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COLLEGE ATTAINMENT, INCOME INEQUALITY, AND ECONOMIC SECURITY: A SIMULATION EXERCISE

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ABSTRACT

We conduct an empirical simulation exercise that gauges the plausible impact of increased rates of college attainment on a variety of measures of income inequality and economic insecurity. Using two different methodological approaches—a distributional approach and a causal parameter approach—we find that increased rates of bachelor's and associate degree attainment would meaningfully increase economic security for lower-income individuals, reduce poverty and near-poverty, and shrink gaps between the 90th and lower percentiles of the earnings distribution. However, increases in college attainment would not significantly reduce inequality at the very top of the distribution.

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A data appendix is available at http://www.nber.org/data-appendix/w26747

I. INTRODUCTION

College-educated workers today have much higher levels of earnings, income, and employment than those without college degrees, with especially large premiums awarded to those who hold a bachelor's degree or higher. As documented by numerous studies, the relative employment and earnings outcomes of individuals without a college degree have fared relatively poorly in the wake of advancements in technology, globalization, and trade, among other factors. Annual earnings of workers with a college degree or more have risen steadily over the past four or five decades, while the earnings of those with lower levels of education have stagnated or fallen (see for example, Autor 2014). Figure 1 shows that the college wage premium—which we initially define in this figure in accordance with previous literature as the difference in log annual earnings between those who have received a bachelor's degree and those who have not—increased steadily from the early 1980s through around 2000, at which point it flattened, but did not reverse. Today this college/high school wage premium remains at 90 percent and is similar for men (88 percent) and women (92 percent).[1]

Divergence in employment rates have exacerbated trends in relative earnings. Prime-age adults with no more than a high school degree have experienced a sizable decline in employment rates in recent decades, while employment rates among college-degree holders have fallen only slightly. For instance, among men age 25 to 34 with a high school degree but no college, employment rates fell from 89 to 82 percent between 1999 and 2018, as compared to a dip from 95 to 94 percent among their counterparts with at least a bachelor's degree (Abraham and Kearney, forthcoming). Not surprisingly, economic insecurity, as captured by the likelihood of

[1] This wage premium calculation holds constant relative shares of sex-education-experience groups (two sexes, six education categories, and four potential experience categories), as relevant for the populations of interest, and roughly follows the methodology of Autor, Katz, and Kearney (2008) and Acemoglu and Autor (2011). See appendix for further details.

living in or near poverty, is much higher among the non-college educated. In 2018, 4.4 percent of college graduates lived below the official federal poverty threshold, as compared to 12.7 percent of high school graduates and 25.9 percent of adults without a high school degree (Semega et al, 2019).

The divergent economic outcomes of those with and without a college degree have led many observers to emphasize the need for increased skill attainment, in particular increased college attainment, to boost individual economic security and address rising income inequality. The emphasis on increasing the supply of college graduates to the workforce as a response to the rise in earnings inequality is consistent with the arguments emphasized in the 2008 book by Goldin and Katz, *The Race Between Education and Technology*. The thesis of the book is based on the canonical supply and demand framework of wage determination. In highly simplified terms, the basic observation of Goldin and Katz (2008) is that during the 1980s and 1990s, the demand for college-educated workers rose faster than the supply of college-educated workers, leading to a rise in their relative wage.[2]

In this paper, we conduct a simulation exercise that gauges the plausible impact of increased rates of college attainment on a variety of measures of income inequality and economic insecurity. Although several channels for increasing college attainment have been proposed—including additional funding for higher education institutions, expanded access to free or reduced tuition for students, and behavioral or information interventions—we set aside any consideration of the costs or effectiveness of these various approaches to focus on outcomes. The results of this simulation exercise reveal that a sizable increase in rates of college attainment would meaningfully increase economic security for individuals near the bottom of the earnings

[2] This point has been suggested in related papers, including but not limited to Goldin and Margo (1992), Katz and Murphy (1992), and Card and Lemieux (2001).

distribution. It would also shrink gaps between the 90th percentile and lower half of the earnings distribution, as well as between the median and bottom in most cases. However, increases in college attainment would not significantly reduce upper tail inequality or the amount of income going to earners in the top percentiles. The policy prescription of increased educational attainment should thus appeal to those whose primary concern is the economic security of poorer individuals, but it will not satisfy the goals of those whose primary concern is the reduction of overall income inequality or income shares at the top of the distribution.[3]

II. DATA AND METHODS

A. Data

Our primary data source for employment, earnings, income, and poverty status is the Annual Social and Economic Supplement of the Current Population Survey (March CPS), as provided by IPUMS (Flood et al. 2019). The March CPS provides detailed information on the composition of annual income for a relatively large, nationally representative sample of households and is released more quickly than other public datasets that contain earnings.[4] To illustrate changes in earnings and inequality over a longer horizon, we consider both the 1980 survey (covering earnings from 1979) and the 2019 survey (covering earnings from 2018).

[3] This paper builds on a 2015 policy memo that Hershbein and Kearney wrote with Larry Summers and posted on the Hamilton Project website (Hershbein, Kearney, and Summers, 2015). That memo described the results of simulating how the distribution of earnings would change if one of every ten men aged 25–64 without a bachelor's degree were to be assigned one, with a random draw from the earnings distribution of existing bachelor's-degree holders. In this paper, we expand on that earlier analysis by including men and women, considering increased attainment of both associate and bachelor's degrees, using both a random distribution method and a causal parameter assignment method, examining multiple thresholds of increased educational attainment, and using current data.

[4] The March CPS microdata are released in the fall of the survey year and contain annual earnings data for the previous calendar year. American Community Survey (ACS) microdata constitute a larger sample but are released with a greater delay and contain less detailed earnings data that covers a longer time period due to the staggered nature of the survey throughout the year. We intend to repeat our simulation exercise with the decennial census and the ACS, for the sake of comparison.

We restrict our sample to adult civilians of prime age, 25–54, to minimize concerns about schooling and retirement decisions.[5] We define four mutually exclusive, exhaustive education categories: less than high school degree, high school graduate, associate degree, and bachelor's degree or higher. High school degree includes GED holders and those who attended college but did not get a degree. We measure employment as a binary variable that equals one if an individual worked a positive number of weeks in the previous calendar year *and* had positive labor earnings; we define full-time, full-year workers (FTFY) as those usually working at least 35 hours per week and at least 40 weeks of the year. We define an individual's annual labor earnings as the sum of wages and salaries and non-negative business income over the same time period.[6] We adjust earnings for inflation to year 2018 dollars using the personal consumption expenditures (PCE) deflator from the Bureau of Economic Analysis. Because poverty status is based on family rather than individual income, we construct an individual's poverty threshold ratio by dividing that individual's total family income by the official poverty thresholds for the individual's family size and type.[7]

Table 1 presents summary statistics showing the earnings and income of adults in 1979 and 2018 for different samples. The first row of each panel reports selected percentiles of the real earnings distributions for all FTFY workers age 25 to 54 in 1979 and 2018, respectively. Subsequent rows show percentiles of the earnings distribution for men and women separately,

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[5] Previous literature has typically focused on the working-age population, 16–64, but since our simulation involves increasing educational attainment, we believe it makes more sense to focus on the population for whom the additional attainment is more reasonable and exclude those for whom further schooling is less likely.

[6] We exclude from the sample individuals for whom either of these components of earning is imputed. About 1% of our 1980 and 2019 samples have a component of earnings topcoded. We do not attempt to adjust for topcoding, but do implement a correction to use current topcoding methods for the 1979 sample, using historical income data generated by Larrimore et al. (2008).

[7] These thresholds are provided annual by the Census Bureau (see https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html) and are already included in the IPUMS extracts we use.

and then the pooled and gender-specific earnings distributions for all individuals age 25 to 54, regardless of work status.

The rise in inequality over this period is evident from these numbers. Among men, unconditional earnings at the 10th, 25th, and 50th percentiles fell between 1979 and 2018, and FTFY earnings at these percentiles were generally stagnant or increased only slightly. At the 75th, 90th, and 99th percentiles, however, earnings rose substantially, both unconditionally and for FTFY men. Among women, both unconditional and FTFY earnings increased at all highlighted percentiles, but the gains were much larger at the higher end of the distribution. Notably, earnings are zero at both the 10th and 25th percentiles of the unconditional sample for women in both 1979 and 2018, and although the 10th percentile of the unconditional earnings distribution is positive for men in 1979, it is zero in 2018. This sharp decline at the bottom reflects a lower likelihood of prime-age men having been employed at any point during the year; this likelihood fell from 92 to 85 percent, with the decline almost entirely concentrated among men without a college degree.[8]

Appendix Table A.1 and Appendix Figure 2 show the earnings distributions of FTFY workers in 1979 and 2018 by level of education. The table and figure show clearly how earnings gaps have increased between education groups. For example, in 1979, median earnings among high school graduate FTFY workers were approximately $38,300 (in 2018 dollars), as compared to about $53,400 among FTFY workers with a bachelor's degree (BA) or higher. In 2018, the comparable numbers were $40,000 and $70,000. The gap between the 90th percentile of earnings among high school graduates and BA holders grew by an even greater amount. In 1979, the 90th percentile of earnings among high school FTFY workers was roughly $72,600, as compared to

[8] Appendix Figures 1 and 2 plot kernel density estimates of the earnings distributions of FTFY workers in 1979 and 2018—pooled, and then separately for men and women.

$113,200 among BA holders, but the comparable numbers in 2018 were $80,000 and $155,000, a near doubling.

These increases in wage inequality across education and time have occurred simultaneously with increases in educational attainment—although, as Goldin and Katz (2008) have argued, at a slower rate than previously. The first panel of Table 2 shows the shares of the FTFY prime-age workforce (group A), FTFY male prime-age workforce (group B), FTFY female prime-age workforce (group C), and all prime-age men (group D) with different levels of education. Among the FTFY workforce, the share with at least a bachelor's degree has risen from about one-quarter in 1979 to 45 percent by 2018, with a much more modest increase in the associate degree share from about 9 to 11 percent. Because of the faster growth in educational attainment for women relative to men, the educational increases for men specifically are smaller, with BA-plus shares rising from 26 to 41 percent for FTFY men and from 25 to 36 percent for all prime-age men, unconditional on work status. Given the observed changes in earnings by education for different groups, our simulation exercise asks how earnings distributions would change were the education shares for these groups to be shifted.

B. Methods

We simulate three counterfactual scenarios. Simulation 1 raises the share of the sample—across the different samples described above—with at least a bachelor's degree (BA share) to 50 percent. Simulation 2 raises the share of the sample with an associate degree (AA share) to 15 percent *and* the BA share to 50 percent. Simulation 3 raises the AA share to 20 percent and the BA share to 60 percent. Both new AA holders and new BA holders are drawn from the existing high school graduate population. For each scenario, we assign the "new" AA and BA holders simulated earnings in two ways. The *distribution method* assigns a random draw from the distribution of existing AA or BA (including those with higher than a BA), conditioning on one of 12 cells: 10-year age category (25–34, 35–44, 45–54), race (white and other), and sex (male and female). The *causal parameter* method assigns a causal estimate of the marginal AA or BA returns using parameters from the existing literature, as described below.[9] One benefit of the distribution method is that it allows an individual who is currently out of the workforce to be assigned positive earnings if they are simulated to earn a college degree. The causal parameter method does not allow for employment responses at the extensive margin. The distribution method also allows for heterogeneity in treatment effects, whereas the causal parameter method uses a uniform percentage increase in earnings among the entire sample. On the other hand, the causal parameter method may come closer to capturing the "marginal" policy parameter of interest. We thus view the two methods as complements.

In the causal parameter approach, high school graduates who are assigned an AA receive a 29 percent annual earnings increase. This estimate is based on averaging the effects found for associate degree receipt in Bahr et al. (2014) and Stevens et al. (2015). These papers identify causal estimates using well-established individual fixed-effects methodologies. We assign the high school graduates who are treated with a BA a 68 percent annual earnings increase. This is an approximation of the likely causal effect of BA attainment for a marginal student admitted to a less selective university, based on the findings of Zimmerman (2014). Zimmerman uses a regression discontinuity approach and estimates that individuals just admitted to a less-selective state university have a 22 percent increase in earnings 8 to 14 years after high school graduation relative to those just missing admission. To get an IV estimate of the effect of BA attainment,

[9] While it would be desirable to use group-specific causal returns to different degree levels, the literature has not produced robust causal estimates for different demographic groups, and so we assign the same AA premium and BA premium to all individuals who have their college status shifted.

Zimmerman scales this earnings increase by the probability of attendance conditional on admissions (49 percent) and the probability of BA completion conditional on attendance (50 percent), yielding an IV estimate of a 90 percent earnings increase as compared to below-threshold earnings. This is almost surely an upper bound because, as Zimmerman acknowledges, admission to the university likely affects earnings through other channels, namely, credit completion without a degree. We thus adjust downward the 90 percent estimate. To do so, we assume that roughly a quarter (or 5 percentage points) of the 22 percent earnings increase associated with admission comes from the attendance without completion channel. We thus apply the scaling to a 17 percent earnings increase, obtaining a 68 percent "IV" estimate of BA attainment, rather than 90 percent.

This 68 percent estimate is likely a conservative measure of the earnings premium because it does not allow for the additional earnings premium that would be associated with a more selective institution.[10] Based on a regression discontinuity admissions cutoff at a more selective university than the one considered by Zimmerman (2014), Hoekstra (2009) estimates a 20 percent local average treatment effect on earnings of enrolling at a state flagship university, as compared to the likely counterfactual of attending a less selective institution. Thus, a reasonable extension to the assignment of a 68 percent causal parameter (which we do not incorporate) would be to assign some share of new BA holders an additional (multiplicative) 20 percent premium.

In both the distribution and causal parameter method, we further adjust earnings for the relative wage effect that is likely to result from an increase in the share of the population with a

[10] Additionally, the baseline earnings from which Zimmerman's estimates are drawn include some individuals who attend community colleges, whose earnings may be somewhat higher than those of high school graduates without any college attendance.

college degree. To incorporate this relative wage response into our simulation exercise, we follow the common paradigm in the academic literature, as described in Autor and Acemoglu (2011), and specify a two-factor CES production function model. In one case, the model includes BA and high school degree workers, and in the other case, the model includes AA and high school degree workers.

Appendix C describes our methodology for estimating relative wage effects and presents the resulting relative wage responses. We estimate that within our sample, a 1 percent increase in the relative supply of labor with a BA or more to non-BA high school graduates will narrow the relative wage premium by 0.25 percent; analogously, a 1 percent increase in the relative supply of AA-degree holders to high school graduates will decrease that relative wage premium by 0.18 percent.[11] For instance, the first simulation raises the BA completion rate from 45.1 to 50.3 percent for our FTFY sample (group A in Table 2). In terms of relative supply effects in the labor market, considering all adults (not just FTFY or prime-age) and weighting each individual by their hours worked last year, this amounts to a change from 41.5 to 44.7 percent, which is roughly a 14 percent increase in the hours-weighted relative supply of BA to non-BA labor [0.415/(1–0.415) = 0.708; 0.447/(1–0.447) = 0.808; 0.808/0.708 = 1.141]. Thus, our simulation adjusts for a 0.14 * 0.25 ≈ 4 percent narrowing of the wage premium. This narrowing is assumed to fall equally on each group, raising non-BA earnings by 2 percent and lowering BA earnings (including BA-plus) by 2 percent. Because we draw from the pool of high school graduates to assign college degrees, the relative supply of associate degree holders and high school graduates also changes for the first simulation, with this ratio increasing by 7 percent, leading to a 0.07 *

[11] Although the relative wage parameter estimates from the regressions are defined for (i) BA (including BA-plus) and high school graduates, and (ii) AA and high school graduates, when applying the adjusted wages to the population, we include individuals without a high school degree in the lower-skill group, implicitly treating them as perfect substitutes.

$0.18 \approx 1$ percent narrowing of that wage premium. When both AA and BA attainment is changed, as in Simulations 2 and 3, we narrow the wage premia sequentially: first adjusting the AA/high school wage premium, then narrowing the BA/high school wage premium. In Simulation 2, the AA/high school wage premium narrows by 7 percent and the BA/high school wage premium shrinks by 4 percent. In Simulation 3, the wage premia fall by 22 and 11 percent, respectively.

III. RESULTS

Table 2 shows the practical impact of the three simulations on the numbers and shares of degree holders for four samples: all FTFY workers, FTFY men, FTFY women, and all men unconditional on work status. We focus on these four samples because the unconditional sample of women includes a large share of non-workers. As shown in the top panel, in 2018 45.1 percent of FTFY prime-age workers held at least a BA and 10.9 percent held an AA. (Among all adults age 25 to 54, 39.9 percent held at least a BA and 10.7 percent held an AA; not shown in the table). Simulation 1 raises the BA share to 50 percent, which is a modest increase when the sample is limited to FTFY workers. For the full sample of prime-age individuals, this increase is more substantial, requiring that 11.1 million more adults hold a bachelor's degree (from 39.9 million to 51.0 million; not shown in the table). Simulation 2 maintains the bachelor's degree share increase to 50 percent and adds an increase in the share of the sample with associate degrees to 15 percent; while the latter is only a 4–5 percentage point bump from 2018 levels, it represents a relatively large proportional increase. Simulation 3 increases the respective shares to 60 and 20 percent. This requires an additional 21 million more prime-age adults to hold a bachelor's degree and 9.9 million more to hold an associate degree, which are ambitiously large gains; even among the FTFY sample, the respective increases are 10 million and 6.2 million (group A, Table 2). As described above, the simulation imparts new degrees to the current population of high school graduates, which in 2018 composed 40.1 percent (41.4 million) of prime-age adults and 37.7 percent (24.8 million adults) of prime-age FTFY workers.[12]

Table 3 illustrates how one of our counterfactual simulations affects the earnings distribution. It reports both observed earnings percentiles and simulated earnings percentiles, for each simulation, using the distribution method, for all FTFY workers, FTFY men, FTFY women, and all men. The simulations raise earnings in all four samples for roughly the lower three-quarters of the earnings distribution, with the strongest gains in the middle. The highest percentiles, however, show much smaller gains, or even losses among FTFY men, due to the general equilibrium effects that lower the college wage premium.

We are particularly interested, however, in how these changes affect distributional outcomes. Table 4a thus reports percentile earnings ratios for the sample of all prime-age FTFY workers, including changes based on all three simulations, according to both the distribution and causal parameter methods. As can be seen in the table, there were large increases in the 90/10, 90/25, and 90/50 percentile earnings ratios between 1979 and 2018, reflecting disproportionate growth at the top of the distribution (Table 1). However, there was actually a slight decrease in the 50/10 ratio over this period.

As the lower panel of Table 4a indicates, the simulation of a sizable increase in the rate of bachelor's degree attainment would lead to meaningful reductions in earnings ratios between the 90th and lower percentiles among FTFY workers, and this is true for either simulation method, as

[12] Note that the simulations for the first three groups (FTFY samples) are based on raising education for *all* FTFY workers by the stated amounts, not men and women separately in the FTFY men and FTFY women samples. For the all-men group, education is raised for all (prime-age) men by the stated amount.

both produce similar results. For example, the 90/10 ratio increased from 4.63 to 5.45 between 1979 and 2018. Simulation 3 (increasing AA rates to 20 percent and BA rates to 60 percent) would bring that ratio down to 5.16 (distribution method) or 5.00 (causal parameter method), reversing from more than half to all of the actual increase over this period.[13] As suggested by Table 3, the reduction stems from increases in the 10th percentile of FTFY earnings and smaller proportional change at the 90th percentile. The same simulation also substantially reduces the 90/50, 90/25, and 50/25 earnings ratios, although the reductions are less dramatic. Simulations 1 and 2, which involve smaller shifts in degree attainment, produce correspondingly smaller, but still sizable, reductions in these inequality measures. Interestingly, the causal parameter method produces slightly larger reductions in the percentile ratios than the distribution method, and the difference increases as the simulation becomes more extreme in the education shifts.[14]

The estimates reported in Table 4a incorporate relative wage effects estimated using data from 1979 to 2018. If we instead estimate relative wage effects using data from 1963 to 2018, consistent with previous literature, the depressive effect of increased BA attainment on relative wages would be larger and the depressive effect of increased AA attainment on relative wages would be smaller (as shown in Appendix Tables C.1 and C.2). Appendix Table A.3 reproduces the results from Table 4a using these relative wage effects instead. As can be seen in the table, the simulated reductions in the 90/10 and 90/25 wage ratios are even larger. Simulation 3 reduces the 90/10 ratio to 4.85 (distribution method) and 4.64 (causal parameter method). It reduces the 90/25 ratio to 3.50 (distribution method) and 3.29 (causal parameter method).

[13] Appendix Table A.2 reports the analogous results when relative wage effects are not taken into account. The resulting reductions in inequality are, as expected, smaller, especially for the causal parameter method. For instance, the simulated 90/10 earnings ratio under simulation 3 becomes 5.20 according to both methods, as compared to 5.06 and 4.95 when relative wages are adjusted.

[14] This gap likely relates to the large earnings variance *among* college graduates; while the causal parameter method unambiguously increases earnings, the distribution method can result in some "treated" individuals having their earnings reduced, if the draw is sufficiently bad.

Tables 4b and 4c report results separately for FTFY men and women, using our baseline approach. As in the pooled sample, the results from both the distribution and causal parameter methods show that for both men and women, a sizable increase in the rate of bachelor's degree attainment would lead to meaningful reductions in earnings ratios between the 90th and lower percentiles. For example, among FTFY men, the 90/10 ratio increased between 1979 and 2018 from 3.86 to 5.58; simulation 3 would bring that ratio down to 5.18 (distribution method) or 5.04 (causal parameter method), reducing the increase in inequality by up to one-third. Among FTFY women, the 90/10 ratio increased from 3.6 to 5.0; simulation 3 would bring that ratio down to 4.44 (distribution method) or 4.28 (causal parameter method), reducing the increase in inequality by about one half. Sizable reductions are also observed for the 90/25 and 50/25 ratios. Again, we see only small reductions (or for FTFY women, increases) in the 99/90 ratio, consistent with the rising dispersion in earnings among college graduates.[15] The causal parameter method produces slightly larger reductions in the percentile ratios than the distribution method, but these should be interpreted with caution as we do not have separate causal parameter estimates for men and women.

As discussed above, employment rates for prime-age men have fallen over time, especially for less-educated prime-age men. Thus, it is also illustrative to examine how our simulations would affect earnings ratios and employment rates (proxied by positive earnings) for all prime-age men, regardless of work status. Table 4d reports observed and simulated earnings ratios for this latter sample.[16] As the 10th percentile of earnings for this sample is zero in both 1979 and 2018, we omit ratios with the 10th percentile in the denominator. The remaining ratios

[15] These reductions would likely be even smaller with better corrections for topcoded earnings.

[16] We do not report analogous results for the unconditional pooled sample of men and women or women separately, as 34.6 percent of women reported no earnings in 1979, making comparisons of unconditional earnings ratios over time less meaningful.

all experienced large increases over the nearly 40-year period, chiefly driven by reductions in earnings at the lower (and even middle) percentiles, which are in turn a symptom of the 7-point reduction in employment rates. The causal method is less useful for this sample, since it only increases earnings of those with positive earnings and does not allow for an extensive margin effect on employment. Not surprisingly, the simulated effects on income inequality for this sample are smaller at the lower end using the causal method than the distribution method. The distribution method results show that increasing the BA rate to 60 percent and the AA rate to 20 percent could lead to meaningful reductions in the 50/25 and 90/25 unconditional earnings ratios. The 50/25 ratio, which rose from 1.71 to 2.18, would fall to 1.88. The 90/25 ratio, which rose from 3.33 to 6.00, would fall to 4.83. As expected, the more intense simulations are associated with larger reductions. The distribution method simulation also suggests the employment rate would rise by 1.2–2.8 percentage points, suggesting gains below the 25th percentile not captured by the displayed ratios.[17]

Table 5 reports the results of the simulated increase in college attainment on measures of individual level economic insecurity, as captured by four poverty measures: deep poverty (family income less than 50 percent of the federal poverty threshold), poverty (family income less than the poverty threshold), near poverty (family income less than 150 percent of the threshold), and low income (family income less than 200 percent of the federal poverty threshold). Here we follow official rules and define an individual's poverty status by whether that individual's *family income* is less than the corresponding Census poverty threshold, which varies by family size and

[17] We consider the employment rate to have increased when individuals switch from zero to positive earnings under the simulation. The causal parameter method affects only the intensive margin and thus the employment rate is unchanged by this method.

composition.[18] As reported in the table, all four measures of poverty increased between 1979 and 2018 among adults age 25 to 54. The share of prime-age adults living below the poverty line increased from 8.2 to 11.3 percent, and the share living in deep poverty increased from 3.0 to 5.6 percent.

To simulate the effect on poverty of increased college attainment, we calculate simulated poverty rates by taking an individual's 2018 family income and adding any of their own additional earnings assigned by the simulation. Our calculation assumes family structure is fixed and there is no induced change in other family members' earnings; nor does it adjust income for any changes in taxes and transfers that would result from an increase in family earnings. Because this approach ignores any potential increase in taxes and reduction in transfer benefits, it likely overstates the increase in "true" household income and corresponding reduction in poverty. (An obvious exception is that some households might see an increase in their Earned Income Tax Credit.) However, because in-kind transfers and taxes are excluded from official poverty estimates, our approach is reasonable when using that measure as reference.[19]

Based on the results of applying the distribution method, the simulated effect of increasing the BA share to 60 percent and the AA share to 20 percent is to reduce the poverty rate by 2.39 percentage points, from 11.3 to 8.91 percent in the sample using all civilian adults age 25 to 54. Reductions in the near-poverty or low-income rate are larger, with the first falling from 18.5 to 14.2 percent, and the second falling from 26.5 to 20.4 percent. Both of these

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[18] For an explanation of how official poverty statistics are calculated and the 2018 federal poverty thresholds, see: https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html.

[19] We experimented with using the NBER Taxsim model to adjust family income for taxes; however, since Taxsim calculates taxes owed and credits received, but does not include information about transfer benefits, the estimated numbers are still not an accurate measure of what would likely happen to household income net of taxes and transfers if earnings increased. In any case, the effects on poverty calculations are likely to be small because official poverty statistics do not adjust household income for taxes paid or tax credits received, nor do they include in-kind benefits such as SNAP. We have thus decided to report two benchmark estimates for poverty effects, one that simply adds earnings to existing household income and one that calculates poverty rates based only on earnings.

simulated rates are lower than their actual levels in 1979. The rate in deep poverty also falls, but only modestly, from 5.6 to 5 percent. This reflects the fact that very few people with a high school degree live in deep poverty (7.1 percent). To decrease rates of deep poverty, an intervention that targets high school dropouts (who have a deep-poverty rate of 12.7 percent) would likely be more effective.

The corresponding estimates from the causal parameter method imply smaller reductions of roughly half the magnitude of those from the distribution method. This, in large part, reflects that the former method does not allow for changes in the likelihood of employment and only increases earnings for those who have positive earnings, while the latter method allows for these changes, which are particularly likely to affect (near-) poverty measures.

Appendix Table A.4 reports the results from calculating poverty rates using only observed family earnings, ignoring other sources of income. These rates do not correspond to official poverty statistics, but they allow us to gauge rates of economic self-sufficiency, as captured by the share of prime-age adults in families who earn enough money to live above the federal poverty threshold, or multiples thereof. In 2018, 19.5 percent of individuals lived in families with earnings less than the federal poverty threshold, up from 17.2 percent in 1979. Using the distribution method, raising the BA share to 50 percent would reduce this poverty measure to 17.3 percent, back to its 1979 level; additionally raising the AA share to 15 percent would reduce this poverty rate to 16.8 percent, and raising the BA share to 60 percent and the AA share to 20 percent would further reduce the poverty rate to 14.8 percent. This total reduction of 4.65 percentage points would correspond to 6 million fewer prime-age adults in poverty (based on 2018 Census population counts). Similar declines would occur for the other poverty thresholds.

The reduction in poverty rates from simulations using the causal parameter method is much smaller, for the reasons discussed above. The difference in the simulated effects of poverty rates between the two methods highlights how important the effect of increased college attainment on the employment margin is for poverty avoidance and basic economic security.

We further consider what increased college attainment of prime-age individuals could do for child poverty rates. The results are presented in Appendix Table A.5. The share of children in poverty (calculated using our data and the official federal poverty threshold) held steady between 1979 and 2018: 16.79 percent and 16.83 percent. These simulations suggest that the increased household earnings associated with increasing the BA attainment rate to 60 percent and the AA rate to 20 percent would reduce child poverty rates to 13.47 percent (distribution method) or 14.84 percent (causal parameter method.) There would be an even larger percentage point reduction in the share of children living in households with income less than 200 percent of the poverty rate. Increased economic security among children should be considered a key benefit that would result from more educated prime-age adults, many of whom are parents to young children.

IV. CONCLUSION

In this analysis we have simulated the effects of increasing college attainment, both bachelor's and associate degrees, of men and women age 25 to 54 to gauge the likely effects on earnings and earnings inequality. We have conducted the simulation using two distinct approaches. The distribution method assigns individuals whose college status is randomly shifted a draw from the earnings distribution of college-educated workers. The causal parameter method assigns workers whose college status is randomly shifted a single earnings premium, based on existing studies in the literature. Both approaches suggest that increasing the educational attainment of adults without a college degree will increase their average earnings, with gains concentrated in the lower half of the earnings distribution. The distribution method further allows for an increase in the likelihood of work, which is particularly important for raising earnings at the bottom of the distribution. The results of the simulation also show meaningful reductions in rates of poverty and near-poverty (family income less than 200 percent of the federal poverty threshold). Increasing rates of college degree attainment will also moderately reduce inequality, mostly by raising the lower-middle part of the earnings distribution relative to the upper-middle. However, increased college attainment will have minimal effects on reducing overall inequality back to the levels in 1979, as a greater share of the population with college degrees will not meaningfully affect earnings at the highest parts of the distribution, where much of the rise in inequality has taken place.

In this paper we have provided a quantitative approximation to what could be achieved in terms of reduced income inequality and increased individual economic security through a meaningful, albeit feasible, increase in the share of prime-age adults with a college degree. We have not attempted to argue for or against any particular way of achieving that result, though obviously the question of *how* to achieve increased college attainment is of the utmost importance. Nor have we made the claim that increasing college attainment is *sufficient* to address the current degree of income inequality or income insecurity. We view the results of this analysis as suggesting that increasing college attainment is an important potential response to the rise in income inequality.

References

Abraham, Katharine, and Melissa S. Kearney. Forthcoming. "Explaining the Decline in the U.S. Employment-to-Population Ratio: a Review of the Evidence." *Journal of Economic Literature*.

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics, Volume 4B*. New York, NY: North Holland. pp. 1043–1171.

Autor, David. 2014. "Skills, Education, and the Rise of Earnings Inequality Among the `Other 99 Percent'." *Science* 344(6186): 843–851.

Bahr, Peter R., Susan Dynarski, Brian Jacob, Daniel Kreisman, Alfredo Sosa, and Mark Wiederspan. 2015. "Labor Market Returns to Community College Awards: Evidence From Michigan." CAPSEE Working Paper.

Card, David, and Thomas Lemiuex. 2001. "Can Falling Supply Explain the Rising Return to College for Younger Men? ACohort-Based Analysis." *Quarterly Journal of Economics* 116(2): 705–746.

Deming, David J., and Christopher R. Walters. 2017. "The Impact of Price Caps and Spending Cuts on U.S. Postsecondary Attainment." NBER Working Paper No. 23736.

Flood, Sarah Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. 2019. *Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]*. Minneapolis, MN: IPUMS. https://doi.org/10.18128/D030.V6.0.

Goldin, Claudia, and Lawrence F. Katz. 2008. *The Race Between Education and Technology*. Cambridge, MA: Harvard University Press.

Goldin, Claudia, and Robert A. Margo. 1992. "The Great Compression: The Wage Structure in the United States at Mid-Century." *Quarterly Journal of Economics* 107(1): 1–34.

Hershbein, Brad, Melissa S. Kearney, and Lawrence H. Summers. 2015. "Increasing Education: What It Will and Will Not Do for Earnings and Inequality." *Brookings Up Front*. March 31. Available at https://www.brookings.edu/blog/up-front/2015/03/31/increasing-education-what-it-will-and-will-not-do-for-earnings-and-earnings-inequality/.

Hoekstra, Mark. 2009. "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach." *Review of Economics and Statistics* 91(4): 717–724.

Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963–1987: Supply and Demand Factors." *Quarterly Journal of Economics* 107(1): 35–78.

Larrimore, Jeff, Richard V. Burkhauser, Shuaizhang Feng, and Laura Zayatz. 2008. "Consistent Cell Means for Topcoded Incomes in the Public Use March CPS (1976-2007)." *Journal of Economic and Social Measurement* 33(2/3): 89–128.

Semega, Jessica, Melissa Kollar, John Creamer, and Abinash Mohanty. 2019. "U.S. Census Bureau Income and Poverty in the United States: 2018." *U.S. Census Bureau Report Number p60-266*. Table B-1: https://www.census.gov/data/tables/2019/demo/income-poverty/p60-266.html

Stevens, Ann H., Michal Kurlaender, and Michel Grosz. 2019. "Career Technical Education and Labor Market Outcomes." *Journal of Human Resources* 54(4): 986–1036.

Zimmerman, Seth. 2014. "The Returns to College Admission for Academically Marginal Students." *Journal of Labor Economics* 32(4): 711–754.

Tables and Figures

Table 1: Summary Statistics by Year and Sample: Earnings Percentiles and Inequality Measures

Year	p10	p25	p50	p75	p90	p99	Gini Coefficient
Panel A: 1979							
Full-time, full-year workers							
Men and women	17,482	27,579	41,206	58,062	80,868	174,185	0.332
Men	22,934	34,837	50,514	67,642	88,544	203,216	0.310
Women	14,515	21,007	29,031	40,170	52,256	87,093	0.275
All individuals							
Men and women	0	2,032	25,257	46,667	69,674	145,155	0.537
Men	5,632	26,128	44,603	63,868	87,093	188,701	0.381
Women	0	0	8,709	26,128	40,643	71,039	0.614
Panel B: 2018							
Full-time, full-year workers							
Men and women	22,000	32,000	50,000	78,000	120,000	320,000	0.403
Men	24,000	35,000	55,000	85,000	134,000	400,000	0.409
Women	20,000	30,000	45,000	68,000	100,000	260,000	0.383
All individuals							
Men and women	0	6,500	34,000	60,000	100,000	268,000	0.565
Men	0	20,000	43,614	75,000	120,000	310,000	0.517
Women	0	0	25,000	50,000	80,000	200,000	0.598

Note: Statistics are calculated for civilian men and women ages 25 to 54. Earnings are defined as the sum of annual wage, salary, and positive business income, adjusted for inflation (to 2018 dollars) using the personal consumption expenditures (PCE) deflator of the Bureau of Economic Analysis. Employment is defined as having positive earnings in the reference year, and full-time, full-year workers are those working at least 40 weeks in the previous calendar year and at least 35 hours usually worked per week.

Source: Authors’ calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table 2: Numbers (in millions) and Shares of Degree Holders: Full-Time Full-Year Workers

	Group A: FTFY			Group B: FTFY Men			Group C: FTFY Women			Group D: All Men		
	High School Graduate	AA Holder	BA or greater	High School Graduate	AA Holder	BA or greater	High School Graduate	AA Holder	BA or greater	High School Graduate	AA Holder	BA or greater
Panel A: Observed												
1979	21.2	3.7	10.7	13.0	2.5	7.5	8.2	1.2	3.2	15.4	2.9	8.4
	49.1%	8.7%	24.8%	45.9%	8.9%	26.4%	55.1%	8.3%	21.7%	45.0%	8.6%	24.6%
2018	24.8	7.2	29.6	15.4	3.8	15.1	9.3	3.4	14.5	21.5	4.7	17.9
	37.7%	10.9%	45.1%	41.4%	10.1%	40.6%	32.7%	11.9%	50.9%	43.8%	9.6%	36.4%
Panel B: Simulations for 2018												
Raise BA share to 50%	21.3	7.2	33.1	13.3	3.8	17.2	8.0	3.4	15.8	15.7	4.7	23.8
	32.4%	10.9%	50.3%	35.7%	10.1%	46.3%	28.2%	11.9%	55.5%	31.9%	9.6%	48.3%
+ Raise AA share to 15%	18.5	10.0	33.1	11.5	5.5	17.2	7.0	4.4	15.8	13.3	7.1	23.8
	28.2%	15.2%	50.3%	31.0%	14.8%	46.3%	24.5%	15.6%	55.5%	27.0%	14.4%	48.4%
20% AA share, 60% BA share	8.7	13.2	39.6	5.4	7.6	21.3	3.3	5.7	18.3	5.4	9.8	29.0
	13.3%	20.1%	60.2%	14.6%	20.3%	57.2%	11.6%	19.8%	64.2%	10.9%	19.9%	59.0%

Note: High school graduates are defined as those with a high school degree (or equivalent) or some college, but no degree. For 1979 data, we define associate degree (AA) holders as those with exactly two years of college education, and "BA or greater" as those with four or more years of college education.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table 3: Simulated Effects of Increasing College Shares on Annual Earnings Distributions: Using Distribution Approach

	Share with AA	Share with BA or greater	Annual Earnings p10	p25	p50	p75	p90	p99	Gini Coefficient
Panel A: 2018 Baseline									
FTFY Men and Women	10.9%	45.1%	22,000	32,000	50,000	78,000	120,000	320,000	0.403
FTFY Men	10.1%	40.6%	24,000	35,000	55,000	85,000	134,000	400,000	0.409
FTFY Women	11.9%	50.9%	20,000	30,000	45,000	68,000	100,000	260,000	0.383
All Men	9.6%	36.4%	0	20,000	43,614	75,000	120,000	310,000	0.517
Panel B: Simulation 1									
FTFY Men and Women	10.9%	50.3%	23,321	33,828	51,255	79,870	122,500	343,000	0.401
FTFY Men	10.1%	46.3%	24,602	35,879	57,406	89,184	141,120	392,000	0.407
FTFY Women	11.9%	55.5%	20,502	30,753	46,130	68,600	100,940	272,677	0.379
All Men	9.6%	48.4%	0	24,000	48,000	81,600	128,050	355,200	0.503
Panel C: Simulation 2									
FTFY Men and Women	15.2%	50.3%	23,520	34,300	52,785	79,178	122,500	343,000	0.397
FTFY Men	14.8%	46.3%	25,337	36,950	58,064	89,735	141,120	392,000	0.402
FTFY Women	15.6%	55.5%	21,114	31,498	47,507	68,621	100,940	274,400	0.375
All Men	14.4%	48.4%	0	24,138	49,140	81,600	129,470	345,600	0.498
Panel D: Simulation 3									
FTFY Men and Women	20.1%	60.2%	24,570	36,538	55,755	84,505	126,758	351,315	0.387
FTFY Men	20.3%	57.2%	27,370	39,816	60,895	94,500	141,750	382,726	0.391
FTFY Women	19.8%	64.2%	23,421	33,075	47,250	70,875	103,950	283,500	0.363
All Men	19.9%	59.0%	0	27,300	51,257	84,630	131,950	364,000	0.480

Note: Results are presented for each simulation under the distributional assignment approach: 1) increasing the share of all individuals with a BA or more (in the FTFY or entire sample) to 50 percent; 2) increasing the share with a BA or more to 50 percent and the share with an AA to 15 percent; and 3) increasing these shares to 60 percent and 20 percent, respectively.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table 4a: Observed and Simulated Percentile Earnings Ratios: Full-Time, Full-Year Workers

	r50/10	r90/10	r50/25	r90/25	r90/50	r99/90	Gini Coefficient
Panel A: Observed							
1979	2.36	4.63	1.49	2.93	1.96	2.15	0.332
2018	2.27	5.45	1.56	3.75	2.40	2.67	0.403
Panel B: 2018 Simulations							
Distribution Method							
1) Raise BA share to 50%	2.20	5.25	1.52	3.62	2.39	2.80	0.401
2) + Raise AA share to 15%	2.24	5.21	1.54	3.57	2.32	2.80	0.397
3) 60% BA share, 20% AA share	2.27	5.16	1.53	3.47	2.27	2.77	0.387
Causal Parameter Method							
1) Raise BA share to 50%	2.20	5.25	1.52	3.62	2.39	2.64	0.397
2) + Raise AA share to 15%	2.24	5.21	1.54	3.57	2.32	2.64	0.394
3) 60% BA share, 20% AA share	2.26	5.00	1.52	3.36	2.21	2.62	0.382

Note: The distribution method assigns "treated" individuals a random draw from the earnings distribution of the assigned group (AA or BA). The causal parameter method increases the earnings of the treated by a factor consistent with existing literature (see text). We include general equilibrium effects on wages in these simulations, as explained in the text.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table 4b: Observed and Simulated Percentile Earnings Ratios: Full-Time, Full-Year Men

	r50/10	r90/10	r50/25	r90/25	r90/50	r99/90	Gini Coefficient
Panel A: Observed							
1979	2.20	3.86	1.45	2.54	1.75	2.30	0.310
2018	2.29	5.58	1.57	3.83	2.44	2.99	0.409
Panel B: 2018 Simulations							
Distribution Method							
1) Raise BA share to 50%	2.33	5.74	1.60	3.93	2.46	2.78	0.407
2) + Raise AA share to 15%	2.29	5.57	1.57	3.82	2.43	2.78	0.402
3) 60% BA share, 20% AA share	2.22	5.18	1.53	3.56	2.33	2.70	0.391
Causal Parameter Method							
1) Raise BA share to 50%	2.32	5.56	1.58	3.79	2.39	2.86	0.402
2) + Raise AA share to 15%	2.31	5.39	1.58	3.68	2.33	2.86	0.399
3) 60% BA share, 20% AA share	2.17	5.04	1.49	3.46	2.32	2.67	0.385

Note: The distribution method assigns "treated" individuals a random draw from the earnings distribution of the assigned group (AA or BA). The causal parameter method increases the earnings of the treated by a factor consistent with existing literature (see text). We include general equilibrium effects on wages in these simulations, as explained in the text.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table 4c: Observed and Simulated Percentile Earnings Ratios: Full-Time, Full-Year Women

	r50/10	r90/10	r50/25	r90/25	r90/50	r99/90	Gini Coefficient
Panel A: Observed							
1979	2.00	3.60	1.38	2.49	1.80	1.67	0.275
2018	2.25	5.00	1.50	3.33	2.22	2.60	0.383
Panel B: 2018 Simulations							
Distribution Method							
1) Raise BA share to 50%	2.25	4.92	1.50	3.28	2.19	2.70	0.379
2) + Raise AA share to 15%	2.25	4.78	1.51	3.20	2.12	2.72	0.375
3) 60% BA share, 20% AA share	2.02	4.44	1.43	3.14	2.20	2.73	0.363
Causal Parameter Method							
1) Raise BA share to 50%	2.25	4.80	1.50	3.20	2.13	2.62	0.375
2) + Raise AA share to 15%	2.23	4.68	1.49	3.12	2.10	2.63	0.371
3) 60% BA share, 20% AA share	2.02	4.28	1.43	3.03	2.12	2.59	0.359

Note: The distribution method assigns "treated" individuals a random draw from the earnings distribution of the assigned group (AA or BA). The causal parameter method increases the earnings of the treated by a factor consistent with existing literature (see text). We include general equilibrium effects on wages in these simulations, as explained in the text.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table 4d: Observed and Simulated Percentile Earnings Ratios: All Men

	r50/25	r90/25	r90/50	r99/90	Gini Coefficient	Employment Rate
Panel A: Observed						
1979	1.71	3.33	1.95	2.17	0.381	92.48%
2018	2.18	6.00	2.75	2.58	0.517	85.41%
Panel B: 2018 Simulations						
Distribution Method						
1) Raise BA share to 50%	2.00	5.34	2.67	2.77	0.503	86.71%
2) + Raise AA share to 15%	2.04	5.36	2.63	2.67	0.497	86.90%
3) 60% BA share, 20% AA share	1.88	4.83	2.57	2.76	0.480	88.21%
Causal Parameter Method						
1) Raise BA share to 50%	2.25	5.87	2.61	2.56	0.506	85.41%
2) + Raise AA share to 15%	2.17	5.65	2.60	2.58	0.503	85.41%
3) 60% BA share, 20% AA share	2.08	5.11	2.46	2.59	0.492	85.41%

Note: The distribution method assigns "treated" individuals a random draw from the earnings distribution of the assigned group (AA or BA). The causal parameter method increases the earnings of the treated by a factor consistent with existing literature (see text). We include general equilibrium effects on wages in these simulations, as explained in the text. Ratios with the 10^{th} percentile as the denominator are not calculated, as the 10^{th} percentile earnings are zero in each case.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

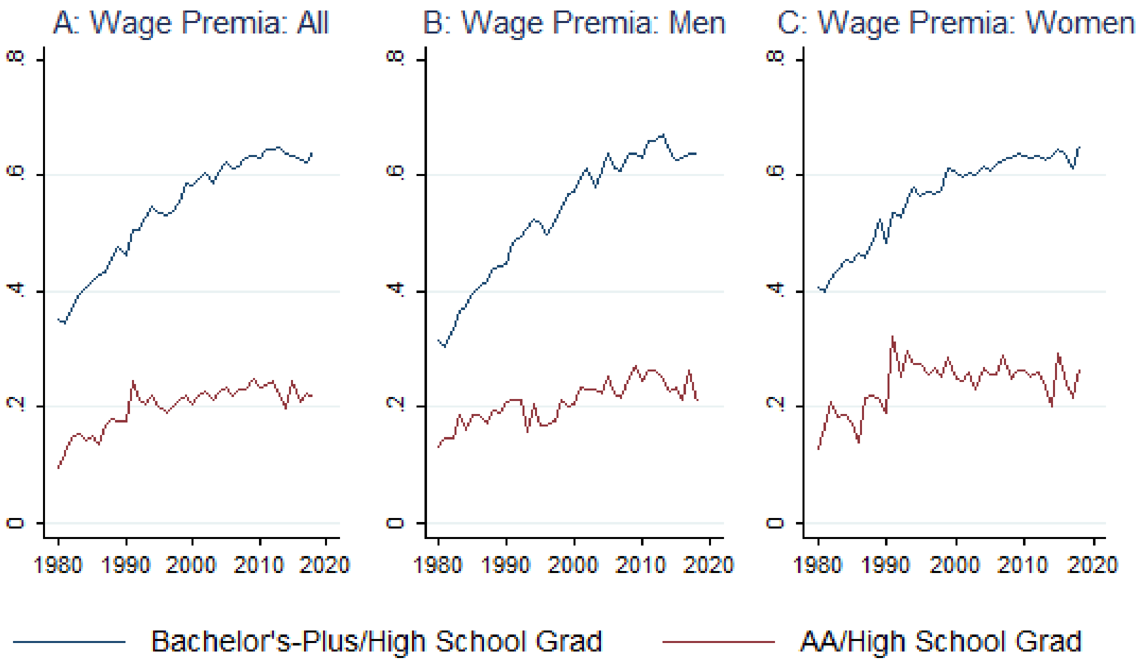
Table 5: Poverty Rates: All Prime-Age Individuals

	Deep Poverty (<50% FPL)	Poverty (FPL)	Near Poverty (<150% FPL)	Low Income (<200% FPL)
Panel A: Observed				
1979	2.97%	8.21%	14.91%	23.22%
2018	5.59%	11.30%	18.48%	26.46%
Panel B: 2018 Simulations				
Distribution Method				
1) Raise BA share to 50%	5.17%	10.17%	16.39%	23.24%
2) + Raise AA share to 15%	5.13%	9.95%	15.88%	22.59%
3) 60% BA share, 20% AA share	4.95%	8.91%	14.19%	20.41%
Causal Parameter Method				
1) Raise BA share to 50%	5.42%	10.72%	17.26%	24.38%
2) + Raise AA share to 15%	5.34%	10.51%	16.81%	23.89%
3) 60% BA share, 20% AA share	5.26%	10.13%	16.08%	22.76%

Note: "FPL" is the federal poverty threshold as calculated by the Census Bureau for different family structures. Simulated changes in poverty rates reflect changes to each household member's income through direct wage or general equilibrium relative wage effects. Any resulting changes to transfer payments are not reflected in this analysis.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Figure 1: Trends in Wage Premia for Bachelor's-Plus/Noncollege and Associate Degree/Noncollege



Note: These wage premia series depict a fix-weighted ratio of bachelor's-plus to high school or AA to high school wages for a composition-constant set of sex-education-experience groups (two sexes, six education categories, and four potential experience categories), similar in methodology to Autor, Katz,and Kearney (2008) and Acemoglu and Autor (2011). See appendix for further details.
Source: 1980-2019 March CPS and author's calculations.

Appendix A: Tables

Table A.1: Summary Statistics by Education: Earnings Distribution and Inequality Measures: FTFY Workers

Year	p10	p25	p50	p75	p90	p99	Gini Coefficient
1979							
Overall	17,482	27,579	41,206	58,062	80,868	174,185	0.332
Less than HS	13,064	20,322	31,112	46,449	62,390	101,608	0.324
HS Degree	17,419	26,128	38,321	55,739	72,577	119,027	0.302
AA	21,773	30,482	43,546	60,965	81,287	145,157	0.293
BA or Greater	26,708	37,740	53,417	75,480	113,221	287,406	0.332
2018							
Overall	22,000	32,000	50,000	78,000	120,000	320,000	0.403
Less than HS	15,000	20,000	28,000	40,000	55,000	130,000	0.328
HS Degree	20,000	27,700	40,000	57,000	80,000	170,000	0.339
AA	24,000	31,200	47,000	65,000	90,000	175,000	0.327
BA or Greater	32,000	47,000	70,000	100,000	155,000	450,000	0.387

Note: Statistics are calculated for civilian men and women ages 25 to 54. Earnings are defined as the sum of annual wage, salary, and positive business income, adjusted for inflation (to 2018 dollars) using the personal consumption expenditures (PCE) deflator of the Bureau of Economic Analysis. Employment is defined as having positive earnings in the reference year, and full-time, full-year workers are those working at least 50 weeks in the previous calendar year and at least 35 hours usually worked per week. See text for description of education categories.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table A.2: Observed and Simulated earnings ratios: Full-Time, Full-Year Workers: No Relative Wage Effects

	r50/10	r90/10	r50/25	r90/25	r90/50	r99/90	Gini Coefficient
Panel A: Observed							
1979	2.36	4.63	1.49	2.93	1.96	2.15	0.332
2018	2.27	5.45	1.56	3.75	2.40	2.67	0.403
Panel B: 2018 Simulations							
Distribution Method							
1) Raise BA share to 50%	2.21	5.43	1.52	3.74	2.46	2.80	0.406
2) + Raise AA share to 15%	2.26	5.43	1.53	3.68	2.41	2.72	0.403
3) 60% BA share, 20% AA share	2.24	5.20	1.56	3.61	2.32	2.85	0.398
Causal Parameter Method							
1) Raise BA share to 50%	2.19	5.30	1.50	3.63	2.42	2.70	0.401
2) + Raise AA share to 15%	2.26	5.43	1.49	3.58	2.40	2.64	0.400
3) 60% BA share, 20% AA share	2.24	5.20	1.56	3.61	2.32	2.62	0.393

Note: These results exclude the relative wage narrowing of the BA/HS and AA/HS wage premia included in Tables 4a-d.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table A.3: Observed and Simulated Earnings Ratios: Full-Time, Full-Year Workers, Using Relative Wage Effects Estimated over 1963–2018 Data

	r50/10	r90/10	r50/25	r90/25	r90/50	r99/90	Gini Coefficient
Panel A: Observed							
1979	2.36	4.63	1.49	2.93	1.96	2.15	0.332
2018	2.27	5.45	1.56	3.75	2.40	2.67	0.403
Panel B: 2018 Simulations							
Distribution Method							
1) Raise BA share to 50%	2.25	5.21	1.54	3.57	2.32	2.80	0.398
2) + Raise AA share to 15%	2.24	5.15	1.56	3.58	2.30	2.80	0.395
3) 60% BA share, 20% AA share	2.08	4.85	1.50	3.50	2.33	2.71	0.378
Causal Parameter Method							
1) Raise BA share to 50%	2.25	5.21	1.54	3.57	2.32	2.64	0.394
2) + Raise AA share to 15%	2.22	5.10	1.54	3.53	2.30	2.64	0.392
3) 60% BA share, 20% AA share	2.08	4.64	1.47	3.29	2.23	2.60	0.375

Note: These results include adjustments for relative wage effects estimated with data from 1963–2018, consistent with earlier literature. (These estimates are displayed in column 2 of Appendix Tables C.1 and C.2; they indicate a larger depressive effect of BA supply on relative wages but a smaller depressive effect of AA supply on relative wages, as compared to estimates using data from 1979–2018.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table A.4: Poverty Rates Relative to Earned Income for Prime-Age Individuals (All Prime-Age Individuals Simulation)

	Deep Poverty (<50% FPL)	Poverty (FPL)	Near Poverty (<150% FPL)	Low Income (<200% FPL)
Panel A: Observed				
1979	12.24%	17.15%	23.72%	31.89%
2018	14.42%	19.47%	26.20%	33.74%
Panel B: 2018 Simulations				
Distribution Method				
1) Raise BA share to 50%	12.89%	17.31%	23.29%	29.89%
2) + Raise AA share to 15%	12.46%	16.76%	22.62%	29.21%
3) 60% BA share, 20% AA share	10.95%	14.82%	20.30%	26.71%
Causal Parameter Method				
1) Raise BA share to 50%	14.21%	18.63%	24.72%	31.45%
2) + Raise AA share to 15%	14.08%	18.37%	24.22%	30.91%
3) 60% BA share, 20% AA share	13.95%	17.89%	23.34%	29.67%

Note: "FPL" is the federal poverty threshold as calculated by the Census Bureau for different family structures. Unlike Table 5, poverty rates here are calculated relative to total wage, salary, and positive business income—but not other cash transfers or unearned income—in each household. Changes in poverty rates reflect changes to each household member's earnings through treatment or general equilibrium effects.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table A.5: Child Poverty Rates (All Prime-Age Individuals Simulation)

	Deep Poverty (<50% FPL)	Poverty (FPL)	Near Poverty (<150% FPL)	Low Income (<200% FPL)
Panel A: Observed				
1979	6.33%	16.79%	27.45%	39.36%
2018	7.54%	16.83%	27.92%	38.23%
Panel B: 2018 Simulations				
Distribution Method				
1) Raise BA share to 50%	6.88%	15.24%	25.09%	34.90%
2) + Raise AA share to 15%	6.78%	15.05%	24.67%	34.40%
3) 60% BA share, 20% AA share	6.50%	13.47%	22.62%	32.21%
Causal Parameter Method				
1) Raise BA share to 50%	7.18%	15.87%	26.01%	36.21%
2) + Raise AA share to 15%	7.07%	15.60%	25.55%	35.75%
3) 60% BA share, 20% AA share	6.89%	14.84%	24.39%	34.49%

Note: "FPL" is the federal poverty threshold as calculated by the Census Bureau for different family structures. Simulated changes in poverty rates reflect changes to each household member's income through direct wage or general equilibrium relative wage effects. Any resulting changes to transfer payments are not reflected in this analysis. Child poverty rates include individuals under age 18 in families with income below the relevant poverty threshold.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Table A.6: Child Poverty Rates Relative to Earned Income: All Individuals Sample

	Deep Poverty (<50% FPL)	Poverty (FPL)	Near Poverty (<150% FPL)	Low Income (<200% FPL)
Panel A: Observed				
1979	25.69%	33.33%	42.27%	52.49%
2018	30.58%	38.73%	47.51%	55.22%
Panel B: 2018 Simulations				
Distribution Method				
1) Raise BA share to 50%	29.17%	36.37%	44.25%	51.79%
2) + Raise AA share to 15%	28.72%	35.95%	43.81%	51.44%
3) 60% BA share, 20% AA share	27.38%	33.90%	41.55%	49.23%
Causal Parameter Method				
1) Raise BA share to 50%	30.21%	37.43%	45.40%	53.20%
2) + Raise AA share to 15%	30.01%	37.13%	44.87%	52.77%
3) 60% BA share, 20% AA share	29.74%	36.30%	43.72%	51.48%

Note: "FPL" is the federal poverty threshold as calculated by the Census Bureau for different family structures. Unlike Table 5, poverty rates here are calculated relative to total wage, salary, and positive business income—but not other cash transfers or unearned income—in each household. Changes in poverty rates reflect changes to each household member's earnings through treatment or general equilibrium effects.

Source: Authors' calculations of March Current Population Survey 1980 and 2019 (Flood et al., 2019).

Appendix B: Figures plotting FTFY earnings distributions

Figure 1: Earnings Distributions: FTFY, by Sex

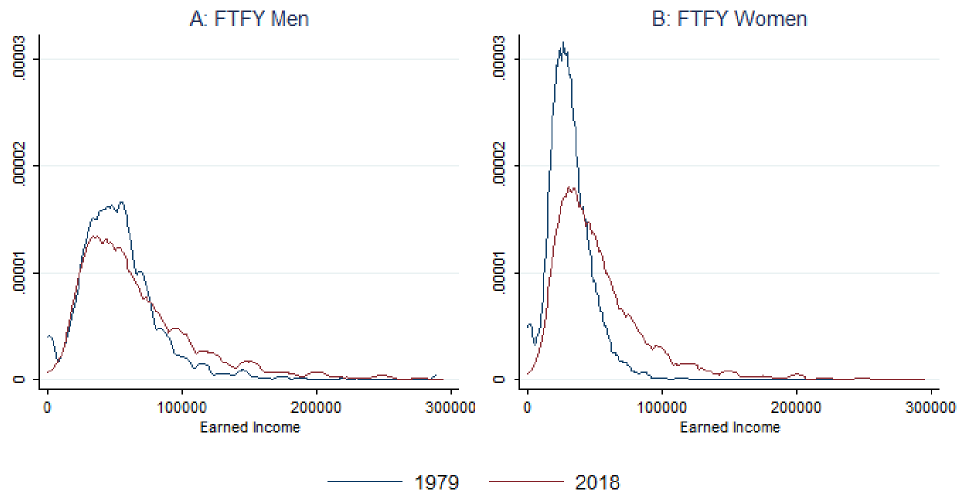
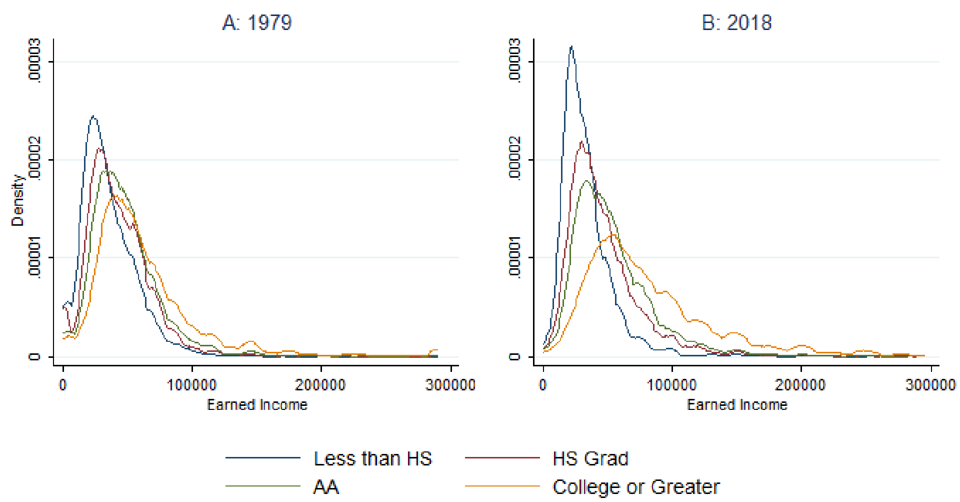


Figure 2: Earnings Distributions: FTFY, by Education



Appendix C: Estimation of Wage Premia and CES Substitution Elasticity Estimates

C.1: Wage Premia

Construction of Relative Wage Series

We calculate composition-adjusted BA/high school and AA /high school relative wages overall and by age or experience using the March CPS sample. These data are sorted into sex-education-experience groups based on a breakdown of the data into two sexes, six education categories (high school dropout, high school graduate, some college, associate's degree, college plus, and greater than college), and four potential experience categories (0–9, 10–19, 20–29, and 30+ years). Log weekly wages of full-time, full-year workers are regressed in each year separately by sex on the dummy variables for four education categories, a quartic in experience, black and other race dummies, and interactions of the experience quartic with three broad education categories (high school graduate, some college, and college plus). The (composition-adjusted) mean log wage for each of the 48 groups in a given year is the predicted log wage from these regressions evaluated for whites at the relevant experience level (5, 15, 25, or 35 years depending on the experience group). Mean log wages for broader groups in each year represent weighted averages of the relevant (composition-adjusted) cell means using a fixed set of weights, equal to the mean share of total hours worked by each group over 1963 to 2018 (or 1979-2018, depending on the specification) from the March CPS.

Construction of Relative Supply Measures

We calculate BA/high school and AA/high school relative supply measures using the March CPS sample. We form a labor "quantity sample" equal to total hours worked by all employed workers (including those in self-employment) with 0 to 39 years of potential experience in 48 gender-education-potential experience cells: experience groups are ten-year categories of 0-9, 10-19, 20-29, and 30-39 years; education groups are high school dropout, high school graduate, some college, associate's degree holder, college graduate, and post-college. The quantity data are merged to a corresponding "price sample" containing real mean full-time weekly (March CPS) wages by year, gender, potential experience, and education. (Wage data used for the price sample correspond to the earnings samples described above.) Wages in each of the 48 earnings cells in each year are normalized to a relative wage measure by dividing each by the wage of high school graduate males with ten years of potential experience in the contemporaneous year. We compute an "efficiency unit" measure for each gender-experience-education cell as the arithmetic mean of the relative wage measure in that cell over 1964 through 2018 (or 1979-2018). The quantity and price samples are combined to calculate relative log college/high school and log associate's degree/high school supplies. We define the efficiency units of labor supply of a gender-education-potential experience group in year *t* as the efficiency unit wage measure multiplied by the group's quantity of labor supply in year *t*. Following Autor, Katz, and Krueger (1998) and Card and Lemieux (2001), we calculate aggregate college-equivalent labor supply as the total efficiency units of labor supplied by college or college-plus workers plus half of the efficiency units of labor supplied by workers with some college. Similarly, aggregate high school–equivalent labor supply is the sum of efficiency units supplied by high school or lower workers, plus half of the efficiency units supplied by workers with some college. Our BA/high school (and AA/high school) log relative supply index is the natural logarithm of the ratio of BA-equivalent to non-BA-equivalent (or AA/non-AA) labor supply (in efficiency units) in each year. This measure is calculated overall for each year and by ten-year potential experience groupings.

C.2: Elasticity Estimates

BA/HS Elasticity of Substitution

We then use these measures of relative wages and relative supply to create estimates of how the wage premia will respond to changes in the relative supply from our simulations. Following Acemoglu and Autor (2011), we begin with a constant elasticity of supply production function with two inputs: high-high skill labor (proxied for by those with a BA or more) and low-skill labor (high school graduates),

$$Y = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where σ is the elasticity of substitution between high- and low-skill labor, and A_L and A_H are factor-augmenting technology terms. We can express the log wage premium as a function of relative supply and technology,

$$\ln w_1 = \ln \frac{w_H}{w_L} = \frac{\sigma - 1}{\sigma} ln\left(\frac{A_H}{A_L}\right) - \frac{1}{\sigma} ln\left(\frac{H}{L}\right).$$

Allowing for a log-linear time trend for demand of skills, we can then estimate the following equation:

$$\ln w_1 = \ln \frac{w_H}{w_L} = \frac{\sigma - 1}{\sigma}\gamma_0 + \frac{\sigma - 1}{\sigma}\gamma_1 t - \frac{1}{\sigma} ln\left(\frac{H}{L}\right). \qquad (1)$$

The resulting coefficient on the relative supply term (from the above log-log specification) measures what percent the wage premium will fall for a given percent increase in the relative supply of BA holders.

AA/HS Elasticity of Substitution

To estimate the analogous relative supply effects for a change in the AA/HS relative supply, we amend the above two-factor production function to allow for a nest within the "low-skill" input: Associate Degree holders (M) and those with a high school degree (L).

$$Y = \left[\left(A_L\left(\alpha L^{\frac{\eta-1}{\eta}} + \beta M^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}\right)^{\frac{\rho-1}{\rho}} + (A_H H)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}},$$

where now ρ is the elasticity of substitution between high- and low-skill labor, η measures the elasticity with the low-skill labor nest, and α and β are also factor-augmenting technology terms. We can express the log wage premium as a function of relative supply and technology,

As above, we can express the AA/High School premium as

$$\ln w_2 = \ln \frac{w_M}{w_L} = \frac{\eta - 1}{\eta} ln\left(\frac{\beta}{\alpha}\right) - \frac{1}{\eta} ln\left(\frac{M}{L}\right).$$

Allowing for a log-linear time trend in demand for skills driven yields

$$\ln w_2 = \ln \frac{w_M}{w_L} = \frac{\eta - 1}{\eta}\delta_0 + \frac{\eta - 1}{\eta}\delta_1 t - \frac{1}{\eta} ln\left(\frac{M}{L}\right). \qquad (2)$$

Estimates

Table C.1 presents estimates of equation (1) above for several sample restrictions. The post-1992 interaction is included to allow for an evident trend change in the demand for skills around 1992. Using the same data and methodology as Acemoglu and Autor (2011) and data from 1963 to 2008 (as they do), we are able to replicate their coefficient estimate of -0.644 (reported in Table 8 of their handbook chapter). In this table we we extend the data through 2018 and obtain an estimated coefficient on the relative BA/HS supply of -0.712. Because our simulations include only 25-54 year-olds and are restricted to the period from 1979 to 2018, it seems appropriate to restrict the estimating data to that age group and time period. Column (2) uses data back to 1963, but restricts the sample to 25-54 year-olds. Column (3) restricts the estimating data to our population sample and later time period. We incorporate the estimate from Column (3) in our main specifications; it implies that a one percent increase in the relative supply of college graduates (relative to high school graduates) will reduce the wage premium by 0.25 percent.

Table C.2 presents estimates of equation (2), the response of the AA/High School or wage premium to changes in the AA/HS-less relative supply. We include the same progression of sample restrictions as before. These estimates are more stable than the BA/HS data above. Column (3), with the preferred sample, suggests that a one percent increase in the AA/HS-less relative supply leads to a 0.18 percent decrease in that wage premium.

Table C.1: Bachelors-Plus/High School Relative Wage Response

	1963-2018		1979-2018
	16-64 y.o.	25-54 y.o.	25-54 y.o.
Relative Supply	-0.712***	-0.480***	-0.252***
	(0.0714)	(0.0407)	(0.0858)
Time	0.0302***	0.0213***	0.0198***
	(0.00249)	(0.00142)	(0.00161)
Time x Post-1992	-0.0128***	-0.00814***	-0.0105***
	(0.00158)	(0.00110)	(0.000106)
R^2	0.964	0.970	0.978

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: AA/High School Relative Wage Response

	1963-2018		1979-2018
	16-64 y.o.	25-54 y.o.	25-54 y.o.
Relative Supply	-0.0972***	-0.0697***	-0.183***
	(0.0303)	(0.0286)	(0.0496)
Time	0.00510***	0.00429***	0.00571***
	(0.000736)	(0.000698)	(0.000882)
R^2	0.837	0.801	0.733

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$