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Explaining Stagnation in the College Wage Premium

Abstract

After growing substantially during the 1980s through the early 2000s, the college wage premium more recently has been largely unchanged, or stagnant. We extend the canonical production-function model of skill premiums to assess supply and demand contributions to the slowdown in the college wage premium, using annual CPS ASEC data from the early 1960s through 2023. To account for the rising importance of women in the college educated workforce, we estimate a hybrid model that incorporates components that are disaggregated by age and gender. We also allow for non-linearities and changes over time in the parameters of the aggregate production function. Our results suggest that the recent stagnation of the college wage premium primarily reflects demand factors, specifically a slowdown in the pace of skill-biased technological change.

Keywords: college wage premium, educational attainment, labor supply, technological change, worker substitutability

JEL codes: **I2, J2, J3**

Explaining Stagnation in the College Wage Premium

I. Introduction

A college degree is consistently linked with better economic outcomes, most notably higher wages. The U.S. college wage premium, defined as the wage gap between working individuals with a college degree and those with a high school diploma, grew substantially during the decades from 1980 to about 2010. Since then, estimates of the premium suggest that it has stagnated, with little change in its level and perhaps an outright decline (Valletta 2018, Ashworth and Ransom 2019, Bengali et al. 2023). The returns to college, which reflect the college wage premium combined with the costs of attending college, are a crucial element for choices about educational attainment. These financial returns likely have declined as college costs have risen and the wage premium has flattened, reducing the incentives to invest in college.

We investigate the factors that are driving the stagnation in the college wage premium. Following Tinbergen (1974), Goldin and Katz (2008) characterized the dynamics of skill gaps as a race between education and technology—i.e., as reflecting the balancing of rising relative supply of educated workers with rising demand for their skills in the workplace. Consistent with this perspective, the literature has largely focused on rising demand for highly skilled and more educated workers due to skill-biased technological change (e.g., Katz and Murphy 1992, Johnson 1997, Lindley and Machin 2014, Bowlus et al. 2023). Some papers have also emphasized that episodic changes in the supply of college graduates overall or by cohort and age group have played an important role in the determination of the college wage premium (Card and Lemieux 2001, Autor, Goldin, and Katz 2020). Can rising supply explain the recent stagnation in the college wage premium (Fortin 2006, Kawaguchi and Mori 2016, Autor 2018)? Or are demand side factors, notably changes in the form and pace of skill-biased technological change, the primary cause (Valletta 2018)?

We address these questions by extending the canonical model of skill gaps along key dimensions. As delineated by Acemoglu and Autor (2011), the canonical model distinguishes between high and low-skill labor inputs in an aggregate production function framework. It accurately summarized the dynamics of the college wage premium into the 1990s but overpredicts the college premium subsequently (Autor 2018). We build out the supply and demand sides of the model to better capture the changes in the college wage premium in recent years.

To account for gender and age effects on supply, we extend the cohort-based framework of Card and Lemieux (2001). We analyze earnings data from the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) over the 62-year period from 1961 to 2023, extending well beyond their sample frame that ended in 1996. Card and Lemieux focused primarily on men in their analyses, although they found that the results are generally invariant to the inclusion of women. Since then, the share of women in the college educated workforce has grown substantially. We therefore broaden their age-based disaggregation to also incorporate gender.

On the demand side, we extend the canonical framework by estimating more flexible forms of the production function parameters—notably the elasticity of substitution between college and high school educated workers—and the pattern of skill-biased technological change over time. Consistent increases in the college wage premium in past decades suggest linear technology trends and a constant elasticity of substitution between college and high school educated workers. By contrast, the flattening of the premium implies a need to account for non-linearities and changes over time in key model parameters. We extend the basic production function-based empirical framework to allow for non-linear technology trends and a changing degree of substitutability between college educated and high school educated workers.

Our disaggregated, flexible estimation scheme improves on prior specifications of the canonical model and yields a good fit over our complete sample frame. We use our framework to develop decompositions that yield the contributions of the underlying model elements to changes in the college wage premium. Our results indicate that the stagnation in the college wage premium is largely due to demand-side changes, specifically a slowdown in the pace of skill-biased technological change and rising substitutability between college and high school educated workers. Rising supply of college educated workers has also contributed, with women playing a key role.

As discussed further in the Conclusion, our findings regarding the roles of supply and demand influences on the college wage premium are important for understanding the broader implications of the changing premium. Increased supply of college educated workers reflects the incentives to invest in education, while slower demand growth implies exogenous changes in skill demands on the part of firms. Assessing their relative contributions is important for designing effective policies related to college access and curriculum content. More broadly, a stagnant college wage premium may help explain the growing challenges for the financing of higher education (Looney and Yannelis 2024).

II. Measuring the College Wage Premium

A. Data sources

We use data from the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) for the years 1962–2024 to calculate and estimate wage and salary income (which we refer to as earnings or wages), the college wage premium, and labor supply variables needed for our analysis.[1] The data on earnings and work hours refer to the prior calendar year, so our analyses cover the reference years of 1961-2023. We largely follow the methods outlined in Card and Lemieux (2001).[2] Our sample includes men and women aged 25–64. For our measure of wages, we use weekly earnings, calculated by dividing annual earnings in the reference year by annual weeks worked in the reference year. All weekly earnings are deflated using the CPI-U, with 2023 used as the base year in graphs below.

We create the wage premium and labor supply variables used in our analysis by group, defined jointly by 5-year age groups and gender. Card and Lemieux focused on an age breakdown for men only. Our incorporation of gender accounts for the rising workforce share of women, particularly among college educated workers (as documented in the next sub-section).

We use full-time wage and salary workers with exactly a high school or exactly a college degree to estimate the college wage premium. We regress log weekly earnings on a college

[1] See Flood et al. (2024). Reference year 1962 (survey year 1963) is dropped because the educational attainment variable is blank for all observations (as indicated in the IPUMS documentation).

[2] Appendix B (available separately) contains details on data construction and handling. We deviate from Card and Lemieux along a few dimensions that reflect common data handling choices made in subsequent research. This includes dropping observations with imputed values of wages, following Lemieux (2006), Autor, Katz, and Kearney (2008), and Valletta (2018). We also adjust for top-coded values of earnings by using a lognormal approximation of the distribution for earnings to estimate what top-coded earnings would be, on average, in the absence of the top code. This follows the approach of the Center for Economic and Policy Research (see https://ceprdata.org/cps-uniform-data-extracts/cps-outgoing-rotation-group/cps-org-faq/). Our main results are largely invariant to these choices, as described in Section IV.B.

graduate dummy, a linear age term, and an indicator for nonwhite race. The coefficient on the college dummy in regressions run separately for each age-by-gender group and year yields an annual estimate of the college wage premium for each group, which we use as our dependent variable in subsequent steps.

To implement our analysis, we need broad measures of the supply of workers in the college and high school attainment groups. We calculate these group-specific labor supplies using annual reference year hours of all part-time and full-time workers, including all education levels and the self-employed as well as wage and salary workers. To create "college labor" and "high school labor" supplies, we weight hours of workers with less than a high school degree, some college, or more than a college degree by their relative earnings. This comprehensive weighting reflects the possibility that individuals with other levels of educational attainment may compete for jobs with workers who have exactly a high school or college degree. This approach directly follows Card and Lemieux (2001). Given the general increase in educational attainment over the past six decades, the inclusion of other educational attainment groups in this manner may not be innocuous for our findings. However, as we discuss when we explore the robustness of our empirical results (Section IV.B), our main findings are largely invariant to the treatment of educational groups other than exactly college and exactly high school graduates.

B. Trends in earnings and supply, by educational attainment, gender, and age

The starting point for our analysis is the well-documented fact that college graduates, on average, earn more than workers with a high school education. The percentage gap between the two groups has generally risen over time, from about 47% in 1961 to 75% by 2023, based on our calculations using the raw data (Figure 1). For both men and women, most of this growth occurred between about 1980 and 2000. Subsequently, the overall college-to-high-school earnings gap ranged between about 67% and 80%, albeit with a slight decline until just before the 2020 recession, as others have documented (Valletta 2018, Ashworth and Ransom 2019). Since the pandemic, the college wage gap has increased slightly for both men and women.[3]

Our estimate of the college wage premium (Figure 2), formed as described above, looks quite similar to the raw earnings ratios.[4] The estimated premia show the percentage difference between earnings for college and high school graduates, exponentiated from the log regression that conditions on age and race. Those individual characteristics are correlated with college completion and could in theory alter estimates of the college premium relative to a model that omits them. However, the key patterns in the premium do not appear to be driven by broad trends in the age and racial composition of the worker pool. For example, the raw series in Figure 1 show that college graduates earned around 75% more than high school graduates by the end of our sample, and the exponentiated log point premium from the regression-adjusted series in Figure 2 is close to that, at 71%.

Given the similarities between the raw and regression-adjusted wage premiums, we focus on real earnings in levels for additional descriptive analyses. One question is whether key trends, for example the notable rise from about 1980 to 2000 and the subsequent stagnation and slight decline, are driven by changes in high school earnings or college earnings. The relevant

[3] This runs counter to the findings of Autor, Dube, and McGrew (2023), who identified more rapid wage gains for less educated workers during the pandemic and early recovery period. Our results may differ due to: (i) our use of weekly earnings inferred from annual earnings rather than hourly earnings measured directly from the monthly CPS earnings records; (ii) different conditioning steps; and (iii) other methodological differences.

[4] Note that for the purposes of this and other summary figures, we run the estimating regressions or analysis for the broader groups noted in each figure, such as all genders and age groups together, rather than separately by age and gender groups, as in our later analysis.

series are shown for the full sample in Figure 3. For high school graduates overall, real earnings have changed little since the 1980s. Real earnings for college graduates rose through the 1980s and 1990s and started a downward trend around the year 2000 before ticking up again during the recovery from the 2007–2009 recession.

Comparing real earnings for male and female college and high school graduates separately shows that the patterns differ slightly for men and women, highlighting the value of adding gender along with age to the demographic breakdowns used in our analysis. For men (Figure 4, panel A), real earnings for high school graduates have been trending down for the most part since 1980, while male college graduates' real earnings rose overall through the 1980s and 1990s (though with some fluctuations). By contrast, for women (Figure 4, panel B), real earnings of both high school and college graduates have been on a general upward trend since the 1980s. Until about 2000, this growth was notably faster for college graduates, likely reflecting the rise of professional working women in the labor force. Since then, real earnings for both education groups have followed roughly similar trajectories, though growth was slightly faster for high school graduates. This suggests that growth in the college premium over this timeframe for men stems from rising earnings of college graduates and falling earnings of high school graduates, whereas for women, real earnings of both high school and college graduates were growing but at a slower pace for the high school group.

These simple comparisons by educational attainment cannot tell us ultimately why the earnings of high school and college graduates evolved as they did. One possibility we explore in this paper is on the supply side: a rising supply of college graduates, relative to high school graduates, could reduce the wage premium for college graduates (Fortin 2006, Kawaguchi and Mori 2016, Autor 2018).

Figure 5 shows that the relative supply of college graduates (formed as described in the preceding sub-section) has been steadily rising over time for both men and women, which would put downward pressure on the wage premium. At the start of our sample, by our measure only about 25% of the labor supply came from college graduates, but the overall supply of college graduates surpassed that of high school graduates around 2018. For men, the proportion of college educated and high school educated labor reached unity only near the end of our sample frame. In contrast, female college educated labor supply overtook that of their high school educated counterparts notably sooner, around 2010, with a notable acceleration after the year 2000. By the end of our sample, the labor supply of female college educated labor was almost 50% larger than the labor supply of female high school graduates.

The rapid growth in the supply of college educated women implies that they account for a growing share of the overall college educated workforce. This is shown in Figure 6. Women's share of the college educated workforce has grown substantially over our sample frame, from under 40% in the early 1960s to about half in recent years.

Breakdowns by age group show that this pattern of rapid growth in the college educated female workforce is relatively broad-based, though the acceleration of female college labor supply since the year 2000, seen above in Figure 5, is particularly evident for the younger age groups (Figure 7, panel B; men are shown in panel A for completeness). This rapid rise in the supply of college educated women overlaps with the flattening of the college wage premium over the last few decades.

Overall, the relative supply patterns highlight that accounting for gender is likely to be important and hence is a useful extension of the Card and Lemieux (2001) framework over our updated sample frame. Moreover, comparing patterns in relative supplies and earnings suggests that labor supply plays a role in explaining variation in the college wage premium over time. However, wage premia fluctuated much more than did relative supply, suggesting that supply is only part of the full story. We therefore turn to a theoretical framework that helps pin down the roles of supply and demand.

III. A Framework for Explaining the College Wage Premium

A. Theoretical framework

We use the theoretical and empirical framework in Card and Lemieux (2001) to explore how the relative supply of and demand for college educated workers affect the college wage premium. This framework represents a straightforward extension of the canonical model of educational gaps in earnings, via the incorporation of imperfect substitution across age cohorts within educational groups. Based on the descriptive analysis in the preceding section, we further extend the model by incorporating gender as a source of growing supply and imperfect substitution within educational groups.

The basis of this framework is a streamlined firm production model in which firms produce output using two types of labor: high school educated workers and college educated workers. Aggregate output is determined by a constant elasticity of substitution (CES) production function; it depends on the quantities of labor provided by the two education groups and also on the elasticity of substitution between them (σ_E).

$$y_t = \left(\theta_{ht} H_t^{\rho} + \theta_{ct} C_t^{\rho}\right)^{\frac{1}{\rho}} \tag{1}$$

The C and H terms capture the aggregate quantity of high school educated and college educated labor, the θ terms capture education-specific technological efficiency, and $\rho = (1 - 1/\sigma_E)$. In our specific formation of these aggregates, we allow for imperfect substitutability within each education group between workers in different age-by-gender groups, indexed by j, and also for productivity (relative efficiency) factors specific to each age-by-gender group (α_j and β_j):

$$H_t = \left[\sum_j \left(\alpha_j H_{jt}^{\eta}\right)\right]^{\frac{1}{\eta}} \tag{2}$$

$$C_t = \left[\sum_j \left(\beta_j C_{jt}^{\eta}\right)\right]^{\frac{1}{\eta}} \tag{3}$$

In these equations, $\eta = (1 - 1/\sigma_A)$, where σ_A is the elasticity of substitution between workers in the same educational attainment group but in different age-by-gender groups.

As noted above, Card and Lemieux focused their analysis on men and groups j defined by age only, yielding eight five-year age groupings spanning our sample age range of 25 to 64. Our incorporation of gender yields 16 corresponding age-by-gender groups. We focus our analysis on the age-by-gender breakdown but also provide some comparison to the age-only breakdown, to establish the value-added of accounting for gender in the disaggregated framework.

Assuming firms optimally choose amounts of high school and college educated labor, the ratio of wages for high school and college educated workers should equal the ratio of their marginal products. Card and Lemieux (2001) show that this equality yields the following expression:

$$\log\left(\frac{w_{jt}^{c}}{w_{jt}^{h}}\right) = \log\left(\frac{\beta_j}{\alpha_j}\right) + \log\left(\frac{\theta_{ct}}{\theta_{ht}}\right) - \left(\frac{1}{\sigma_E}\right)\log\left(\frac{C_t}{H_t}\right) - \left(\frac{1}{\sigma_A}\right)\left[\log\left(\frac{C_{jt}}{H_{jt}}\right) - \log\left(\frac{C_t}{H_t}\right)\right] \qquad (4)$$

B. Empirical specification

Equation 4 lends itself to a regression of the form:

$$\log\left(\frac{w_{jt}^{c}}{w_{jt}^{h}}\right) = b_j + f(t) - \left(\frac{1}{\sigma_E}\right)\log\left(\frac{C_t}{H_t}\right) - \left(\frac{1}{\sigma_A}\right)\left[\log\left(\frac{C_{jt}}{H_{jt}}\right) - \log\left(\frac{C_t}{H_t}\right)\right] + e_{jt} \qquad (5)$$

Here, j indexes age-by-gender group and t indexes the survey reference year. The dependent variable is the college wage premium (estimated as described above) with wages w for college (c) and high school graduates (h). Uppercase C_{jt} and H_{jt} are supplies of college educated and high school educated labor, respectively, formed for each group j as described in the preceding sub-section, and C_t and H_t are supply measures aggregated across groups, as defined in Equations 2 and 3. Finally, b_j are group fixed effects (representing $\log(\beta_j/\alpha_j)$ in Equation 4) and *f(t)* is a flexible function of time (representing $\log(\theta_{ct}/\theta_{ht})$ in Equation 4). Card and Lemieux assumed linear time effects, representing a consistent annual pace of skill-biased technological change and a corresponding rise in the college wage premium (following others in the early literature, such as Katz and Murphy 1992). To account for possible changing demand contributions, we allow for more flexible functional forms, settling on a quadratic specification that readily accommodates interactions with the aggregate relative supply variable (described below).

In addition to the time effects, the key coefficients of interest are those on the variables representing aggregate relative labor supply ($-(1/\sigma_E)$) and group-specific relative labor supply ($-(1/\sigma_A)$). In this framework, σ_E is interpreted as the elasticity of substitution between college and high school educated labor, and σ_A is the elasticity of substitution between age-by-gender groups within an educational attainment group.

To estimate Equation 5, we need the college wage premium, labor supply for each group, and aggregate labor supply. The college wage premium and the group-specific supplies (C_{jt} and H_{jt}) are readily created as described above in Section II. To create the aggregate supply measures (C_t and H_t), we need estimates of σ_A and of α_j and β_j for each of our groups j (see Equations 2 and 3). Card and Lemieux (2001) show that we can obtain an estimate of σ_A by regressing our constructed wage premium on the group-specific ratio of college and high school labor ($\log(C_{jt}/H_{jt})$) with group (b_j) and year (d_t) fixed effects, as shown in Equation 6 below. As before, j indexes age-by-gender groups and t indexes the survey reference year.[5]

$$\log\left(\frac{w_{jt}^{c}}{w_{jt}^{h}}\right) = b_j + d_t - \left(\frac{1}{\sigma_A}\right)\log\left(\frac{C_{jt}}{H_{jt}}\right) + e_{jt} \tag{6}$$

The coefficient of interest is σ_A, which is the partial elasticity of substitution between different age-by-gender groups with the same level of education. Since the α_j and β_j terms are assumed to be constant over time, they can be obtained from auxiliary regressions, one for each education group (high school and college), of a model-derived transformation of wages on a full set of year dummies and a full set of group dummies, described in Appendix B. The

[5] Regression weights are inverse sampling variances of the estimated wage premia.

exponentiated coefficients on the group dummies are α_j (from the high school regression) and β_j (from the college regression). With this, we have all the components we need to estimate Equation 5.

An important restriction in Equation 5, which appears throughout the literature on education and skill gaps in earnings, is that the elasticity of substitution between skill groups is constant over time (as in the CES production function in Equation 1). We relax this assumption to allow for changing substitutability between college and high school educational groups.[6] The extended model is represented by the following equation:

$$\log\left(\frac{w_{jt}^{c}}{w_{jt}^{h}}\right) = b_j + f(t) - \left(1 - g(t)\right) * \left(\frac{1}{\sigma_E}\right)\log\left(\frac{C_t}{H_t}\right) - \left(\frac{1}{\sigma_A}\right)\left[\log\left(\frac{C_{jt}}{H_{jt}}\right) - \log\left(\frac{C_t}{H_t}\right)\right] + e_{jt} \quad (7)$$

This equation is identical to the preceding estimating Equation 5, but with the inclusion of an interaction term between a general function of time *g(t)* and the aggregate relative supply variable, $\log(C_t/H_t)$. This interaction term accommodates changes over time in the degree of substitutability between college and high school educated workers in the aggregate production function.[7]

Our main specification for estimating Equation 7 relies on quadratic functions for the general time effect *f(t)* and the interaction terms *g(t).* These two time functions may differ in

[6] The possibility of such changes in production function parameters is consistent with alternatives to the canonical model of skill premia, such as the technology diffusion framework of Beaudry, Green, and Sand (2016).

[7] Changes in production function parameters could alternatively be incorporated by using a more general functional form, for example the translog. Such functions, however, do not readily yield the parameter estimates that are the focus of the canonical skill premium model and associated literature, including this paper. We therefore rely on the flexible function of time specified in Equation 7.

principle, and we explore this specification issue below; we find that a quadratic specification for both functions of time fits well and yields straightforward interpretations. Note also that in principle the age-by-gender elasticity of substitution σ_A may vary over time, meriting additional time interaction effects in the model. We find that estimates of this parameter are largely stable over time and hence do not include this additional time interaction element in the estimation.

IV. Model Results and Interpretation

A. Regression steps and results

We implement the multi-step estimation procedure from Card and Lemieux (2001) as described in the preceding section. We update and extend their results by: (i) performing separate estimation for 1961–1996 (a close approximation of their timeframe), the subsequent period of 1997–2023, and the combined sample frame;[8] (ii) accounting for the growing presence of women in the college educated workforce by extending their age-based framework to account for age-by-gender groups as well; (iii) allowing for the aggregate elasticity of substitution between college educated and high school educated workers to change over time.

As described in Section III, in order to estimate our complete regression model (Equations 5 and 7), we need to create the aggregate supply measures (C_t and H_t). To do so, we need estimates of the elasticity of substitution across age-by-gender groups (σ_A) and the

[8] Because Card and Lemieux combined 1960 Census data with CPS ASEC data, our 1961–1996 sub-sample does not exactly match their original sample frame of 1959–1996. Also, we rely on ASEC data back to 1962 (reference year 1961) and perform our analyses based on the complete set of annual microdata files. By contrast, Card and Lemieux focus their analysis on 5-year periods and do not use ASEC surveys from the 1960s. With these small differences in data and sample, we largely replicate their results for our early sample period, as described below.

efficiency parameters for high school and college educated workers in each group (α_j and β_j; see Equations 2 and 3).

We obtain σ_A via estimation of the restricted regression shown in Equation 6. The results of this first-stage estimation for age-by-gender groups are listed in Table 1. In all cases, we obtain precise estimates of the group elasticity of substitution that are similar across the two sub-periods and the combined full sample frame. They indicate a high degree of substitutability across our 16 age-by-gender groups, with an implied elasticity of substitution ranging from about 9 to 13.[9] One implication is that firms can readily switch between male and female workers within educational groups, and as such accounting for female labor supply and educational attainment patterns is an important part of understanding trends in the college wage premium over our full sample frame.

We obtain estimates of the efficiency parameters α_j and β_j from Equations 2 and 3 using the auxiliary regressions described in Section III. These equations specify fitting a transformation of high school and college group wages to group and year dummies (see Appendix B for the equations; results not displayed). In conjunction with these estimates of α_j and β_j, the results from Table 1 can be used to construct the measure of aggregate relative supply of college educated labor inputs that accounts for imperfect substitution across age-by-gender groups, which we use in our second-stage analysis. For comparison, and because we use it in our subsequent analyses, we also construct a corresponding aggregate relative supply measure that

[9] Table A1 in Appendix A shows the first-stage model results using age rather than age-by-gender groups. The estimated coefficient on the group relative supply is larger for the age-only specification for the early period and full sample, implying less substitutability across age groups than across age-by-gender groups.

assumes perfect substitution across groups. This simplified measure imposes that $\sigma_A = \infty$ (equivalently that $\eta = 1$).[10]

The resulting measures of aggregate relative supply of college graduates are displayed in Figure 8.[11] The perfect substitution version corresponds closely to the raw ratio of college educated to high school educated labor supply (in natural log form). Both measures show especially rapid growth from the mid-1960s to the early 1980s, followed by more modest but mostly steady growth through 2023. The measured level of the aggregate supply index with imperfect substitution is consistently higher than the perfect substitution version. This likely reflects higher estimated relative efficiency of selected college educated age-by-gender groups in this framework.

We use these measures of aggregate relative supply as inputs into the second-stage estimation specified by Equations 5 and 7, as described in Section III. For the second-stage analysis, we maintain the division of our sample into the two sub-periods listed in Table 1, corresponding to the approximate Card and Lemieux timeframe and subsequent years, plus the combined full sample frame.

Table 2 presents the results of the second-stage estimation. We present the results from several specifications for each time period, one with a linear time trend (columns 1, 3, and 5) and another with a quadratic time trend (columns 2, 4, and 6).[12] For the full sample frame, we include

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[10] For simplicity, for the perfect substitution aggregate relative supply measure, we directly sum group-specific supplies (C_{jt} and H_{jt}) rather than using the auxiliary regressions described above. That is, we directly use Equations 2 and 3 with η, α_j, and β_j all equal to one. This simplification does not materially impact our results.

[11] A version of the aggregate relative supply measure calculated using age group breakdowns is quite similar to the version using age-by-gender breakdowns.

[12] We include quadratic time trend models for the two sub-samples for completeness (columns 2 and 4) but focus on linear time trend models for the sub-samples (columns 1 and 3). The instability of some

two additional specifications (following Equation 7) that allow the coefficient on the aggregate relative supply index to vary over time, using either a linear (column 7) or quadratic (column 8) time trend interaction.[13]

Column 1 of Table 2 shows the combination of specification and sample that is most analogous to the original in Card and Lemieux (2001). Our estimate of the coefficient on the linear time trend is identical to theirs (0.20; see column 2 of their Table IV). However, our estimates of the coefficients on the group-specific and aggregate relative supply variables are somewhat smaller than the corresponding Card and Lemieux (2001) estimates. As noted above, for the group-specific relative supply variable, this likely reflects higher substitutability across age-by-gender groups than across age groups alone. The coefficients on the group-specific relative supply variable are similar across the early, later, and complete timeframes (columns 1, 3, and 5); they are also similar to their analogs in Table 1, with the implied elasticity of substitution from the Table 2 estimates ranging from about 8 to 13. For the aggregate relative supply variable, discussed further below, our smaller estimates than Card and Lemieux's likely reflect our slightly different data and timeframe.

The basic Card and Lemieux model provides a good fit for the early sample period. However, the model fit breaks down when applied to the full sample.[14] In particular, extrapolating the model from Table 2, column 1, to the full time period substantially overestimates subsequent changes in the college wage premium. This can be seen in Figure 9,

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coefficients and the relatively small increase in model fit going from linear to quadratic time trends suggests that the extra flexibility is less useful in these short sample periods.

[13] The results are broadly similar when we simplify the procedure by assuming perfect substitution between age-by-gender groups; see Appendix Table A2.

[14] As we noted in the Introduction, this same breakdown in fit is evident for the basic canonical model estimated using annual data with no group breakdown (see Autor 2018).

panel A: extrapolating the early sample linear trend model yields a steadily increasing overstatement of the college wage premium after the late 1990s, peaking at about 25 log points in 2023 (compare the red to the black line).[15] This is a stark contrast to the good fit provided by our preferred model with full quadratic time and interaction effects (blue line), from column 8 of Table 2, which we discuss further below.

The complete results in Table 2 suggest that this over-prediction of growth in the college wage premium based on the early sample model reflects changes in key model parameters, notably the coefficient on the aggregate relative supply variable and the form of the time effects. Regarding aggregate supply, Table 2 shows substantial changes in this variable's coefficient and thus the implied elasticity of substitution across our two sub-samples. Based on the original timeframe and specification (Table 2, column 1), our results suggest that the elasticity of substitution between college and high school labor is around 2.5, compared with Card and Lemieux's estimate of 2.1. For the later sample period of 1997–2023 (column 3), the estimated coefficient declines by more than half in absolute magnitude. This smaller coefficient implies more than a doubling of the elasticity of substitution between college and high school workers, to about 6.0.

Regarding time effects, our results suggest that while relative demand for college graduates generally increased over time, the pace of that increase has slowed. For example, the estimated linear time trend is greatly diminished in size between the early and late sample periods, falling by a factor of four between columns 1 and 3. This suggests the need for a more flexible function of time to capture the underlying changes in demand affecting the college wage

[15] The early sample extrapolation is calculated using parameters (η, α_j, and β_j) that are estimated from the early sample only but then applied to the full sample to create the right-hand-side variables in Equation 5. Using parameters estimated from the full sample yields a nearly identical result.

premium over our full sample frame. A quadratic time trend works well for this purpose. This can be seen via the comparison of columns 5 and 6 in Table 2. The specification in column 6 yields a negative coefficient on the quadratic trend term. This implies that the relative demand effects represented by annual changes have slowed over time, consistent with the comparison across our two sub-samples.

We combine these two features of the model—a changing elasticity of substitution and flexible time effects—to yield the full sample results listed in the final two columns of Table 2 (columns 7 and 8). These specifications combine quadratic time effects and interactions between time and the aggregate relative supply variable, to account for changes in the latter variable's effects over time. We use a linear interaction in column 7 and a full quadratic interaction in column 8. Both specifications indicate that the coefficient on the aggregate relative supply index fell toward zero in absolute magnitude over our full sample frame of 1961–2023. This implies a rising elasticity of substitution over time, although the negative coefficient on the quadratic interaction term in column 8 indicates that the pace of this rise slowed over time.[16] This rising substitutability between college and high school educated workers reflects the underlying production function and hence is a demand-side effect; we explore these demand effects further in Section IV.C below.

The implied overall time effects from column 8 of Table 2 are obtained from the combined coefficients on the quadratic time trend and its full interaction with the aggregate relative supply variable.[17] The results are displayed in Appendix Figure A2, which shows a

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[16] Rolling regression estimates of the coefficient on the aggregate relative supply index also yield a non-linear pattern, with an initially rapid convergence toward zero followed by a plateau or slight decline (see Appendix Figure A1). This supports a model with a quadratic interaction over a linear one.

[17] The value of the aggregate relative supply variable is set to its full sample mean for this calculation.

pronounced slowdown in the calculated time effects over our sample frame and an outright decline starting shortly after the year 2000.[18] This implies that relative demand for college graduates rose more quickly in the early part of our sample, contributing to the rise in the college wage premium. In the later part of our sample, relative demand growth slowed and reversed course, contributing to the flattening of the college wage premium.[19]

Figure 9, panel B, provides a broad comparison of our different specification choices for model estimation over our complete sample frame. Our preferred fully interacted quadratic specification (column 8 of Table 2; blue line in the figure) provides the best fit. It accurately captures the decline in the college wage premium in the 1970s and the rapid growth followed by slowing in subsequent decades. The alternatives with linear and quadratic time trends but no interactions with the aggregate supply variable (columns 5 and 6 in Table 2, red and yellow lines in Figure 9, panel B) provide a poorer fit than our preferred interacted quadratic specification. We decompose the results from this preferred model in Section IV.C, after first examining model robustness in the next sub-section.

[18] Appendix Figure A2 also shows the implied time effects from a model without the interactions between time and the aggregate relative supply variable (Table 2, column 6). This specification yields a less curved profile with no reversal of direction within our full sample frame.

[19] Consistent with slowing relative demand, we find a decline since 2010 in the relative number of online job postings seeking college vs. high school graduates (see Appendix Figure A3). These data are aggregated across many job websites by Lightcast. We determine the level of education sought by using the minimum educational requirement associated with each job as identified by Lightcast. When no minimum is available, we use the Lightcast crosswalk that maps detailed occupations to the most common education and/or training requirements. Occupations requiring less than two years of training are mapped to “high school;” those requiring two-year degrees or a sub-BA and BA mix are mapped to “some college;” those requiring a BA are mapped to “college;” and those requiring a professional degree are mapped to “more than a college degree.” Jobs with no available minimum and no detailed occupation are dropped from the calculation. We are unable to examine years prior to 2010 to confirm whether the decline in the figure represents a longer-term trend. However, the help wanted job ad data used by Abel and Deitz (2019) go a bit further back, to 2006. Their results also are consistent with slowing relative demand for college graduates over the past few decades.

B. Alternative specifications and robustness

To clarify the value-added of our approach that relies on age-by-gender groups, we compare our main set of results in Table 2 to versions that: (i) use age rather than age-by-gender groups (as in Card and Lemieux 2001); (ii) exclude the group component (i.e., all variables are simple annual aggregates, as used in early implementations of the canonical skill premium model).

When we use age breakdowns alone or omit groups altogether, our findings reveal broadly similar patterns to those reported in Table 2 (Appendix Tables A3 and A4, respectively). The coefficient estimates for the aggregate supply and time variables are mostly similar across the three specifications. One exception is the linear trend specification for the later sample period of 1997–2023 (column 3 in the tables), for which our age-by-gender specification in Table 2 yields a more precise estimate for the coefficient on the aggregate supply variable.

Most notably, for our preferred fully interacted specification in column 8, the age-only and no-groups models in the appendix yield a positive coefficient on the quadratic interaction term. This contrasts with the negative coefficient on that term in our age-by-gender model in Table 2. This causes the age-only and no-groups models to produce a poorer fit to the dynamics of the college wage premium over our complete sample frame. This can be seen in Appendix Figure A4. The two alternative models overpredict the college wage premium in the 1960s and 1970s, understate the pace of increase in the 1980s and 1990s, and underpredict the level during the recent period of stagnation.

We also explored the robustness of our findings to several methodological choices that may not be innocuous (discussed in Section II.A above). One such choice is to apportion work hours of the "some college" group into "high school" labor and "college" labor using relative wage weights, as in Card and Lemieux (2001). Appendix Table A5 shows a version of our main results with the "some college" group completely omitted from the sample. The coefficient estimates show only minimal deviations from our main estimates in Table 2. Another such choice is our set of adjustments to reported earnings, which entails dropping observations with imputed earnings and adjusting earnings to account for top-coded values (see Section II.A). These choices have little effect on our main findings, as seen in Appendix Table A6, which includes imputed earnings records and makes no top code adjustment.

We conclude that our quadratic, fully interacted age-by-gender model accurately characterizes the factors driving changes in the college wage premium over time. Changes in the estimated model parameters over time indicate significant changes in the demand and supply dynamics that contribute to the evolution of the college wage premium. We assess these contributions in the next sub-section.

C. Quantifying the demand and supply contributions

We use the regression results from our preferred model (Table 2, column 8) to decompose changes in the college wage premium into contributions from factors related to demand and from factors related to supply. We distinguish between demand and supply effects as follows.

Demand effects: measured as changes in the coefficient on the aggregate relative supply index and changes in the values of the linear and quadratic time trends.[20]

[20] The coefficient on the aggregate relative supply index is a production function parameter and hence represents changes in the structure of demand, although the corresponding variable represents supply.

Supply effects: measured as changes in the values of the relative supply variables (both the aggregate index and the group-specific variables).

More precisely, for each group *j* and year *t*, we decompose the total change in the model-predicted college wage premium (Table 2, column 8) as follows. First, write the model that results from estimating Equation 7, copied below, as Equation 8:

$$\log\left(\frac{w_{jt}^{c}}{w_{jt}^{h}}\right) = b_j + f(t) - \left(1 - g(t)\right) * \left(\frac{1}{\sigma_E}\right)\log\left(\frac{C_t}{H_t}\right) - \left(\frac{1}{\sigma_A}\right)\left[\log\left(\frac{C_{jt}}{H_{jt}}\right) - \log\left(\frac{C_t}{H_t}\right)\right] + e_{jt} \quad (7)$$

or

$$\widehat{CWP}_{jt} = b_j + \beta_T f(t) + \beta_A AggS_t + \beta_{Int} g(t) * AggS_t + \beta_R RelS_t \quad (8)$$

where β_T, $f(t)$, β_{Int}, and $g(t)$ are vectors.[21] The change in the college wage premium from year *t-1* to *t* can be written as:

$$\begin{aligned}\widehat{\mathrm{CWP}}_{jt} - \widehat{\mathrm{CWP}}_{jt-1} \\ &= \beta_T\left(f(t) - f(t-1)\right) + \beta_A(AggS_t - AggS_{t-1}) \\ &+ [\ \beta_{Int}(g(t) * AggS_t - g(t-1) * AggS_{t-1})\ ] + \beta_R(RelS_t - RelS_{t-1}). \quad (9)\end{aligned}$$

The term in brackets can be further broken down into three terms, in a modification of a standard Oaxaca-Blinder decomposition of contributions from coefficients and variables (Blinder 1973, Oaxaca 1973):

[21] For clarity regarding the subsequent calculations, equation 8 incorporates explicit coefficients that are omitted from Equation 7.

$$\begin{bmatrix} \beta_{Int} g(t-1) * (AggS_t - AggS_{t-1}) \\ +\left(\beta_{Int} g(t) - \beta_{Int} g(t-1)\right) * AggS_{t-1} \\ +\left(\beta_{Int} g(t) - \beta_{Int} g(t-1)\right) * (AggS_t - AggS_{t-1}) \end{bmatrix} \tag{10}$$

The annual change (with rearrangement) then becomes:

$$\widehat{\mathrm{CWP}_{Jt}} - \widehat{\mathrm{CWP}_{Jt-1}} = \tag{11}$$

$$\beta_T\left(f(t) - f(t-1)\right) + \left(\beta_{Int} g(t) - \beta_{Int} g(t-1)\right) AggS_{t-1}$$

$$+ \beta_A(AggS_t - AggS_{t-1}) + \beta_{Int} g(t-1) * (AggS_t - AggS_{t-1}) + \beta_R(RelS_t - RelS_{t-1})$$

$$+ \left[\left(\beta_{Int} g(t) - \beta_{Int} g(t-1)\right) * (AggS_t - AggS_{t-1}) \right],$$

$$= \textit{change due to change in demand}$$

$$+ \textit{change due to change in supply}$$

$$+ \textit{change due to change in supply/demand interaction.}$$

We then form each annual aggregate change as the labor-supply-weighted average of the group values. Figure 10 shows the results of this aggregated decomposition. Through about the mid-1980s, year-to-year changes in the college wage premium arising from demand effects were positive and largely stable. Subsequently, relative demand continued to increase but at a slower pace, likely due a slowdown in skill-biased technological change and rising substitutability between college and high school educated workers. Starting around 2010, demand factors put downward pressure on the college wage premium. This pattern suggests that a slowdown in relative demand for college educated workers in the later part of the sample helps explain the recent flattening of the college wage premium.[22]

Changes in supply factors reflect changes in the relative supply of college educated labor, holding constant the estimated elasticity of substitution between college and high school educated labor. Through about 2005, changes in supply put downward pressure on changes in the college wage premium, with large effects evident in the early part of the sample prior to the 1980s. This is consistent with earlier findings that there was a slowdown in growth of the relative supply of college educated labor starting in the 1980s that allowed the college wage premium to increase more rapidly (Card and Lemieux 2001). The supply contributions diminished in subsequent decades and turned positive after about 2005. The sign change occurs because the coefficient on the aggregate relative supply index becomes positive by the end of our sample, due to the inclusion of linear and quadratic interactions. We hesitate to place much emphasis on this sign change, given that our time-varying coefficient estimates remain below zero in the later part of the sample (from the rolling regression results, Appendix Figure A1). Instead, we loosely interpret the changing supply effects in Figure 10 as a broad indication that aggregate relative supply has generally exerted less downward pressure on the college wage premium over time. Moreover, as high school and college educated workers have generally become more substitutable over time, changes in their relative supplies will have a diminishing effect on the college wage premium.

The supply and demand contributions in Figure 10 generally are opposite signed. This validates the characterization of the college wage premium as reflecting a race between

[22] As noted in Section IV.A, this timing is broadly consistent with a decline in the fraction of job postings requiring college vs. high school degrees (Appendix Figure A3).

education (supply) and technology (demand) (Goldin and Katz 2008). The demand contributions typically dominate, putting upward pressure on the college wage premium early in our sample frame but switching to downward pressure towards the end, which contributed to the flattening of the college wage premium.

V. Conclusions

Consistent with past research, we find that a supply-demand model of the race between education and technology accurately characterizes the dynamics of the U.S. college wage premium since the early 1960s (Autor, Goldin, and Katz 2020). This approach emphasizes the role of skill-biased technological change and slower growth of the relative supply of college educated labor, particularly starting in the 1980s, in increasing the college wage premium over time.

We focused on assessing the contributions of demand and supply factors to the recent stagnation in the college wage premium. We extended the supply and demand framework of Card and Lemieux (2001) to account for the rising importance of women in the college-educated workforce in recent decades, incorporating gender along with age into a disaggregated analysis of changes in the college wage premium. We also relied on a more flexible model of the supply and demand factors, incorporating non-linearities and interactions among elements of the underlying production function.

Our extended framework can help explain notable changes in the dynamics of the college wage premium over our complete sample frame of 1961–2023. The demand-side contribution of skilled-biased technological change was large early in our sample frame but diminished over time and appears to have turned negative in recent years. This is the main factor explaining the stagnation in the college wage premium over the past decade or so. Moreover, our results indicate that the elasticity of substitution between college and high school educated workers rose substantially over time, contributing to the overall decline in relative demand for more educated labor. The specifics of this apparent slowdown in skill bias merits additional research exploring its extent and sources.

Although the college wage premium remains high in absolute terms, its recent stagnation likely erodes the overall returns to a college education, which include both the benefits and costs of a degree. These costs are complex and vary substantially across educational institutions and individual students, but they may have risen in recent years as returns have stagnated (Looney 2024). The changing calculus of investments in higher education underscores the value of additional research work that directly examines the precise returns and costs of college (such as Mountjoy 2024).

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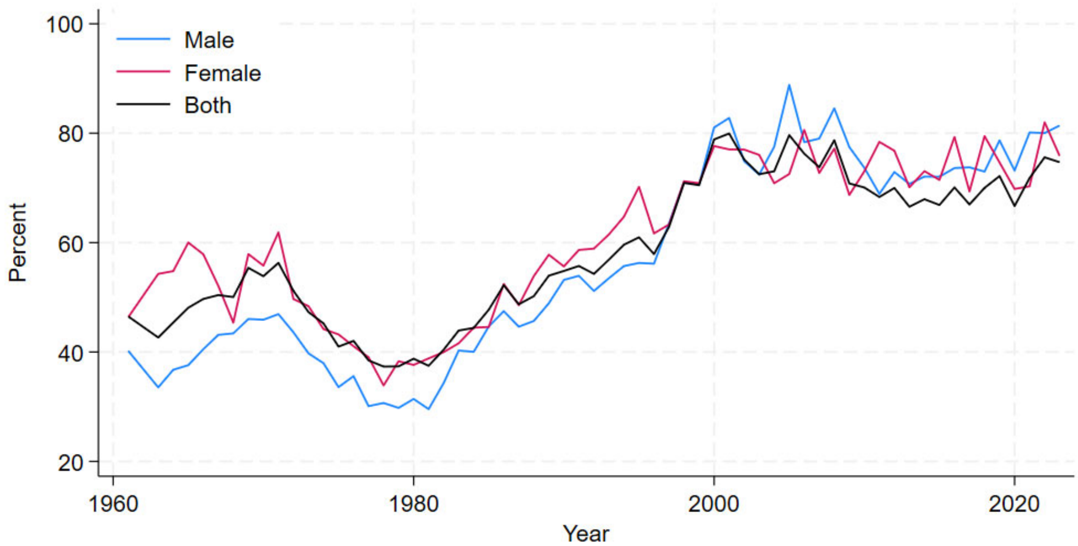
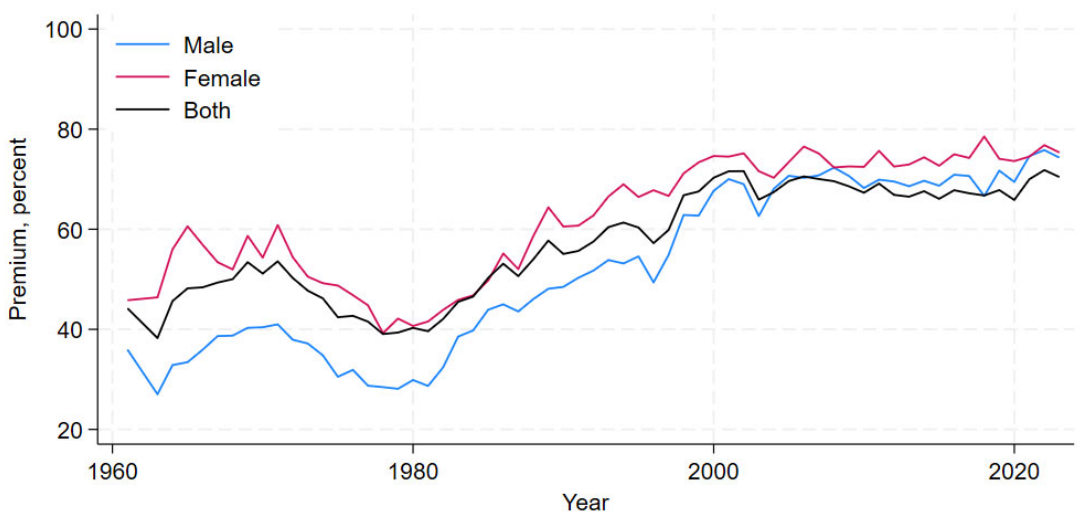
Displays

Figure 1: College to high school earnings gap, overall and by gender



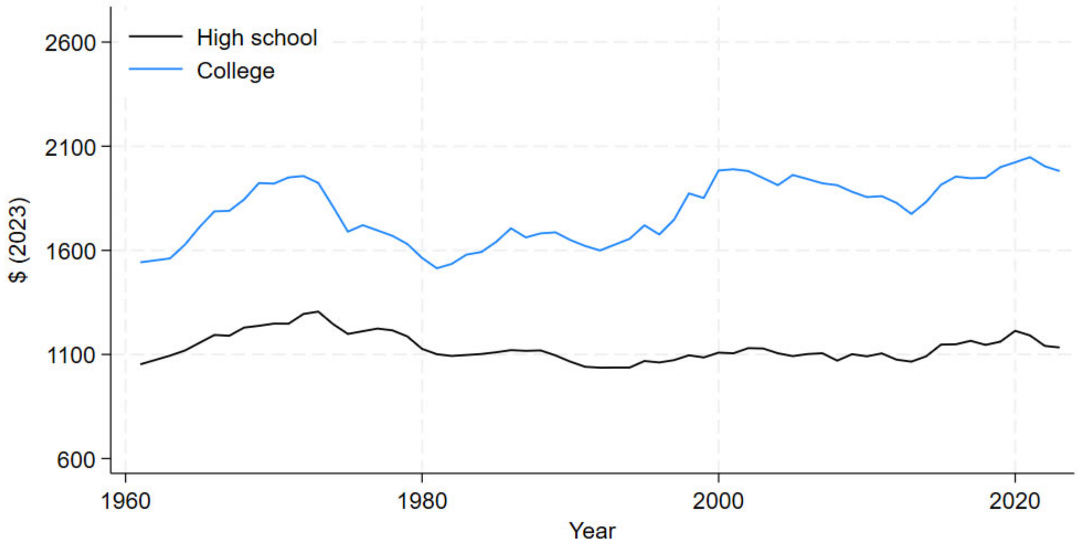
Note: Years are survey reference years. Earnings are weekly earnings, measured as defined in the text. The sample used to compute earnings includes only full-time wage and salary workers aged 25–64 with exactly a college or high school degree who earn at least $50 per week (in 1989 dollars).
Source: Authors' calculations from CPS ASEC microdata.

Figure 2: Regression-estimated college wage premium, overall and by gender



Note: Years are survey reference years. The premium shown is the exponentiated log premium estimated from regressions described in the text; however, relative to the text description, the regressions used to generate the series for this figure are run for men, women, or men and women ('both') of all age groups. The estimation sample includes only full-time wage and salary workers aged 25–64 with exactly a college or high school degree who earn at least $50 per week (in 1989 dollars).
Source: Authors' calculations from CPS ASEC microdata.

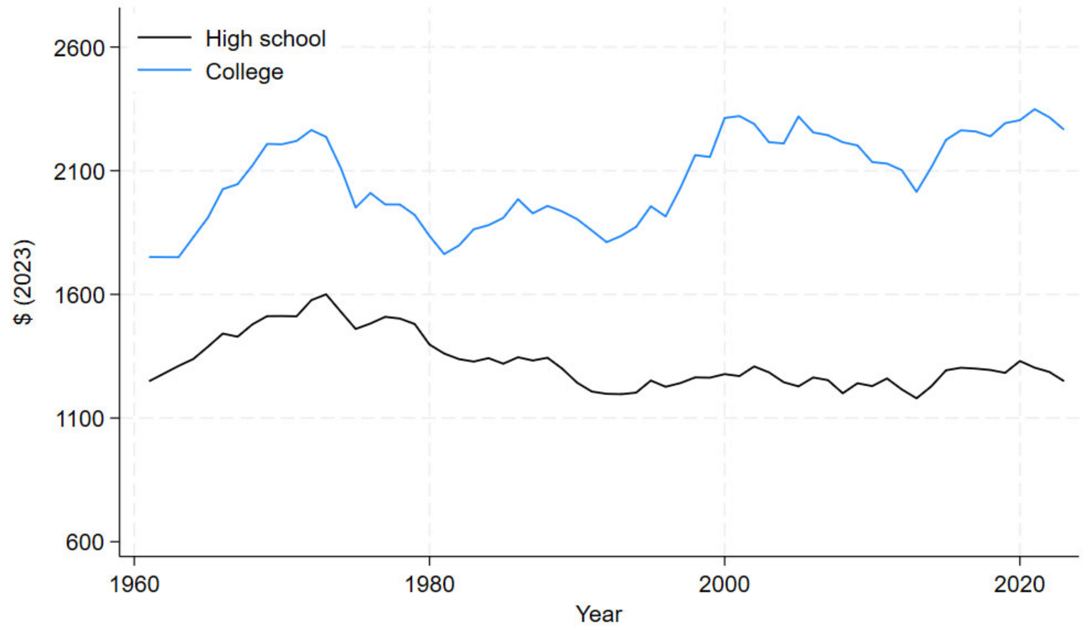
Figure 3: Overall real weekly earnings, college graduates and high school graduates



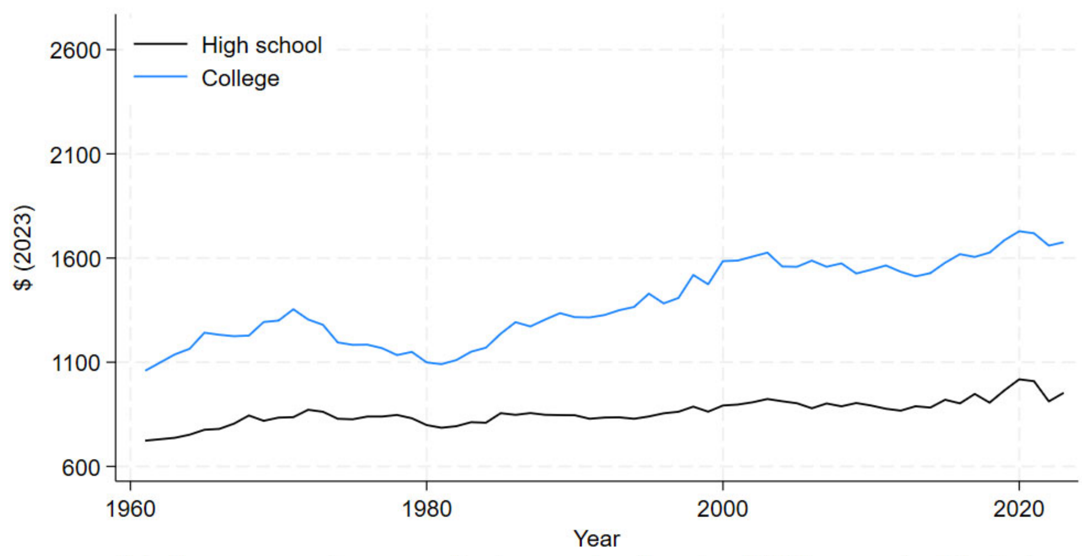
Note: Years are survey reference years. Earnings are real weekly earnings ($ 2023), measured as defined in the text. The sample used to compute earnings includes only full-time wage and salary workers aged 25–64 with exactly a college or high school degree who earn at least $50 per week (in 1989 dollars).
Source: Authors' calculations from CPS ASEC microdata.

Figure 4: Real weekly earnings, college graduates and high school graduates, by gender

Panel A: Men

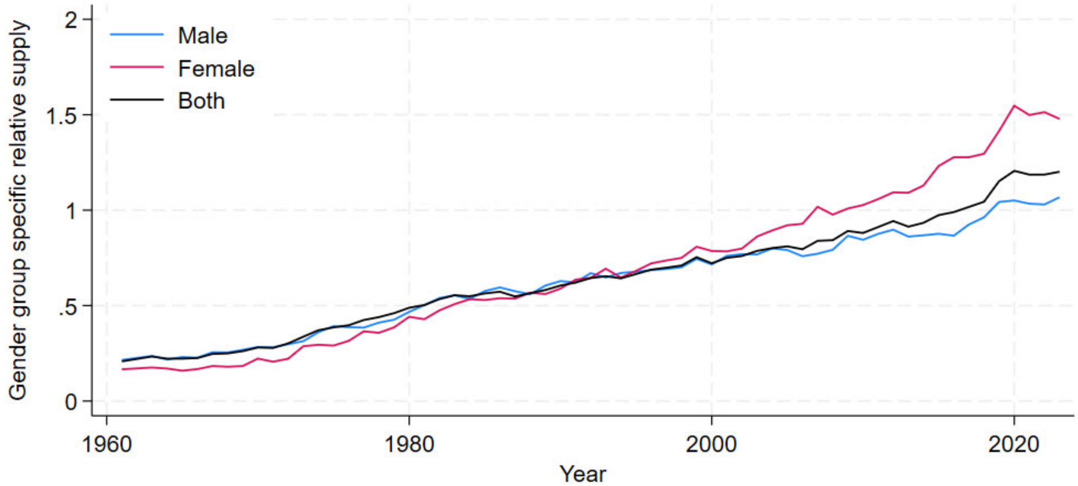


Panel B: Women



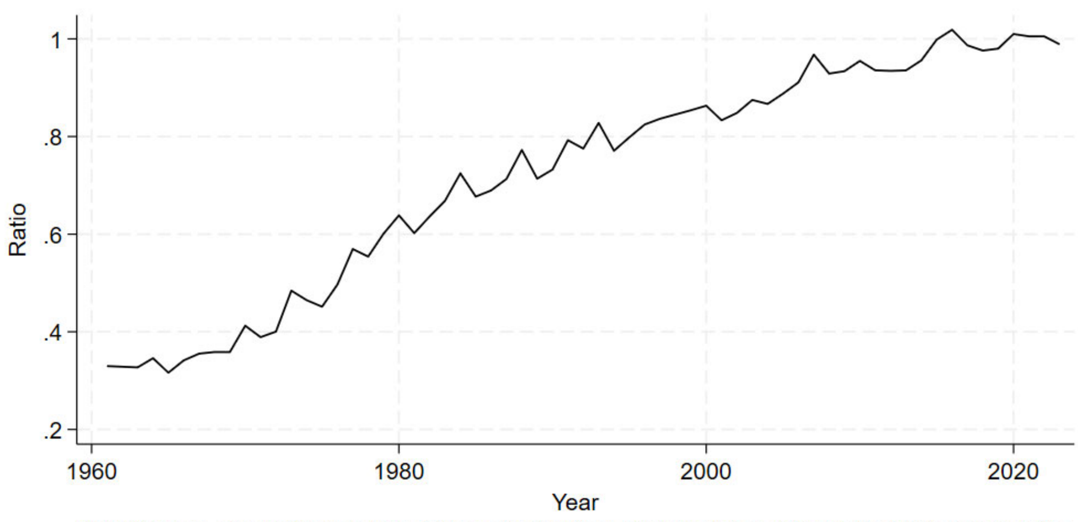
Note: Years are survey reference years. Earnings are real weekly earnings ($ 2023), measured as defined in the text. The sample used to compute earnings includes only full-time wage and salary workers aged 25–64 with exactly a college or high school degree who earn at least $50 per week (in 1989 dollars).
Source: Authors' calculations from CPS ASEC microdata.

Figure 5: Relative supply of college educated and high school educated labor, overall and by gender



Note: Years are survey reference years. Relative supply is the ratio of the college-educated labor supply to the high-school-educated labor supply, as defined in the text; however, relative to the text description, the series in this figure are calculated for all age groups of men or women together. The sample used to compute supply includes all classes of part- and full-time workers of all education levels, aged 25–64. Labor supplied by individuals with less than a high school degree, some college, or above a college degree is allocated to 'college-educated labor' and 'high-school-educated labor' as described in the text.
Source: Authors' calculations from CPS ASEC microdata.

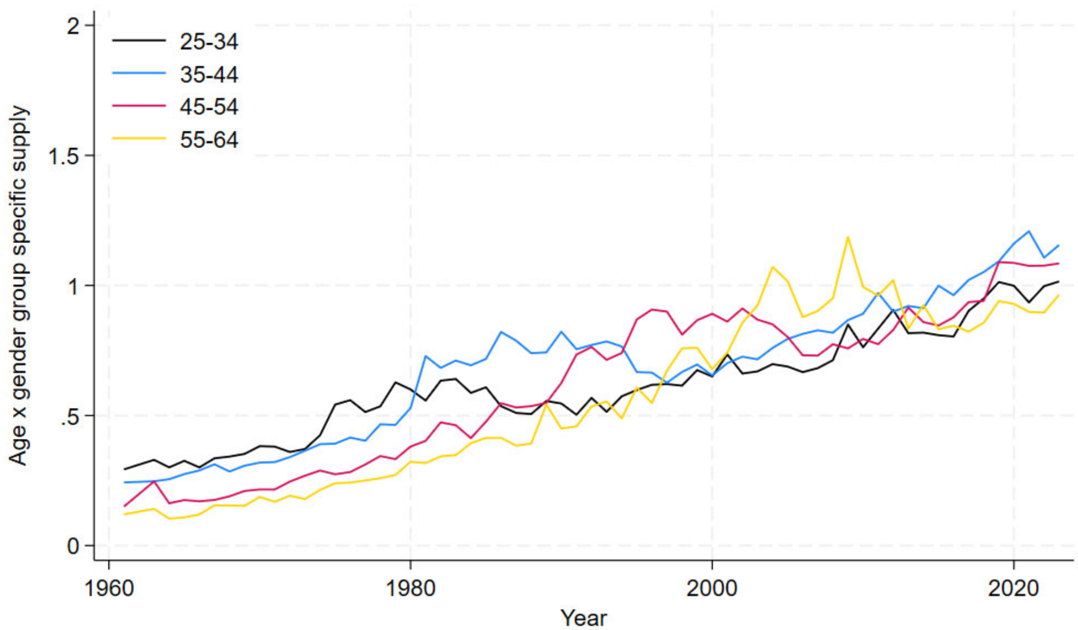
Figure 6: Relative supply of female to male college educated labor



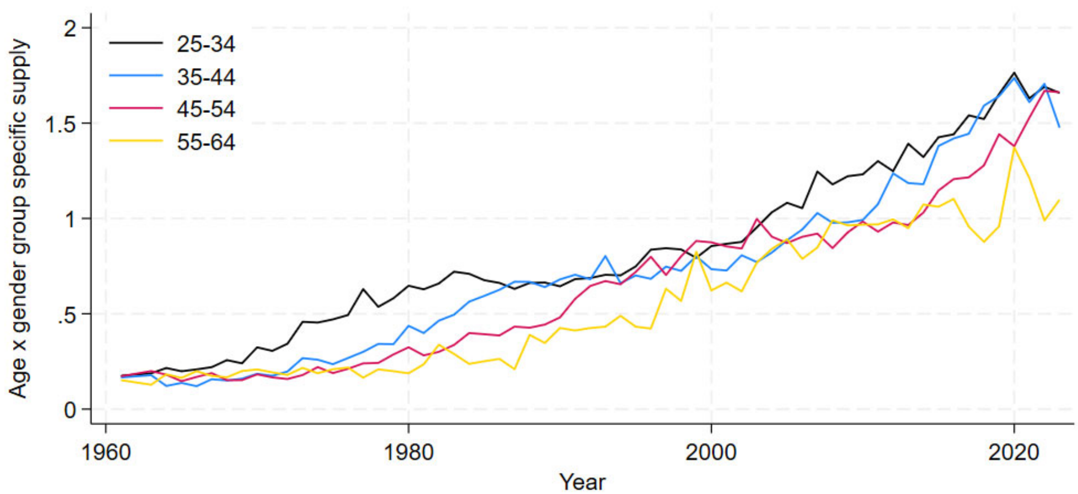
Note: Years are survey reference years. College-educated labor supply created as defined in the text; however, relative to the text description, the series used to create this figure are calculated for all age groups of men or women together. The sample used to compute supply includes all classes of part- and full-time workers of all education levels, aged 25–64. Labor supplied by individuals with some college or above a college degree is allocated to 'college-educated labor' as described in the text.
Source: Authors' calculations from CPS ASEC microdata.

Figure 7: Relative supply of college educated and high school educated labor, by gender and broad age group

Panel A: Men

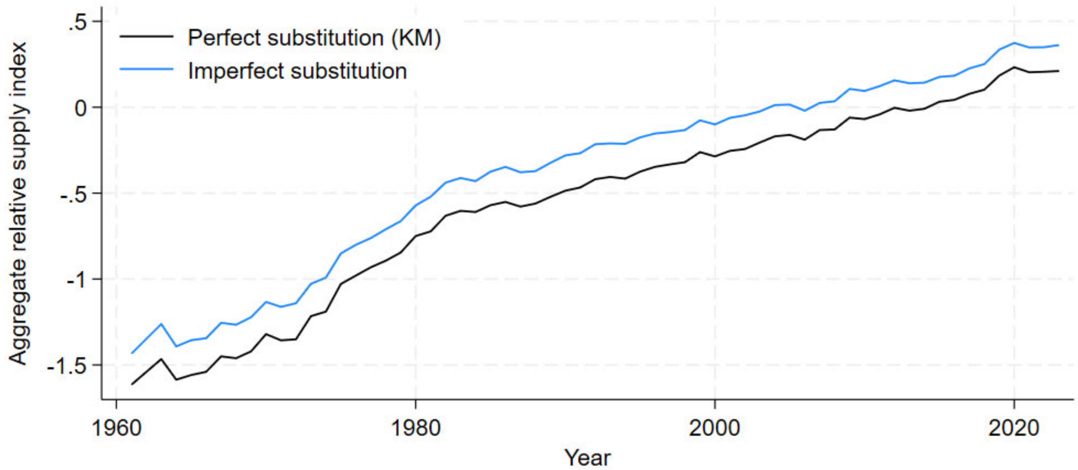


Panel B: Women



Note: Years are survey reference years. Relative supply is the ratio of the college-educated labor supply to the high-school-educated labor supply, as defined in the text; however, relative to the text description, the series in this figure are calculated for broader, 10-year age groups. The sample used to compute supply includes all classes of part- and full-time workers of all education levels, aged 25–64. Labor supplied by individuals with less than a high school degree, some college, or above a college degree is allocated to 'college-educated labor' and 'high-school-educated labor' as described in the text.
Source: Authors' calculations from CPS ASEC microdata.

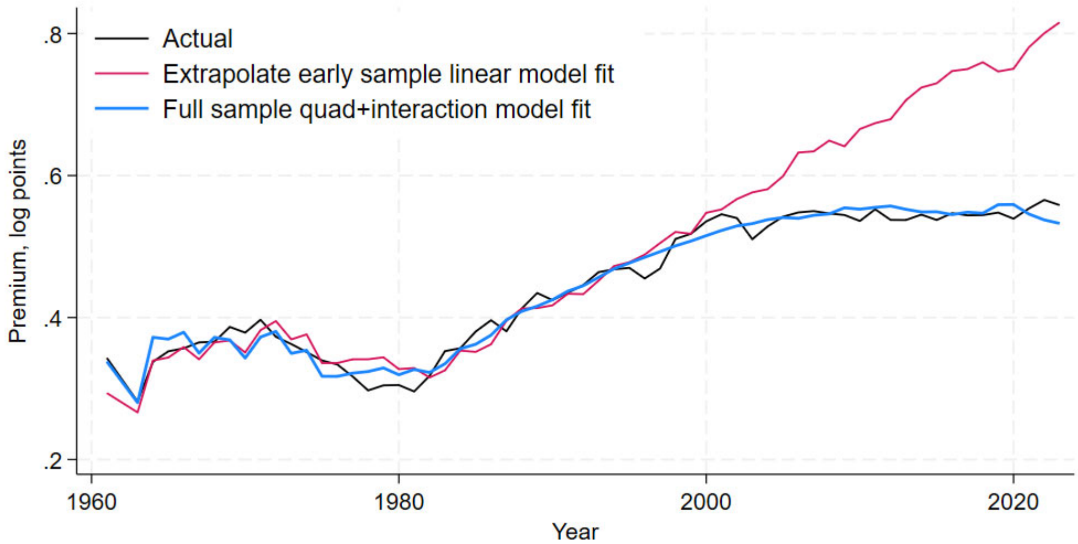
Figure 8: Aggregate relative supply of college to high school labor (model based)



Note: Years are survey reference years. The aggregate relative supply index is the log ratio of the aggregate college-educated labor supply to the aggregate high-school-educated labor supply. Age-by-gender group supplies of college- and high-school-educated labor (sample and construction as defined in the text) are directly summed to get aggregate college- and high-school-educated labor supplies for the perfect substitution (Katz-Murphy) aggregate relative supply index. For the imperfect substitution aggregate relative supply index, aggregate college- and high-school-educated labor supplies are obtained from the corresponding age-by-gender group supplies that have been transformed following the first-stage model described in the text.
Source: Authors' calculations from CPS ASEC microdata.

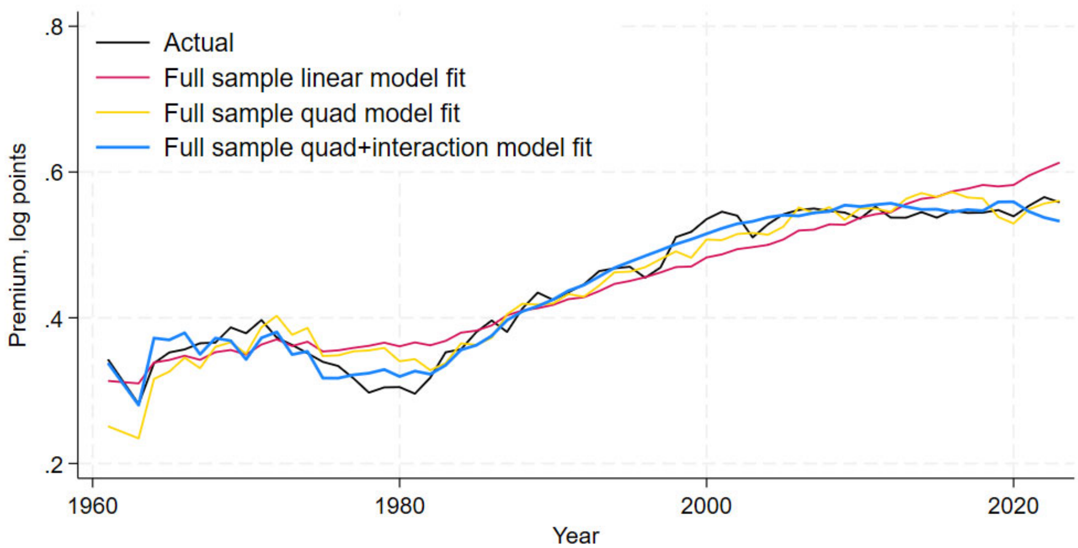
Figure 9. College wage premium, actual and model fits

Panel A: Early sample (1961–1996) linear fit, full quadratic interaction



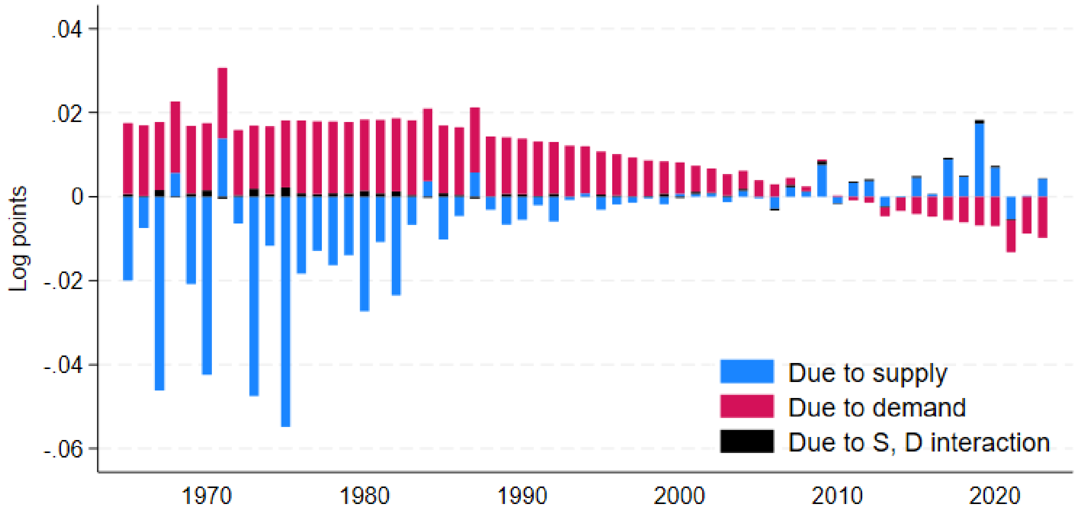
Note: Years are survey reference years. Model fits are fitted premia from regressions described in the text. Regressions used are those that allow for imperfect substitution between age-by-gender groups. Annual series formed as labor-supply-weighted averages of the predicted wage premia for age-by-gender groups.
Source: Authors' calculations from CPS ASEC microdata.

Panel B: Full sample linear and quadratic/interacted fits



Note: Years are survey reference years. Model fits are fitted premia from regressions described in the text. Regressions used are those that allow for imperfect substitution between age-by-gender groups. Annual series formed as labor-supply-weighted averages of the predicted wage premia for age-by-gender groups.
Source: Authors' calculations from CPS ASEC microdata.

Figure 10: Supply and demand contributions to year-to-year changes in the college wage premium



Note: Years are survey reference years. Bars show year-to-year change in the fitted college wage premium due to demand factors, supply factors, and the interaction of both, as described in the text. Fitted premium from quadratic trend plus interaction model that assumes imperfect substitution across age-by-gender groups. Annual series formed as labor-supply-weighted averages of age-by-gender groups. Decomposition shown starting in 1965 due to relatively large early sample fluctuations in the premium that dominate and make variation in the remaining years harder to read.
Source: Authors' calculations from CPS ASEC microdata.

Table 1: First-stage estimation of the college wage premium, age-by-gender groups

	(1) 1961-1996	(2) 1997-2023	(3) 1961-2023
Age x gender group specific relative supply	-0.078***	-0.091***	-0.109***
	(0.014)	(0.015)	(0.008)
Constant	0.083***	0.304***	0.035
	(0.025)	(0.016)	(0.021)
Observations	560	432	992
R^2	0.807	0.686	0.876

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Authors' estimates of text Equation 6 using group values tabulated from CPS ASEC microdata. Robust standard errors are in parentheses. Models are fit by weighted least squares to the group by year college-high school wage premium. Weights are inverse sampling variances of the estimated wage premium. All models include group and year dummies.

Table 2: Second-stage estimation of the college wage premium, age-by-gender groups with imperfect substitution

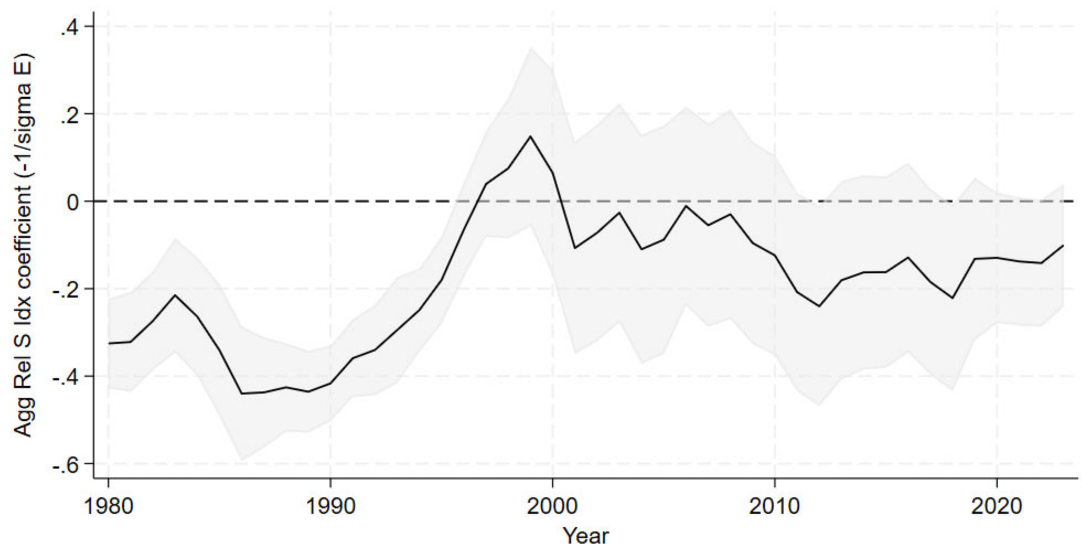
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1961-1996	1961-1996	1997-2023	1997-2023	1961-2023	1961-2023	1961-2023	1961-2023
Age x gender group	-0.080***	-0.079***	-0.093***	-0.094***	-0.120***	-0.114***	-0.110***	-0.110***
relative supply	(0.018)	(0.016)	(0.016)	(0.016)	(0.011)	(0.011)	(0.009)	(0.009)
Aggregate relative supply	-0.399***	-0.283***	-0.168**	-0.079	-0.142***	-0.418***	-0.694***	-0.614***
index	(0.031)	(0.043)	(0.071)	(0.077)	(0.017)	(0.030)	(0.035)	(0.046)
Linear trend	0.020***	0.008***	0.005***	0.006***	0.009***	0.027***	0.053***	0.045***
	(0.001)	(0.003)	(0.001)	(0.002)	(0.000)	(0.002)	(0.003)	(0.004)
Quadratic trend/100		0.017***		-0.010***		-0.015***	-0.057***	-0.047***
		(0.004)		(0.004)		(0.001)	(0.004)	(0.005)
(Agg supply)*trend							0.018***	0.018***
							(0.002)	(0.002)
(Agg supply) x (quad trend/100)								-0.007***
								(0.002)
Constant	-0.441***	-0.219***	0.354***	0.331***	-0.065***	-0.539***	-0.871***	-0.722***
	(0.046)	(0.070)	(0.016)	(0.018)	(0.023)	(0.048)	(0.050)	(0.076)
Observations	560	560	432	432	992	992	992	992
R-squared	0.754	0.766	0.648	0.654	0.802	0.833	0.857	0.859

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

Note: Authors' estimates of text Equation 7, using group and aggregate values tabulated from CPS ASEC microdata. Robust standard errors are in parentheses. Models are fit by weighted least squares to the group by year college-high school wage premium. Weights are inverse sampling variances of the estimated wage premium. All models include group dummies.

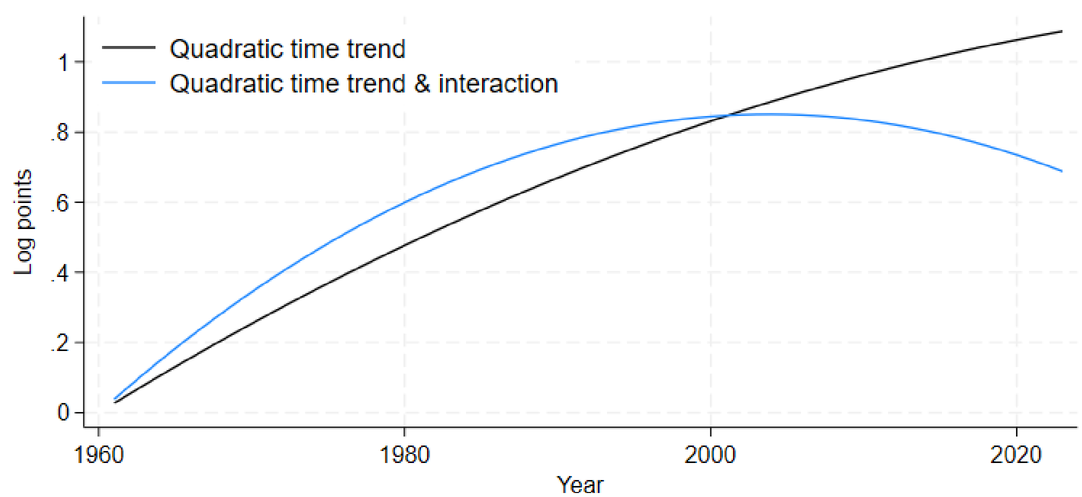
Appendix A. Additional Displays

Figure A1: Coefficient on aggregate relative supply index from rolling regression estimation



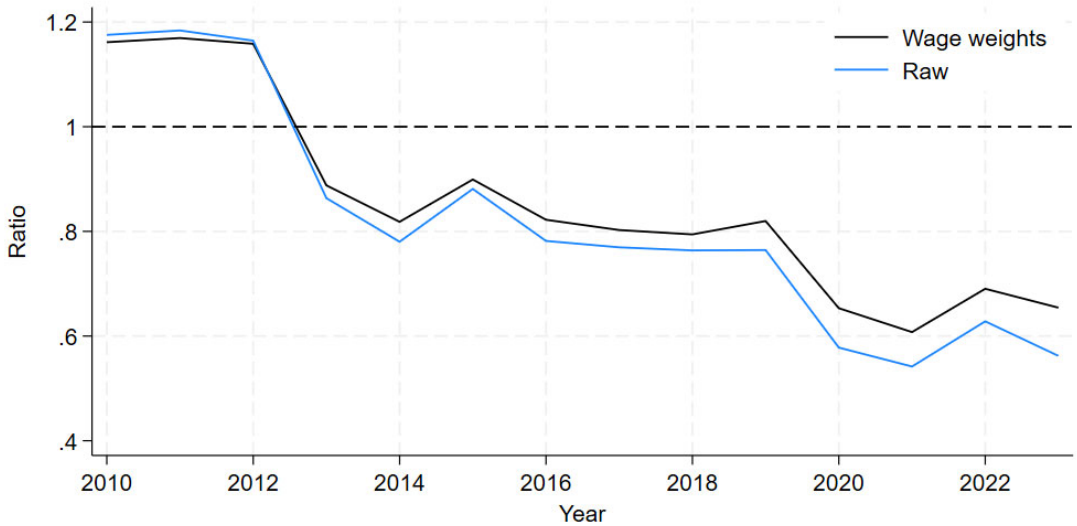
Note: Years are survey reference years. Coefficients are from rolling regressions over 20 years plotted at each roll's end year. Regression specification includes a linear time trend, the relative and aggregate supply measures (imperfect substitution), and age-by-gender group dummies. Shading shows 95% CI.
Source: Authors' calculations from CPS ASEC microdata.

Figure A2: Implied time effect on college wage premium, various models



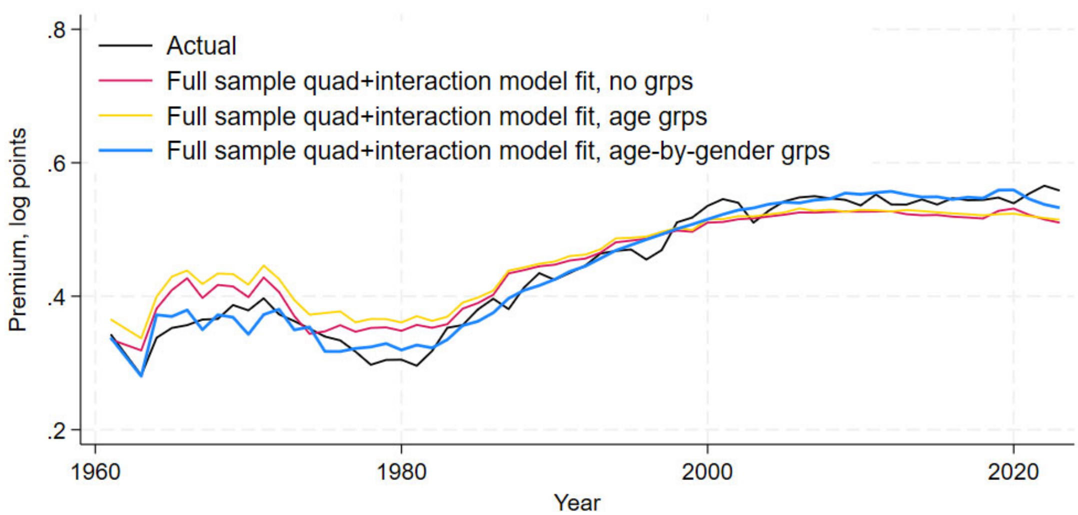
Note: Years are survey reference years. Time effects are from full sample (1961 - 2023) regressions that allow for imperfect substitution between age-by-gender groups, described in the text. 'Quadratic time trend' model includes linear and quadratic time trends, and 'interaction' indicates the inclusion of interactions between the time trends and the aggregate relative supply index. Implied time effects are obtained from coefficients on the time trends and (for the interaction model) their full interactions with the aggregate relative supply variable. The latter case uses the full sample mean of aggregate relative supply in the calculation of the implied time effect.
Source: Authors' calculations from CPS ASEC microdata.

Figure A3: Ratio of Lightcast job postings that require a college vs a high school degree



Note: Raw ratio calculated directly from job posting counts. Counts of postings by degree requirement created as described in the text. Weighted ratio uses annual wages (CPS ASEC) to combine high school jobs with (a portion of) 'some college' jobs and the remaining 'some college' jobs and graduate degree jobs with college jobs (as in the formation of the supply variables, see text).
Source: Authors' calculations from Lightcast job posting data and CPS ASEC (weights).

Figure A4: College wage premium, actual and model fits (preferred specification with age-by-gender grouping and alternative groupings)



Note: Years are survey reference years. Model fits are fitted premia from regressions that include quadratic time trends and interactions with the aggregate relative supply index (details in the text). Models based on different groupings (age, age-by-gender) or no grouping at all (year). Age and age-by-gender groupings allow for imperfect substitution between groups and annual series formed as labor-supply-weighted averages of the predicted wage premia for age or age-by-gender groups.
Source: Authors' calculations from CPS ASEC microdata.

Table A1: First-stage estimation of the college wage premium, **age groups**

	(1) 1961-1996	(2) 1997-2023	(3) 1961-2023
Age group specific relative supply	-0.140***	-0.081***	-0.134***
	(0.011)	(0.020)	(0.008)
Constant	0.076***	0.355***	0.086***
	(0.029)	(0.014)	(0.026)
Observations	280	216	496
R-squared	0.857	0.754	0.895

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

Note: Authors' estimates of text Equation 6 using group values tabulated from CPS ASEC microdata. Robust standard errors are in parentheses. Models are fit by weighted least squares to the group by year college-high school wage premium. Weights are inverse sampling variances of the estimated wage premium. All models include group and year dummies.

Table A2: Second-stage estimation of the college wage premium, **age-by-gender groups with perfect substitution**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1961-1996	1961-1996	1997-2023	1997-2023	1961-2023	1961-2023	1961-2023	1961-2023
Age x gender group	-0.078***	-0.078***	-0.092***	-0.092***	-0.116***	-0.111***	-0.109***	-0.109***
relative supply	(0.017)	(0.016)	(0.016)	(0.016)	(0.011)	(0.010)	(0.009)	(0.009)
Aggregate relative supply	-0.394***	-0.287***	-0.195**	-0.123	-0.160***	-0.439***	-0.699***	-0.604***
index	(0.030)	(0.043)	(0.077)	(0.081)	(0.018)	(0.031)	(0.036)	(0.048)
Linear trend	0.020***	0.009***	0.006***	0.007***	0.009***	0.028***	0.058***	0.048***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.004)
Quadratic trend/100		0.017***		-0.010**		-0.015***	-0.059***	-0.047***
		(0.004)		(0.004)		(0.001)	(0.004)	(0.005)
(Agg supply)*trend							0.018***	0.017***
							(0.002)	(0.002)
(Agg supply) x (quad trend/100)								-0.008***
								(0.002)
Constant	-0.512***	-0.279***	0.310***	0.324***	-0.096***	-0.629***	-1.002***	-0.806***
	(0.051)	(0.078)	(0.030)	(0.030)	(0.027)	(0.053)	(0.059)	(0.087)
Observations	560	560	432	432	992	992	992	992
R-squared	0.757	0.767	0.649	0.655	0.803	0.837	0.856	0.858

* p < 0.1, ** p < 0.05, *** p < 0.01.

Note: Authors' estimates of text Equation 7 (modified to assume perfect substitution between age-by-gender groups), using group and aggregate values tabulated from CPS ASEC microdata. Robust standard errors are in parentheses. Models are fit by weighted least squares to the group by year college-high school wage premium. Weights are inverse sampling variances of the estimated wage premium. All models include group dummies.

Table A3: Second-stage estimation of the college wage premium, **age groups with imperfect substitution**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1961-1996	1961-1996	1997-2023	1997-2023	1961-2023	1961-2023	1961-2023	1961-2023
Age group relative supply	-0.141***	-0.142***	-0.085***	-0.085***	-0.154***	-0.140***	-0.134***	-0.134***
	(0.011)	(0.011)	(0.021)	(0.021)	(0.010)	(0.009)	(0.008)	(0.008)
Aggregate relative supply index	-0.332***	-0.410***	-0.112	-0.073	-0.151***	-0.396***	-0.559***	-0.606***
	(0.029)	(0.052)	(0.072)	(0.088)	(0.019)	(0.027)	(0.039)	(0.050)
Linear trend	0.014***	0.021***	0.003	0.003*	0.007***	0.022***	0.037***	0.041***
	(0.001)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.004)
Quadratic trend/100		-0.010*		-0.004		-0.012***	-0.036***	-0.040***
		(0.005)		(0.005)		(0.001)	(0.004)	(0.005)
(Agg supply)*trend							0.010***	0.009***
							(0.002)	(0.002)
(Agg supply) x (quad trend/100)								0.004
								(0.003)
Constant	-0.206***	-0.345***	0.401***	0.393***	0.061**	-0.335***	-0.536***	-0.623***
	(0.043)	(0.087)	(0.014)	(0.018)	(0.026)	(0.041)	(0.054)	(0.081)
Observations	280	280	216	216	496	496	496	496
R-squared	0.830	0.833	0.696	0.696	0.819	0.863	0.872	0.873

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

Note: Authors' estimates of text Equation 7, using group and aggregate values tabulated from CPS ASEC microdata. Robust standard errors are in parentheses. Models are fit by weighted least squares to the group by year college-high school wage premium. Weights are inverse sampling variances of the estimated wage premium. All models include group dummies.

Table A4: Estimation of the college wage premium, **annual data only (single stage, no sub-groups)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1961-1996	1961-1996	1997-2023	1997-2023	1961-2023	1961-2023	1961-2023	1961-2023
Aggregate relative supply index	-0.377***	-0.438***	-0.052	-0.037	-0.146***	-0.421***	-0.651***	-0.704***
	(0.038)	(0.051)	(0.075)	(0.090)	(0.032)	(0.040)	(0.051)	(0.056)
Linear trend	0.017***	0.022***	0.001	0.001	0.007***	0.024***	0.048***	0.052***
	(0.001)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.005)
Quadratic trend/100		-0.008		-0.001		-0.014***	-0.047***	-0.050***
		(0.005)		(0.009)		(0.002)	(0.005)	(0.006)
(Agg supply)*trend							0.014***	0.012***
							(0.002)	(0.002)
(Agg supply) x (quad trend/100)								0.005*
								(0.003)
Constant	-0.247***	-0.366***	0.498***	0.502***	0.139***	-0.361***	-0.691***	-0.800***
	(0.062)	(0.093)	(0.034)	(0.029)	(0.050)	(0.070)	(0.080)	(0.096)
Observations	35	35	27	27	62	62	62	62
R-squared	0.863	0.869	0.015	0.017	0.779	0.907	0.945	0.947

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

Note: Authors' estimates of text Equation 7 (modified to annual data excluding groups), using aggregate values tabulated from CPS ASEC microdata. Robust standard errors are in parentheses. Models are fit by weighted least squares to the yearly college-high school wage premium. Weights are inverse sampling variances of the estimated wage premium.

Table A5: Second-stage estimation of the college wage premium, age-by-gender groups with imperfect substitution
("some college" group omitted)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1961-1996	1961-1996	1997-2023	1997-2023	1961-2023	1961-2023	1961-2023	1961-2023
Age x gender group	-0.094***	-0.094***	-0.083***	-0.084***	-0.114***	-0.107***	-0.103***	-0.103***
relative supply	(0.011)	(0.011)	(0.013)	(0.013)	(0.008)	(0.007)	(0.006)	(0.006)
Aggregate relative supply	-0.400***	-0.299***	-0.211***	-0.106	-0.194***	-0.447***	-0.710***	-0.608***
index	(0.027)	(0.034)	(0.076)	(0.090)	(0.016)	(0.024)	(0.037)	(0.048)
Linear trend	0.022***	0.012***	0.008***	0.008***	0.012***	0.030***	0.062***	0.051***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.005)
Quadratic trend/100		0.015***		-0.010**		-0.014***	-0.069***	-0.053***
		(0.004)		(0.004)		(0.001)	(0.006)	(0.007)
(Agg supply)*trend							0.017***	0.016***
							(0.002)	(0.002)
(Agg supply) x (quad trend/100)								-0.006***
								(0.002)
Constant	-0.503***	-0.290***	0.378***	0.349***	-0.152***	-0.635***	-1.021***	-0.815***
	(0.047)	(0.067)	(0.015)	(0.020)	(0.026)	(0.046)	(0.059)	(0.089)
Observations	560	560	432	432	992	992	992	992
R-squared	0.768	0.776	0.655	0.660	0.816	0.847	0.862	0.864

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

Note: Authors' estimates of text Equation 7 (modified to omit 'some college' from supply calculation), using group and aggregate values tabulated from CPS ASEC microdata. Robust standard errors are in parentheses. Models are fit by weighted least squares to the group by year college-high school wage premium. Weights are inverse sampling variances of the estimated wage premium. All models include group dummies.

Table A6: Second-stage estimation of the college wage premium, age-by-gender groups with imperfect substitution
(data used include imputed earnings values and no top code adjustment)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1961-1996	1961-1996	1997-2023	1997-2023	1961-2023	1961-2023	1961-2023	1961-2023
Age x gender group	-0.089***	-0.089***	-0.082***	-0.082***	-0.122***	-0.117***	-0.113***	-0.113***
relative supply	(0.013)	(0.012)	(0.015)	(0.015)	(0.009)	(0.008)	(0.007)	(0.007)
Aggregate relative supply	-0.456***	-0.287***	-0.182***	-0.121*	-0.120***	-0.455***	-0.686***	-0.585***
index	(0.030)	(0.043)	(0.066)	(0.070)	(0.016)	(0.030)	(0.033)	(0.045)
Linear trend	0.022***	0.007**	0.006***	0.007***	0.009***	0.029***	0.051***	0.042***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.004)
Quadratic trend/100		0.020***		-0.010***		-0.017***	-0.053***	-0.041***
		(0.004)		(0.004)		(0.001)	(0.003)	(0.004)
(Agg supply)*trend							0.016***	0.017***
							(0.001)	(0.001)
(Agg supply) x (quad trend/100)								-0.008***
								(0.002)
Constant	-0.527***	-0.220***	0.362***	0.342***	-0.042*	-0.602***	-0.864***	-0.677***
	(0.045)	(0.070)	(0.016)	(0.018)	(0.023)	(0.048)	(0.048)	(0.074)
Observations	560	560	432	432	992	992	992	992
R-squared	0.769	0.782	0.663	0.670	0.818	0.851	0.874	0.876

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Authors' estimates of text Equation 7 (modified to include observations with imputed earnings values and to skip top code adjustment procedure), using group and aggregate values tabulated from CPS ASEC microdata. Robust standard errors are in parentheses. Models are fit by weighted least squares to the group by year college-high school wage premium. Weights are inverse sampling variances of the estimated wage premium. All models include group dummies.