

4 From Grants to Spending

A potential drawback of FAHP grants is that changes in grants apportioned to a program do not necessarily imply a change in total *spending* on the program since federal grants could crowd out state spending. In this section I demonstrate that increases in FAHP grants *do* increase total spending on roads and highways in my sample.

Since Bradford and Oates (1971*a*,*b*) the public finance literature has argued that inter-governmental grants may be fungible. If true, recipient (state) governments should treat FAHP funds from the donor (federal) government as interchangeable with its own highways and roads. As a result, theory implies state funds should be fully crowded out by federal grants, save an income effect generated by the grant.

The phenomenon of recipient governments actually increasing net total spending on projects earmarked by the donor governments is called the flypaper effect. Evidence of the presence of flypaper effects are abundant. In fact, most studies that analyze the effect of grants on recipient spending find evidence of some form of a flypaper effect. Hines and Thaler (1995), summarize early literature on inter-governmental grants in the following way:, "[A]ll studies surveyed report some degree of flypaper. The variation comes from whether the estimated flypaper effect is simply large or if it is enormous". Leduc and Wilson (2013*b*, 2017) go further. They find that highway funds actually crowd *in* state investment. That is, states *increase* total spending on highways in response to highway grants.

Though most studies find a flypaper effect, some find the type of crowding out that theory predicts. Particularly relevant is Knight (2002) since he focuses on highway grants. The essential insight of his study is that federal grants may be endogenous. States that value highway spending will fight harder in the political process to get more funds. Using an instrumental variables approach, Knight's estimates are unable to reject a null hypothesis of full crowding out using several measures or political strength of a state in Congress.[19] Knight's contributions are a key reason why I use FAHP apportionments instead of FAHP allocations or expenditures, and include the political controls mentioned in the last section in each of my empirical specifications.

To determine if there is evidence of either a flypaper effect or crowding out in my sample, I estimate the relationship between total highway disbursements in a state and FAHP grants:

[19]Knight's findings may not be robust, however, due to issues of weak instruments. Stock and Yogo (2002) find that weak instruments can suffer from severe size distortions and bias. Knight's instruments fail to reject the null hypothesis of more than 25% size distortion and 30% (relative to OLS) bias.

$$TotalDisbursements_{it} = \sum_{p=0}^{q} \beta_p Infrastructure_{i,t-p} + \gamma X_{it} + \alpha_i + \alpha_t + u_{it} \qquad (17)$$

where the subscripts denote state i in year t. $TotalDisbursements_{it}$ denotes total state highway disbursements (expenditures), including those reimbursed by the federal government.[20] $Infrastructure_{it}$ denotes per capita FAHP apportionments. To control for political influences and the income effect, X_{it} includes the three political variables described in the data section and (the growth rate of) real per capita state income. α_i and α_t are sets of state and time dummies, respectively. Following Gordon (2004), I include the summation of $Infrastructure_{i,t-p}$ over p=*1,...,q* lags of time to allow for the possibility that crowding out (or in) may take several years to occur.[21]

Table 3 reports estimates of Equation (17).[22] Each column reports estimates with progressively longer lags of $Infrastructure$. Since Equation (17) relates total spending on highways across all forms of government, the β coefficients represent the response of total spending to an increase in FAHP grants. Therefore, complete crowding out implies that the sum of the contemporaneous and lagged effects of $Infrastructure$ should be zero.

I find strong evidence against complete crowding out. The third to last row (denoted by $\sum_{p=0}^{q} \beta_p$) reports the sum of coefficient estimates on $Infrastructure$ and its lags. Without accounting for lags, a one dollar increase in FAHP grants increase state disbursements of highway dollars by approximately 50 cents. However, after the inclusion of five lags of $Infrastructure$, the cumulative effect of a one dollar increase in FAHP grants is an approximately 80 cent increase in state disbursements. As the second to last row (denoted by $H_0 : \sum_{p=0}^{q} \beta_p = 0$) illustrates, each of the specifications strongly rejects the null hypothesis of full crowding out.

Furthermore, as the last row (denoted by $H_0 : \sum_{p=0}^{q} \beta_p = 1$) demonstrates, the cumulative effect of an increase in grants is not statistically different from one, after accounting for several lags of $Infrastructure$. This implies that I cannot reject the null hypothesis

[20]See Tables SF-21 in the *Highway Statistics* series for more details.

[21]The inclusion of these lags are particularly important in this analysis because state funded projects data is available only for expenditures (as opposed to apportionments), thereby generating a timing discrepancy between federal highway apportionments and state disbursements.

[22]Studies pertaining to the flypaper effect have historically focused on the effect of grants on total spending in levels. As a result, both FAHP apportionments ($Infrastructure_{it}$) and state highway expenditures ($TotalDisbursements_{it}$) are measured in levels in this section for consistency with that literature. However, since I use the natural logarithm of infrastructure apportionments and total expenditures throughout the rest of the paper, I have estimated Equation (17) in a log-log specification report those estimates in Table 23 of the Appendix. I find that the log-log estimation gives qualitatively similar results. Furthermore, the exclusion of the control variables only minimally impacts the results

that a one dollar increase in FAHP grants eventually leads to a one dollar increase in total state highway disbursements. Therefore, my estimates suggest a strong flypaper effect in my sample.

Relative to other recent studies, my point estimates are rather conservative. As mentioned earlier in this section, Leduc and Wilson (2017) find crowding in of state spending in response to federal grants. However, their findings are likely influenced by their measure of highway grants (forecast errors in obligations of grants) and the fact that their analysis primarily focuses on the Great Recession.

5 Empirical Specification

5.1 Motivation

The empirical model that I present in the next subsection includes spatial lags of the independent variables, which implies that the value of covariates in spatially neighboring states can have an impact on the income inequality of a state. The literature on fiscal federalism and tax competition has long shown states do not exist in a vacuum, their actions and outcomes are highly interdependent (Gordon, 1983; Mintz and Tulkens, 1986; Haufler and Wooton, 1999; Wildasin, 2003). FAHP grants in particular are likely to have an especially large impact in other states. Geographic distance and transportation costs play a key role in the size of the spillover effects of models in various literatures, with larger transportation costs reducing the size of potential spillover effects (Eugster, Parchet et al., 2013; Agrawal, 2015; Gallen and Winston, 2017). Projects funded by FAHP grants, such as the Interstate Highway System, reduce transportation costs. Therefore, FAHP grants amplify existing spillover effects. Furthermore, due to the inter-state nature of FAHP grants, many FAHP projects occur near state borders. Therefore, the implementation of FAHP projects (ie the construction of a highway) are likely to impact the labor markets of neighboring states.

the proximity of many FAHP projects to state borders increase the probability of the effects of the projects (i.e. construction of roads) themselves to spill over into nearby states.[23]

My empirical specification includes neighboring values of inequality as well, which implies that changes in income inequality in one state results in changes in income inequality in other nearby states.[24] This relationship, referred to as spatial autocorrelation

[23]For example, firms working on a project near the border between two states are more likely to attract workers from the neighboring state to construct the road than projects in the geographic center of a state.

[24]The spatial literature typically refers to the inclusion of neighboring values of the dependent variable as either a spatial lag of the dependent variable or a spatially endogenous dependent variable

or spatial dependence, allows the model to capture spatial feedback loops (discussed in Section 2.2) and general equilibrium conditions. For example, consider three connected states, Texas, New Mexico, and Colorado. An increase in the demand for low-skilled labor in Texas places upward pressure on wages for low-skilled work in Texas, which could induce immigration into Texas from New Mexico. As a result income inequality declines not only in Texas, but in New Mexico as well. However, emigration from New Mexico into Texas generates a wage gap for low skilled workers between Colorado and New Mexico (assuming they were initially at equilibrium). As a result, emigration from New Mexico to Texas induces emigration from Colorado to New Mexico, thereby reducing income inequality in Colorado as well. This process continues until the labor market equalizes again.

Spatial autocorrelation is a testable hypothesis. Table 2 reports test statistics and p-values of Moran's I test, a test of spatial correlation, against both the Gini coefficient and the growth rate of the Gini coefficient. Under the null hypothesis of Moran's I, inequality in a given state is spatially uncorrelated with inequality in neighboring states. I find strong evidence of spatial dependence in both the level and growth rate of the Gini coefficient.[25] Furthermore, in all statistically significant cases the sign of the test statistic is positive, which means income inequality and its growth rate are spatially clustered; high levels of income inequality in one state are associated with, on average, high levels of income inequality in neighboring states.

Last, my empirical specification features a lagged dependent variable. The inclusion of a (temporal) autoregressive variable in the DSDM controls for the persistence of shocks and allows for the separation of short versus long run effects. Doing so helps account for the fact that the income distribution may be slow to adjust to shocks, and that there can be potentially long lags between apportionment and completion of FAHP projects (Leduc and Wilson, 2013*b*).

5.2 Model

To estimate the effect of federal infrastructure grants on state-level income inequality I employ a variant of the well-known dynamic spatial Durbin model (DSDM). Spatial models relax the assumption that units (states) are independent, and explicitly define the relationship between states by assigning weights to state pairs. Let:

[25] Since Moran's I is a cross sectional test, these results cannot be attributable national trends, as the test purely exploits the within variation of the panel data.

$$W = \begin{bmatrix} 0 & \omega_{11} & \cdots & \omega_{1N} \\ \omega_{21} & 0 & \cdots & \omega_{2N} \\ \vdots & \vdots & 0 & \vdots \\ \omega_{N1} & \omega_{N2} & \cdots & 0 \end{bmatrix}$$

where W is called the spatial weight matrix, and ω_{ij} defines the spatial weight state i assigns to state j (i = *1,...,N; j=1,...,N*). The columns of the spatial weights matrix describe the impact *of* a particular state *on* all other states, while the rows of the spatial weights matrix describe the impact *on* a particular state *by* all other states.

Throughout this analysis I define W as a first order contiguity matrix. That is, if states i and j share a common border then ω_{ij} takes on a value of one and zero otherwise. Contiguity matrices are the most commonly used spatial specification (I discuss the other most commonly used weight matrix, the inverse distance weights matrix, in Appendix B).

The main diagonal of W is set to zero by construction. Doing so allows the separation of direct (own state) and indirect (spillover) effects in later estimation. Furthermore, there is no obvious interpretation of a non-zero element along the main diagonal. With contiguous state weights matrix, non-zero elements along the main diagonal would imply some states are their own neighbors, but others are not.

Following common practice in the spatial econometrics literature, I row normalize W by dividing by all elements in a row by the sum of the row, such that the sum of the normalized weights equals one for each row. That is, $\omega_{ij}^{normalized} = \frac{\omega_{ij}}{\sum_{j=1}^{N}\omega_{ij}}$. [26]

Having defined the weight matrix, I turn now to my main empirical model. My basic empirical specification is a variant of the dynamic spatial Durbin model:[27]

$$\begin{aligned} Inequality_t = \tau Inequality_{t-1} + \rho W Inequality_t + \beta_1 Infrastructure_t \\ + \beta_2 X_t + \theta_1 W Infrastructure_t + \theta_2 W X_t + \gamma Time_t + \alpha + u_t \end{aligned} \tag{18}$$

[26]This method of normalization equalizes the impact of each spatial unit by all other units. To illustrate, consider the difference in contiguous state weights assigned between Texas and Oklahoma. Texas shares borders with four other states while Oklahoma shares borders with six other states. Pre-normalization, both states assign a value to one for all its shared border states and zero otherwise, whereas post-normalization Texas assigns a weight of $\frac{1}{4}$ to each of its shared border states and Oklahoma assigns a weight of $\frac{1}{6}$ to each of its shared border states.

[27]Typically DSDMs include a spatio-temporal lagged dependent variable. I exclude this for two reasons. First, because economically interpreting such a parameter in this context is difficult at best. Secondly, the full DSDM is controversial because of concerns over weak identification of all its parameters. The latter of these reasons is also a key reason why I do not include temporal lags of the independent variables. See Elhorst (2014) for a more thorough discussion.

For notational simplicity, Equation (18) stacks all states (i=1...N) for each year t. $Inequality_t$ denotes an NT×1 vector consisting of the growth rate (in percent) of the Gini coefficient.[28] $Infrastructure_t$ denotes an NT×1 vector consisting of the natural logarithm of real per capita FAHP apportionments. X_t denotes an NT×4 vector of control variables.[29] The (temporal) autoregressive parameter τ captures the effect of temporal dependence in the dependent variable, and the spatial autoregressive parameter ρ captures contemporaneously endogenous spatial dependence. θ_1 and θ_2 capture the effects of neighboring covariates, but cannot be interpreted directly (Elhorst, 2014). $Time_t$ is a second order polynomial of the time in years, α captures spatial (fixed) effects, and u_t is the error term.

5.3 Spillover Effects

The parameters of Equation (18) cannot be directly interpreted to ascertain the presence of spillover effects since the dependent variable appears on both the right and left hand side (LeSage and Pace, 2009). This section derives the direct (recipient state) and indirect (spillover) effects of changes in a covariate for both the short and long run.

Since the partial effect of a unit change in infrastructure depends only on $Inequality_t$ and $Infrastructure_t$ Equation (18) can be rewritten as:

$$Inequality_t = (I - \rho W)^{-1}(\beta_1 Infrastructure_t + \theta_1 W Infrastructure_t) + R \tag{19}$$

where R contains all terms that are not a contemporaneous function of $Infrastructure_t$ or $Inequality_t$. LeSage and Pace (2009) note that β and θ cannot be interpreted directly as the effects of a change in $Infrastructure_t$ since the change in $Inequality_t$ also depends on $(I - \rho W)^{-1}$. Instead, they suggest taking the partial derivative of Equation (19). In

[28] The dependent variable is measured in growth rates because of explosiveness of the model when measured in levels. Lee and Yu (2010) demonstrate that DSDMs become unstable if $\tau+\rho>1$. Under these conditions the Quasi-Maximum Likelihood procedure described in Yu, De Jong and Lee (2008) has unknown asymptotic properties and therefore cannot be used. When estimated in growth rates of the Gini coefficient, all estimates of Equation (18) are stable. Alternative methods have been proposed to account for the explosiveness of some DSDMs. Instead of temporally differencing, Lee and Yu (2009) propose transforming the data by spatially differencing all variables. The procedure has the advantage of being stable for values of $\tau+\rho$ not much greater than 1, it is unable to account for the potential (temporal) unit root in the Gini coefficient.

[29] From Section 3 I include the three political control variables: an indicator variable for the chair of the House of Representatives Committee on Appropriations, indicator variable for the chair of the Senate Committee on Appropriations, and the percent of representation by each state on the House of Representatives Committee on Appropriations. From Section 4 I include state disbursements on highways and roads to control for crowding out of FAHP funds.

the short run, for a given t, the partial effect of a one unit change on the k^{th} independent variable (X_k=$Infrastructure_t$) on the dependent variable (Y=$Inequality_t$) is:

$$\begin{bmatrix} \frac{\partial Y}{\partial X_{1k}} & \cdots & \frac{\partial Y}{\partial X_{Nk}} \end{bmatrix}_t = (I - \rho W)^{-1} \begin{bmatrix} \beta_k I_N + \theta_k W \end{bmatrix} \quad (20)$$

So long as there is no temporal unit root ($|\tau| < 1$), the effect of a change in $Infrastructure$ on $Inequality$ eventually fades. At this point, $Inequality_t$=$Inequality_{t-1}$ since a change in $Infrastructure$ from previous periods no longer has an additional impact on $Inequality$. Solving Equation (18) for this condition yields:

$$\begin{bmatrix} \frac{\partial Y}{\partial X_{1k}} & \cdots & \frac{\partial Y}{\partial X_{Nk}} \end{bmatrix} = \begin{bmatrix} (1 - \tau)I - \rho W \end{bmatrix}^{-1} \begin{bmatrix} \beta_k I_N + \theta_k W \end{bmatrix} \quad (21)$$

The diagonal elements of Equations (20) and (21) show the effect of a unit change in X_k in state i on the dependent variable of state i. Unlike traditional linear panel models, the diagonal elements of both the short and long run effects are not the same since

$$(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 ... \quad (22)$$

is not symmetric even though W is. The spatial literature denotes the diagonal elements of Equation (20) as short run direct effects and Equation (21) as long run direct effects.

The off diagonal elements of Equations (20) and (21) show the effect of a unit change in X_k in state j on the dependent variable of state i. The spatial literature denotes the off-diagonal elements of Equation (20) as short run indirect effects or short run spillover effects and Equation (21) as long run indirect effects or long run spatial spillover effects. As with the direct effects, the asymmetry of Equation (20) and (21) imply spillover effects vary by state.

Equation (22) further implies that spatial spillover effects are not necessarily limited to neighboring states, so long as $\rho \neq 0$. To wit, orders of W represent the order of neighbors state of state i. The weight matrix, W=W^1 contains nonzero elements only for state i's first order (direct) neighbors, while W^2 contains nonzero elements for state i's first and second order neighbors (neighbors of neighbors), and so forth. As the order of W grows, all spatial units are eventually impacted by a change in an independent variable of state i. Since changes in one state leads to changes in all states, indirect effects from DSDMs are referred to as *global* spillover effects.

Furthermore, note that the main diagonal of the higher orders of W is non-zero since one of the neighbors of a neighboring state to state i is state i itself. This feedback loop ($i \to j \to i$) means that the direct effects depend on the neighbors of state i as well.

Since both the direct and indirect effects depend on the spatial relationship of each spatial unit to one another, there are N direct effects and N*(N-1) indirect effects, which may all differ (i.e. the model implies the direct and indirect effects of a change in infrastructure grants will be different for Iowa and Maine). Since describing the direct, indirect, and total effects of every ij and ji state pairs is cumbersome, LeSage and Pace (2009) propose using three summary scalar measures. They propose defining direct effects as the average of the N diagonal elements of Equation (20) and (21), indirect effects as the average of the row sum of the off diagonal elements of Equation (20) and (21) and the total effect as the sum of their direct and indirect effects. I use their proposed measures to report the direct, indirect, and total effects in my results.

6 Results

Section 6.1 reports the main results of this paper. I show that in both the short and long run, FAHP grants reduce the growth rate of the state-level Gini coefficient in recipient states and that this effect spills over into other states. Section 6.2 decomposes the Gini coefficient to better quantify the winners and losers of the direct effects uncovered in the main results. Section 6.3 relates the results to previous literature on the effect of policy on income inequality.

6.1 Gini Coefficient Results

The first through fourth rows of Table 4 report estimates for parameters that are used in constructing the partial effects. As previously mentioned, direct interpretation of the estimated coefficients of the DSDM to test for direct and spillover effects is inappropriate, but they do contain useful information. The negatively signed estimate of τ indicates that short run effects will tend to be larger than the long run effects. The negatively signed estimate for θ_1 implies that the instantaneous *local spillover* effects of FAHP grants are negative. This means that without accounting for the feedback loop generated by the spatial autoregressive term, ρ, increases in FAHP grants reduce the growth rate of Gini coefficient. The estimate of ρ indicates that changes in the growth rate of a state's Gini coefficient are positively correlated (conditional on the covariates) with changes in the growth rate of the Gini coefficient of its neighbors, which is consistent with Moran's I test. Additionally, since the estimates for τ and $\tau+\rho$ are each within the unit circle, the results are stationary and non-explosive, respectively Lee and Yu (2010).

The remaining rows of Table 4 report estimates for the short run (rows 5-7) and long run (rows 8-11) effects of FAHP grants. Reported standard errors are constructed using 10,000 Monte Carlo simulations and are clustered at the state level.

The direct effect of an increase in infrastructure implies that a 100% increase in FAHP apportionments leads to a .361 percentage point decrease in the growth rate of the Gini coefficient.

The indirect effect of an increase in infrastructure can be interpreted either as the cumulative effect of an increase in apportionments from every other state j on state i, or as the cumulative effect on state i of an increase in infrastructure on every other state. The first interpretation implies that if every state in the sample except state i received 100% increase in FAHP apportionments, the growth rate of the Gini coefficient of state i would decline by 1.402 percentage points. The second interpretation implies that a 100% increase in FAHP apportionments to state i will decrease the Gini coefficient in all other states by a total of 1.402 percentage points.

Recall that DSDMs exhibit global spillover effects via the feedback loop generated by the spatial autoregressive term. Therefore, the short run indirect effects (and by extension the total effects) are spread across all spatial units. However, these effects do spatially dissipate. Following LeSage and Pace (2009) I expand Equation (20) into a linear combination of powers of W by substituting Equation (22) into Equation (20). The powers of W represent the spatial distance of state i to j, with W^0 corresponding to state i itself, W^1 corresponding to it neighbors, W^2 neighbors of its neighbors, and so forth.

Table 5 reports the partition of the short run direct, indirect, and total effects from Table 4. Each row represents the cumulative effect up to that order of neighbors. For example, the third row (W^2) represents the cumulative effect of a 100% increase in FAHP apportionments in state i on state i, its neighbors, and neighbors of its neighbors. Results in Table 5 would eventually converge to estimates reported in Table 4 if the W-order were to go toward infinity. However, as Table 5 demonstrates, the bulk of spillover effects are generated from lower-ordered neighbors. Nearly 95% of the spatial spillover effects within the first two orders of W (neighbors of neighbors). For example, nearly 95% of the spillover effects from Texas to its neighbors occur within eleven states - four first-order neighbors and seven second-order neighbors.

The total effects of FAHP grants are the sum of the short run direct and indirect effects. Since the direct effect refers to state i and the indirect effect refers to all other states, it is informative to consider the total effects in terms of the effect of a change in FAHP grants across all states on the growth rate of the Gini coefficient of all states. The estimated short run total effects imply that a 100% increase in FAHP grants to every state would decrease the growth rate of the Gini coefficient of each state by 1.763 percentage points in the short run. The long run total effects imply that doubling FAHP apportionments to every state would decrease the growth rate of the Gini coefficient in each state by an attenuated 1.302 percentage points in the long run. The direct, indirect, and total effects remain significant into the long run.

6.2 Decomposing The Gini Coefficient

In this section I decompose the Gini coefficient into quintiles of the income distribution using the SOI series from which the Gini coefficients used in the main results were constructed. Details on the construction of the income quintiles are provided in Appendix A.1.1. To estimate the direct effect of FAHP grants on each quintile, I estimate the following system of equations:[30]

$$\begin{aligned}
Income_{1it} &= \tau_1 Income_{1it-1} + \beta_1 Infrastructure_{it} + \gamma_1 X_{it} + \alpha_{1i} + \alpha_{1t} + u_{1it} \\
Income_{2it} &= \tau_2 Income_{2it-1} + \beta_2 Infrastructure_{it} + \gamma_2 X_{it} + \alpha_{2i} + \alpha_{2t} + u_{2it} \\
Income_{3it} &= \tau_3 Income_{3it-1} + \beta_3 Infrastructure_{it} + \gamma_3 X_{it} + \alpha_{3i} + \alpha_{3t} + u_{3it} \\
Income_{4it} &= \tau_4 Income_{4it-1} + \beta_4 Infrastructure_{it} + \gamma_4 X_{it} + \alpha_{4i} + \alpha_{4t} + u_{4it} \\
Income_{5it} &= \tau_5 Income_{5it-1} + \beta_5 Infrastructure_{it} + \gamma_5 X_{it} + \alpha_{5i} + \alpha_{5t} + u_{5it}
\end{aligned} \tag{23}$$

$Income_{qit}$ $(q = 1, ..., 5)$ is defined as the (log) total aggregate income per capita captured by quintile q for state i at time t. $Infrastructure_{it}$ is defined, as before, by the natural log of per capita FAHP apportionments. Likewise, X_{it} contain the same control variables as before. The coefficient β_q, therefore, reflects the percent change in per capita aggregate income captured by quintile q in response to a 100% increase in FAHP apportionments. Equation 23 is estimated using the three step procedure outlined in Zellner and Theil (1962).

Table 6 reports estimates for Equation (23).[31] The largest elasticity is in the bottom quintile - with a point estimate nearly twice that as any other quintile. However, it is not statistically significant at typical levels. The effect of increasing FAHP apportionments is significant for both the second and third quintiles. Point estimates imply that if FAHP apportionments were to double, aggregate gross income would increase by 1.6% and 1.7% for the second and third quintiles respectively. Though positive, there appears to only be a negligible effect of FAHP grants on aggregate income per capita accruing to the top two quintiles.

[30]Ideally, one would estimate Equation (23) as a system of DSDMs in order to better mirror Equation (18). However, that is beyond the scope of this paper. Furthermore, estimates for the aggregate gross income captured by the lowest quintile is negative in several years, which prevents me from expressing the dependent variable as a natural logarithm. Additionally, while there is sufficient variation in the Gini coefficient to reliably identify the effects of FAHP grants, its decomposition is naturally more statistically noisy. As Table 5 notes, the direct effect depends in part on the spillover effects, Therefore the estimates in this section provide a conservative estimate of the effect of FAHP grants.

[31]Note, Table 6 includes fewer observations than Table 4 because several values of the bottom quintile were negative, and therefore could not be logged

6.3 Comparison to Literature

My results add to the existing body of work literature that has analyzed the effect of policy changes on income inequality. As mentioned in the introduction, most of the policy proposals aimed at curbing income inequality aim to do so explicitly. Unsurprisingly, I find that the equalizing effect FAHP grants is smaller than many, though not all, of these policies. [32]

Several studies have examined the effect of government policies on income inequality. In particular Wu, Perloff and Golan (2006) estimate the elasticity of various government programs to the Gini coefficient during their sample of urban and rural areas from 1981 to 1997, including the top income tax rate, the generosity of the Earned Income Tax Credit (EITC), the EITC phase out rate, the Aid to Families with Dependent Children (AFDC) program, and minimum wage.

FAHP grants are less effective at reducing income inequality than most policies they consider.[33] Specifically, Wu, Perloff and Golan (2006) find elasticity estimates for changing the top marginal tax rate, increasing maximum EITC benefits, and increasing generosity of AFDC payments that are five times larger than the implied elasticity of the short run effect of FAHP grants. Their estimate for the effect of decreasing the EITC phase-out rate is about twelve times larger than my estimate for the effect of FAHP grants on the Gini coefficient. For rural areas, Wu, Perloff and Golan (2006)'s elasticities for changing the top marginal tax rate, increasing maximum EITC benefits, decreasing the EITC phase out rate, and increasing generosity of AFDC payments are respectively two, eleven, nineteen, and six times larger than the short run total effect of doubling FAHP grants.[34]

Others studies have focused on the effect of policies for specific portions of the income distribution. DeNavas-Walt and Proctor (2015) find that the EITC is the most effective anti-poverty tool available to policymakers, with nearly three quarters of the benefits accruing to the bottom quartile of the income distribution. This almost certainly implies the EITC is more effective at equalizing income than FAHP grants, as the estimates reported in Table 6 imply that the plurality of benefits, approximately 36%, accrue to

[32] I explore the effects of a non-explicitly re-distributive program, military spending, in Section 8.4

[33] At the average growth rate of the Gini coefficient across my sample (.5814654%), the implied elasticity of the Gini coefficient to the short run total effect of an increase in FAHP grants is -.008205. That is, doubling FAHP grants (to all states) will lead to a .8205 percent decrease in the Gini coefficient.

[34] Wu, Perloff and Golan (2006) consider both pre-tax and post-tax income inequality. The comparisons I report reflect their post-tax inequality estimates. Additionally, despite its growth in recent years, FAHP apportionments and the EITC were about equally large in the last year (1997) of Wu, Perloff and Golan (2006)'s sample period (about $20 billion in 1997 dollars each, therefore the different estimated elasticities are not driven by differences in the size of the programs.)

the middle (third) quintile, while only approximately 18% accrue to the lowest quintile.[35] Similarly, Bollinger, Gonzalez and Ziliak (2009) find that the elasticity of income to the EITC subsidy rate is extremely large (as high as 2.4) for the lowest two quintiles of the distribution of single-female family heads between the ages of 16 and 54 with dependent children present under the age of 18. While the distribution of these women is different than the overall distribution of income, their elasticities imply far larger equalizing effects of the EITC than FAHP grants, especially for the very poor.

That said, FAHP grants appear to be more effective at equalizing income than two commonly mentioned policies. The first policy is increasing the minimum wage. A multitude of papers find that changes in the minimum wage result in greater household income inequality, possibly because the minimum wage may generate employment losses (Burkhauser, Couch and Wittenburg, 2000) or because many minimum wage workers are teenagers from relatively wealthy families. (Neumark, Schweitzer and Wascher, 2005; Wu, Perloff and Golan, 2006). Burkhauser and Sabia (2007) estimate that 87% of workers who would benefit from an increase in the minimum wage live in non-poor families, and that less than 4% of benefits would be reaped by poor single mothers. Likewise, FAHP grants appear to be more effective at equalizing income differences than the Child Tax Credit (CTC). Hoynes and Rothstein (2016) demonstrate that the CTC is ineffective at reducing income inequality because it is effectively nonrefundable for the working poor and families with incomes as high as $170,000 (2016 dollars) are eligible to claim it. In contrast, my point estimates suggest that more than 70% of the benefits of FAHP grants accrue to the bottom three quintiles of the income distribution.

It is not surprising that most explicitly re-distributive policies have a greater impact on reducing income inequality than FAHP grants. It is, after all, their sole purpose. However, for a program which does not explicitly aim to reduce income inequality, my results suggest investment in public infrastructure can be a powerful, previously unrecognized, re-distributive tool for policymakers. Furthermore, whereas other re-distributive policies are potentially distortionary and inefficient (e.g., Albouy, 2012), I find that FAHP grants increase average total income, which is consistent with a large body of previous research

[35] These values were calculated by multiplying the estimated elasticities from Table 6 by their mean values. Though the elasticity for the lowest quintile is substantially larger than the other categories, it receives relatively little of the absolute benefits because it's share of aggregate income is small. Note, the estimated percent of benefits accruing to each quintile have very wide implied confidence intervals, since several of the point estimates used in this estimate a based on all the coefficients on Infrastructure in Table 6, several of which are very imprecisely estimated. Still, the average aggregate income captured by the third quintile is approximately four times larger in my sample than the first quintile. Consequently, it is reasonable to conclude the effect of changes in FAHP grants on the poorest quintile is not as large as those estimated by DeNavas-Walt and Proctor (2015)

(e.g., Aschauer, 1989; Mamuneas and Nadiri, 1996; Leduc and Wilson, 2013*a*). Therefore, FAHP may serve as a potentially less distortionary alternative re-distributive policy for lawmakers interested in equalizing income differences.

7 Underlying Mechanism

In this section I present evidence in favor of plausible mechanisms that account for the re-distributive effect of FAHP grants. I use annual micro-level data from the March Current Population Survey (hereafter CPS) for the years spanning between 1977 and 2013.[36] I use the CPS to measure the heterogeneous effects of an increase in FAHP grants on the total income of a person, conditional on individual characteristics. These characteristics reveal two plausible mechanisms, both of which disproportionately help the poor and leave the wealthy mostly unaffected.

First, FAHP grants may disproportionately increase the demand for low-skilled labor. As a result, income for low skilled workers increases relative to high-skilled labor, thereby reducing income inequality. Therefore, variation in worker skill levels can partially account for the heterogeneous effect of FAHP grants on income inequality. [37]

Second, FAHP grants may have heterogeneous effects on the productivity industries. Since certain industries are characterized by lower average wages, this heterogeneity can result in a differentially larger increase in income for workers in certain industries than others. I find that workers working in low-skilled industries benefit more from FAHP grants than high skilled industries.

7.1 Heterogeneity by Skill Level

I consider a worker low-skilled if he has completed no more than high school or obtained an equivalent degree. In my basic specification a worker is either high or low-skilled, however in later specifications I break up the high-skilled sector into medium and high-skilled. In those specifications I consider a worker high-skilled if he has completed at least 4 years of college. A worker is classified as medium skilled if he is neither a high nor low-skilled workers. This includes all workers who have attended college but do not have degrees and those who have attended vocational training.[38]

[36] I include all workers between the ages of 25 and 75 that reported at least $2,000 in real total income and worked at least 10 hours last week at the time of being surveyed.

[37] Since this and the next approach both condition on personal characteristics, I cannot use the spatial panel data approach used in the main results.

[38] In 1992 the CPS changed how it reported educational attainment. Prior to 1992 it recorded number of years of college completed. Since then, it has reported in terms of degrees completed. Implicitly I assume that anyone who completed at least four years of college prior to 1992 completed their degree.

To test for the heterogeneous effect of infrastructure spending by skill I estimate the following reduced form income equation:

$$\begin{aligned} Income_{pit} =& \beta X_{it} + \eta Skill_{pit} + \zeta Infrastructure_{it} + \\ & \psi(Infrastructure_{it} \times Skill_{pit}) + u_{pit} \end{aligned} \tag{24}$$

where $Income_{pit}$ is defined as the natural log of real total personal income of person p, who lives in state i at time t. X_{it} is a vector containing the same set of control variables that were detailed in Section 3. $Infrastructure_{it}$, as before, is defined as the natural log of per capita real FAHP apportionments. $Skill_{it}$ is a vector containing indicator variables that describe the skill level (low, medium, high) of person p. η controls for the innate differences in average income between each skill-level. ζ controls for the effects of a change in FAHP apportionments that are common to all workers, irrespective of skill. The primary parameter of interest is ψ, which can be interpreted as the differential effect (by skill type) of FAHP grants on (log) income.

Table 7 reports estimates for Equation (24). Columns 1-3 report estimates where $Skill_t$ is dichotomously defined between low-skill (1) and high-skill (0). Columns 4-6 include indicator variables for both low and high-skilled workers, leaving medium-skilled workers as the base case. For each of these sets of columns, I report estimates for three types of fixed effects: state fixed effects (columns 1 and 4), state and year fixed effects (columns 2 and 5), and state fixed effects, year fixed effects, and state-specific trends (columns 3 and 6).

Estimates of the heterogeneous effects of infrastructure by skill are robust across specifications. Columns 1-3 report that a 1% change in infrastructure increases income for low-skilled workers between .086 and .094 percentage points more than their low and medium skilled counterparts while columns 4-6 report the effect is between .067 and .077 percentage points greater than their medium skilled counter parts. The last row of columns 4-6 show the effect of increasing infrastructure is statistically different for high and low-skilled workers.

The coefficients on the indicator variables for skilled (High Skilled and Low Skilled) represent the wage gap between low-skilled workers and their more skilled counterparts. These estimates confirm intuition as well as previous studies (e.g. Card and DiNardo, 2002), which have consistently found low-skilled workers earn less than high-skilled workers. The estimated wage gap is about 47% for low-skilled workers compared to medium and high-skilled workers, and 25% compared to medium skilled workers alone. These estimates are in line with findings on the college wage premium (see, e.g. (Goldin and Katz, 2007)).[39]

[39]

Expanding on this, Table 8 reports deciles of the income distribution for the full sample, low skilled workers, and high skilled workers. Low-skilled workers not only have lower *average* wages, but each decile of low-skilled workers is lower than equivalent deciles for high-skilled workers. The average income of a worker in the top decile of the low skilled income distribution is barely more than that of a worker in the eighth decile of the high skilled income distribution.

The average income of a worker in the second decile of the high-skilled income distribution earns nearly as much as the median income for the low skilled distribution. These results suggest the top 2 deciles are occupied almost entirely by high-skilled workers. Consequently, results from Table 7 imply that FAHP grants decrease income inequality.

Note that the estimate total effect of increasing FAHP grants on income, $\frac{\partial Income_{pit}}{\partial Infrastructure_{it}}$ can give insight into the total effect of infrastructure spending on average total income. The estimates reported in column 3 of Table 7 show that the total effect of an increase in infrastructure for a high-skilled worker (ζ) is -.016% and not statistically different from zero, while the total effect for a low-skilled worker ($\zeta+\psi_{low}$) is .078% and highly significant. Just under half (45%) of the full sample of respondents reported to be low skilled, therefore the average effect of doubling FAHP apportionments on average income implied by my analysis is approximately (.45*.078)+(.55*(-.078))= 2.63%.[40] This estimate is consistent with previous literature (e.g Aschauer, 1989; Leduc and Wilson, 2013*a*) and my own findings in Section 6.2 in that both are positive. However, my work builds upon this literature by demonstrating nearly all of the gain comes from low skilled workers.

7.2 Heterogeneity by Industry

FAHP grants fund projects that are used to construct roads, bridges, and highways - each of which may heterogeneously impact industries. In this subsection I show that changes in infrastructure lead to larger gains in total personal income for industries with a high proportion of low-skilled workers compared to those with a low proportion of low-skilled workers.

Table 9 ranks industries the by percent of workers that are low-skilled, using the same definition of skill as before. I denote industries with a highest percent of low-skilled workers as low-skilled industries, and industries with lowest percent of low-skilled workers as high-skilled industries.[41]

To test the heterogeneous effect of FAHP grants on total income by industry of em-

[40]The proportion of low skilled workers has decreased over time. However, the estimated average effect on income is still positive even for the last year in my sample, 2013.

[41]Reported industry classifications use the Census' 1990 concept of industry. Ranking the degree of skill based on percent of workers with bachelors degrees yields almost identical rankings.

ployment, I augment Equation (24) to:

$$\begin{aligned} Income_{pit} =& \beta X_{it} + \eta Industry_{pit} + \zeta Infrastructure_{it} + \\ & \psi(Infrastructure_{it} \times Industry_{pit}) + u_{pit} \end{aligned} \tag{25}$$

Instead of interacting infrastructure apportionments with a collection of indicator variables describing person p's education, Equation (25) interacts it with an indicator variables describing the industry group person p works in.

Ideally Equation (25) would be estimated using disaggregated industry-level data. However, in several industry-state-years the CPS reports either no workers or unreliably few of them, especially for earlier years of the sample.[42] To avoid this issue, I aggregate across industries to form high and low-skilled sectors. I define the low-skilled sector to be the aggregation of industries that are classified as low-skilled industries and the high-skilled sector to be the aggregation of industries classified as high-skilled. In each case the base case of the medium skilled sector is defined by all industries not classified as either high or low-skilled.

Even though the transportation industry does not qualify as either a high or low-skilled industry, it is clearly an industry where highway grants should matter. As a result, I include the transportation industry as its own quasi-sector in each specification.

Table 10 reports estimates for Equation (25). Since there is no obvious cutoff for what to consider a high or low-skilled sector, I report results for various levels of aggregation. The first column of Table 10 reports estimates that includes the three highest and lowest skilled industries from Table 9. Column 2 and Column 3 include the four and five highest and lowest skilled industries respectively. Each column includes state and year fixed effects as well as a state specific trend.[43]

Coefficient estimates on the indicator variables Low Skilled and High Skilled are statistically negative and positive respectively. Total personal income is lower on average in the low-skilled sector relative to medium skilled industries (controlling for other covariates), and vice versa for high-skilled industries.

[42]The sample size of the CPS has grown over time. The sample used in this paper contains 72,425 valid observations in 2013 but only 46,069 valid observations in 1977. My analysis in this subsection requires industry-state-year level data. which means 1977 data contains only an average of 64 observations per industry-state-year. Of course, not all industries are the same size, so certain industries in the sample have substantially less. For example, there were 0 respondents in 1997 from Washington that reported working in the mining industry. The problem is less severe in later years, but still exists. For example, only one of 492 respondents reported working in the mining industry in Vermont in 1991.

[43]Though not reported, exclusion of the state specific trends, year fixed effects, or both do not substantially affect the results apart from changes in the estimate of the un-interacted effect infrastructure (ζ).

The coefficients on the interaction terms ($Transportation \times Infrastructure$, $LowSkilled \times Infrastructure$ and $HighSkilled \times Infrastructure$) indicate the differential effect of infrastructure (FAHP grants) relative to the medium skilled sector. A 1% increase in infrastructure grants increases income between .051% and .125% more for those working in the low-skilled sector than the medium skilled sector. The estimates are significant in two of the three specifications, while there is no indication that the effect of increasing infrastructure spending on average income is different for the high-skilled sector relative to the medium skilled sector. However, as the last row of the table ($p(\psi_{low} = \psi_{high})$), illustrates, the effect of infrastructure spending on average income is statistically different for the low-skilled sector compared to the high-skilled sector. Unsurprisingly, the effect of infrastructure spending leads to a statistically larger effect on total income for the transportation sector than the medium-skilled sector.

A potential reason for the heterogeneity is the degree to which industries use transportation, trucking transportation in particular, as an intermediate good. Table 11 shows the requirements for trucking in each of 71 industries reported in the BEAs 2007 version of it's input-output total requirements tables. The table include all input costs into production, both direct and indirect.[44] The table ranks industries by the percent of total intermediate costs attributable to the truck transportation industry. The first three columns report industries use trucking transportation more intensively as an intermediate good. The last three columns report industries that use trucking transportation less intensively as an intermediate good. There is substantial variation in the degree to which industries use truck transportation as an input. For example, the second-most truck intensive industry (Food and beverage and tobacco products) uses trucking transportation (as a share of inputs) nearly one hundred times more than the lowest trucking intensive industry (Performing Arts).

There is a clear difference between high and low truck intensity firms. Namely, almost all the highest truck intensity industries belong to the goods-producing super-sector (farms, construction, manufacturing, etc.), whereas low sensitivity industries are almost all in the service sector (legal services, finance, telecommunications, etc).

It is straightforward why goods-producing industries would require higher shares of truck transport intermediate costs, firms in those industries must move a physical product. IO codes and the CPS 1990 industry concepts are not directly comparable, but note that the high truck intensity industries listed in Table 11 correspond to the least educated industries listed in Table 9, and vice versa for the low cost industries.

Since high truck intensity firms rely more on transportation infrastructure for production, they also benefit most from increased transportation infrastructure (lower trans-

[44] More aggregated measures are available, but they do not distinguish between forms of transportation.

portation costs). Therefore, gains in productivity from transportation infrastructure expansion are concentrated in high truck intensity industries. These same industries tend to employ more low-skilled workers, therefore low-skilled workers are disproportionately employed in the industries that gain the most productivity from transportation infrastructure spending. Greater productivity implies greater demand for inputs, plausibly causing a decrease in the demand for low skilled labor (relative to high skilled labor), causing wages to increase for low-skilled workers, but not for high skilled workers. As a result industry heterogeneity plausibly explains why FAHP grants result in declining income inequality.

8 Robustness Checks

This section provides various robustness and falsification checks to the main estimates (presented in Table 4) and the underlying mechanism (presented in Tables 7 and 10). The first check shows the main results are robust to different measures of income inequality. The second check shows the results are robust to the choice of spatial modeling specification. The third check demonstrates robustness of the main results to the inclusion of controls for the progressiveness of the federal tax system. The fourth check presents a falsification test of the main results by replacing FAHP grants with another large federal program: defense spending. The falsification test demonstrates the main results are not purely the result of more federal spending.

8.1 Measures of Inequality

In this section I show the results are robust to measuring income inequality differently. Specifically, the results are robust to using the Theil Entropy Index and the Relative Mean Deviation instead of the Gini coefficient in the estimation of Equation (18). Although each measure is slightly different, they are each highly correlated.

For ease of comparison, the first column of Table 12 replicates Table 4, while the second and third columns report estimates where $Inequality_t$ is measured using (the growth rate of) the Theil Index and Relative Mean Deviation respectively. Each measure quantifies income inequality slightly differently, so the coefficients are not necessarily directly comparable, but the signs and significance levels are. The direct effect of FAHP grants on the growth rate of inequality, while insignificant, is negative across the alternative specifications both in the short and the long run. As was the case for the indirect effects using the Gini coefficient, spatial spillover effects reported are large and statistically negative using the alternative specifications. Likewise, the total effect of infrastructure grants is statistically negative in both the short and long run for each specification.

8.2 Spatial Specification

Sections 3 and 5 outlined the motivation for the preferred spatial specification. In this section I demonstrate the results are robust to common alternative spatial specifications.

Table 13 lists some of the most common spatial models which are capable of generating spatial spillover effects.[45] The last column of each row reports limitations, if any, on the type of spatial spillover effects for that model. Naturally static models cannot distinguish between the short and long run. The SAR model is only capable of generating global spillover effects, and therefore the ratio of the direct to indirect effects is the same for all covariates. By contrast, since the SLX model does not include the spatially endogenous interaction term, it is only capable of generating local spillover effects - implying there is no spatial feedback loop.

Table 14 reports estimates for most of the models presented in Table 13.[46] Each column reports a variation of the main results, except the first column which replicate the main results for ease of comparison. The second column reports estimates for a classic DSDM. The third column reports estimates for a static SDM. The fourth column reports estimates for the DSDM that I use, but one in which the "Durbin terms", WX, are restricted to only include Infrastructure (FAHP grants). The last two columns report estimates for dynamic and static spatial autoregressive models. Standard errors for each set of columns clustered at the state level and are constructed using 10,000 Monte Carlo simulations, following the procedure laid out in LeSage and Pace (2009).

There are, of course, differences in the size of the estimates for the direct, indirect, and total effects of changes in infrastructure grants, but the estimates consistently confirm the primary findings the paper: FAHP grants decrease the growth rate of income inequality both in the recipient state and neighboring states. The results are statistically significant, and, while the spillover effects vary in size, they remain economically large across all specifications.

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[45] Another broad class of models, known as spatial error models, correct for spatial relationships in the error term. However, in doing so they rule out the possibility of spatial spillover effects which can be quantified. Since testing for these spillovers is a key part of this paper, I do not consider this class of models.

[46] Because of practical limitations, I do not report all estimates. For example, the General Spatial Nesting model is not reported because parameter values would not converge within 1,000 iterations. For comparison, all other estimates converged within 15 iterations.

8.3 Taxation

FAHP is nominally financed through the Highway Trust Fund (HTF). The HTF is funded through various usage taxes, primarily a set of federal taxes on gasoline and diesel. However, dedicated taxes have been insufficient to keep up with outlays for several years. As a result, Congress has made numerous authorizations to use general budget funds to finance the HTF. Since the general budget is largely financed by a modestly progressive income tax, a concern could be that the progressiveness of FAHP financing drive my estimates. In this section I argue that the structure of the data limits this possibility and find that my results are largely robust to controlling for measures of tax progressiveness.

First, the state-level Gini coefficient that I use to measure income inequality is derived from the SOI. The SOI series reports detailed tabulations on adjusted gross income, which measures *taxable* income, not after tax income. Hence, even if FAHP grants are de-facto financed by a progressive income tax system, my main results are largely insulated from this fact.

Still, since taxes can change incentives, thereby impacting labor-force decisions, they may indirectly result in changes in income inequality (Bollinger, Gonzalez and Ziliak, 2009). To empirically test this relationship, I add measures of progressivism in the controls of Equation (18) using annual data from the National Bureau of Economic Research's (NBER) TaxSim tool for the years spanning between 1977 and 2013. Specifically, I include the effective marginal income and capital gains tax rates for very high income earners to the control variables, X_{it}. These effective marginal tax rates are defined as the increase in taxes paid by a household who receives an additional \$1,000 on an initial income of \$1,500,000. By adding these two variables to X_{it} in Equation (18) I am able to capture the tax treatment of the wealthy, and thereby test for omitted variable biased created by not including these measures in my main results.

In Table 15 I show the results hold when I add the two tax controls. As before, the total effect of infrastructure spending on the Gini coefficient is negative both in the short and long run. The loss of 21 panels clearly reduces the precision of the estimates, but estimated coefficients, especially in the short run, are very close to those reported in the baseline specification. Therefore, even if the source of financing has some effect, it does not appear to be a first order concern.

8.4 Falsification: Military Spending

How does the effect of investment in public infrastructure on income inequality compare to the effect of other forms of government spending? Would income inequality drop by the same amount if the same dollar was spent on a different program? To answer these questions I use military spending as a falsification to my main estimates. In this section I show that increases in military spending actually increase (the growth rate of) state-level income inequality. I further show that the difference in the effectiveness of these two programs in reducing income inequality is consistent with one of the mechanism put forth in Section 7.

Military spending is a natural candidate for this falsification test. First, military spending is plausibly exogenous, with changes in military spending arising primarily in response to external threats (Romer and Romer, 2010). Additionally, as with FAHP grants, military spending is a large enough program that it can significantly impact the income distribution of a state.[47]

Table 16 reports estimates for the effect of military spending on the growth rate of income inequality. Each column reports estimates for a variation of Equation (18), in which military spending takes the place of infrastructure grants as the independent variable of interest. The first column reports estimates that use the main measure of military spending employed by Nakamura and Steinsson (2014). Their measure covers the years spanning from 1966 to 2006, and records the total value of military procurement forms for purchases greater than \$10,000 before 1983 and greater than \$25,000 thereafter. Their data is sourced from the Department of Defense. The second column combines military procurement data with military compensation, which is obtained from the BEA (SA5 and SA5N) for the same period. The last column reports estimates in which the measure of military spending does not include Nakamura and Steinsson (2014)'s military procurement series, but extends the BEA military compensation series to encompass the period spanning from 1958 to 2013.[48]

Under the null hypothesis that all government programs affect income inequality in the same way, changes in military spending should produce similar estimates to those reported in Table 4. However, estimates reported in Table 16 tell a different story. Irrespective of the military spending measure, (the growth rate of) income inequality *rises* in response to increases in military expenses.

Therefore, the effect of military spending on income inequality has the opposite sign

[47] This reduces the possibility of failing to reject a null hypothesis of no statistical relationship between military spending and income inequality simply because of the imprecise nature of state-level Gini coefficients.

[48] Data obtained from Nakamura and Steinsson (2014) and data directly obtained from the BEA contain numerous differences. For the most part I report their measures directly, but I made minor edits to the military procurement data. For example, their data had several state-year observations with zero military spending. I required the natural log of military spending to allow for comparability with my baseline results, so I treated zeros as missing and linearly interpolated over all missing values.

as the effect of FAHP grants. These estimates reveal that FAHP grants do not reduce income inequality simply because they represent an increase in government spending more generally. Furthermore, since military and highway spending are both de facto financed similarly, the markedly different estimates for the effect of military spending versus FAHP grants on income inequality suggest the main results are not generated by taxes.

8.4.1 A Possible Explanation

What can account for the difference in the results? The mechanisms provided in Section 7.2 provide some insight. Whereas FAHP grants largely increase demand for low-skilled labor (i.e. construction), defense spending increases the demand for high skilled labor.

Table 17 reports characteristics of construction workers and military personnel. Military personnel are substantially more educated, on average, For example, military officers are more than ten times more likely to have an advanced degree than a construction worker.[49] Additionally, military personnel earn more than construction workers. Total personal income for enlisted members is approximately fifty percent greater than the average total personal income of construction workers. Military officers earn even more, approximately double the income of construction workers, on average.

This leads to a plausible reason for why military spending increases state-level income inequality whereas FAHP grants reduces it. Expansions in military spending result in increased demand for high-skilled labor, whereas increases in FAHP grants result in increased demand for low-skilled labor.[50] Since low-skilled laborers already earn less on average than high-skilled labor (Tables 7 and 8), military spending tends to increase income inequality and FAHP grants tend to decrease it.

9 Conclusion

In this paper, I analyze the public infrastructure investment (proxied for by federal-aid highway (FAHP) grants) on income inequality. Decomposing the Gini coefficient into pre-tax income quintiles reveals that the average Using a dynamic spatial Durbin model of the contiguous United States, for the period spanning between 1956 and 2013, I find that doubling FAHP grants would reduce the growth rate of state-level Gini coefficients by 1.76 percentage points in the short run, and an attenuated 1.3 percentage points in

[49] approximately 20% of military personnel are officers.

[50] An alternative possibility is that military contractors are better able to rent seek than construction workers, thereby resulting in greater accumulation of income towards owners of these firms. Though I cannot distinguish between these possible narratives empirically, they both imply that military spending does in fact behave differently than construction spending.

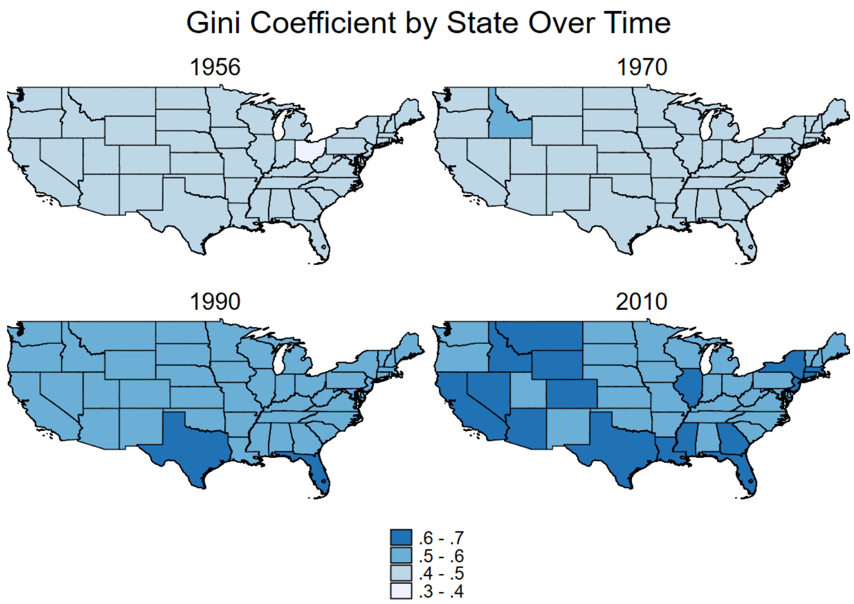
the long run. These estimates are robust to falsification, specification, data sources, and alternative control variables.

I decompose the Gini coefficient into state-level income groups and find that the average effect of increasing FAHP grants on income is positive, which is consistent with previous literature Aschauer (1989); Leduc and Wilson (2013*b*). However, I find that the average effect masks the heterogeneous effects of these grants across the income distribution. I find that the elasticity of income to public infrastructure investment is positive for all state-income quintiles, but the effect is much largest for the lowest three quintiles. In contrast, income for the top two quintiles appear virtually unaffected by these grants. In Section 7 I present evidence in favor of two potential sources of these heterogeneous effects. First, I find that low-skilled workers benefit from infrastructure grants, while high-skilled workers are virtually unaffected. Second, I find that FAHP grants increase income for workers working in low-skilled industries, but not for workers in high skilled industries. I find that this is plausibly explainable by the fact that low-skilled industries are concentrated in the tangible good sector - and are therefore more sensitive to changes in highway investment.

This paper expands on the previous literature that has examined the relationship between income inequality and infrastructure investment by focusing on a developed nation, whereas the existing literature has focused on developing countries. Drawing on the literature that has sought to explain the spatial spillover effects of infrastructure investment on average income (e.g. Chandra and Thompson, 2000), I show that spatial spillover effects are an important component of the distributional effects of infrastructure investment grants.

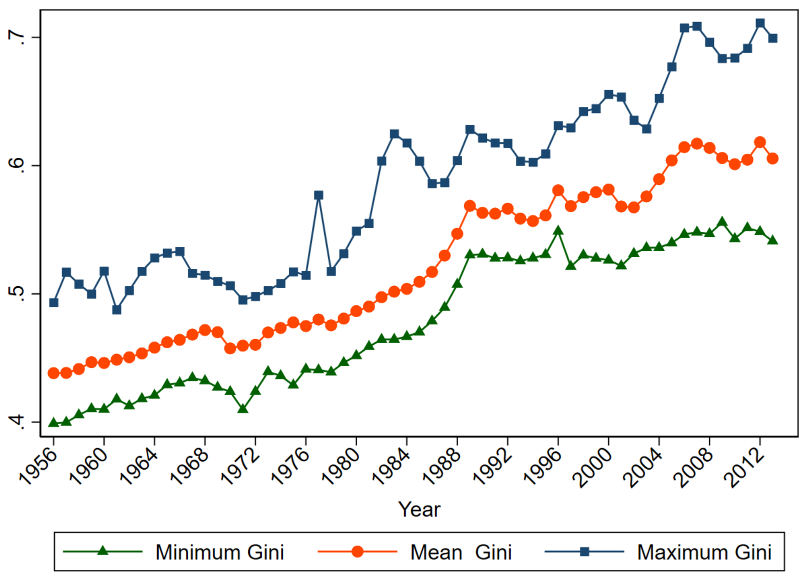
Relative to other studies which have examined the effects of government policy on income inequality, the effect of federal highway grants is modest. Implied elasticities of income to infrastructure investment around a fifth to a tenth as effective as the EITC and other re-distributive government programs (Wu, Perloff and Golan, 2006). However, these explicitly re-distributive policies are likely distortionary and unproductive relative to infrastructure spending Piketty and Saez (2013). Therefore, my estimates have important implications for policymakers, since they reveal that highway infrastructure grants can serve as a less distortionary policy tool for equalizing income than oft-proposed alternatives.

Figure 1



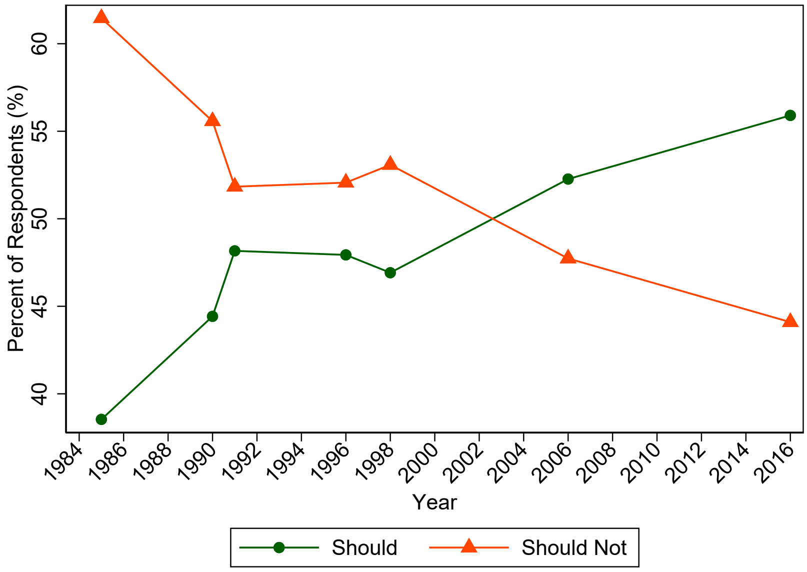
Note: Calculations by author using data provided by Frank (2014).

Figure 2: State-Level Gini Coefficients Over Time



Note: Calculations by author using data provided by Frank (2014).

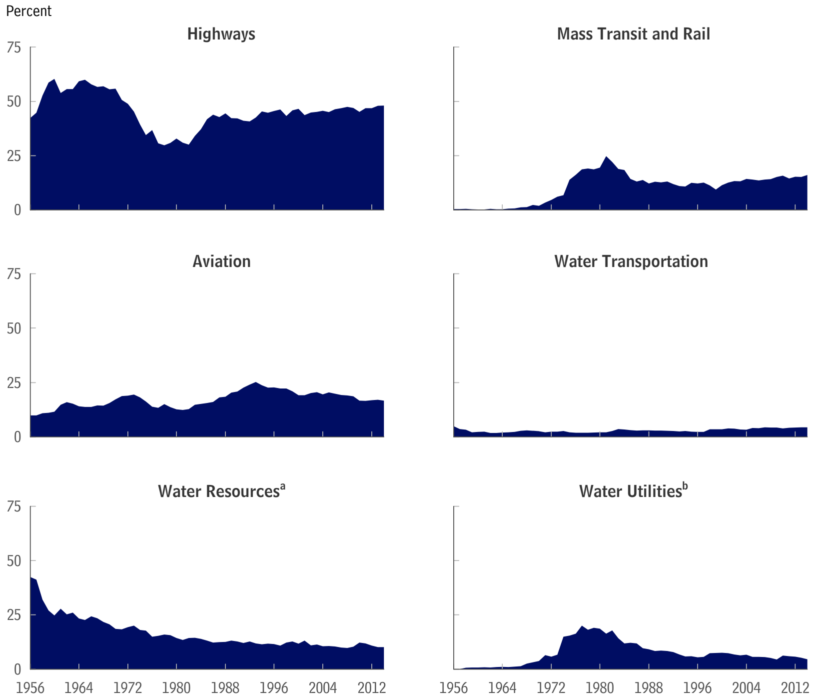
Figure 3: Should Government Reduce Income Differences?



Note: Sourced from General Social Survey (GSS), various years, with an average response sample of 1,157. The question reads, "On the whole, do you think it should or should not be the government's responsibility to [r]educe income differences between the rich and poor?" I group "Definitely should" and "probably should" together under "Should", and "definitely should not" and "probably should not" together under "Should Not" see GSS question "equalize" for more.

Figure 4

Federal Spending on Transportation and Water Infrastructure, by Type of Infrastructure, 1956 to 2014



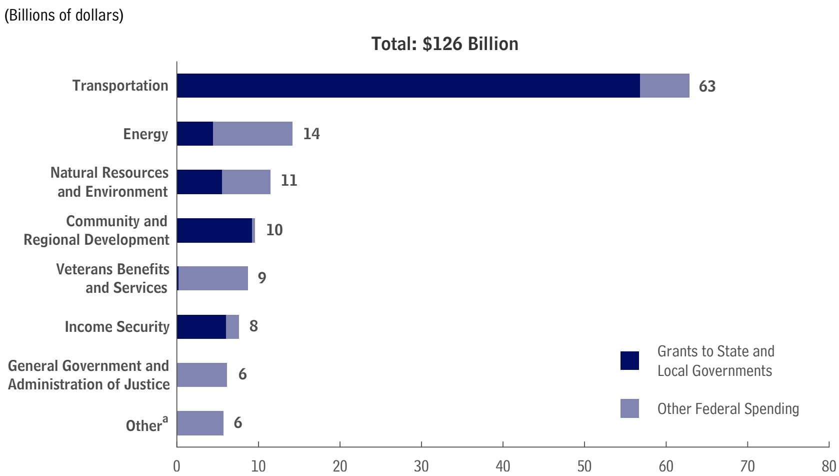
Source: Congressional Budget Office based on data from the Office of Management and Budget and the Census Bureau.

a. Includes water containment systems (dams, levees, reservoirs, and watersheds) and sources of freshwater (lakes and rivers).

b. Includes water supply and wastewater treatment facilities.

Figure 5

Physical Capital: Federal Nondefense Investment by Budget Function, 2012



Source: Congressional Budget Office, using data provided by Office of Management and Budget and the American Transportation Association.

Table 1: Formulas for Major FAHP Programs

Program	Factor	Weight
National Highway System	Share of total lane miles	25%
	Share of total vehicle miles traveled	35%
	Share of diesel fuel used	30%
	Share of total lane miles/share of total population	10%
Surface Transportation	Share of Federal-aid Highway lane miles	25%
	Share of total vehicle miles traveled	40%
	Share of contribution to Highway Trust Fund	35%
Interstate Maintenance	Share of interstate lane miles	33.3%
	Share of interstate vehicle miles traveled	33.3%
	Share of contributions Highway Trust Fund attributable to commercial vehicles	33.3%

Formulas vary by authorization bill. Formulas in this table correspond to those under SAFETEA-LU, which was in effect between 2010 and 2012. This table excludes some smaller programs.

Table 2: Moran's I

Year	Gini		Growth Rate of Gini	
	Z-Statistic	p-value	Z-Statistic	p-value
1956	2.82	0.002	1.26	0.103
1960	2.95	0.002	0.12	0.45
1965	1.98	0.024	2.24	0.013
1970	3.36	0.000	0.48	0.318
1975	5.42	0.000	1.80	0.036
1980	4.86	0.000	-0.56	0.289
1985	6.10	0.000	2.49	0.006
1990	4.13	0.000	2.87	0.002
1995	2.69	0.004	3.09	0.001
2000	2.53	0.006	0.62	0.269
2005	4.52	0.000	4.04	0.000
2010	2.55	0.005	2.93	0.002

Moran's I is a test of spatial dependence. Under the null hypothesis, variables are not spatially dependent. Rejection of the null implies spatial dependence. Statistically positive dependence implies clustering, meaning high growth rates in one state are associated with high growth rates in spatially neighboring states.

Table 3: Flypaper Effect

	No Lags	1 Lag	2 Lags	3 Lags	4 Lags	5 Lags
$Infrastructure_{i,t}$	0.483***	-0.0615	0.0238	-0.149	-0.174	-0.189
	(0.107)	(0.120)	(0.133)	(0.139)	(0.127)	(0.139)
$Infrastructure_{i,t-1}$		0.636***	0.150**	0.363***	0.250***	0.236***
		(0.120)	(0.0642)	(0.0753)	(0.0790)	(0.0824)
$Infrastructure_{i,t-2}$			0.482***	0.135**	0.325***	0.162**
			(0.140)	(0.0579)	(0.115)	(0.0804)
$Infrastructure_{i,t-3}$				0.350**	0.117	0.386**
				(0.136)	(0.0948)	(0.158)
$Infrastructure_{i,t-4}$					0.218**	-0.0280
					(0.0886)	(0.0530)
$Infrastructure_{i,t-5}$						0.216**
						(0.0966)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2784	2736	2688	2640	2592	2544
$\sum_{p=0}^{q} \beta_p$	0.483	0.574	0.656	0.699	0.736	0.782
$H_0 : \sum_{p=0}^{q} \beta_p = 0$	0.000	0.000	0.000	0.000	0.000	0.000
$H_0 : \sum_{p=0}^{q} \beta_p = 1$	0.000	0.000	0.004	0.019	0.052	0.132

Dependent variable is real per capita total disbursements on highways. Infrastructure is real per capita FAHP apportionments in levels. Control variables are included in estimation, but not reported for exposition. Standard errors are reported in parentheses and clustered at the state level. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4: Main Results

dependent variable: growth rate of Gini coefficient (%)

τ (Lag of Inequality)	-0.180***	(0.03)
β_1 (Infrastructure)	-0.242	(0.17)
θ_1 (W*Infrastructure)	-0.656***	(0.23)
ρ (W*Inequality)	0.491***	(0.03)
Short Run Direct Effect $n^{-1}tr(S_{sr}(W))$	-0.361**	(0.16)
Short Run Indirect Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n - n^{-1}tr(S_{sr}(W))$	-1.402***	(0.32)
Short Run Total Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n$	-1.763***	(0.30)
Long Run Direct Effect $n^{-1}tr(S_{lr}(W))$	-0.283**	(0.14)
Long Run Indirect Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n - n^{-1}tr(S_{lr}(W))$	-1.019***	(0.25)
Long Run Total Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n$	-1.302***	(0.22)
N	2736	

The dependent variable is the percent growth rate of the Gini coefficient. Infrastructure is the log of per capita Federal Aid Highway apportionments. Control variables are included in estimation, but not reported for exposition. The first four rows of output are used in the construction of the short and long run direct, indirect, and total effects. $S_{sr}(W) = [I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$ and $S_{lr}(W) = [(1-\tau)I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$. Standard errors are reported in parentheses, clustered at the state level, and computed using 10,000 replications of the Monte Carlo simulation procedure laid out in LeSage and Pace (2009). * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 5: Spatial Partitioning of Effects.
dependent variable: growth rate of Gini coefficient (%)

W-order	Direct	Indirect	Total
W^0	-0.242	-0.656	-0.898
W^1	-0.317	-1.022	-1.339
W^2	-0.341	-1.214	-1.555
W^3	-0.352	-1.309	-1.662
W^4	-0.357	-1.357	-1.714
W^5	-0.359	-1.381	-1.740
W^6	-0.360	-1.393	-1.752
W^7	-0.360	-1.398	-1.758
W^8	-0.360	-1.401	-1.761
W^9	-0.360	-1.403	-1.763
W^{10}	-0.360	-1.403	-1.763

This table reports the spatial decomposition of the short run (contemporaneous) direct, indirect, and total effects of Table 4. The W-order corresponds to the degrees of spatial separation between states i and j. W^1 corresponds to neighbors of state i, W^2 corresponds to neighbors of neighbors of state i, and so on. Reported estimates are cumulative.

Table 6: Quintile Estimates
dependent variable: log aggregate income per capita

	Bottom Quintile	2nd Quintile	3rd Quintile	4th Quintile	Top Quintile
$Income_{i,t-1}$	0.569***	0.742***	0.734***	0.814***	0.817***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Infrastructure	0.034	0.016*	0.017***	0.003	0.002
	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)
Observations	2662				

Each column represents an equation within a system of equations. The dependent variable is the log of aggregate gross income (AGI) per capita within a quintile for a given state-year. Infrastructure is the log of per capita Federal Aid Highway apportionments. Estimation follows the three-step procedure laid out by Zellner and Theil (1962). Standard errors are reported in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 7: Heterogeneity by Skill
dependent variable: log total personal income

	High Low			High Medium Low		
	(1)	(2)	(3)	(4)	(5)	(6)
Infrastructure	0.017	-0.054***	-0.007	0.037**	-0.037*	0.000
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Low Skilled × Infrastructure	0.084***	0.087***	0.094***	0.065***	0.069***	0.077***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
High Skilled × Infrastructure				-0.009	-0.006	-0.005
				(0.02)	(0.02)	(0.02)
Low Skilled	-0.477***	-0.477***	-0.478***	-0.252***	-0.252***	-0.253***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
High Skilled				0.408***	0.407***	0.407***
				(0.00)	(0.00)	(0.00)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
State Trends	No	No	Yes	No	No	Yes
Observations	2171327	2171327	2171327	2171327	2171327	2171327
p($\psi_{low} = \psi_{high}$)				0.010	0.008	0.004

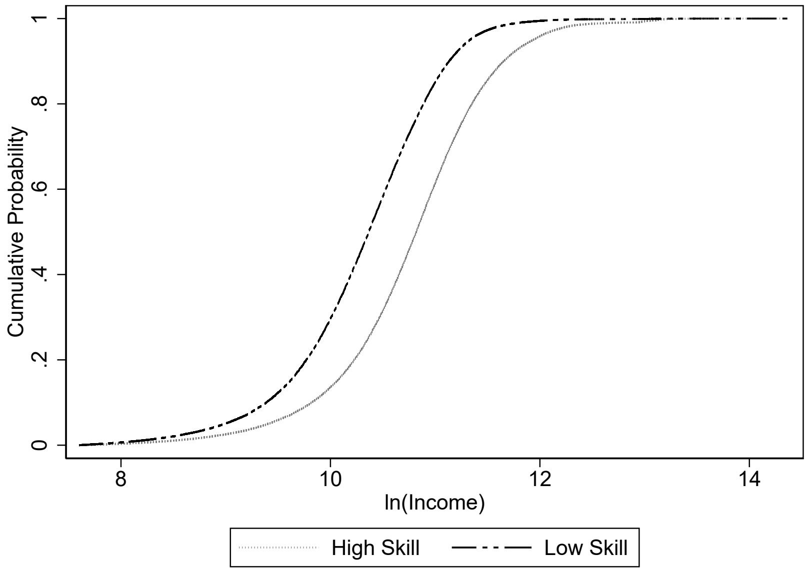
The dependent variable is the natural log of real total personal income. Infrastructure is the natural log of real per capita Federal Aid Highway apportionments. The sample includes all workers between the ages of 25 and 75 that reported at least $2,000 in total real income (2013 dollars) and working at least 10 hours last week. Low Skilled is an indicator variable equal to one if the respondent has completed no more than a high school diploma. High Skilled is an indicator variable equal to one if a the respondent has completed at least four years of college. The interaction between skill and infrastructure represents the heterogenous effect of Infrastructure by skill level. Columns 1-3 and 4-6 differ in that the former tests low-skilled workers against a base case of medium and high-skilled workers, while the latter tests low and high-skilled workers against a base case of medium-skilled workers. Standard errors are reported in parentheses. * $p<0.1$, ** p<0.05, *** p<0.01.

Table 8: Average Income by Decile and Skill
dependent variable: log total personal income

Decile	Full Sample	Low Skilled	High Skilled
1	\$9,156	\$7,668	\$14,122
2	\$18,016	\$14,834	\$28,986
3	\$24,532	\$19,868	\$38,638
4	\$30,699	\$24,460	\$46,832
5	\$37,063	\$29,215	\$55,053
6	\$44,090	\$34,424	\$64,362
7	\$52,468	\$40,573	\$75,913
8	\$63,260	\$48,552	\$91,678
9	\$80,588	\$60,046	\$117,511
10	\$156,431	\$98,690	\$229,952
Total	\$51,622	\$37,829	\$76,300

This table reports average income by deciles of CPS respondents (2013 dollars), based on skill. The sample of workers includes all workers between the ages of 25 and 75 that reported at working at least 10 hours last week and made least \$2,000 in total real income (2013 dollars). Low-skilled workers are defined as workers who have completed no more than a high school diploma. High-skilled workers are defined as workers who have completed at least four years of college.

Figure 6: Distribution of High vs Low Skilled Workers



The sample of workers includes all workers between the ages of 25 and 75 that reported at working at least 10 hours last week and made least $2,000 in total real income (2013 dollars). Low-skilled workers are defined as workers who have completed no more than a high school diploma. High-skilled workers are defined as workers who have completed at least four years of college.

Table 9: Percent Low-Skilled by Industry

Professional Services	26.64%
Government	32.34%
FIRE	32.79%
Communications	36.91%
Business Repair	45.97%
Wholesale	47.98%
Utilities	50.83%
Durables	55.18%
Transportation	56.79%
Retail	58.64%
Mining	59.33%
Nondurables	61.42%
Construction	65.04%
Personal Services	65.50%
Agriculture	66.58%

This table reports the percent of workers working in each industry that that have no more than a high school education (i.e. are low-skilled). The sample is the pooled average of CPS respondents from 1977 to 2013 who were between 25 and 75 years old, reported working at least ten hours last week, and had a total income of at least $2,000 (in 2013 dollars). Census' 1990 concept of industry used for classification of industries.

Table 10: Response of Personal Total Income By Industry
dependent variable: log total personal income

	(1)	(2)	(3)
Infrastructure	0.040**	0.041**	0.008
	(0.02)	(0.02)	(0.02)
Transportation × Infrastructure	0.054**	0.057***	0.092***
	(0.02)	(0.02)	(0.02)
Low Skilled × Infrastructure	0.090***	0.051	0.125***
	(0.02)	(0.03)	(0.04)
High Skilled × Infrastructure	-0.017	-0.019	0.023
	(0.03)	(0.03)	(0.02)
Transportation	0.124***	0.147***	0.151***
	(0.01)	(0.01)	(0.01)
Low Skilled	-0.213***	-0.093***	-0.076***
	(0.01)	(0.02)	(0.02)
High Skilled	0.072***	0.107***	0.095***
	(0.02)	(0.01)	(0.01)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State Trends	Yes	Yes	Yes
Observations	2171327	2171327	2171327
p($\psi_{low} = \psi_{high}$)	0.000	0.070	0.017

The dependent variable is the natural log of real total personal income. Infrastructure is the natural log of real per capita Federal Aid Highway apportionments. High Skilled and Low Skilled are indicator variables indicating whether a person works in an industry in the low-skilled or high-skilled sector, irrespective of his own skill level (education). The skill level of an industry is determined by the percent of low skilled workers that work in it (see Table 9). In order, industries in the High Skilled sector are: Professional Services, Government, FIRE, Communications, and Business Repair. In order, industries in the Low Skilled sector are: Agriculture, Personal Services, Construction, Non-durables, Mining. Column 1 includes the top and bottom three industries, column 2 includes the top and bottom four industries, and column 3 includes the top and bottom five industries. See table 9 for remaining industries that compose the base case. Standard errors are reported in parantheses and are clustered at the state level. * $p<0.1$, ** p<0.05, *** p<0.01.

Table 11: Transportation Intensity by Industry

Highest Truck Transport Intensive Industries			Lowest Truck Transport Intensive Industries		
Industry Name	BEA IO Code	% of Intermediate Input Costs	Industry Name	BEA IO Code	% of Intermediate Input Costs
Truck transportation	484	47.61%	Insurance carriers and related activities	524	0.09%
Food and beverage and tobacco products	311FT	1.73%	Housing	HS	0.11%
Nonmetallic mineral products	327	1.54%	Funds, trusts, and other financial vehicles	525	0.11%
Primary metals	331	1.42%	Computer systems design and related services	5415	0.13%
Wood products	321	1.34%	Legal services	5411	0.13%
General merchandise stores	452	1.2%	Fed. Reserve banks, credit intermediation, etc.	521CI	0.13%
Farms	111CA	1.28%	Management of companies and enterprises	55	0.18%
Textile mills and textile product mills	313TT	1.14%	Securities, commodity contracts, and investments	523	0.19%
Furniture and related products	337	1.13%	Rental and leasing services and lessors of intangible assets	532RL	0.19%
Paper products	322	1.12%	Motion picture and sound recording industries	512	0.20%
Construction	23	1.04%	Oil and gas extraction	211	0.22%
Apparel and leather and allied products	315AL	1.01%	Broadcasting and telecommunications	513	0.22%
Motor vehicles, bodies and trailers, and parts	3361MV	0.99%	Other real estate	ORE	0.23%
Electrical equipment, appliances, and components	335	0.99%	Federal general government (nondefense)	GFGN	0.24%
Fabricated metal products	332	0.99%	Performing arts, spectator sports, museums, etc.	711AS	0.25%

Data is sourced from the 2007 Input-Output Commodity by Industry Total Requirements (After Redistribution), 71 summary industries. Cost rankings report the percent of trucking transportation costs to total output requirements. BEA IO Code is shorthand for Bureau of Economic Analysis Input Output codes. Codes are map-able to NAICs codes, but are not directly comparable to 1990 concept of industry that is used in the CPS results. See BEA for details.

Table 12: Response of Inequality to a 100% Increase in Infrastructure Apportionments

	Gini	Theil	Rel. Mean Dev.
τ (Lag of Inequality)	-0.180***	-0.069***	-0.285***
	(0.03)	(0.02)	(0.03)
β_1 (Infrastructure)	-0.242	0.486	-0.148
	(0.17)	(0.44)	(0.19)
θ_1 (W*Infrastructure)	-0.656***	-2.420***	-0.517**
	(0.23)	(0.62)	(0.23)
ρ (W*Inequality)	0.491***	0.669***	0.384***
	(0.03)	(0.02)	(0.03)
Short Run Direct Effect $n^{-1}tr(S_{sr}(W))$	-0.361**	-0.067	-0.211
	(0.16)	(0.42)	(0.18)
Short Run Indirect Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n - n^{-1}tr(S_{sr}(W))$	-1.402***	-5.779***	-0.870***
	(0.32)	(1.32)	(0.29)
Short Run Total Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n$	-1.763***	-5.846***	-1.081***
	(0.30)	(1.38)	(0.28)
Long Run Direct Effect $n^{-1}tr(S_{lr}(W))$	-0.283**	-0.003	-0.150
	(0.14)	(0.39)	(0.14)
Long Run Indirect Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n - n^{-1}tr(S_{lr}(W))$	-1.019***	-4.836***	-0.588***
	(0.25)	(1.11)	(0.21)
Long Run Total Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n$	-1.302***	-4.839***	-0.739***
	(0.22)	(1.14)	(0.19)
N	2736	2736	2736

The dependent variable varies by column. The first column recreates the main results, using the percentage growth rate of the Gini coefficient as the dependent variable.. The second and third column report estimates in which the growth rate of the Gini coefficient is replaced with the growth rate of the Theil entropy index and the relative mean deviation respectively. Infrastructure is the log of per capita Federal Aid Highway apportionments. Control variables are included in estimation, but not reported for exposition. The first four rows of output are used in the construction of the short and long run direct, indirect, and total effects. $S_{sr}(W) = [I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$ and $S_{lr}(W) = [(1-\tau)I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$. Standard errors are reported in parentheses, clustered at the state level, and computed using 10,000 replications of the Monte Carlo simulation procedure laid out in LeSage and Pace (2009). * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 13: Common Spatial Specifications

$DSDM = Y_t = \tau Y_{t-1} + \rho W Y_t + \beta X_t + \theta W X_t + u_t$		
Model	Difference from DSDM	Spillovers?
General Spatial Nesting	Adds u_t=$\lambda W u_t$ and $\eta W Y_{t-1}$	Fully flexible
Classic DSDM	Adds $\eta W Y_{t-1}$	Fully flexible
Static Spatial Durbin	τ=0	Long-run only
Dynamic spatial autoregressive	θ=0	Constant ratio
Static spatial autoregressive	θ=τ=0	Long run only and constant spillover ratio
Dynamic Spatial lag of X (SLX)	ρ=0	Local only
Static Spatial lag of X (SLX)	ρ=τ=0	Long run only and local spillovers only

$Y_t = Inequality_t$. $\theta = [\theta_1 + \theta_2]$, $\beta = [\beta_1 = \beta_2]$. Fully flexibile means spillover effects can exist in the short and long run, and be both local and global. Long-run only applies for all static models. Constant spillover ratio means all spillovers in the model are global. Local only means the model does not account for spatial feedback loops.

Table 14: Robustness Checks on SDM Model
dependent variable: growth rate of the Gini coefficient

	(1) Baseline	(2) Lag W Dep	(3) Static SDM	(4) Restricted Wx	(5) Dynamic SAR	(6) Static SAR
τ (Lag of Inequality)	-0.180***	-0.275***		-0.180***	-0.178***	
	(0.0287)	(0.0267)		(0.0286)	(0.0287)	
β_1 (Infrastructure)	-0.242	-0.225	-0.264	-0.243	-0.507***	-0.413***
	(0.172)	(0.164)	(0.162)	(0.175)	(0.129)	(0.122)
θ_1 (W*Infrastructure)	-0.656***	-0.442*	-0.441**	-0.525***		
	(0.227)	(0.226)	(0.208)	(0.199)		
ρ (W*Inequality)	0.491***	0.508***	0.470***	0.492***	0.494***	0.472***
	(0.0274)	(0.0263)	(0.0266)	(0.0274)	(0.0273)	(0.0266)
Short Run Direct Effect $n^{-1}tr(S_{sr}(W))$	-0.361**	-0.316**		-0.343**	-0.546***	
	(0.160)	(0.153)		(0.167)	(0.138)	
Short Run Indirect Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n - n^{-1}tr(S_{sr}(W))$	-1.402***	-1.041***		-1.171***	-0.456***	
	(0.321)	(0.333)		(0.279)	(0.117)	
Short Run Total Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n$	-1.763***	-1.357***		-1.514***	-1.001***	
	(0.302)	(0.332)		(0.288)	(0.250)	
Long Run Direct Effect $n^{-1}tr(S_{lr}(W))$	-0.283**	-0.280**	-0.343**	-0.271*	-0.452***	-0.439***
	(0.136)	(0.121)	(0.154)	(0.142)	(0.115)	(0.130)
Long Run Indirect Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n - n^{-1}tr(S_{lr}(W))$	-1.019***	-1.093***	-0.988***	-0.846***	-0.288***	-0.341***
	(0.246)	(0.322)	(0.297)	(0.213)	(0.0731)	(0.104)
Long Run Total Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n$	-1.302***	-1.373***	-1.331***	-1.117***	-0.740***	-0.780***
	(0.223)	(0.335)	(0.298)	(0.211)	(0.185)	(0.231)
Observations	2736	2736	2784	2736	2736	2784

The dependent variable is the percent growth rate of the Gini coefficient. Infrastructure is the log of per capita Federal Aid Highway apportionments. Control variables are included in estimation, but not reported for exposition. Column 1 replicates the baseline results presented in Table 4. Column 2 reports estimates of a traditional dynamic spatial Durbin model, with the spatio-temporal lagged dependent variable ($\eta W * Inequality_{t-1}$) included. Column 3 reports estimates of a static spatial Durbin Model (τ=0). Column 4 reports estimates of a DSDM with only Infrastructure spatially lagged (θ_2=0). Column 5 reports estimates of a dynamic spatial autoregressive (SAR) model ($\theta_1 = \theta_2 = 0$). Column 6 reports estimates of a static SAR model ($\theta_1 = \theta_2 = \tau = 0$).The first four rows of output are used in the construction of the short and long run direct, indirect, and total effects. $S_{sr}(W) = [I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$ and $S_{lr}(W) = [(1-\tau)I - (\rho + \eta)W]^{-1}[\beta_1 I_N + \theta_1 W]$. Standard errors are reported in parentheses, clustered at the state level, and computed using 10,000 replications of the Monte Carlo simulation procedure laid out in LeSage and Pace (2009). * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 15: TaxSim Top Marginal Tax Rates
dependent variable: growth rate of the Gini coefficient

τ (Lag of Inequality)	-0.004
	(0.03)
β_1 (Infrastructure)	-0.126
	(0.21)
θ_1 (W*Infrastructure)	-0.438*
	(0.24)
ρ (W*Inequality)	0.630***
	(0.03)
Short Run Direct Effect $n^{-1}tr(S_{sr}(W))$	-0.247
	(0.22)
Short Run Indirect Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n - n^{-1}tr(S_{sr}(W))$	-1.279**
	(0.53)
Short Run Total Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n$	-1.525**
	(0.64)
Long Run Direct Effect $n^{-1}tr(S_{lr}(W))$	-0.245
	(0.22)
Long Run Indirect Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n - n^{-1}tr(S_{lr}(W))$	-1.265**
	(0.53)
Long Run Total Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n$	-1.510**
	(0.64)
N	1728

This table reports estimates where measures of progressivity are included as covariates. The dependent variable is the percent growth rate of the Gini coefficient. Infrastructure is the log of per capita Federal Aid Highway apportionments. Control variables are included in estimation, but not reported for exposition. The first four rows of output are used in the construction of the short and long run direct, indirect, and total effects. $S_{sr}(W) = [I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$ and $S_{lr}(W) = [(1-\tau)I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$. Standard errors are reported in parentheses, clustered at the state level, and computed using 10,000 replications of the Monte Carlo simulation procedure laid out in LeSage and Pace (2009). * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 16: Military Spending
dependent variable growth rate of the Gini coefficient

	NS2014		NS2014 Broad		BEA Compensation	
τ (Lag of Military)	-0.170***	(0.03)	-0.177***	(0.03)	-0.170***	(0.03)
β_1 (Infrastructure)	0.330**	(0.14)	0.774***	(0.19)	0.231**	(0.10)
θ_1 (W*Infrastructure)	1.027***	(0.21)	1.097***	(0.23)	0.178	(0.15)
ρ (W*Military)	0.510***	(0.03)	0.509***	(0.03)	0.505***	(0.03)
Short Run Direct Effect $n^{-1}tr(S_{sr}(W))$	0.523***	(0.13)	1.013***	(0.18)	0.277***	(0.10)
Short Run Indirect Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n - n^{-1}tr(S_{sr}(W))$	2.252***	(0.34)	2.797***	(0.40)	0.550**	(0.25)
Short Run Total Effect $n^{-1}\iota_n' S_{sr}(W)\iota_n$	2.775***	(0.33)	3.810***	(0.43)	0.827***	(0.26)
Long Run Direct Effect $n^{-1}tr(S_{lr}(W))$	0.410***	(0.11)	0.811***	(0.16)	0.226***	(0.08)
Long Run Indirect Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n - n^{-1}tr(S_{lr}(W))$	1.647***	(0.25)	1.989***	(0.29)	0.388**	(0.19)
Long Run Total Effect $n^{-1}\iota_n' S_{lr}(W)\iota_n$	2.058***	(0.24)	2.800***	(0.31)	0.614***	(0.19)
N	1920		1920		2640	

The dependent variable is the percent growth rate of the Gini coefficient. Infrastructure is the log of per capita Federal Aid Highway apportionments. Control variables are included in estimation, but not reported for exposition. The first four rows of output are used in the construction of the short and long run direct, indirect, and total effects. $S_{sr}(W) = [I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$ and $S_{lr}(W) = [(1-\tau)I - \rho W]^{-1}[\beta_1 I_N + \theta_1 W]$. The first column reports estimates that use military procurement data provided by Nakamura and Steinsson (2014) for the military spending measure. The second column rreports estimates in which military compensation to the first measure. The last column uses military compensation, taken directly from the BEA, as the military spending measure. Standard errors are reported in parentheses, clustered at the state level, and computed using 10,000 replications of the Monte Carlo simulation procedure laid out in LeSage and Pace (2009). * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 17: Comparing Construction Worker Characteristics to Military Personnel

Characteristic	Construction	Military (Enlisted)	Military (Officer)
Entry level educational requirement	None	High school degree	High school degree
Public educational benefits	None	G.I. Bill	G.I. Bill
Percent with a bachelors degree	14%	19%	42%
Percent with advanced degree	3%	9%	40%
Average income	\$50,000	\$73,000	\$114,000

The G.I. Bill refers to the series of bills passed by Congress which provide education subsidies to military personnel. Construction worker pay is based on 2013 CPS grand mean of state averages for construction worker income. Military income is the Regular Military Compensation, which includes ameneties such as the housing allowance and subsistence pay. Values reported for enlisted members are for single E-6 grade members, serving for 10 years, and stationed at Fort Hood. Offier pay is calculated for a single O-3 rank member who has served for 10 years and is stationed at Fort Hood. For further details on how military pay was calculated, visit `https://militarypay.defense.gov/Calculators/RMC-Calculator/`. Income averages are rounded ot the nearest \$1,000.

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A Data

Format: **variable_name** - data description. [Used in Results] (Source) {Link, if applicable}[51]

Gini - State-level Gini coefficients of income by state. Obtained from Frank (2014). Frank uses the Statistics of Income series from the Internal Revenue Service to construct his series. Data is available on his personal website.
[Table 2]
Frank (2014)
{`http://www.shsu.edu/eco_mwf/inequality.html`}

grGini - The log differennce of **Gini**.
[Table 2]
Frank (2014)
{`http://www.shsu.edu/eco_mwf/inequality.html`}

grTheil - Growth rate of the Theil Entropy Index of income by state. Obtained from Frank (2014). Frank uses the Statistics of Income series from the Internal Revenue Service to construct his series. Data is available on his personal website.
[Table 12]
Frank (2014)
{`http://www.shsu.edu/eco_mwf/inequality.html`}

grRMeanDev - Growth rate of the Relative Mean Deviation of income by state. Obtained from Frank (2014). Frank uses the Statistics of Income series from the Internal Revenue Service to construct his series. Data is available on his personal website.
[Table 12]
Frank (2014)
{`http://www.shsu.edu/eco_mwf/inequality.html`}

CPI - Current Price Index. Used in construction of all "real" variables.
[Baseline]

[51] For brevity I report "Baseline" if results were used in the main results. Many of these variables appear in other regressions as well, though. Sources listed are where I derived the data from. In some cases that is not the original source. For example, Nakamura and Steinsson (2014) use BEA data in part of their analysis, but I report Nakamura and Steinsson (2014), not the BEA as the source. In some cases data comes from multiple links or locations within an agency. Links provided either link to a specific instance of the data, or the parent web page where applicable.

(Federal Reserve Bank of Minneapolis)
{https://www.minneapolisfed.org/community/financial-and-economic-education/cpi-calculator-information/consumer-price-index-and-inflation-rates-1913}

Popn - Total state population, annual average.
[Baseline]
(United States Census Bureau)
{http://www.census.gov/popest/data/state/asrh/1980s/80s_st_totals.html}

grlnrStatePcapPincome - The first difference of the log of real per capita personal income. Sourced from BEA's interactive data tool for regional data, series SA1.
[Baseline]
(Bureau of Economic Analysis)
{https://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1#reqid=70&step=1&isuri=1}

rsf2Pcap - Real per capita total disbursements by states. Sourced from the Department of Transportation's Federal Highway Administration's Highway Statistics series which is published annually by their Office of Highway Policy Information. Total disbursements are reported in table SF2 and is defined by the sum of capital outlays, maintenance, administration and research planning, highway law enforcement and safety, interest, bond retirement, grants-in-aid to local governments. Capital outlays and maintenance compose about two thirds of this total.
[Table 3]
(DOT-OHPI)
{https://www.fhwa.dot.gov/policyinformation/statistics.cfm}.

lnrsf2Pcap - The natural logarithm of **rsf2Pcap**.
[Baseline]
(DOT-FHWA-OHPI)
{https://www.fhwa.dot.gov/policyinformation/statistics.cfm}.

SenateAppropriationsChair - An indicator variable for state that the Chairperson of the Senate Committee on Appropriations represents. 1 means the state are represented by the chairperson in a given year.
[Baseline]
(Government Publishing (Printing) Office)

{https://www.gpo.gov/fdsys/pkg/CDOC-110sdoc14/pdf/CDOC-110sdoc14.pdf}

HRCommitteeChair - An indicator variable for state that the Chairperson of the Senate Committee on Appropriations represents. 1 means the state are represented by the chairperson in a given year.
[Baseline]
(United States House of Representatives and Congressional Profiles)
{https://democrats-appropriations.house.gov/sites/democrats.appropriations.house.gov/files/migrated/uploads/House_Approps_Concise_History.pdf and http://history.house.gov/Congressional-Overview/Profiles/84th/; various years}

PctHRAprCommittee - Percent of the House of Representatives Committee on Appropriations occupied by members of a given state in a given year.
[Baseline]
(United States House of Representatives and Congressional Profiles)
{https://democrats-appropriations.house.gov/sites/democrats.appropriations.house.gov/files/migrated/uploads/House_Approps_Concise_History.pdf and http://history.house.gov/Congressional-Overview/Profiles/84th/; various years}

rpcapFA4_total - Real per capita value of the total Federal Aid Highway Program apportionments, prior to post apportionment set-asides, and before penalties, Table FA-4. Programs vary by year.
[Table 3]
(DOT-FHWA-OHPI)
{https://www.fhwa.dot.gov/policyinformation/statistics.cfm}

lnrpcaptotalpmaNS2014 - Total value by state of DD-350 Military procurement, available through the US department of Defense. This is the main measure of military spending used in Nakamura and Steinsson (2014). To transform the data into log real per capita terms I interpolate zeros.
[Table 16]
Nakamura and Steinsson (2014)
{http://www.columbia.edu/~en2198/papers/fiscal.pdf}

lnmilBroadNS2014 - The log per capita value of the broader measure of military spending reported in Nakamura and Steinsson (2014). This measure includes military compensation from the BEA. The data is transformed into log real per capita terms.

[Table 16]
Nakamura and Steinsson (2014)
{http://www.columbia.edu/~en2198/papers/fiscal.pdf}

lnrpcapMilitarySpending - the log of real per capita military compensation, BEA. Regional Data, Personal income by major component and Earnings by industry (SA5,SA5H,SA5N).
[Table 16]
(Bureau of Economic Analysis)
{$https://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1#reqid=70&step=1&isuri=1$}

FedCapGain - The effective tax rate on an additional $1,000 of capital gains earned by a household with an original income of $1,000,000. Created using NBER's TaxSim tool.
[Table 15]
(National Bureau of Economic Analysis) {http://users.nber.org/~taxsim/state-rates/}

FedMargTaxTopBracket - The effective tax rate on an additional $1,000 of income earned by a household with an original income of $1,000,000. Created using NBER's TaxSim tool.
[Table 15]
(National Bureau of Economic Analysis)
{http://users.nber.org/~taxsim/state-rates/}

$lnAGI_q1$ **-** $lnAGI_q5$ - Log estimates of aggregate gross income captured by each quintile. Computed by logging the product of AGI by the estimated share of income captured by that group. See Appendix A.1.1 for more details.

[Table **??**]

(Internal Revenue Service - Statistics of Income)

https://www.irs.gov/statistics/soi-tax-stats-statistics-of-income

lnrinctot - The natural log of real per capita total personal income (inctot). Data was sourced from the CPS through IPUMS.
[Table 7 and 10]
(Current Population Survey)
{https://cps.ipums.org/cps/}

HS_or_Less - Definition of low-skilled worker used in the paper. Defined as a worker

who reports having an education no higher than high school graduation. Data was sourced from the CPS through IPUMS. The variable is defined with CPS' educ variable. HS_or_Less is constructed as an indicator for all valid responses less than or equal to educ code 73.
[Table 7]
(Current Population Survey)
{https://cps.ipums.org/cps/}

BAmore - Definition of high-skilled worker used in the paper. Defined as a worker who reports having an education of at least four years of college. Data was sourced from the CPS through IPUMS. The variable is defined with CPS' educ variable. BAmore is constructed as an indicator for all valid responses greater than or equal to educ code 110.
[Table 7]
(Current Population Survey)
{https://cps.ipums.org/cps/}

dlowskill3-dlowskill5 - And indicator variable equal to one if a person works in a low-skilled sector. The number represents the aggregation of industries in the sectors. Industry codes used are from the 1990 census concept of industries, given by CPS code ind1990. Data was sourced from the CPS through IPUMS.
[Table 10]
(Current Population Survey)
{https://cps.ipums.org/cps/}

dhighskill3 - dhighskill5 - And indicator variable equal to one if a person works in a high-skilled sector. The number represents the aggregation of industries in the sectors. Industry codes used are from the 1990 census concept of industries, given by CPS code ind1990. Data was sourced from the CPS through IPUMS.
[Table 10]
(Current Population Survey)
{https://cps.ipums.org/cps/}

A.1 Statistics of Income

The key advantage of the SOI is it's length, quality, and consistency. Whereas the SOI has been recorded since 1918, other publicly available data source are not capable of providing consistent estimates of state-level income inequality until the mid 1970's when the Current Population Survey (CPS) was expanded enough to cover all states.[52]

An important advantage of the SOI over the CPS is that the SOI is not top coded. Because data are censored at the top for the (public use) CPS, it is unable to capture variations at the very top of the income distribution. As Piketty (2017) as strongly argued, such top coding hides important dynamics in total income inequality. For example If the CPS were top coded at $250,000, it would not capture the effect of the average income of earners in the top income bracket increasing from, say, $400,000 to $1 million, even though such changes could be incredibly important for changes in total income inequality. Top coding is contributes to the relatively more commonly used partial inequality measures like the 90/10 ratios, but those fail to capture total income inequality.

That said, there are limitations to the SOI Series. The SOI uses pre-tax data, which presents three obstacles. First, not everyone files taxes. The poor, in particular, file at a much lower rate than other portions of the income distribution. Trends over time in the proportion of people who do not file could lead to spurious changes in measured income inequality. Fortunately, this does not seem to be a first order concern. Figure 8 shows that the growth rate of individual tax returns has closely tracked the growth rate of the United States population, implying the proportion of non-filers has not drastically changed over time.

A second obstacle is that inequality measured derived from SOI data miss important features of the tax code like the Earned Income Tax Credit (EITC). Since most of these programs redistribute wealth from the relatively more wealthy to the relatively more poor, inequality measures in this paper likely overstate true income inequality. However, using non-public CPS data, Burkhauser et al. (2012) find that series of tax adjusted and tax un-adjusted Gini coefficients are very highly correlated across time. Thus, while the level of pre-tax Gini coefficients used in this paper are arguably too high, the dynamics do not appear substantially affected.

The last obstacle deals with constructing the Gini coefficient itself. Because of practical limitations and privacy concerns, The SOI does not provide exact income values for each filer. Rather, it constructs a series of non-overlapping income bins and reports aggregate adjusted gross income (AGI) and number of filers per state in each income bin. In order to construct a Gini coefficient, an income distribution must be approximated using these bins, which leads to potential measurement error. There is no evidence that the number of bins or the intervals they cover appear to change non-randomly, so the measurement error is likely classical. Still, this does imply the inequality measures suffer

[52]As Figure 7 illustrates, the state-level inequality series used in this paper are highly correlated with the well known national analysis of Piketty and Saez (2003), especially for the post World War II period. This is unsurprising as they use the same methodology.

from greater statistical noise. I turn to this issue in greater detail in the next subsection.

Figure 7

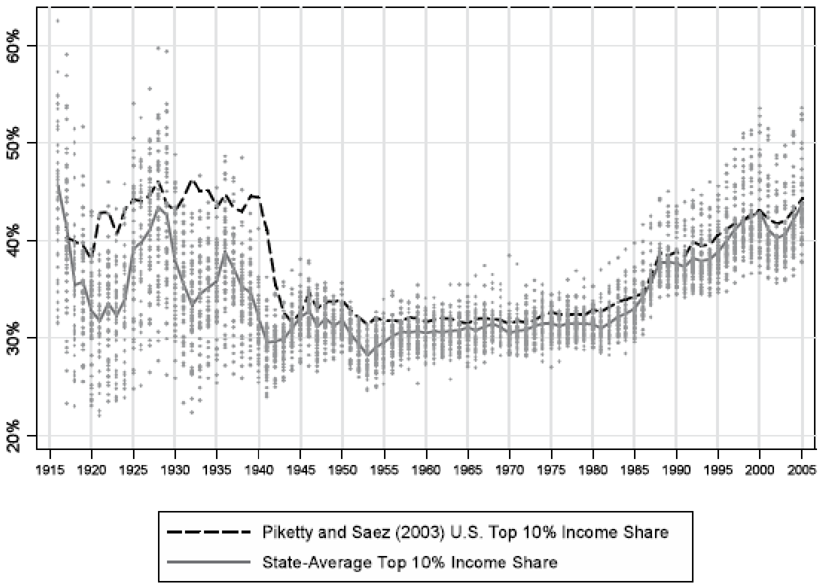
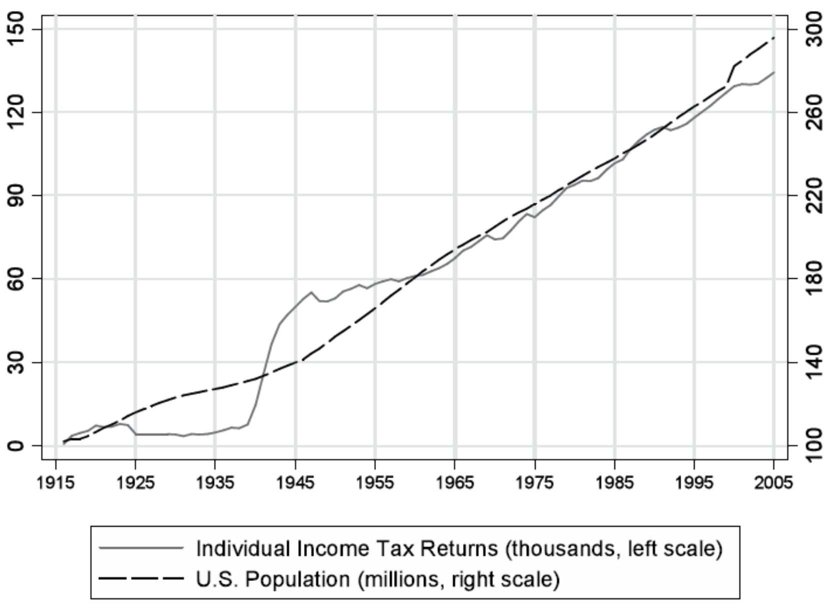


Figure 8: Tax Filers vs Population



A.1.1 Construction of Statistics of Income Series

This section decomposes the Gini coefficient into an approximation of the CDF of the income distribution in order to evaluate it along various percentile intervals.

The As the main text described, the SOI consists of detailed tabulations of pre-tax aggregate income by state. Income is reported in intervals that are cross sectionally consistent but vary with time. That is, in a given year all states are evaluated along the same number of bins and cut-off points, but both the number of bins and their cut-offs vary by year. Figure 18 reports the number of intervals, as well as the upper cut-off, for the lowest and highest interval bins. For the years for which I have data, the average number of intervals is 13.66 per year, though it ranges between between 5 and 25 across the sample.

The remainder of this section follows one state in one year (Delaware, 1979) to provide concreteness in the methodology. I follow the same process for each other state-year observation. Figure 9 displays a copy of the SOI series for Delaware, 1979. Data for earlier years had to be digitized, but later years were available from the IRS in excel format. Figure 19 displays how the SOI data is formatted. The first three columns of Figure 19 simply restate the information provided by the SOI. For example, the third row of data reports the number of returns and adjusted gross income for the $10,000-$15,000 interval. In 1979, 37,964 people reported (adjusted gross) incomes between $10,000 and $15,000, totaling to a cumulative $474,625,000 AGI (in 1979 dollars).

The share of returns and share of AGI, reported in columns four and five, are calculated by dividing each row by the total number of returns and AGI respectively. Returns with AGI between \$10,000 and \$15,000 accounted for approximately 15% of total tax returns (fourth column)and 11.34% of total AGI (column 5). The last two columns create the cumulative share of returns and AGI respectively. The last two columns give snapshots of the income distribution. For example, 22.38% of AGI accrued to the poorest 56.29% of the (tax filing) population.

Clearly snapshots of the income distribution alone are insufficient and some form of interpolation is required to approximate the income distribution.Cowell and Mehta (1982) find that relatively few income bins, as few as five in his paper, can very closely approximate total income inequality. I rely somewhat heavily on this finding, as the number of income bins become quite small in the later portion of my sample (Figure 18). Cowell and Mehta (1982) additionally find that the type of interpolation method used to compute total income inequality makes very little difference in the estimation of the Gini coefficient. Consequently, sine more involved methods appear to add little value, they argue for simplicity and transparency.

I linearly interpolate between intervals to approximate the income distribution and evaluate the cumulative density at each quintile endpoint (corresponding to the 20^{th}, 40^{th}, 60^{th}, 80^{th}, and 100^{th} percentiles). Unsurprisingly, given Cowell and Mehta (1982)'s results, estimates do not change substantially if a cubic spline interpolation method is used instead. The two interpolation methods are highly correlated with each other (within state correlation coefficient of .949). Frank does not provide estimates for shares accumulating to lower portions of the income distribution, but he does provide estimates for the top 10%. My estimates are highly correlated with his (within state correlation coefficient of .913).

Note that it would possible to more granularly evaluate the estimated cumulative density of income (for example with deciles or percentiles). However, doing so risks unacceptable exposure to measurement error in certain years because of relatively few identifying data-points to interpolate on. This could potentially lead to estimates of income accruing to portions of the income distribution for which there is not necessary data. For example, there is no data point for the cumulative share accruing to the 30^{th} to the 40^{th} percentiles. Thus, decile estimates of the share of income accruing to the 3^{rd} and 4^{th} deciles contain no additional information than simply estimating the second quintile.

Table 20 reports values for the CDF and quintile shares for Delaware, 1979. The top panel reports the cumulative density of income evaluated at the end of the each quintile. The bottom panel reports share of (adjusted gross) income captured specifically by that quintile. For example, the poorest 60% of income earners earned and estimated 25.9% of AGI (See top panel). The majority of this (about 60%) went to the third quintile (40^{th}

and 60^{th} percentiles) of income earners captured 15.4% of total AGI (see bottom panel).

For certain years and states, data was missing. In these cases I linearly interpolate the shares going to each state in a given year. For example, due to a clerical error, Delaware (1962) is missing from the official SOI photocopied manuscript. I had to linearly interpolate the years 1982 to 1985 because data was not available during these years.

Once I obtain the shares, I multiply the total AGI for each state-year by the share of AGI for that income interval in order to approximate total AGI for each quintile.

Figure 9: Example of SOI Data: Delaware 1979

Size of adjusted gross income	Number of returns	Adjusted gross income less deficit
	(1)	(2)
Delaware		
Total	**248,170**	**4,183,990**
Under $5,000	57,619	130,210
$5,000 under $10,000	44,120	331,866
$10,000 under $15,000	37,964	474,625
$15,000 under $20,000	28,952	505,373
$20,000 under $25,000	24,523	541,262
$25,000 under $30,000	21,521	593,179
$30,000 under $50,000	25,814	942,685
$50,000 under $100,000	6,529	415,679
$100,000 under $200,000	859	112,816
$200,000 under $500,000	208	60,558
$500,000 under $1,000,000	33	22,595
$1,000,000 or more	28	53,140

Table 18: Number of Intervals by Year

Year(s)	Number of Intervals	Lowest Cut-Off	Highest Cut-Off
1956	17	$0	$1,000,000
1957-1958	21	$0	$1,000,000
1959-1960	20	$1,000	$1,000,000
1961-1962	24	$1,000	$1,000,000
1963	25	$0	$1,000,000
1964-1965	19	$0	$1,000,000
1966	20	$0	$1,000,000
1967	18	$0	$200,000
1968-1969	22	$0	$1,000,000
1970-1975	24	$1,000	$1,000,000
1976-1978	18	$2,000	$1,000,000
1979-1981	12	$5,000	$1,000,000
1982-1985	NA	NA	NA
1986-1988	5	$10,000	$50,000
1989-1995	7	$15,000	$200,000
1996	7	$20,000	$200,000
1997-2001	12	$0	$1,000,000
2002	7	$20,000	$200,000
2003	6	$30,000	$200,000
2004-2009	5	$50,000	$200,000
2010-2011	9	$1	$1,000,000
2012-2013	10	$1	$1,000,000

The third column indicates the top dollar value for the lowest income interval. The fourth column indicates the minimum dollar amount to be in the top income bin. All dollar amounts are nominal.

Table 19: Example of SOI Data: Delaware 1979 cont.

Income Interval	Number of Returns	AGI (Thousands)	Share of Returns	Share of AGI	Cumulative Share of Returns	Cumulative Share of AGI
					0	0
Under5k	57619	130210	0.2321	0.0311	0.2321	0.0311
5k-10k	44120	331866	0.1777	0.0793	0.4099	0.1104
10k-15k	37964	474625	0.1529	0.1134	0.5629	0.2238
15k-20k	28952	505373	0.1166	0.1207	0.6795	0.3446
20k-25k	24523	541262	0.0988	0.1293	0.7784	0.4740
25k-30k	21521	593179	0.0867	0.1417	0.8651	0.6158
30k-50k	25814	942685	0.1040	0.2253	0.9691	0.8411
50k-100k	6529	415679	0.0263	0.0993	0.9954	0.9404
100k-200k	859	112818	0.0034	0.0269	0.9989	0.9674
200k-500k	208	60559	0.0008	0.0144	0.9997	0.9818
500k-1m	33	22595	0.0001	0.0054	0.9998	0.9872
1m+	28	53140	0.0001	0.0127	1	1
Total	248170	4183990				

Table 20: Constructing Quintile Shares; Delaware 1979 Continued

Cumulative	
Percentiles	Percent of AGI
20	2.3
40	10.4
60	25.9
80	50.8
100	100.0

Quintiles	
Quintile	Quintile Share
Bottom	0.023
2^{nd}	0.087
3^{rd}	0.154
4^{th}	0.249
Top	0.492

Shares do not sum to one because of rounding.

A.2 The Life-Cycle of FAHP grants

This appendix describes the institutional details behind FAHP grants. FAHP grants are congressionally determined. FAHP obtain their budget in two steps: authorization and appropriation. Both steps require an act of Congress. In the first step, Congress passes an authorization bill which authorizes a program or agency to exist and lays out the provisions governing the mandates of the program and how much it intends to allocate towards it. However, authorization bills do not actually allow these programs to draw money from the Treasury. In order to do so, funds must be appropriated. These appropriations bills determine the final size of the funds allocated toward each program.[53].

In each chamber of Congress, the Committee on Appropriations (HCoA and SCoA hereafter for the House of representatives and Senate respectively) is tasked with bringing authorization bills before the floor of their respective chambers. HCoA and SCoA therefore have the ability to effectively block legislation pertaining not just to FAHP, but a vast array of spending. Thus, HCoA and SCoA effectively hold Congress' purse strings and its members are in a batter position to able to extract rents in the form of spending and grants for their respective states.

Within each chamber, the chairperson of the committee wield even more power. The chairperson has the responsibility to call legislation to the committee and bring it to the floor. The chairperson is a member of all subcommittees on appropriations and has the ability to effectively kill a bill by stalling it out. Since the chairperson is responsible for bringing bills to a committee vote, they hold tremendous power. As a result, projects favorable to the chairperson, even though they may not otherwise have received funding, are not uncommon. [54]

I exclude the percent of representation by each state on the SCA because there is very little variation from year to year since senators have long terms, each state only has two senators, and composition of the committee does not often change. Including it never changes the results meaningfully. However, the HCoA is arguably more powerful because

[53]Most FAHP programs actually have contract authority, which essentially allows them to make contracts (obligations) based on the provisions of an authorization bill, but they may not actually expend these funds without an authorization bill.

[54]Some of these projects are quite glaring. One example is the 'Bridge to Nowhere' which would have connected Gravina Island, Alaska to Ketchikan, Alaska. Despite both towns having less than 10,000 inhabitants and a fully functioning ferry already connecting the two towns, the $400 million project was initially funded. The primary champion of the bridge at the time was Senator Ted Stevens, chair of the SoCA. The project was heavily criticized as being the epitome of pork-barrel spending as it was massively expensive and seemed to provide very little economic benefit. Due to public outrage, the bridge was never built, but many similar projects - euphemistically denoted as "High Priority Projects" in recent incarnations of authorization bills- have been completed.

constitutionally all appropriations bills must originate in the House of Representatives.

Once funds have been appropriated, FAHP is authorized to distribute the funds. FAHP grants go through three major phases: apportionment, obligation, and outlays (expenditures). In the first phase, funds are distributed to states. Specifically these funds are made available to state Departments of Transportation (DoT) who can then either directly use the funds or distribute them to local partner agencies within the state. Distributions can either come in the form of either apportionments or allocations. Apportionments are disbursed via statutory formulas, whereas allocations are not. Nearly all "earmarked" spending is disbursed via allocations. I only include apportionments in my analysis, thereby avoiding most of the politically motivated grants.

In the second phase, funds are obligated by states. During this phase the state DoTs select projects either directly or via local partner agencies, subject to FAHP guidelines. Essentially, the federal government sets aside apportionments and designates them towards specific projects for the future payment of work. Once funds for projects are obligated, work begins. By law, apportioned funds must be obligated within four years, but in practice about 70% of apportioned funds are obligated within the first year Leduc and Wilson (2013*a*), and almost all of the remaining funds are obligated the following year.

In the final phase, funds are outlaid (expended) to states as project costs occur. FAHP grants are both reimbursable and matching, therefore states or local agencies initially finance projects and the federal government pay for a certain share of the costs after expenses have occurred. Table 21 gives further details on the federal share for various programs in 2014. The federal share for most programs is 80%, but several programs go as high as 100%. However, those programs are typically small. This final phase is when expenses are recorded in GDP.

Table 21: Programs in FAHP: MAPS-21

Program	Percent of Apportionments	Federal Share of Project Costs	Description
National Highway Performance Program	59.25%	80%	Expand and maintain the National Highway System and connect strategically important highways and roads.
Surface Transportation program	27.25%	80%	Block grants to states for transportation programs, including non-highway programs.
Highway Safety Improvement Program	5.92%	90 %	Reduce serious injuries and fatalities.
Railway-Highway Crossings Program	0.58%	90%	Reduce hazards at railway-highway crossings.
Congestion Mitigation & Air Quality Improvement Program	6.12%	80%	Help states meet National Ambient Air Quality Standards for ozone, carbon monoxide, or particulate matter.
Metropolitan Planning Program	0.84%	80%	Expand and maintain access to highway principal and minor arterials and roads in metropolitan areas.

MAP-21 denotes Moving Ahead for Progress in the 21^{st} Century Act. It covered fiscal years 2012-2014. Values in this table are applicable to MAP-21 only. Programs and percent of total apportionments varies by authorization bills, but the NHPP program consists of the bulk of funding for most recent authorizations. This table only includes programs which are determined via apportionments, thus excluding allocated funds (see Appendix A.2)

B Inverse Distance Weights

The second most commonly used weights are inverse distance weights. This method of weighing weighs by the geographic distance between some geographic centroid within the spatial unit. In general inverse distance weights are defined as $\omega_{ij} = f(d_{ij})^{-1}$, with $f(d_{ij})$ being a nondecreasing function of the distance between states i and j (d_{ij}). In practice, most empirical papers define as a $f(d_{ij})$ linear function so that $\omega_{ij} = \frac{1}{f(d_{ij})}$. My results are mostly robust to using linear inverse distance weights instead of contiguity weights.

A common criticism of spatial models is that the choice of W is somewhat arbitrary. That said, contiguity weights have several advantages over inverse distance weights. First, the interpretation of first order contiguity matrices is straightforward distorted less by later normalization. Second, inverse distance weights are prone to inconsistent results from what amounts to a spatial unit root (see Elhorst (2012) for a more complete discussion). Last, as N gets large, the number of necessary computations increases exponentially. This problem can be mitigated somewhat by use of spare matrix algorithms, which can substantially reduce computing time for matrices with many zeros. Thus, since contiguity matrices are more spare than inverse distance matrices, they are more computationally efficient to estimate.

C Supplementary Tables and Figures

Table 22: Data Sources for Main Results

Variable	Data Manipulations	Source
Inequality	% Growth Rates	Frank(2014)
Federal Apportionments	Real logged per capita	FHWA
State Transportation disbursements	Real logged per capita	FHWA
Senate Appr. Comm. Chair	NA	Federal Registrar
House Appr. Comm. Chair	NA	Federal Registrar
% House Appr. Comm.	NA	Congress Profiles, USHR

Table 23: Flypaper Effect, Log-Log Specification

$Infrastructure_{i,t}$	0.180***	-0.00294	-0.0151	-0.0588	-0.0608	-0.0725
	(0.0597)	(0.0452)	(0.0476)	(0.0577)	(0.0521)	(0.0537)
$Infrastructure_{i,t-1}$		0.210***	0.0253	0.0426	-0.00216	0.00512
		(0.0458)	(0.0210)	(0.0273)	(0.0236)	(0.0221)
$Infrastructure_{i,t-2}$			0.224***	0.0481*	0.0787**	0.0172
			(0.0510)	(0.0270)	(0.0294)	(0.0363)
$Infrastructure_{i,t-3}$				0.219***	0.135***	0.182***
				(0.0609)	(0.0360)	(0.0444)
$Infrastructure_{i,t-4}$					0.109**	0.0205
					(0.0456)	(0.0351)
$Infrastructure_{i,t-5}$						0.117**
						(0.0575)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2784	2736	2688	2640	2592	2544
$\sum_{p=0}^{q} \beta_p$	0.180	0.207	0.234	0.251	0.259	0.270
$H_0 : \sum_{p=0}^{q} \beta_p = 0$	0.004	0.001	0.000	0.000	0.000	0.000
$H_0 : \sum_{p=0}^{q} \beta_p = 1$	0.000	0.000	0.000	0.000	0.000	0.000

* $p < .1$, ** $p < .05$, *** $p < .01$; Standard errors in parentheses are clustered at the state level. Dependent variable log is real per capita state disbursements on highways. Infrastructure is log real per capita FAHP apportionments in levels.

Table 24: Probability of Construction Occupations Being Computerized

Rank	Probability	Occupation Title
154	0.069	Construction Managers
199	0.17	First-Line Supervisors of Construction Trades and Extraction Workers
300	0.5	Installation, Maintenance, and Repair Workers, All Other
350	0.63	Construction and Building Inspectors
352	0.64	Maintenance and Repair Workers, General
390	0.71	Construction and Related Workers, All Other
411	0.75	Painters, Construction and Maintenance
434	0.79	Helpers – Installation, Maintenance, and Repair Workers
499	0.86	Maintenance Workers, Machinery
511	0.87	Highway Maintenance Workers
512	0.88	Construction Laborers
528	0.89	Rail-Track Laying and Maintenance Equipment Operators
617	0.95	Operating Engineers and Other Construction Equipment Operators

Sourced from Frey and Osborne (2017). Selected based on occupations which contained at least one of the following terms: Construction, Maintenence, Highway.

Figure 10

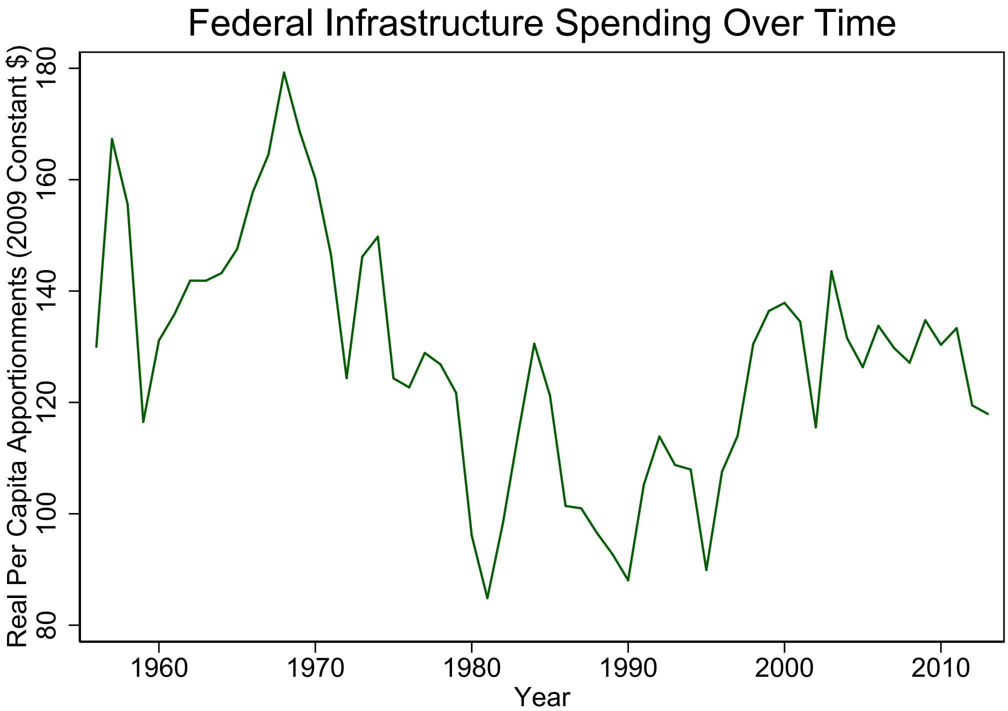
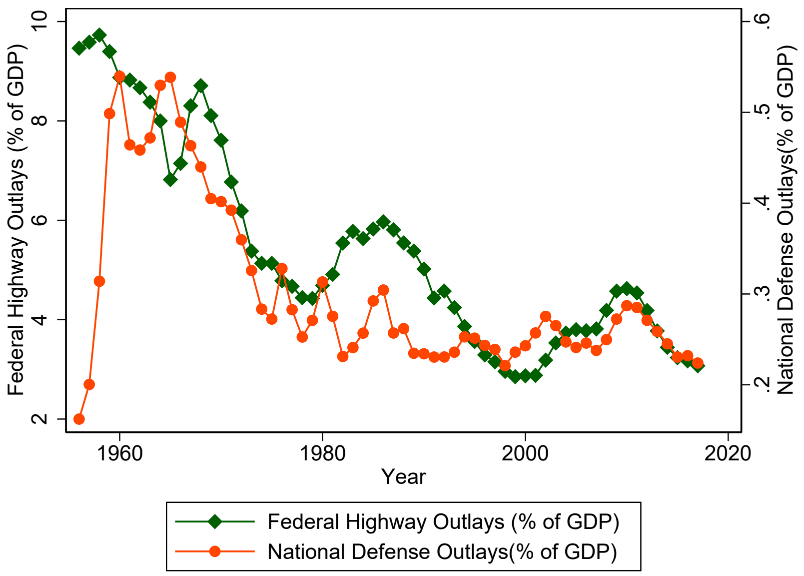


Table 25: Probability of Transportation Occupations Being Computerised

Rank	Probability	Occupation Title
105	0.029	First-Line Supervisors of Transportation and Material − Moving Machine and Vehicle Operators
227	0.25	Ambulance Drivers and Attendants, Except Emergency Medical Technicians
279	0.42	First-Line Supervisors of Helpers, Laborers, and Material Movers,
372	0.67	Bus Drivers, Transit and Intercity
380	0.69	Light Truck or Delivery Services Drivers
431	0.79	Heavy and Tractor-Trailer Truck Drivers
483	0.85	Laborers and Freight, Stock, and Material Movers
525	0.89	Bus Drivers, School or Special Client
531	0.89	Taxi Drivers and Chauffeurs
674	0.98	Driver/Sales Workers

Sourced from Frey and Osborne (2017). Selected based on occupations which contained at least one variation of the following terms: Drive, Move.

Figure 11



This figure compares Federal highway outlays as a share of GDP (left axis) to national defense outlays as a share of GDP. Federal highway outlays are sourced from the Office of Management and Budget Historical Tables

Figure 12

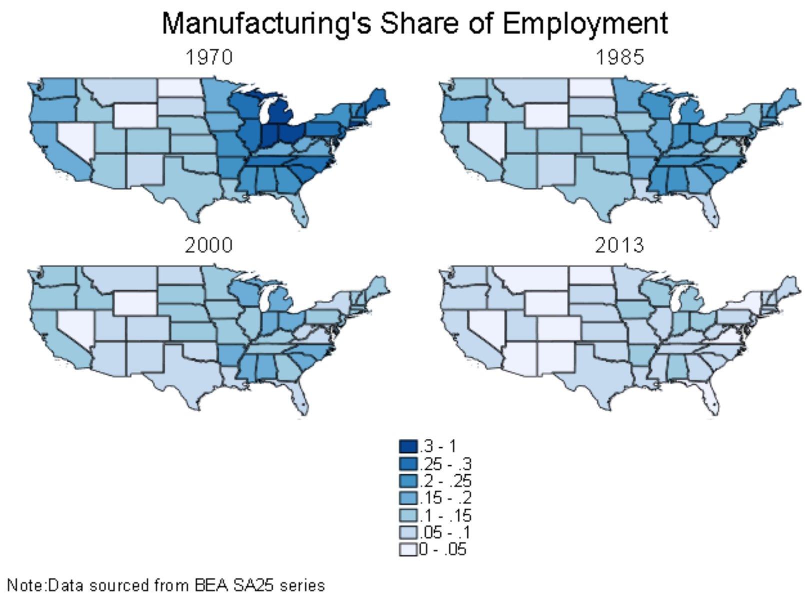


Figure 13

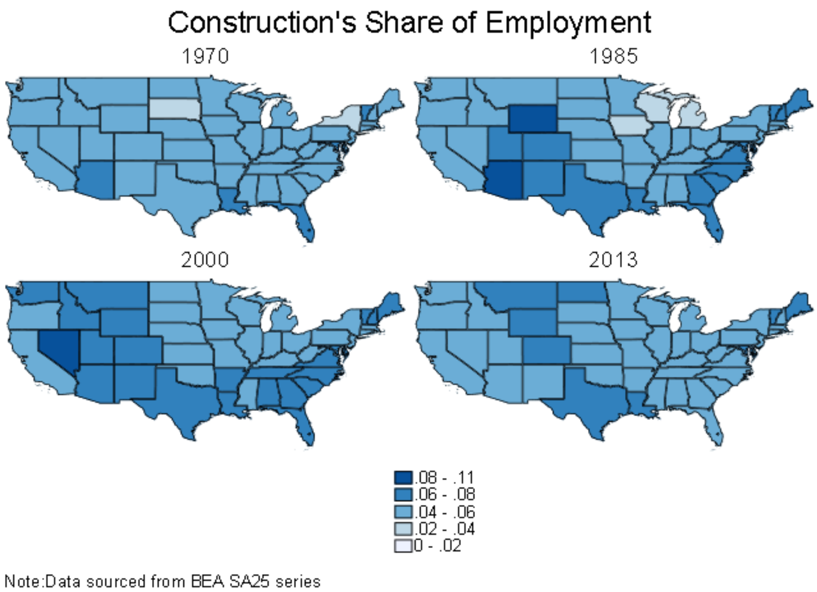
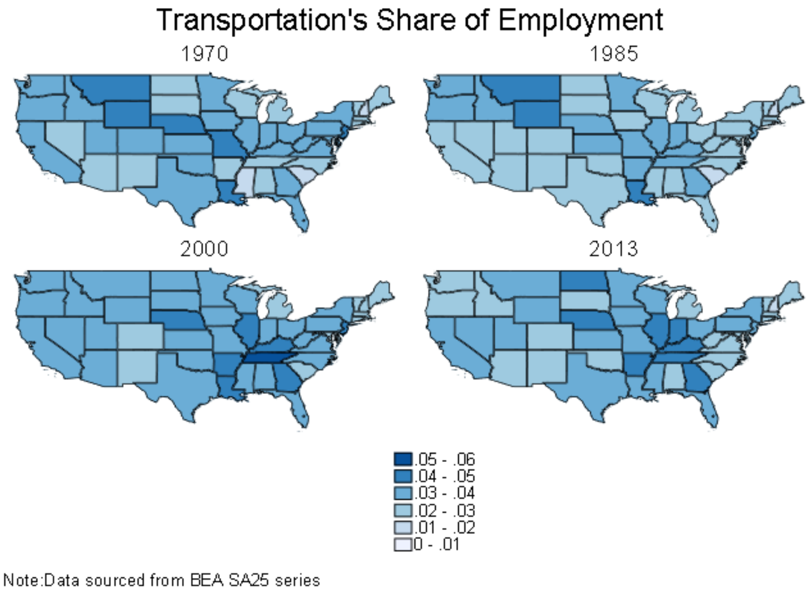

Construction's Share of Employment
1970
1985
2000
2013
.08 - .11
.06 - .08
.04 - .06
.02 - .04
0 - .02
Note:Data sourced from BEA SA25 series

Figure 14



Transportation's Share of Employment
1970
1985
2000
2013
.05 - .06
.04 - .05
.03 - .04
.02 - .03
.01 - .02
0 - .01
Note:Data sourced from BEA SA25 series