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Does Race and Gender Inequality Impact Income Growth?

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Abstract

Using Integrated Public Use Microdata Series–United States micro-census data from 1960 to 2010, this paper examines whether racial and gender income disparities beget inequality by differentially impacting the growth prospects of the poor, the middle class, and the rich. Racial and gender inequality is found to be bad for income growth of the poor, but not for that of the rich. An investigation into the channels of this effect suggests that higher racial and gender inequality is associated with lower human capital accumulation among the poor and a reduction in the quality of their jobs.

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Does Race and Gender Inequality Impact Income Growth?[1]

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1. Introduction

Race and gender are two of the most important factors explaining income disparities between US citizens.[2] Since the racial gap and the gender gap may confluence and reinforce each other, they have been referred to as 'the double gap' (Holder, 2020). Chetty et al. (2020) show that, after controlling for parental income, black individuals have lower earnings than white individuals for 99% of Census tracts in the US. The gender pay gap too is large in the US when compared to other advanced countries. Blau and Kahn (2000) observe that this is in large part due to the high level of wage inequality in the US. A direct consequence of racial and gender inequality is the misallocation of talent, which could be detrimental to aggregate economic performance (Hsieh et al., 2019).

This study investigates whether and how racial and gender inequality (RGI) have differential impacts on the income growth prospects of the poor, the middle class and the rich. RGI could cause inefficiency and slower income growth through different channels. We consider the accumulation of human capital and success on the labor market as the channels of transmission through which RGI may affect both the rate and the structure of income growth. These channels capture two distinct stages of an individual's life cycle. This allows us to evaluate whether the effects of RGI primarily manifest themselves early in life (during school years) versus later in life (when the individual enters the labor market).

Using individual-level data from the IPUMS-USA that samples between 1 and 5 percent of the US population, we build a state-level database covering the period 1960 to 2010 (every ten years) that tracks overall income inequality, race and gender inequality, measures of education attainment and labor market outcomes, and income growth rates across the income distribution.[3] The effect of within-state RGI on income growth for the different income groups is estimated by means of a reduced-form growth equation. To isolate the effect of RGI on income growth, we control for state and time fixed effects, and overall inequality.[4]

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[2] See Card and Krueger (1992), Oliver and Shapiro (1995), Darity et al. (1998), Goldsmith et al. (2007), Loury (2009), Conley (2009), and Heywood and Parent (2012), among many others.

[3] The IPUMS-USA is the largest individual-level database available for the US that includes data on individual income, education, age, race and gender. Information is available every ten years, and data are representative at the country and state levels.

[4] The IPUMS-USA is used to derive a set of controls including variables on demographics, education, and employment. Additional controls such as exposure to imports from China and the percentage of routine

Pooled OLS estimation of the growth equation may suffer from endogeneity problems. To address this concern, we adopt an instrumental variables (IV) approach based on Brueckner et al. (2012) and Brueckner and Lederman (2018). Our instrument for income, which is needed to construct the instruments for inequality and RGI, is obtained by interacting the (sectoral) occupation composition of each state in 1960 with a common time trend over the period under consideration (Luttmer, 2005).

Our main finding is that RGI leads to stagnant income growth of the poor and the lower middle class. This result is robust to using different methods of estimation (Pooled-OLS with fixed effects and System-GMM), different model specifications (static versus dynamic), different samples, and alternative inequality indices (the Mean Logarithmic Deviation versus the Gini index).

We furthermore test an alternative explanation for our finding that has largely been overlooked in the literature on the inequality-growth relationship: between-state migration. It is plausible that disadvantaged individuals looking for better opportunities migrate from high to low RGI states. These movements could conceivably explain the negative relationship between RGI and income growth of the poor. To analyze this possibility, we re-calculate overall inequality, RGI and growth using only non-migrant observations, and re-estimate the growth regressions. Although migration from high RGI states to low RGI states is indeed observed, the flows are relatively small and do not alter our main result.

Next, we explore the role of human capital accumulation and labor market success as potential channels of transmission through which RGI might affect the income growth rates of the poor. Our findings are three-fold. First, RGI has a negative and significant effect on education attainment among the poor. This resonates with the findings of Card and Krueger (1992), who conclude that improvements in the educational system for the black population explain about 20 percent of the narrowing of the black-white earnings gap between 1960 and 1980. Second, higher RGI is associated with greater employment among the poor, which is an unexpected result. A further exploration of the labor market channel reveals that RGI helps to create more jobs for the poor but of lower quality, which marks our third finding. Sorting into lower quality jobs may stem from lower quality education and hence lower skills, although we cannot test this with our data. In summary,

jobs are obtained from Autor et al. (2013). Note that the effect of inequality on growth due to factors other than race and gender could accrue to RGI if overall inequality is omitted from the growth equation.

we find that RGI hampers the income growth prospects of the poor by reducing their attained years of education and the quality of their jobs.

Our findings are important for two reasons. First, they provide a rationale for policies that aim to reduce race and gender disparities.[5] Second, they help pinpoint the components of inequality that are bad for growth.[6]

The rest of the paper is organized as follows. Section 2 describes the database and presents the estimation of RGI. Section 3 presents the empirical model and our main results. Section 4 analyzes whether between-state migration may explain the observed relationship between RGI and income growth at the state level. In Section 5, we examine whether human capital accumulation and labor market success act as potential channels of transmission through which RGI impacts income growth. Finally, Section 6 concludes.

2. Data and measurement of racial and gender inequality

Using individual level data from the IPUMS-USA from 1960 to 2010 (at 10-year intervals), we build a state-year panel database that tracks total income inequality, RGI, education attainment, employment, and income growth at selected percentiles of the income distribution. In this section, we describe the IPUMS-USA database, introduce our measure of RGI, and show the trends and patterns in overall inequality, RGI and income growth across the US states.

[5] Beyond promoting fairness (Rawls, 1971; Sen, 1980; Roemer, 1993), such public interventions can increase economic growth by reducing inefficiencies.

[6] Early theoretical work viewed inequality as a positive factor. Among the arguments put forward is that income inequality facilitates saving (Kaldor, 1956), investing (Barro, 2000), and hard work (Mirrlees, 1971). More recent studies have found conditions under which inequality may be bad for growth. Galor and Zeira (1993) and Banerjee and Newman (1993) put the emphasis on credit market imperfections. Persson and Tabellini (1994) and Alesina and Rodrik (1994) on redistributive policies. Dasgupta and Ray (1987) and Murphy et al. (1989) on the development process and Kremer and Chen (2002) on the fertility channel. Empirical findings are also mixed (Barro, 2000; Banerjee and Duflo, 2003; Panizza, 2002; and Voitchovsky, 2005). Our findings complement recent studies that hypothesize that inequality has distinct offsetting effects on growth (Voitchovsky, 2005; Marrero and Rodríguez, 2013), which may cancel out in the aggregate. These inequalities may furthermore affect the poor, the middle-class, and the rich differentially (van der Weide and Milanovic, 2018).

2.1. The IPUMS-USA database

The IPUMS-USA database contains the largest sample of the US population – between 1 and 5 percent of the total population – that spans a period of 50 years at regular decennial intervals: 1960, 1970, 1980, 1990, 2000 and 2010.[7] The database is representative at the state level. The large size of the IPUMS-USA means that the sampling errors are reduced to a minimum. For their special features, Alaska, Hawaii, District of Columbia and Puerto Rico are omitted.

The total annual income variable measures the sum of eight different sources of income: (*i*) wages, salary, commissions, bonuses and tips; (*ii*) self-employment income; (*iii*) interest, dividends, net rental income, and income from estate/trusts; (*iv*) social security and railroad retirement; (*v*) supplemental security income; (*vi*) public assistance and welfare payments; (*vii*) retirement, survivor and disability pensions; and (*viii*) other regular sources of income, such as veterans payments, unemployment compensation, child support or alimony. All incomes are expressed in 2010 prices by means of national CPI to adjust for inflation.

The measures of inequality are computed using individual income for the highest income earner within the household (i.e., the household's head) and for our baseline sample, we restrict individuals to be between 25 and 65 years old. We use individual income for our measures of inequality because the estimation of RGI requires the observation of individual attributes, notably race and gender, as discussed in more detail below. Income growth is evaluated for total household income per capita.

The IPUMS-USA database is also used to construct a set of control variables, namely: (*i*) the percentage with a graduate college degree among individuals between the ages of 21 and 39 ('*Share of graduates* (*age 21-39*)');[8] (*ii*) the population share aged 15 or younger ('*Pop. aged 0-15* (*%*)'); and (*iii*) the population share aged 65 or older ('*Pop. aged 65+* (*%*)'). We expand the number of controls by considering two variables that are important for explaining growth in the US, namely *the percentage of routine jobs* and *exposure to*

[7] The data cover 1 percent of the population for the years 1960-70 and 2010, and 5 percent of the population for the years 1980-2000.
[8] We use the share of young, graduated adults rather than considering all adults because the former exhibits more variation over time and hence carries more information over and above the state fixed effects.

imports from China (Autor et al., 2013). The data on these two variables cover all decades between 1960 and 2000.

2.2. Measuring racial and gender inequality

This section presents the measures of between-race-gender inequality used. The proposed approach accounts for the interactions between race and gender that are found to be relevant for the US (Chetty et al., 2020).[9] We first partition the population into groups according to individuals' race and gender. More specifically, consider a finite population of individuals indexed by $i \in \{1, \dots, N\}$ and suppose that the population is partitioned into mutually exclusive and exhaustive groups denoted by $\Phi = \{1, \dots, M\}$, where all individuals of a given group m share the same race-gender pair. In our case, we have a total of eight groups, resulting from the combination of two groups for gender (women and men) and four groups for race (non-Hispanic whites, Hispanic whites, Blacks and Others).

Individual income will be independent of race and gender when the corresponding income distributions across groups would coincide, i.e., $F^m(y) = F^{m'}(y), \forall\, m, m' \in \Phi$, where $F^m(y)$ and $F^{m'}(y)$ denote the income distribution for individuals of groups m and m', respectively. One could test for this property by estimating the income distribution of each group and evaluating the significance of the difference. If one distribution dominates the other, then this would offer unambiguous evidence against equality of income by race and gender. Unfortunately, relying on stochastic dominance does not generally guarantee to rule one way or the other. Distributions can be significantly different yet cross each other in which case it is unclear whether one group is better off than the other (Atkinson, 1970).

To break potential ties and to obtain a comparable measure for the different groups, a practical alternative is to focus on a specific moment of the corresponding income distributions. Consider, for example, mean income. Let the vector $y = (y^1, \cdots, y^M)$ be the partition of income into the M groups, μ_m the mean of the income distribution y^m and N_m the population size associated with y^m, where $N = \sum_{m=1}^{M} N_m$. Let $\bar{y} = (\mu_1 1^{N_1}, \mu_2 1^{N_2}, \dots, \mu_m 1^{N_m})$ where 1^N is an N-coordinated vector of ones, denote the N-dimensional smoothed version of y, where each individual of group m receives the mean

[9] For the approach we borrow from Roemer (1993 and 1998), van de Gaer (1993), and Fleurbaey (2008).

income level of that group. Then, a measure of inequality by race and gender can be obtained by evaluating $I(\bar{y})$, where $I(\cdot)$ is a particular inequality index.

Of all the possible inequality indices that fulfill the basic principles found in the literature on inequality (progressive transfers, symmetry, scale invariance and replication of the population), only those of the Generalized Entropy class are additively decomposable into a between-group and a within-group component (Bourguignon, 1979 and Shorrocks, 1980).[10] We use the Mean Logarithmic Deviation (I_{MLD}), because it belongs to the Generalized Entropy class, has a path-independent decomposition and respects the principle of monotonicity in distance.[11] For an income distribution y, with mean μ, the Mean Logarithmic Deviation is defined as:

$$I_{MLD}(y) = \frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{\mu}{y_i}\right), \tag{1}$$

where N denotes the number of income recipients. Then, taking advantage of the additive decomposability property of the Mean Logarithmic Deviation and grouping individuals by racial and gender groups, total inequality can be exactly decomposed as follows:

$$I_{MLD}(y) = I_{MLD}(\mu_1 1^{n_1}, \mu_2 1^{n_2}, \ldots, \mu_m 1^{n_m}) + \sum_{m=1}^{M} \frac{N_m}{N} I_{MLD}(y^m). \tag{2}$$

Expression (2) provides a breakdown of overall income inequality into between-group and within-group terms. The between-group component (i.e., the first term in (2)) is our measure of the double gap (RGI), and the within-group component (i.e., the second term in (2)) represents the weighted sum of income inequalities within racial and gender groups.[12]

Between-group inequality can be estimated either non-parametrically (Rodríguez, 2008 and Checchi and Peragine, 2010) or parametrically (Bourguignon et al., 2007b, and Ferreira and Gignoux, 2011). There is a premium for imposing additional structure by

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[10] When different income groups overlap, which occurs in our case, the Gini coefficient is decomposable in three terms: a between-group component, a within-group component and a residual. The problem here is how to assign the residual to the between-group versus the within-group components. For this reason, we use the Mean Logarithmic Deviation (I_{MLD}) as our baseline inequality measure and consider the Gini coefficient for robustness.

[11] The path-independent property implies that the result of the decomposition is independent of the component that is eliminated first, the between-group inequality or the within-group inequality (Foster and Shneyerov, 2000). On the other hand, only the I_{MLD} satisfies both principles, transfers and monotonicity in distance, simultaneously (Cowell and Flachaire, 2018).

[12] It follows that variation in between-group inequality will reflect both variation in group populations shares in each state and the differences in incomes across race and gender. See Elbers et al. (2008) for a discussion and an alternative measure of between-group inequality that is normalized with respect to the number of groups and their relative sizes.

means of the parametric approach when the data are limited (and/or the number of groups is large relative to the amount of data). Since our database covers between 1 and 5 percent of the total population, however, we can take full advantage of the flexibility and minimal assumptions offered by the non-parametric approach.

2.3. A first look at the data: Trends in racial and gender inequality in the US

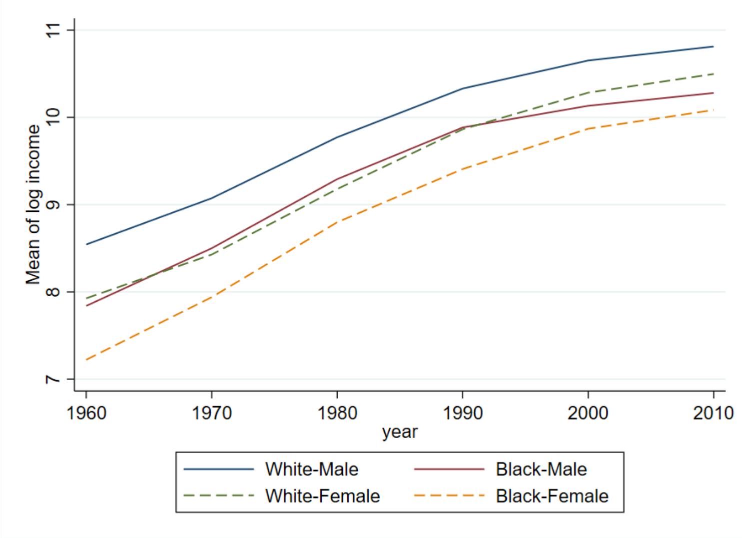
This section provides a brief overview of the trends and patterns in race-gender inequality, total inequality, and income growth for the period 1960 to 2010. Similar results for the control variables are presented in Appendix A. Figure 1 plots the income levels by race and gender in the US for each decade.[13] White individuals consistently earn more than Blacks (regardless of their gender), and men consistently earn more than women (regardless of their race). However, the racial gap is high and stable for men, while it is more modest and declining for women.

The gender gap has narrowed for both racial groups, yet the convergence is most notable for the black population.[14] Overall, white men (the initially most advantaged group) maintain their income advantage. While we see a narrowing of the gender gap (between white men and women), we observe a slight increase in the racial gap (between white and black men). The decline in relative incomes of black men is most visible after 1990. Over the entire 50 years period, black women (the initially most disadvantage group) are seen to have gradually improved their income position with respect to all groups considered.

Figure 2 plots the Growth Incidence Curves (GIC) that evaluate the decennial income growth rates for each gender-race group across their income distribution. Low- and middle-income households are observed to have experienced visibly different trends in income growth rates compared to top-income households. The 1960s can be characterized as a period of inclusive growth since lower income households (approximately, the bottom 25%) enjoyed higher growth rates than the other income groups. Although this trend is observed for all four gender-racial groups, it is most notable for black women, which is initially the most disadvantaged group (as shown in Figure 1).

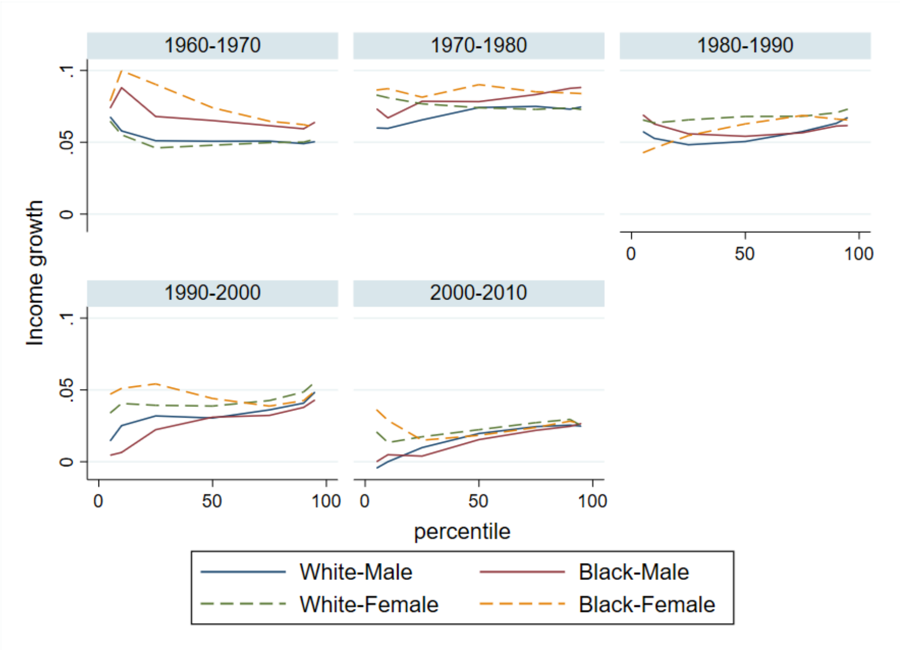
[13] To simplify the exposition of this section, we only show the results for non-Hispanic whites and Blacks. The results for Hispanics and Others are available from the authors upon request.
[14] Chetty et al. (2020) for intergenerational mobility and Bishop et al. (2021) for intragenerational mobility find that the differences between Whites and Blacks in the US arise primarily from the labor market experiences of black men, rather than of black women.

Figure 1. Average income by race and gender in the US (1960-2010).



Note: Data by decades are from IPUMS-USA (1960-2010).

Figure 2. Growth Incidence Curves by race and gender in the US (1960-2010).



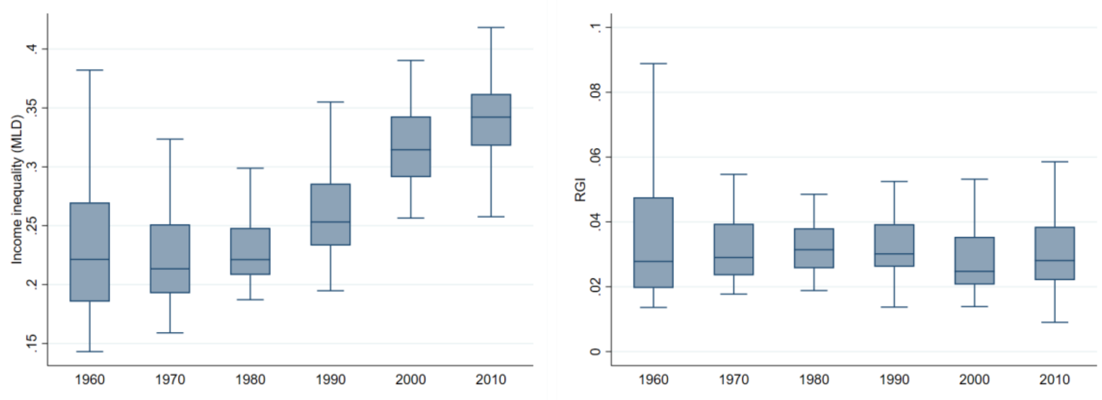
Note: Data by decades are from IPUMS-USA (1960-2010).

Looking at general trends, however, the 1970s mark the transition from inclusive to exclusive growth (i.e., poor and middle-class population groups experienced lower income growth rates than the rich), as far as most GICs turns upward sloping above the

25th-50th percentile, depending on the group and decade. There are some exceptions to this trend, see for example the GIC for the poorest black women in the 1990s and 2000s.

The divergence in growth rates between lower income and top-income households since the 1980s resulted in an increase in inequality. This is confirmed in Figure 3 (left panel), which shows the time-trend in total income inequality (measured by the MLD). Over the same period, income differences across race and gender have been rather stable (Figure 3, right panel). When only income differences across racial groups are considered, estimates (not reported here) show that between-group inequality has in fact increased since the 1980s. Accounting for gender in addition to race is found to flatten the trend in between-group inequality since the gender gap, especially for the black population, has decreased.[15]

Figure 3. Inequality (MLD; left panel) and RGI (right panel) in the US (1960-2010).



Note: Data by decades are from IPUMS-USA (1960-2010).

3. Racial and gender inequality versus income growth

We estimate a reduced-form growth equation at different percentiles of the income distribution, including both overall inequality and our measure of RGI, added to an otherwise standard set of growth determinants.

[15] The share of overall inequality due to RGI is relatively high by international standards (Ferreira et al., 2018), as of 2010 about 10 percent of total inequality, but has come down in recent decades (not reported). This suggests that the rise in overall income inequality is due to increasing inequality within populations of given race and gender rather than due to increases in the income differences between them.

3.1. The reduced-form growth equation

The reduced-form growth equation that describes the link between income growth and RGI for different segments of the population takes the form:

$$y_{qit} - y_{qit-1} = \beta_q y_{qit-1} + \alpha_{qi} + \delta_{qt} + \theta_q RGI_{it-1} + \gamma_q I_{it-1} + \omega_q^T x_{it-1} + \varepsilon_{qit}, \quad (3)$$

where y_{qit} denotes the log of per capita income for population segment q in state i at year t; α_{qi} and δ_{qt} denote state and time-fixed effects for each segment q. Income is expressed in real terms, and explanatory variables are always lagged one period (10 years in our case). I_{it-1} and RGI_{it-1} are measures of lagged overall inequality and between-race-gender inequality in state i at time $t-1$, and y_{qit-1} is the lag of income (in logs) to control for conditional convergence between US states. Other than lagged income and overall inequality, the vector of control variables is denoted by x_{it-1}, which includes the variables described in the previous section. We consider the following selection of percentiles: 5th, 10th, 25th, 50th, 75th, 90th and 95th and use data from the following non-overlapping decades: 1960, 1970, 1980, 1990, 2000 and 2010. The parameters in equation (3) are estimated for each q separately. Two observations concerning equation (3) are worth noting. First, by omitting total inequality from the growth regression, we are forcing the impact of inequality due to factors not related with race and gender (for example, socioeconomic background) on growth to accrue to RGI. Therefore, to isolate the effect of race and gender inequality on growth, both lagged RGI and lagged total inequality need to be included. Second, we are interested in the sign of θ_q, for all q. If income gaps due to race and gender have a growth deterring effect at a particular percentile q, then we should find that $\theta_q < 0$. On the contrary, if $\theta_q > 0$, income differences by race and gender would enhance growth at this particular position in the income distribution.

3.2. Baseline: Pooled-OLS with state and time fixed effects

Table 1 presents, for each income percentile considered, robust pooled-OLS estimates for our baseline specification with state and time fixed effects.[16] For illustrative purposes, we also show the results for average income (2nd column). The coefficient for total inequality is found to be insignificant for all income percentiles except the 5th for which it is positive.

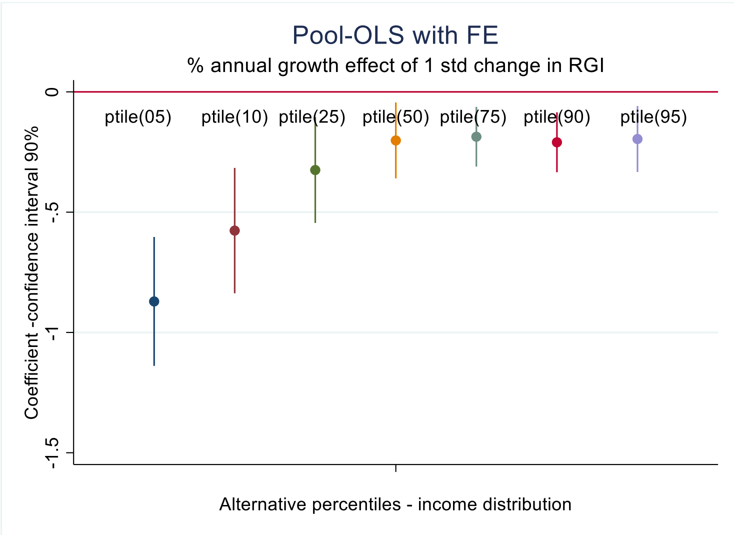
[16] To facilitate robustness, we drop outliers (observations for which the studentized jackknifed residual is greater than 2). For this reason, the sample size *N* may slightly change across regressions.

This result mirrors the inconclusive nature of the empirical literature on inequality and growth.

By contrast, the effect of RGI is negative and significant for income growth across the income distribution. Strikingly, this negative effect is largest for the poor and the lower middle-income class (Figure 4). The coefficient is near-zero for the upper middle-income class and the rich (albeit still negative and still statistically significant).

INSERT TABLE 1 ABOUT HERE

Figure 4. Pool-OLS with FE estimates by percentiles.



Let us also briefly comment on the effects of the controls on income growth. Higher levels of education (measured by the share of young adults who have a college degree) are positively correlated with growth across the income distribution. Likewise, a larger share of the working age population registers as a positive factor for income growth. The share of routine jobs has a positive and significant effect on income growth for low and middle-income households. Conditional convergence between states captured by the coefficient for lagged (log) income is always negative and significant. Finally, the exposure to trade from China is found to be insignificant in the income growth regressions.

3.3. Instrumental variables approach with state and time fixed effects

The objective is to resolve potential reverse causality bias of our key parameters, θ_q and γ_q, from equation (3). We closely follow the proposal developed by Brueckner et al.

(2012) and Brueckner and Lederman (2018). Their IV approach consists of two steps. In the first step, to capture the reverse causality effect from income to RGI and total inequality, we estimate, for each income percentile q, the following two equations:

$$RGI_{it} = \eta_{qi} + \kappa_{qt} + \pi_q y_{qit-1} + \varsigma_q^T x_{it-1} + u_{qit}, \tag{4}$$

$$I_{it} = \lambda_{qi} + \psi_{qt} + \varphi_q y_{qit-1} + \mu_q^T x_{it-1} + \nu_{qit}, \tag{5}$$

where x_{it-1} is the vector of control variables included in (3) and the variables η_{qi}, λ_{qi}, κ_{qt} and ψ_{qt} denote state and time fixed effects for each regression.

For the construction of the instrument for y_{qit-1}, which is needed to obtain unbiased estimates of π_q and φ_q from equations (4) and (5) (Brueckner et al., 2012), we follow Luttmer (2005) and Boustan et al. (2013) and use the cross-industry variation in employment as a source of identification. More specifically, the instrument for y_{qit-1} is the predicted value of y_{qit} (and lagged ten years) derived from the following pooled-OLS regression:

$$y_{qit} = \vartheta_{qi} + \varrho_{qt} + \zeta_q^T w_{it} + \xi_{it}, \tag{6}$$

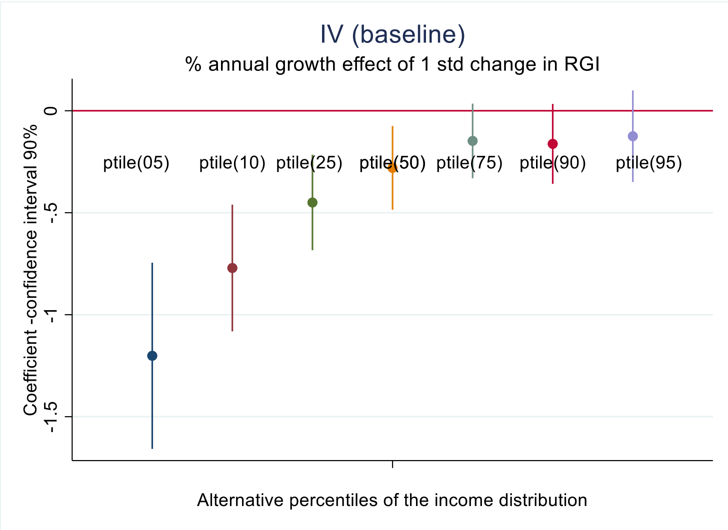
where ϑ_{qi} and ϱ_{qt} denote state and time fixed effects, and w_{it} is a vector of the occupation composition of each state (the employment shares of agriculture, construction, manufacturing, transportation, finances and public sector) measured in 1960 and multiplied by a common time trend.

In the second step, we construct the instruments for RGI and inequality, denoted by (RGI^{ins} and I^{ins}), which are the parts of RGI and I that are not explained by the lag of per capita income (in logs), once we have controlled for fixed effects and x_{it-1}, i.e., $RGI_{qit}^{ins} = RGI_{it} - \hat{\pi}_q^{IV} y_{qit-1}$ and $I_{qit}^{ins} = I_{it} - \hat{\varphi}_q^{IV} y_{qit-1}$. Finally, with these instruments in hand, we are ready to estimate equation (3) by means of IV.[17]

[17] Our approach departs from the strategy proposed in Brueckner et al. (2012) and Brueckner and Lederman (2018) in two ways. First, we include the array x_{it-1} and consider y_{it-1} instead of y_{it} (they estimate contemporaneous regressions) in equations (4) and (5). We add the vector of explicative variables x_{it-1} to reduce omitted variable bias to a minimum, and use y_{it} and x_{it} with lags to avoid strict multicollinearity when using I_{it-1}^{ins} and RGI_{it-1}^{ins} as instruments for I_{it-1} and RGI_{it-1} in the estimation of equation (3). Second, following Luttmer (2005) and Boustan et al. (2013), we use cross-industry variation in employment for the identification of y_{it-1} in equation (6), for the average income and for each percentile q.

Table 2 and Figure 5 present the results.[18] The effect of RGI is negative and significant for average income (second column) and the bottom half of the income distribution (percentiles 5th, 10th, 25th and 50th). Also, the negative effect of RGI is strongest for the poor and lower middle-class (see Figure 5). Interestingly, total inequality is found to be positive and significant for the income growth of the 5th and 10th percentiles. When RGI is accounted for, total inequality has a positive influence over the income growth of the lowest quantiles.

Figure 5. Instrumental variable estimates by percentiles.



The Kleibergen Paap F-statistics for weak identification are well above the critical values tabulated in Stock and Yogo (2005), rejecting the null of weak instruments. The LM test statistics for underidentification furthermore reject the null hypothesis that instruments are irrelevant in all cases (see the *p*-values of the underidentification LM statistics).

For the controls, the results closely match those obtained with Pooled-OLS. Higher education and larger shares of the working age population enhance growth across the different income quantiles. Exposure to trade from China does not significantly affect growth, while the share of routine jobs prompts the growth of low and middle-income

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[18] To test the validity of the instruments, we use a test of weak identification based on the Kleibergen-Paap Wald *F*-statistic and a test of underidentification based on the *F*-statistic. The validity of the instruments used in the first stage (equation 6) is not rejected. These results are not reported here but they are available from the authors upon request.

households. Conditional convergence between states is again negative and significant for all percentiles of the income distribution.

INSERT TABLE 2 ABOUT HERE

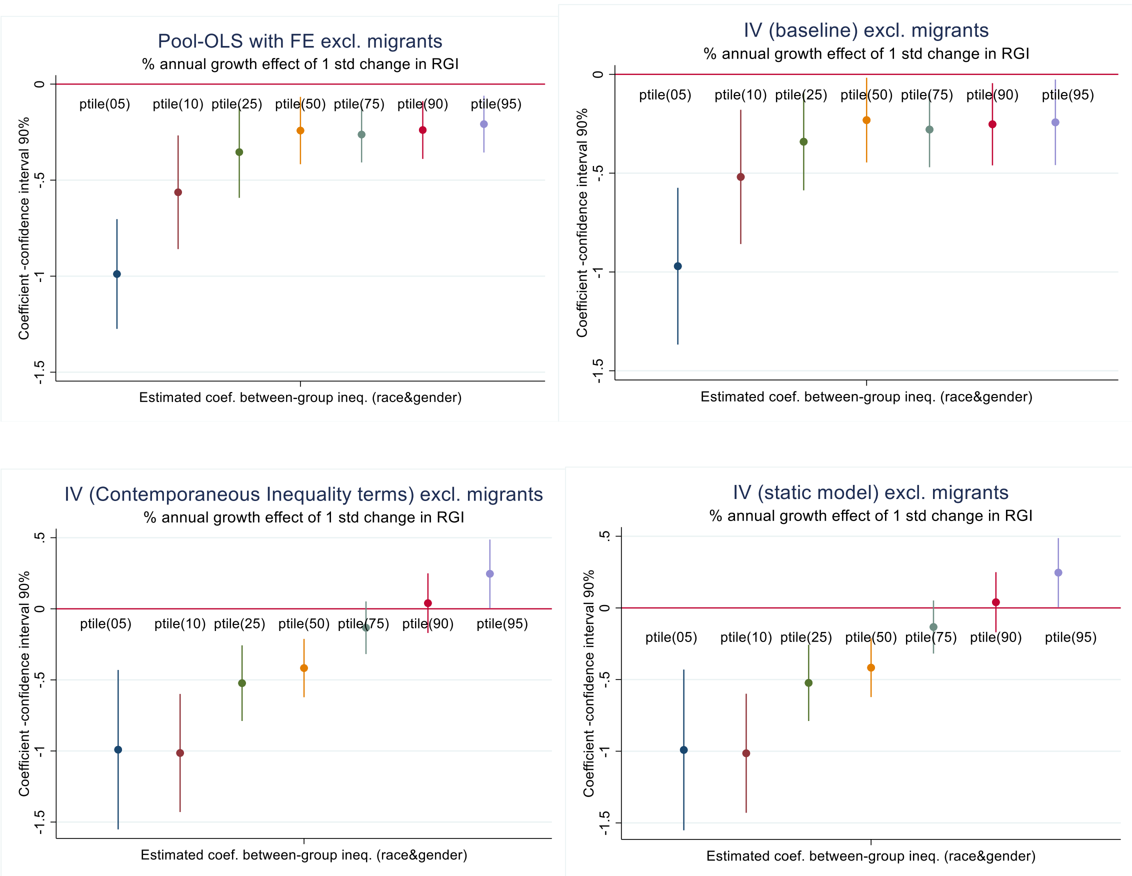
To evaluate the robustness of our main result – that RGI disproportionally hurts the growth prospects of the poor – we carry out a set of alternative exercises (see Appendix B). First, we estimate – using IV – two alternative model specifications: (*i*) model (3) with contemporaneous RGI and total inequality, and (*ii*) a static model with contemporaneous RGI and total inequality but without the lag of per capita income. Second, we use an alternative method of estimation, the System-GMM (Arellano and Bover, 1995; Blundell and Bond, 1998), that employs internal instruments to address the endogeneity of regressors. Third, we modify the sample under consideration in two different ways: *i*) the measures of inequality are calculated only for head households between the age of 30 and 50, and *ii*) the state-year observations for which the share of white population is larger than 95% are dropped. Finally, we estimate the baseline model (3) using IV after measuring inequality and RGI by two different inequality indices: *i*) the Gini index (recall footnote 10), and *ii*) the share of between-race-gender inequality over total inequality, $I_{MLD}(\bar{y})/I_{MLD}(y)$. All alternative specifications, methods of estimation, samples and inequality measures reproduce the same result: RGI has a negative and significant effect on income growth for the bottom half of the income distribution.

4. The role of between-state migration

It is conceivable that the negative effect of income differences by race and gender on growth of the poor is in part driven by between-state migration. For ease of exposition, suppose that the US can roughly be divided into two types of states, low and high RGI states. Let us assume that, between periods t and $t+1$, poor individuals with black origin migrate from high RGI to low RGI states. Keeping all else equal, this migration could increase (decrease) the growth rate at low percentiles between time t and $t+1$ in high (low) RGI states, and hence predicts a positive correlation between initial RGI and future growth of the poor. Consider now the possibility that it takes time for poor migrant individuals to adjust to the low RGI states that they have migrated into. As a result of the arrival of poor individuals (for example, poor Blacks), the low RGI states will probably report now an increased level of RGI (due to the widening of the income gap between whites and blacks). Higher income gaps by race and gender will then combine with lower levels of growth for poor households in the low RGI states. But this result would not be because of a high initial level of RGI in these states, in fact quite the opposite.

To examine whether our main results are generated by this migration mechanism, we re-compute total inequality, RGI and income growth using only non-migrant observations (i.e. dropping all migrants from the sample), and re-estimating equation (3). The IPUMS-USA database includes a variable that records in what state the individual was residing 5 years earlier, with the exception of the 2000/10 round where a 1-year recall is adopted. We use this variable to compute between-state migration flows, and then to drop all respondents that are defined as migrants on the basis of this variable. The migration flows are defined as the number of migrants moving from origin state to destination state divided by the population of the origin state.

Figure 6. Pool-OLS with FE and IV estimates by percentiles without migrants.



The migration flows are estimated to range between 3% and 20%, and just below 10% on average. They are furthermore found to be counter-cyclical, suffering severe reductions after the oil crisis in the 1980s and the financial crisis in the 2010s. A further exploration of migration flows data reveals that high out-migration is disproportionally white. We also observe evidence of "racial sorting" across US states: white individuals are more likely to migrate out of states with lower proportion of whites (and are more likely to migrate to states with higher proportion of Whites), while the same holds true for Blacks, i.e. black individuals migrate from "non-black" to "black" states.[19]

The observation that migration flows are reasonably modest in size and individuals do not necessarily favor states with low RGI over states with high RGI make between-state migration a less likely candidate for explaining the negative relationship we observe between racial and gender inequality and future income growth among the poor. Nonetheless, we test this hypothesis by dropping all migrants from the database and re-estimating the growth regressions for Pool-OLS with FE, IV (baseline model) and IV with contemporaneous RGI and inequality (dynamic and static models). The results obtained without migrants, presented in Figure 6, are nearly identical to those obtained using the entire population (including migrants). This suggests that between-state migration is unlikely to explain the negative effect of between-race-gender inequality on income growth of low-income households.

5. Channels of transmission: Education and the labor market

The negative effect of RGI on income growth could operate through different channels. In this section we evaluate education and the labor market as the potential channels of transmission from RGI to income growth of the poor. Note that these channels capture two distinct stages of an individual's life cycle. This allows us to evaluate to what extent the negative effects of RGI manifest themselves early in life (during school years) versus later in life (when the individual enters the labor market).

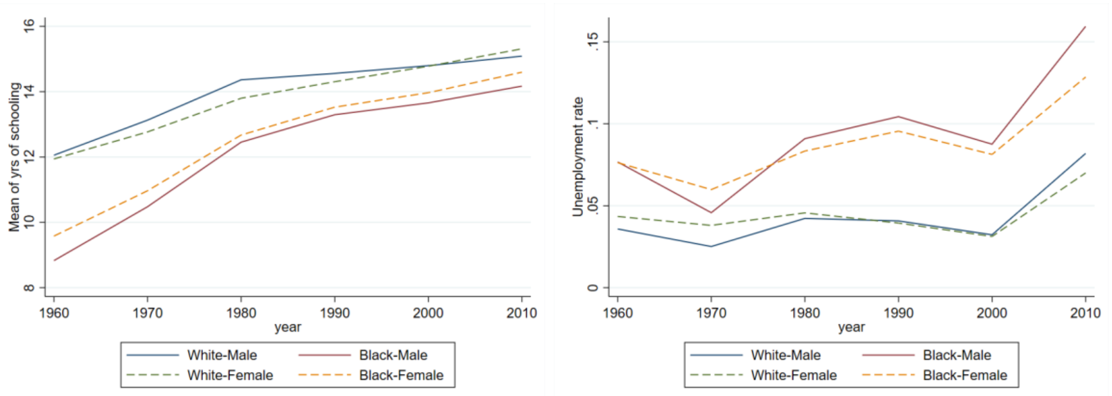
The IPUMS-USA database does not offer any variables that measure the quality of education. We will use the attained years of education instead (Schütz et al., 2008). To proxy the functioning of the labor market, we use the unemployment rate of adults aged 25-60 and the percentage of workers whose jobs have low occupational prestige according to the Hauser and Warren socioeconomic index (HWSEI, Hauser and Warren, 1997).[20] The education and labor market variables are evaluated for three subsets of the

[19] Results are not shown in the paper but are available from the authors upon request.
[20] For robustness, we replicate our results for the Nakao-Treas prestige score (PRENT, Nakao and Treas, 1994), see Appendix C.

population that broadly correspond to the poor, the middle-class, and the rich (which we refer to as: low, middle and high).

Before presenting the regression analysis, let us briefly inspect the trends and patterns in years of schooling and unemployment rates by race and gender. Figure 7 (left panel) plots the average years of schooling by race (black and white) and gender, which can be compared with Figures 1 and 2 for income. A number of observations stand out: (*i*) on average, white individuals have more years of schooling than black individuals; (*ii*) unlike what we observed for income, there is no clear gender ordering for years of schooling; thus, for white individuals, men are on average more educated than women, but this ordering is reversed for black individuals; (*iii*) regardless of ordering, the gender gap in education is of a secondary magnitude when compared to the racial gap; and (*iv*) there is a visible convergence over time: from a gap of more than 3 years in 1960 down to around 1 year in 2010.

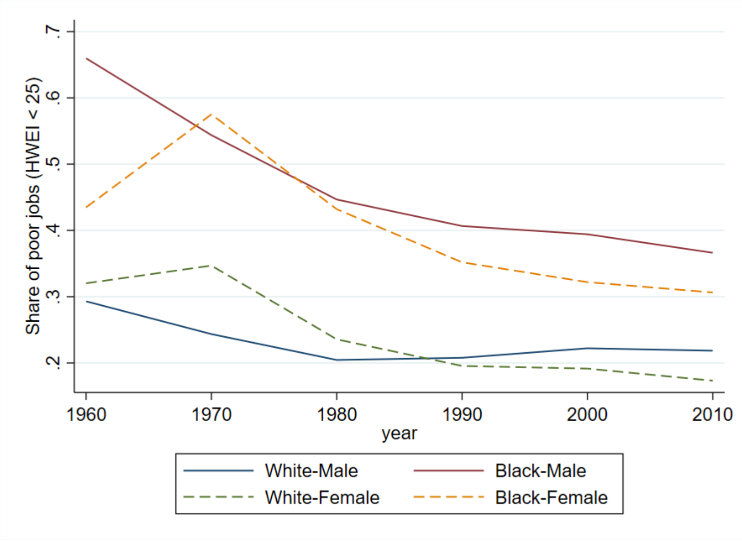
Figure 7. Years of schooling (left panel) and unemployment (right panel) by race and gender in the US (1960-2010).



The trends in unemployment by race (black and white) and gender are shown in Figure 7 (right panel). As for education, racial gaps visibly and persistently dominate gender gaps and, if anything, they have increased over time. In comparison with the racial gap, the gender gap is almost negligible. By 2010, unemployment rates of black men and black women were roughly double the unemployment rates of white men and white women (approximately 14-16 percent versus 7-8 percent). However, contrary to the educational channel, no evidence of convergence between these groups is observed.

Figure 8 plots the time-series of the share of individuals who are employed in a job with low occupational prestige (HWSEI < 25), which we will refer to as a "low-quality" job, by race and gender. White individuals, both men and women, are an average employed in higher quality jobs than black individuals. There is some indication of convergence with the share of white males employed in low-quality jobs slightly increasing after 1980 (following a decline prior to 1980), while employment in low-quality jobs shows a continued decline over time for black individuals and women. By 2010, however, a black individual is still approximately 50 percent more likely to be employed in a low-quality job than a white individual regardless of gender.

Figure 8. Share of workers with low-prestige jobs (HWSEI < 25) by race and gender in the US (1960-2010).

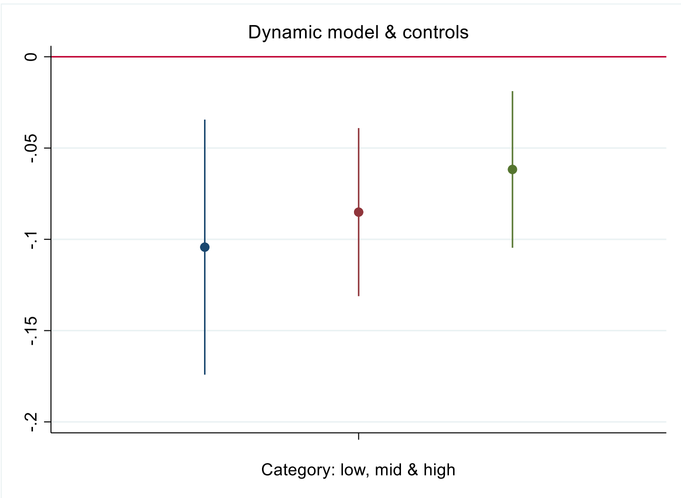


5.1. Human capital accumulation

Education is arguably a critical determinant of income success. If education is a key channel of transmission from RGI to future income growth, we should observe first a significant effect of RGI on the changes in education. To test this hypothesis, we estimate a version of equation (3), where the dependent variable is the change in attained years of education for the different segments of the population (the low, middle, and upper income groups) and where the lag of income in the right-hand side of (3) is substituted by the lag of attained years of education.

Because we do not have good external instruments for this auxiliary regression, we adopt Pooled-OLS with state and time fixed effects.[21] To examine robustness, we consider four different model specifications: a dynamic model with and without controls and a static model with and without controls. Figure 9 shows results for our preferred model specification (dynamic with controls). Results for other specifications are shown in Appendix C (Table C1-C4 and Figure C1). We find that RGI has a negative effect on the attained years of education for the low-income group across all specifications. This suggests that RGI primarily lowers human capital accumulation among the poor.

Figure 9. RGI effect on the change in attained years of education.

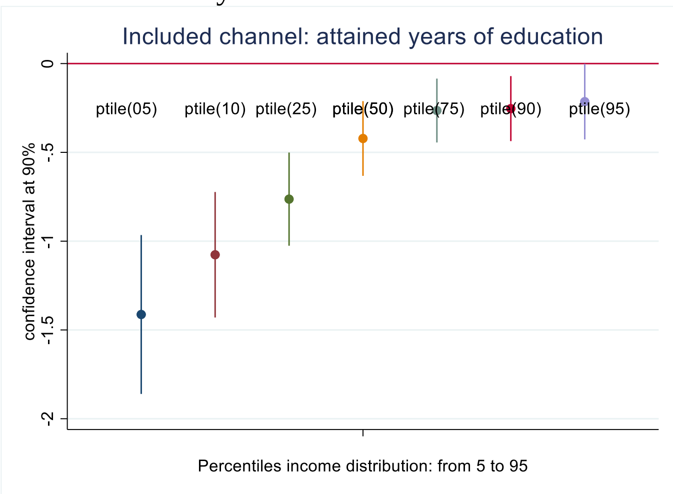


Having established that RGI has a significant effect on the change in attained years of education, we next evaluate the strength of this channel of transmission by including the education variable into equation (3) (in the baseline specification). If the effect of RGI on income growth is entirely channeled through the educational variable, its inclusion in the growth equation would absorb the negative correlation between RGI and income growth among the poor. The resulting model is estimated using our preferred IV approach. This confirms the significance of the education channel (not shown), although the coefficient of RGI remains significant when attained years of education is included as shown in

[21] The IV approach described in Section 3 requires a valid external instrument for per capita income (according to equation (6)). Unfortunately, this strategy cannot be used for our channel variables (education, unemployment and occupational prestige of jobs).

Figure 10. This suggests that human capital accumulation, albeit significant, is not the sole channel through which RGI impacts income growth.

Figure 10. IV estimates of the RGI effect on growth: models extended with attained years of education.

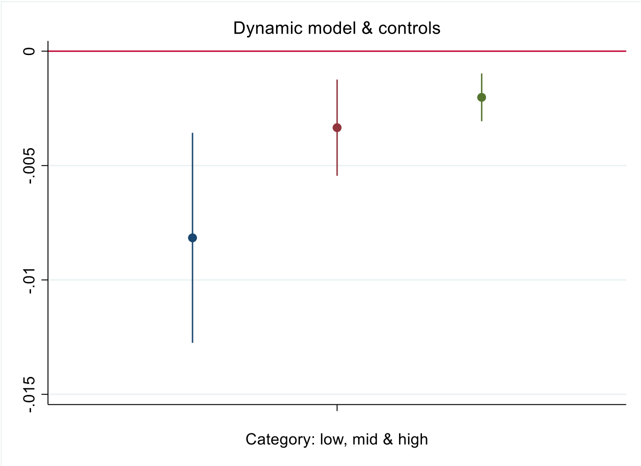


5.2. Labor market: Employment versus quality of jobs

We consider now (un)employment as a channel of transmission between RGI and posterior income growth. In this case, our dependent variable in (3) is the change of the unemployment rate for low, middle, and upper income groups, and the lag of income is substituted by the lag of the unemployment rate.

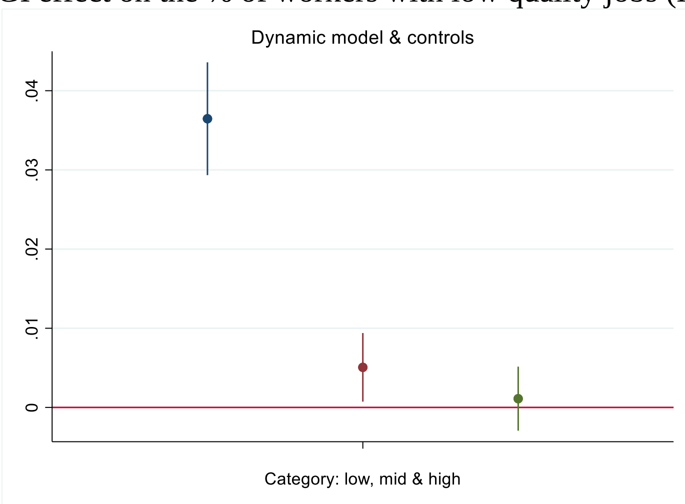
Figure 11 shows results for our preferred model specification (dynamic with controls). As for the attained years of education channel, results for other specifications are shown in Appendix C (Figure C2 and Tables C5-C8). RGI is found to reduce the unemployment rate for all income groups – especially for the poor – and all model specifications. One possible explanation is that the new jobs generated for the poor are of low quality.

Figure 11. RGI effect on the unemployment rate.



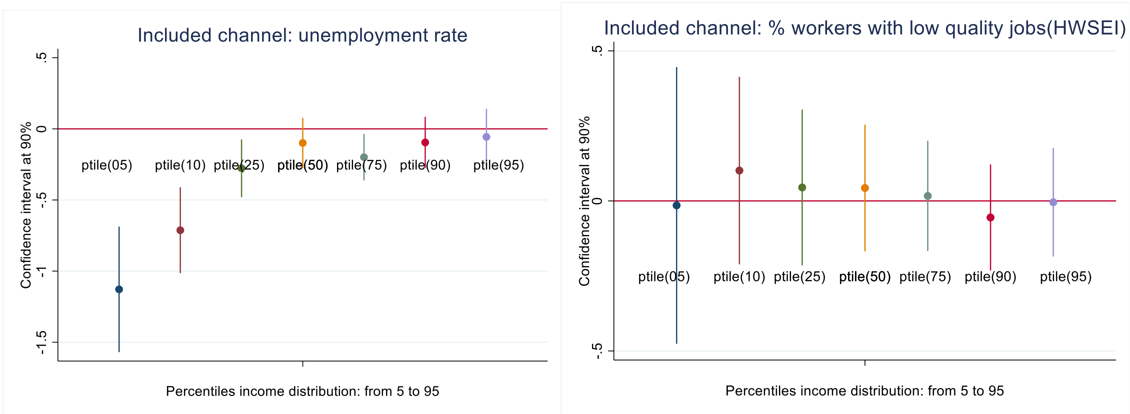
To test this hypothesis, we estimate a version of equation (3) where the dependent variable is the change of the share of workers whose jobs have low occupational prestige. To identify low-quality jobs, we use the HWSEI occupational prestige index, as described above (results for an alternative index, PRENT, are shown in Appendix C). In these cases, the lag of income in (3) is substituted by the lag of the percentage of workers with a low-quality job. As shown in Figures 12 (and Figures C3 and Tables C9-C12 in Appendix C; Figure C4 and Tables C13-C16 in Appendix C for the PRENT variable) we find that, regardless of the model specification, RGI has a positive and significant effect on the percentage of workers whose jobs are of low quality for the low-income group. This provides suggestive evidence that race and gender inequality increase employment among the poor but at the expense of reducing the quality of their jobs.

Figure 12. RGI effect on the % of workers with low quality jobs (HWSEI < 25).



Finally, as we did for attained education, we evaluate the significance of the labor market channel by estimating equation (3) extended with the unemployment rate and the measures of workers with low quality jobs one by one (using the baseline model with IV estimation). All labor market variables enter the income growth regressions significantly (not shown), although here the coefficient of RGI loses significance only when including the quality of jobs variable. This can be seen in Figure 13 (left panel for unemployment; right panel for HWSEI), which plots the corresponding estimates of θ_q where equation (3) is extended with each of the labor market variables (see Figure C5 in Appendix C for the PRENT variable).

Figure 13. IV estimates of the RGI effect on growth: models extended with labor market variables



In conclusion, our findings suggest that attained years of education, employment, and quality of jobs all serve as channels of transmission through which RGI impacts future income growth, but only the share of low-quality jobs is sufficiently strong to absorb the impact of lagged RGI on posterior income growth of the poor. Higher RGI is detrimental for growth among the poor because it reduces their attained years of education and, above all, increases their share of low-quality jobs.

A lower quality of education among the disadvantaged group could partially explain the significance of the latter channel, although we do not have the data to test this hypothesis. Empirical support for "quality sorting" has been obtained by Hirsch and Schumacher (1992) and Hirsch and Macpherson (2004). Beyond not having access to high quality education, sorting into low skills and low-quality jobs may also in part be tied to early employment activity, see for example Ahituv and Tienda (2004), who find that early employment helps explain comparatively high drop-out rates for Hispanic girls and young black women in the US. As a result, "youth employment risks long-run wage stagnation and possibly also higher racial inequality" (Ahituv and Tienda, 2004).

6. Discussion

This paper characterizes the within-state effect of RGI on posterior income growth along the income distribution in the US. Using an IV strategy developed by Brueckner et al. (2012) and Brueckner and Lederman (2018), we estimate a dynamic state level panel data model and find that RGI is detrimental to income growth of the poor and the lower middle class. The result is robust to alternative methods of estimation, different model specifications (static and dynamic), different sample choices, and different choices for inequality indices. We can furthermore reject between-state migration as an alternative explanation for our findings.

Income inequality across race and gender may stem from unequal access to good schooling and/or discrimination in the labor market, either of which signifies inefficiencies that will disproportionally affect the growth prospects of the disadvantaged. Our exploratory investigation into the channels of transmission suggests that between-race-gender inequality slows income growth of the poor by lowering their human capital accumulation and by shifting their employment towards low quality jobs. Our findings provide support for public policies that aim to equalize individual opportunities across racial groups and gender. Also, policies that do not explicitly address race and gender inequality but are instead designed to shift employment towards higher quality jobs, think of minimum wage and unemployment benefits (see Acemoglu, 2001), may indirectly help the minorities who have disproportionally been sorted into the low-quality jobs.

We see a number of avenues for further research. One is to verify whether the findings from our study extend to other countries, including less developed economies. Countries that are stuck in a poverty trap with low accumulation of human capital (Azariadis and Stachurski, 2005), an increase in inequality need not be harmful for the growth prospects of the poor and could conceivably even help such a country exit their poverty trap (Castelló-Climent and Mukhopadhyay, 2013).

A second avenue is to further unpack the sorting into low-quality jobs as a key channel through which RGI is found to lead to stagnant income growth among the poor. To what extent is this due to unequal access to good education that may lead to “quality sorting” (Hirsch and Macpherson, 2004), differential access to credits (Coibion et al., 2020), or differences in early employment activity that may lead to different school continuation decisions (Ahituv and Tienda, 2004)?

A third avenue is an investigation into the conditions under which economic growth yields opportunities for racial minorities and women. Such an effect would raise the possibility of a positive cycle where economic growth lowers inequality across race and gender, and this reduction in between-group inequality in turn generates future economic growth through improvements in efficiency. By the same token, group inequality may prove to be persistent even in the absence of labor market discrimination and credit constraints (see for example Bowles et al., 2014).

Finally, one could consider tracking income growth by individual characteristics such as race and gender, building on the study by Peragine et al. (2014) who developed the concept of the Opportunity Growth Incidence Curve. It is conceivable that unequal societies are more likely to hold black people back than whites regardless of where they stand on the socio-economic ladder.

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TABLES.

Table 1. Pool-OLS estimation with state and time fixed effects.

	All	p05	p10	p25	p50	p75	p90	p95
Race & gender Inequality (RGI)	-0.329***	-0.871***	-0.577***	-0.325**	-0.202**	-0.187**	-0.210***	-0.196**
	(0.100)	(0.162)	(0.158)	(0.133)	(0.095)	(0.075)	(0.075)	(0.083)
Lagged (log) income	-0.108***	-0.087***	-0.085***	-0.094***	-0.116***	-0.122***	-0.109***	-0.094***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
Total inequality	-0.0688	0.905*	0.466	-0.0493	-0.226	-0.152	-0.00354	0.167
	(0.198)	(0.471)	(0.346)	(0.225)	(0.176)	(0.141)	(0.126)	(0.122)
Share of graduates (age 21-39)	0.149***	0.096**	0.096**	0.133***	0.179***	0.181***	0.171***	0.153***
	(0.028)	(0.048)	(0.042)	(0.032)	(0.026)	(0.024)	(0.023)	(0.025)
Pop. aged 15 (%)	-0.272***	-0.333***	-0.305***	-0.254***	-0.277***	-0.263***	-0.207***	-0.175***
	(0.052)	(0.090)	(0.074)	(0.060)	(0.049)	(0.042)	(0.036)	(0.037)
Pop. aged 65 (%)	-0.021	-0.026	-0.042	-0.013	-0.033	-0.031	-0.003	0.001
	(0.052)	(0.090)	(0.073)	(0.061)	(0.052)	(0.043)	(0.039)	(0.042)
Exposure to imports from China	-0.165	0.241	-0.483	-0.402	-0.601	0.085	0.392	0.570
	(0.679)	(1.320)	(1.130)	(0.755)	(0.663)	(0.618)	(0.533)	(0.573)
Share of routine jobs	0.137***	0.338***	0.267***	0.206***	0.137***	0.061**	0.013	-0.004
	(0.032)	(0.071)	(0.057)	(0.040)	(0.031)	(0.029)	(0.030)	(0.032)
Adj. R^2	0.865	0.829	0.845	0.865	0.861	0.846	0.853	0.872
Observations	237	238	238	238	236	237	235	236

Note: The dependent variable is per capita income growth for the entire population (All) and for different percentiles in the income distribution (5th, 10th, 25th, 50th, 75th, 90th and 95th). A constant term, time dummies (1970, 1980, 1990, 2000 and 2010) and state fixed effects are included in all models. The coefficients of 'Exposure to imports from China' have been multiplied by 1000. Outliers (observations for which the studentized jackknifed residual is greater than 2) were dropped and robust standard errors are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. IV estimation with state and time fixed effects.

	All	p05	p10	p25	p50	p75	p90	p95
Race & gender Inequality (RGI)	-0.428***	-1.201***	-0.771***	-0.450***	-0.280**	-0.148	-0.162	-0.125
	(0.124)	(0.277)	(0.189)	(0.142)	(0.125)	(0.111)	(0.119)	(0.136)
Lagged (log) income	-0.130***	-0.101***	-0.105***	-0.117***	-0.142***	-0.143***	-0.124***	-0.109***
	(0.01)	(0.012)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.009)
Total inequality	0.131	1.844***	1.036***	0.173	-0.119	-0.178	-0.046	0.100
	(0.205)	(0.513)	(0.355)	(0.246)	(0.185)	(0.157)	(0.149)	(0.174)
Share of graduates (age 21-39)	0.174***	0.083*	0.103***	0.152***	0.208***	0.202***	0.189***	0.165***
	(0.028)	(0.050)	(0.038)	(0.032)	(0.027)	(0.024)	(0.023)	(0.024)
Pop. aged 15 (%)	-0.310***	-0.379***	-0.345***	-0.314***	-0.329***	-0.296***	-0.227***	-0.211***
	(0.054)	(0.089)	(0.073)	(0.064)	(0.053)	(0.044)	(0.037)	(0.036)
Pop. aged 65 (%)	-0.056	-0.078	-0.071	-0.038	-0.068	-0.058	-0.037	-0.011
	(0.067)	(0.118)	(0.092)	(0.077)	(0.066)	(0.057)	(0.053)	(0.056)
Exposure to imports from China	0.207	0.661	0.235	0.284	-0.349	0.229	0.350	0.347
	(0.603)	(1.150)	(0.955)	(0.667)	(0.587)	(0.557)	(0.499)	(0.497)
Share of routine jobs	0.142***	0.378***	0.297***	0.229***	0.138***	0.037	-0.007	-0.037
	(0.031)	(0.067)	(0.050)	(0.036)	(0.028)	(0.031)	(0.031)	(0.037)
Adj. R^2	0.791	0.743	0.780	0.778	0.777	0.775	0.816	0.869
Kleibergen Paap F-test	15668.7	770.7	1673.3	7408.5	42442.8	2340.1	1154.2	431.3
Underidentification F-stat	43.47	42.77	42.96	42.44	40.38	45.97	45.42	43.32
(p-value)	4.30e-11	6.15e-11	5.59e-11	7.27e-11	2.09e-10	1.20e-11	1.59e-11	4.65e-11
Observations	190	190	190	191	189	190	188	188

See note in Table 1.

APPENDIX A

Here we briefly inspect the time-trends in selected control variables. As Table A1 shows, the U.S. has undergone a significant transformation over the 50 year period under consideration: (*i*) higher education has become more widespread (where 9 percent of young adults had a graduate degree in the 1960s, that number is closer to 28 percent 50 years later); (*ii*) the country has steadily aged over time (with the percent of children steadily declining and the percent of elders steadily increasing); (*iii*) exposure to imports from China has increased rapidly after the 1980s but was negligible before then; (*iv*) the share of routine jobs increased until the 1980s but has stabilized afterwards.

Table A1. Selected controls over time (sample average across states).

	1960	**1970**	**1980**	**1990**	**2000**	**2010**
Total inequality (MLD)	0.232	0.221	0.227	0.260	0.318	0.342
RGI	0.037	0.035	0.032	0.031	0.026	0.031
Share of graduates (age 21-39)	0.093	0.133	0.194	0.211	0.236	0.282
Pop. aged 0-15 (%)	0.339	0.314	0.253	0.242	0.230	0.212
Pop. aged 65+ (%)	0.089	0.100	0.112	0.125	0.128	0.137
Exposure to imports from China*	0.070	0.083	0.160	1.135	2.578	-
Share of routine jobs (%)*	0.254	0.295	0.313	0.311	0.311	-

(*) Data from Author et al. (2013) are available only until 2000.

APPENDIX B. Robustness of main result

We evaluate in this appendix the robustness of our main result by considering different model specifications, alternative methods of estimation, different samples, and an alternative choice of inequality measure (that is used to measure RGI). For ease of exposition, we present the results in the form of coefficient plots.

Robustness to different model specifications

We consider two alternative model specifications: (*i*) equation (3) with contemporaneous RGI and total inequality, and (*ii*) a static model with contemporaneous RGI and total inequality but without the lag of per capita income in equation (3). Both models are estimated using IV. Panel a of Figure B1 shows the results for option (*i*) (left) and for option (*ii*) (right). Both alternative specifications reproduce the same finding that is obtained with the baseline IV specification: RGI has a negative and significant effect on income growth for the bottom half of the income distribution.

Robustness to alternative methods of estimation

We estimate equation (3) using System-GMM (Arellano and Bover, 1995; Blundell and Bond, 1998), which employs internal instruments to address the endogeneity of regressors. The proliferation of instruments in System-GMM tends to introduce additional over identifying problems, which calls for a reduction in the instruments count (Roodman, 2009a).[22] With this in mind, our baseline System-GMM model considers a maximum of one instrument from each variable and lag distance (results in Figure B1, panel b, left).[23] Our second System-GMM specification collapses the matrix of instruments (results in Figure B1, panel b, right). In both cases, the variance-covariance matrix is computed using the small sample correction of Windmeijer (2005). We find that RGI lowers the growth prospects of the households up to the median for the baseline

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[22] Acemoglu et al. (2015) have adopted one-step System-GMM with a reduced set of instruments (the one we use here) for the estimation of a dynamic panel model featuring growth, human capital, inequality and institutions.

[23] Considering 2 or 3 lags in the matrix of instruments leads to a Hansen test with a *p*-value that tends to one, which is a clear symptom of a 'too-many instruments' problem (Roodman, 2009b). We initially considered *t-2* for the first-difference equations and *t-1* for the level equations to construct the matrix of instruments. Because the test for second-order serial correlation in the first differences of the errors (the *m2* test) rejects the null in most of the specifications, the set of instruments is lagged one more period to *t-3* for the first-difference equations and to *t-2* for the level equations. This set of instruments remains valid even in the presence of second (but no higher) order serial correlation of the residuals, which is tested using an $AR(3)$ test for the first differences of the errors (these results are not shown here but are available from the authors upon request).

System-GMM. When we collapse the matrix of instruments in the second case, the negative effect of RGI on growth is found for the whole income distribution except the 95th percentile.

Robustness to sample choices

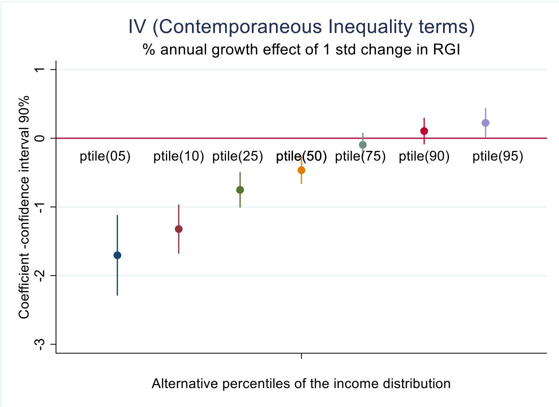
In our third robustness check, we modify the sample under consideration in two different ways (Figure B1, panel c). In the first case, we calculate the measures of inequality using individual income for the highest income earner within the household who is between the age of 30 and 50. The age restriction is considered to mitigate the life-cycle composition effect on an individual's income (Roemer et al., 2003; Marrero and Rodríguez, 2012). In the second case, we drop from our sample those state-year observations for which the share of white population is larger than 95%. When racial diversity is nearly non-existent, studying the effect of racial inequality becomes less relevant. Using our baseline specification from equation (3) and our preferred IV approach, we again find that RGI disproportionally slows the growth rate of the poor, up to the 25th percentile in the first case (panel c, left) and up to the 75th percentile in the second case (panel c, right).

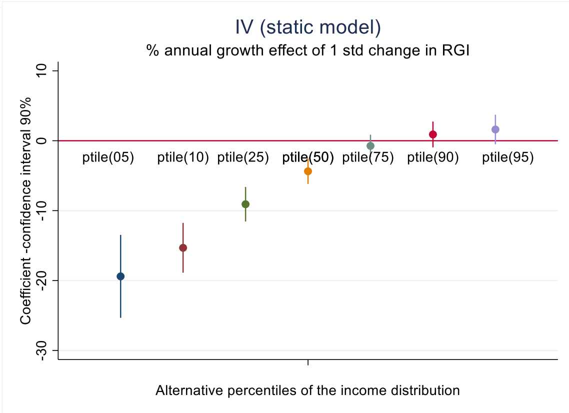
Robustness to the choice of inequality measures

Finally, we consider different choices of inequality indices for the measurement of inequality and RGI. Under option (*i*), we use the Gini index. While the Gini coefficient is not an additive decomposable inequality index (recall footnote 10), it has been used to estimate between-group inequality (Brunori et al., 2019). Under option (*ii*), instead of $I_{MLD}(\bar{y})$, we use the share of between-race-gender inequality over total inequality, $I_{MLD}(\bar{y})/I_{MLD}(y)$. Both options are implemented using the baseline model from equation (3) and IV estimation. The results are shown in panel d of Figure B1 (left: option (*i*); right: option (*ii*)). Also, we find that the negative effect of RGI on income growth primarily affects the poor and lower middle-class under option (*i*). In the case of option (*ii*) however, when race-gender is measured as a share of total inequality, the negative effect of RGI is only observed for the poor.

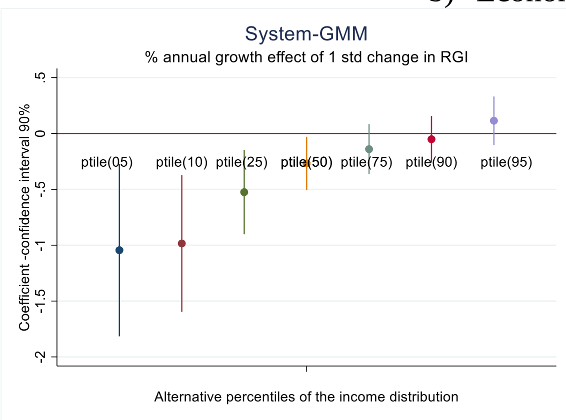
Figure B1. Robustness analysis.

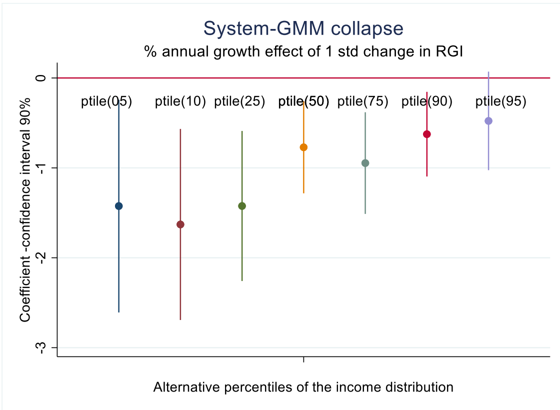
a) Model specifications



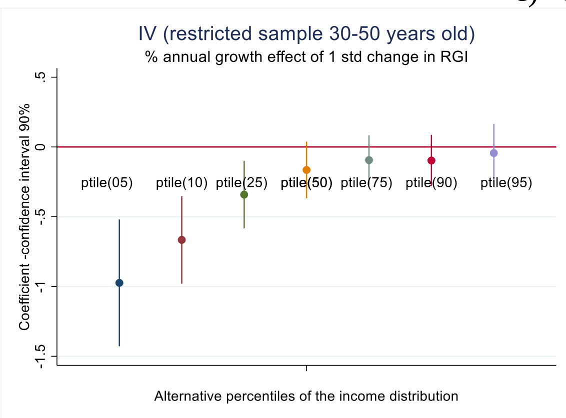


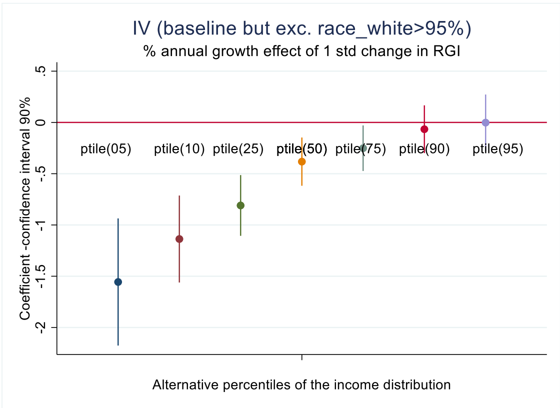
b) Econometric methods



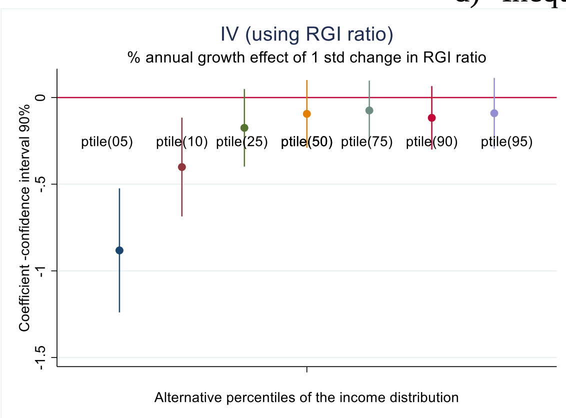


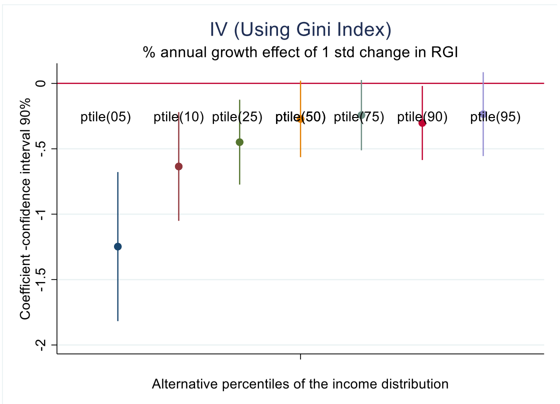
c) Samples





d) Inequality indices





APPENDIX C. Robustness of channel results

Figure C1. RGI effect on the change in attained years of education. Alternative models.

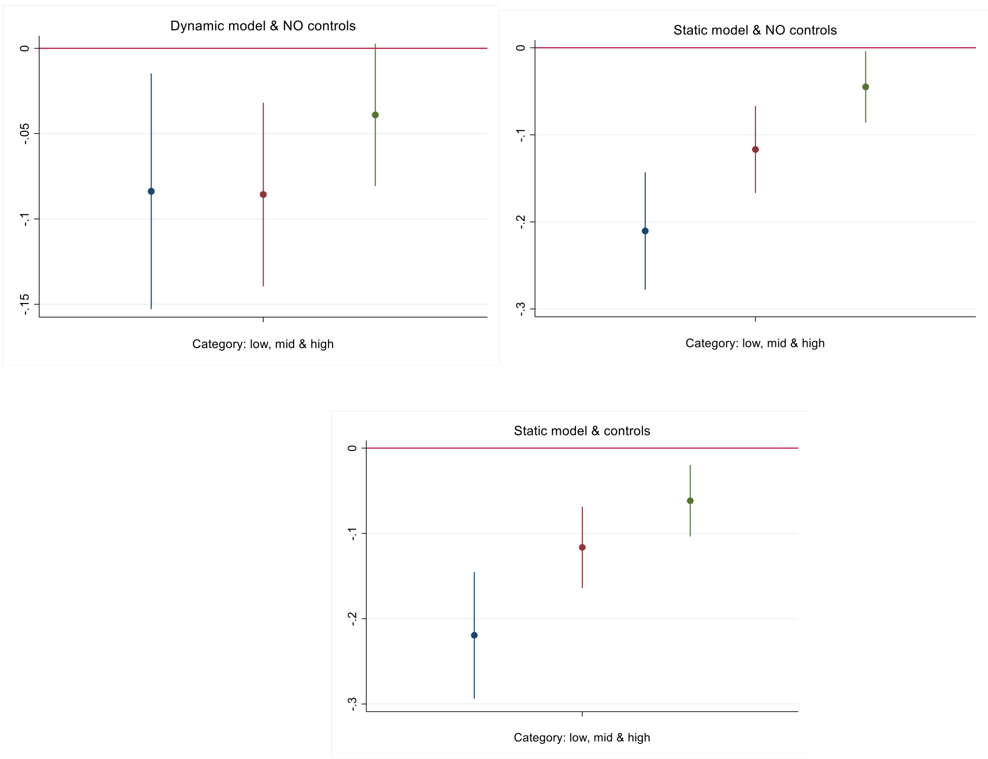


Figure C2. RGI effect on the unemployment rate. Alternative models.

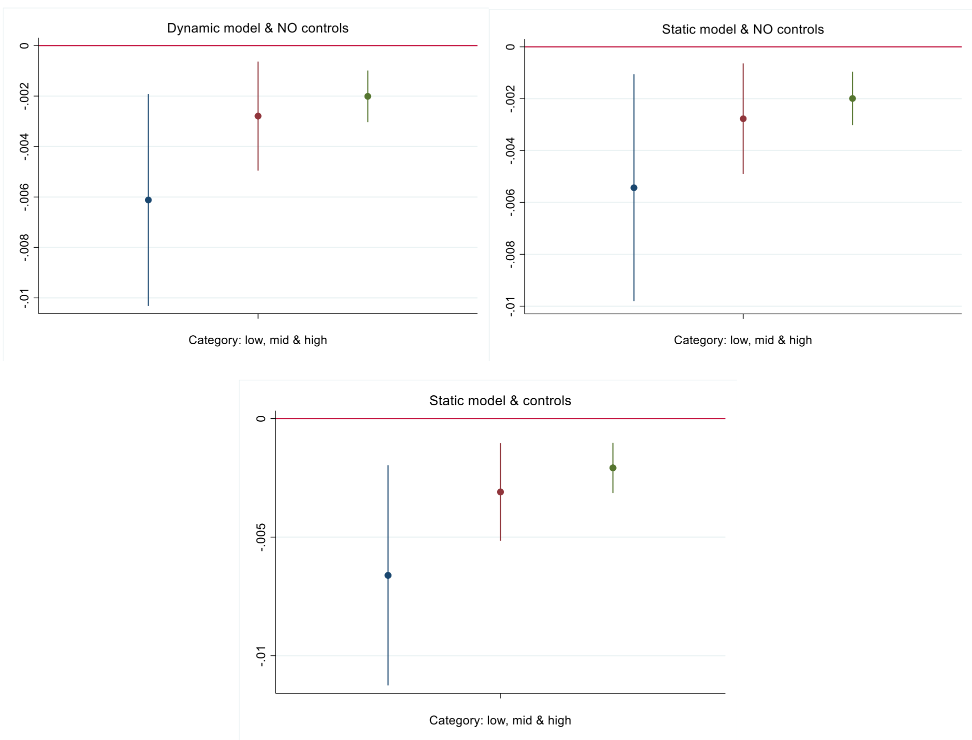


Figure C3. RGI effect on the % of workers with low quality jobs (HWSEI). Alternative models.

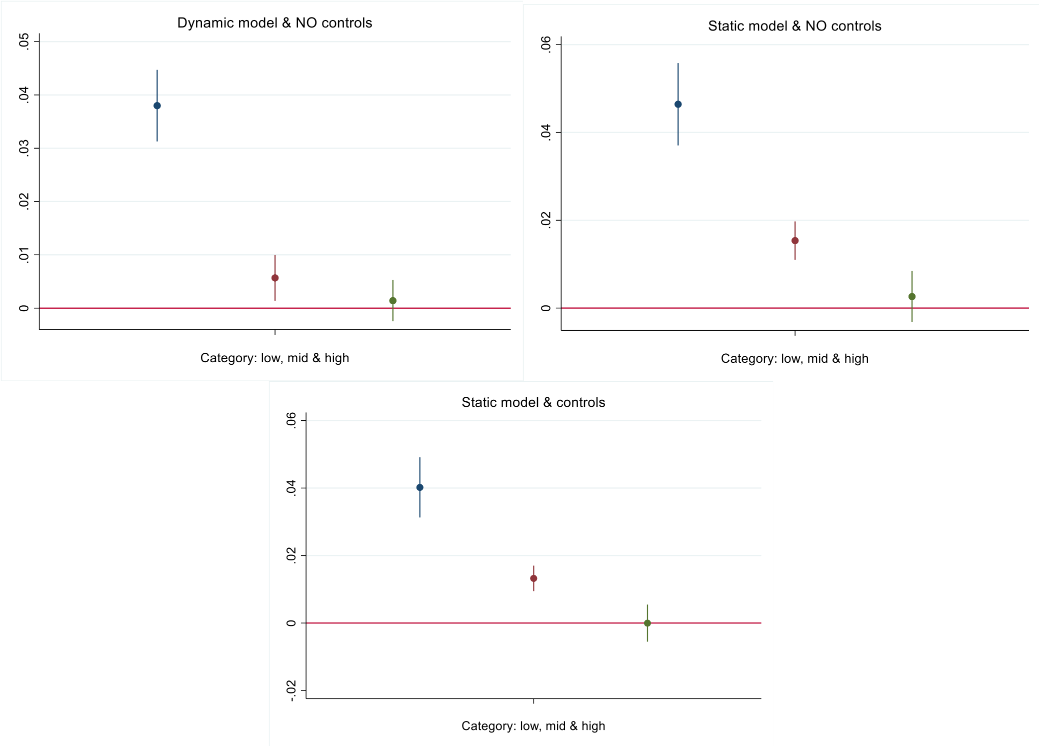


Figure C4. RGI effect on the % of workers with low quality jobs (PRENT). Robustness analysis.

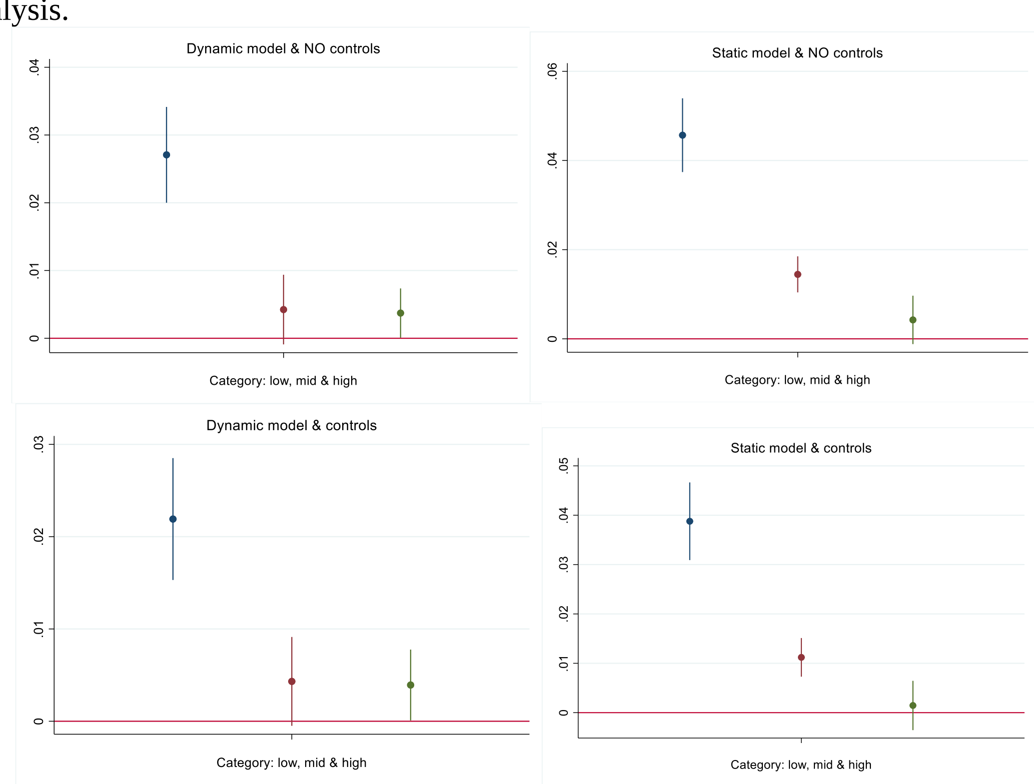


Figure C5. IV estimates of the RGI effect on growth: models extended with PRENT.

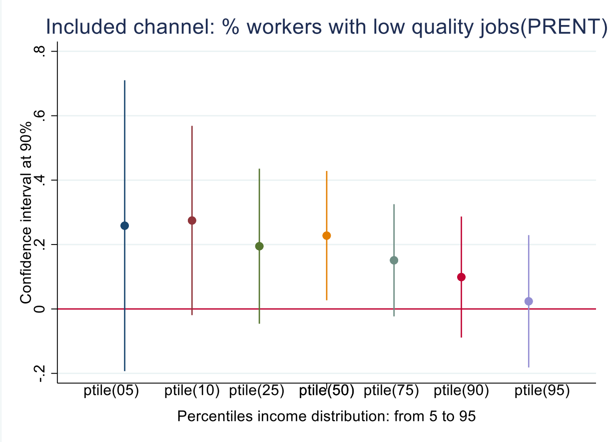


Table C1. Years of education channel: Dynamic model without controls.

	low	mid	high
Race & gender Ineq (RGI)	-0.084**	-0.086***	-0.039
	(0.042)	(0.033)	(0.025)
Lagged years of education	0.210***	0.171***	-0.037
	(0.062)	(0.058)	(0.063)
Total inequality	0.031	-0.020	-0.033
	(0.050)	(0.043)	(0.037)
adj. R^2	0.832	0.836	0.768
Num. observations	232	232	232

Note: The dependent variable is the change in attained years of education for the different segments of the population (low, middle, and upper income groups). A constant term, time dummies and state fixed effects are included in all models. The lagged years of education is included as a control. No additional controls are included. Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C2. Years of education channel: Static model without controls.

	low	mid	high
Race & gender Ineq (RGI)	-0.210***	-0.117***	-0.0450*
	(0.041)	(0.030)	(0.025)
Lagged years of education	--	--	--
Total inequality	0.082	-0.016	-0.019
	(0.056)	(0.045)	(0.038)
adj. R^2	0.826	0.825	0.759
Num. observations	232	234	233

Note: The dependent variable is the change in attained years of education for the different segments of the population (the low, middle, and upper income groups). A constant term, time dummies and state fixed effects are included in all models. The lagged years of education is NOT included as a control. No additional controls are included. Outliers were dropped and robust standard errors in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C3. Years of education channel: Dynamic model with controls.

	low	mid	high
Race & gender Ineq (RGI)	-0.104**	-0.085***	-0.062**
	(0.042)	(0.028)	(0.026)
Lagged years of education	0.212***	0.249***	-0.000
	(0.057)	(0.057)	(0.064)
Total inequality	0.058	-0.049	0.047
	(0.054)	(0.042)	(0.042)
adj. R^2	0.840	0.857	0.766
Num. observations	232	231	234

Note: The dependent variable is the change in attained years of education for the different segments of the population (the low, middle, and upper income groups). A constant term, time dummies and state fixed effects are included in all models. The lagged years of education is included as a control. Additional controls are included in the model (see Table 1). Outliers were dropped and robust standard errors in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C4. Years of education channel: Static model with controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	-0.219***	-0.116***	-0.062**
	(0.045)	(0.029)	(0.025)
Lagged years of education	--	--	--
Total inequality	0.102*	-0.049	0.047
	(0.060)	(0.045)	(0.042)
adj. R^2	0.828	0.830	0.768
Num. observations	233	234	234

Note: The dependent variable is the change in attained years of education for the different segments of the population (the low, middle, and upper income groups). A constant term, time dummies and state fixed effects are included in all models. The lagged years of education is NOT included as a control. Additional controls are included in the model (see those controls in Table 1). Outliers were dropped and robust standard errors in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C5. Unemployment channel: Dynamic model without controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	-0.006**	-0.003**	-0.002***
	(0.003)	(0.001)	(0.001)
Lagged unemployment	-0.205**	-0.186**	-0.028
	(0.084)	(0.080)	(0.073)
Total inequality	0.009**	0.005**	0.003***
	(0.004)	(0.002)	(0.001)
adj. R^2	0.884	0.766	0.603
Num. observations	231	233	235

Note: The dependent variable is the change of the unemployment rate for low, middle, and upper income groups. A constant term, time dummies and state fixed effects are included in all models. The lagged unemployment rate is included as a control. No additional controls are included. Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C6. Unemployment channel: Static model without controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	-0.005**	-0.003**	-0.002***
	(0.003)	(0.001)	(0.001)
Lagged unemployment	--	--	--
Total inequality	0.008*	0.006***	0.003***
	(0.004)	(0.002)	(0.001)
adj. R^2	0.886	0.767	0.605
Num. observations	230	233	235

Note: The dependent variable is the change of the unemployment rate for low, middle, and upper income groups. A constant term, time dummies and state fixed effects are included in all models. The lagged unemployment rate is NOT included as a control. No additional controls are included. Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C7. Unemployment channel: Dynamic model with controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	-0.008***	-0.003***	-0.002***
	(0.003)	(0.001)	(0.001)
Lagged unemployment	-0.251***	-0.156*	-0.032
	(0.091)	(0.082)	(0.075)
Total inequality	0.004	0.002	0.001
	(0.005)	(0.002)	(0.001)

adj. R^2	0.875	0.777	0.615
Num. observations	235	235	235

Note: The dependent variable is the change of the unemployment rate for low, middle, and upper income groups. A constant term, time dummies and state fixed effects are included in all models. The lagged unemployment rate is included as a control. Additional controls are included in the model (see those controls in Table 1). Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C8. Unemployment channel: Static model with controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	-0.007**	-0.003**	-0.002***
	(0.003)	(0.001)	(0.001)
Lagged unemployment	--	--	--
Total inequality	0.001	0.001	0.002
	(0.005)	(0.002)	(0.001)
adj. R^2	0.870	0.783	0.614
Num. observations	235	234	234

Note: The dependent variable is the change of the unemployment rate for low, middle, and upper income groups. A constant term, time dummies and state fixed effects are included in all models. The lagged unemployment rate is NOT included as a control. Additional controls are included in the model (see those controls in Table 1). Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C9. Job quality channel (HWSEI): Dynamic model without controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	0.038***	0.006**	0.001
	(0.004)	(0.003)	(0.002)
Lagged % low jobs	0.352***	0.501***	0.430***
	(0.049)	(0.051)	(0.033)
Total inequality	-0.004	0.0065*	0.002
	(0.006)	(0.005)	(0.004)
adj. R^2	0.910	0.957	0.954
Num. observations	233	230	233

Note: The dependent variable is the change of the share of workers whose jobs have low occupational prestige for low, middle, and upper income groups (using the HWSEI occupational prestige index). A constant term, time dummies and state fixed effects are included in all models. The lagged percentage of people with low quality jobs is included as a control. No additional controls are included. Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C10. Job quality channel (HWSEI): Static model without controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	0.046***	0.015***	0.003
	(0.006)	(0.003)	(0.004)
Lagged % low jobs	--	--	--
Total inequality	-0.014**	-0.005	-0.006
	(0.007)	(0.005)	(0.005)
adj. R^2	0.881	0.928	0.920
Num. observations	236	232	235

Note: The dependent variable is the change of the share of workers whose jobs have low occupational prestige for low, middle, and upper income groups (using the HWSEI occupational prestige index). A constant term, time dummies and state fixed effects are included in all models. The lagged percentage of people with low quality jobs is NOT included as a control. No additional controls are included. Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C11. Job quality channel (HWSEI): Dynamic model with controls.

	low	**mid**	**high**

Race & gender Ineq (RGI)	0.037***	0.005*	0.001
	(0.004)	(0.003)	(0.003)
Lagged % low jobs	0.311***	0.469***	0.418***
	(0.056)	(0.060)	(0.038)
Total inequality	-0.011	0.005	0.002
	(0.007)	(0.004)	(0.004)
adj. R^2	0.915	0.953	0.953
Num. observations	233	233	233

Note: The dependent variable is the change of the share of workers whose jobs have low occupational prestige for low, middle, and upper income groups (using the HWSEI occupational prestige index). A constant term, time dummies and state fixed effects are included in all models. The lagged percentage of people with low quality jobs is included as a control. Additional controls are included in the model (see those controls in Table 1). Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C12. Job quality channel (HWSEI): Static model with controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	0.040***	0.013***	-0.000
	(0.005)	(0.002)	(0.003)
Lagged % low jobs	--	--	--
Total inequality	-0.013*	0.001	0.003
	(0.007)	(0.004)	(0.005)
adj. R^2	0.904	0.942	0.929
Num. observations	234	231	235

Note: The dependent variable is the change of the share of workers whose jobs have low occupational prestige for low, middle, and upper income groups (using the HWSEI occupational prestige index). A constant term, time dummies and state fixed effects are included in all models. The lagged percentage of people with low quality jobs is NOT included as a control. Additional controls are included in the model (see those controls in Table 1). Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C13. Job quality channel (PRENT): Dynamic model without controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	0.027***	0.004	0.004*
	(0.004)	(0.003)	(0.002)
Lagged % low jobs	0.354***	0.393***	0.476***
	(0.054)	(0.058)	(0.046)
Total inequality	-0.004	0.002	-0.003
	(0.006)	(0.004)	(0.003)
adj. R^2	0.922	0.940	0.958
Num. observations	235	234	236

Note: The dependent variable is the change of the share of workers whose jobs have low occupational prestige for low, middle, and upper income groups (using the PRENT index). A constant term, time dummies and state fixed effects are included in all models. The lagged percentage of people with low quality jobs is included as a control. No additional controls are included. Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C14. Job quality channel (PRENT): Static model without controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	0.046***	0.015***	0.004
	(0.005)	(0.002)	(0.003)
Lagged % low jobs	--	--	--
Total inequality	-0.017***	-0.006	-0.012**
	(0.006)	(0.004)	(0.005)
adj. R^2	0.900	0.931	0.929
Num. observations	237	232	236

Note: The dependent variable is the change of the share of workers whose jobs have low occupational prestige for low, middle, and upper income groups (using the PRENT index). A constant term, time dummies and state fixed effects are included in all models. The lagged percentage of people with low quality jobs is NOT included as a control. No additional controls are included. Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C15. Job quality channel (PRENT): Dynamic model with controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	0.022***	0.004	0.004*
	(0.004)	(0.003)	(0.002)
Lagged % low jobs	0.364***	0.299***	0.474***
	(0.056)	(0.063)	(0.050)
Total inequality	-0.009	0.003	-0.002
	(0.006)	(0.004)	(0.004)
adj. R^2	0.935	0.951	0.957
Num. observations	234	231	236

Note: The dependent variable is the change of the share of workers whose jobs have low occupational prestige for low, middle, and upper income groups (using the PRENT index). A constant term, time dummies and state fixed effects are included in all models. The lagged percentage of people with low quality jobs is included as a control. Additional controls are included in the model (see those controls in Table 1). Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C16. Job quality channel (PRENT): Static model with controls.

	low	**mid**	**high**
Race & gender Ineq (RGI)	0.039***	0.011***	0.002
	(0.005)	(0.002)	(0.003)
Lagged % low jobs	--	--	--
Total inequality	-0.014**	-0.000	-0.002
	(0.006)	(0.004)	(0.005)
adj. R^2	0.920	0.940	0.937
Num. observations	236	233	235

Note: The dependent variable is the change of the share of workers whose jobs have low occupational prestige for low, middle, and upper income groups (using the PRENT index). A constant term, time dummies and state fixed effects are included in all models. The lagged percentage of people with low quality jobs is NOT included as a control. Additional controls are included in the model (see those controls in Table 1). Outliers were dropped and robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.