Declining Teen Employment: Causes and Consequences*

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Abstract

Employment among U.S. high school students has halved since 2000. We provide causal evidence that (1) crowding out by adults accounts for the majority of this decline and (2) high school work experience raises lifetime earnings for non-college workers. Disciplined by these findings, we develop a general equilibrium model where teenagers accumulate human capital through work and school and adults choose between "teen" and "non-teen" occupations. Of the decline caused by adult crowding out, 53% occurs as competition pushes teen wages below the minimum wage, 27% as lower wages reduce the immediate return to work, and 20% through stronger schooling incentives. Aggregate welfare falls, and the effects are highly heterogeneous, with the largest losses of 1.2% among non-college workers. A lower teen-specific minimum wage and a vocational training policy mitigate these losses, each raising aggregate welfare by 0.3%. More broadly, our results show how changes in adult labor markets can propagate to younger workers, with persistent consequences beginning before adulthood.

JEL Codes: E24, I26, I28, J13, J23, J24

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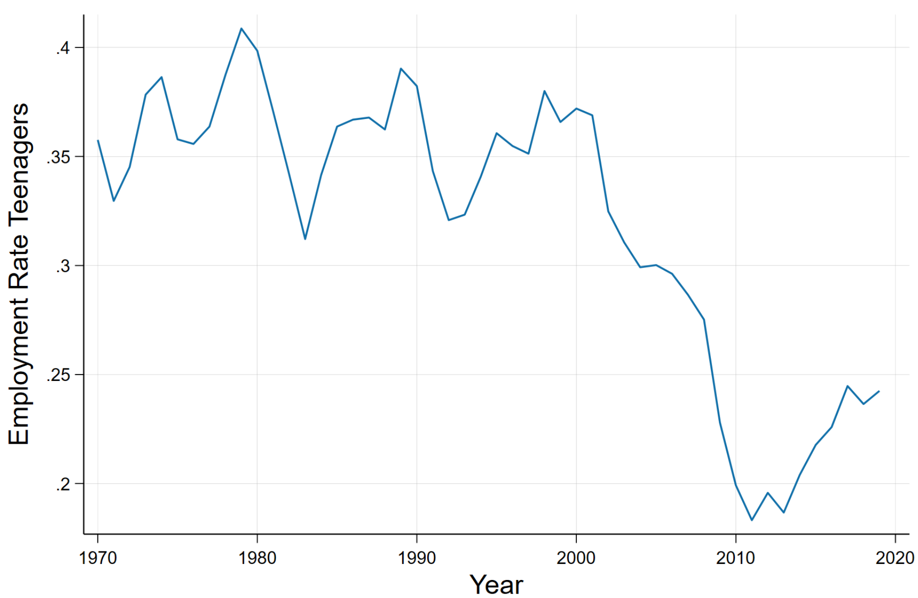
1 Introduction

Since 2000, teen employment has declined by nearly 50%. Historically, employment among teenagers enrolled in high school ranged between 30 and 40%. However, beginning in the early 2000s, there was a stark break from trend, and teen employment fell below 20% by 2010. *Figure 1* plots this trend in the employment rate for 16-18 year-olds currently enrolled in high school.[1]

This paper studies two aspects of this dramatic decline: (1) What are the underlying causes? (2) What are the macroeconomic implications for human capital development and the distribution of lifetime earnings? To answer these research questions, the analysis combines reduced-form identification with a quantitative general equilibrium framework, linking causal evidence from microdata to aggregate welfare and policy implications.

Our empirical analysis provides two necessary inputs into the quantitative analysis. We first identify the main driver of the decline in teen employment. We then estimate the life-cycle earnings returns to employment while in high school, which discipline the long-run consequences of reduced teen employment for human capital accumulation and earnings.

Figure 1: **Teen Employment Rate Over Time**



Notes: This figure plots the employment rate for 16-18 year-olds currently enrolled in high school. *Source:* Current Population Survey (CPS).

[1] *Section 3* discusses *Figure 1* in significantly more detail. *Appendix B.1* reports extensive robustness analysis and discusses additional details.

Together, these empirical results motivate the model's structure and the need for a quantitative framework, while also disciplining key parameters governing teen employment and human capital accumulation.

We begin by examining whether the decline in teen employment is driven primarily by demand- or supply-side forces. Aggregate evidence suggests that the decline in teen employment is driven by demand-side forces, particularly the crowding out of teenagers by adults. After 2000, adult employment in occupations typically held by teenagers (e.g., retail and food service) increased sharply, while relative wages in these occupations declined. This pattern coincided with deteriorating adult labor market conditions driven by recessions, manufacturing decline, and job polarization, which pushed adults toward lower-skill jobs.[2]

We then estimate the causal effect of adult crowding out using variation across U.S. commuting zones. We construct three complementary shift-share instruments that interact lagged local occupational, age, and education compositions with subsequent national inflows of adults into teen jobs. The instruments generate differential exposure across commuting zones to groups of adults who, following post-2000 labor market shocks, were more likely to move into teen jobs. Identification requires that these initial compositions affect subsequent changes in teen employment only through adult entry into teen occupations. Our preferred estimates imply that adult crowding out accounts for more than 50% of the decline in teenage employment between 2000 and 2010.

Our second empirical exercise estimates the lifecycle returns to employment while in high school. Prior work finds mixed evidence on these returns, which we reconcile by documenting substantial heterogeneity by college attendance (Ruhm, 1997; Light, 2001; Hotz et al., 2002; Ashworth et al., 2021). Because high school employment choices may reflect unobserved abilities and preferences that also affect later earnings, we instrument individual work experience with local teen-employment rates using geocoded National Longitudinal Survey of Youth (NLSY) data. We find that a one-standard-deviation increase in average weekly hours worked is associated with 1% higher average lifetime earnings for workers who do not attend college, but has no significant effect for those who do. Thus, teen employment provides an important source of on-the-job human capital for non-college workers, implying persistent costs for those crowded out of work.

However, the reduced-form evidence cannot (1) decompose the mechanisms through which declining teen employment operates, (2) quantify its macroeconomic and welfare consequences, or (3) evaluate policies that can mitigate these consequences. Disciplined by our

[2]See, for example, Yagan (2019) for the long-term employment effects of the Great Recession and Autor and Dorn (2013) for the eroding work opportunities of middle-skilled manufacturing workers. Foote and Ryan (2015) show how the post-2000 recessions have accelerated this polarization of the labor market.

empirical estimates, the quantitative model provides results for (1)-(3).

In particular, we develop a general equilibrium overlapping-generations model. Teenagers differ in their ability to accumulate human capital through schooling, à la Ben-Porath (1967), or work experience via learning-by-doing. Teens then decide on the time spent on each activity and on leisure. At the end of high school, teens decide whether to attend college or enter the workforce immediately. Adults accumulate human capital, make a labor-leisure choice, and choose between working in "adult" or "teen" occupations. A negative productivity shock to adult occupations (capturing the joint effects of recessions and job polarization) drives adults into teenage occupations. This leads to the crowding out we identify in the empirical analysis. Importantly, crowding out interacts with existing labor market frictions. To model this interaction, we include a minimum wage, an important friction in the labor market for low-skill workers, particularly young or teenage workers (Neumark and Shirley, 2022; Clemens and Strain, 2025).

The model is estimated to match cross-sectional and transitional moments on teen work and schooling choices, adult occupational choices, lifecycle earnings dynamics, and the reallocation of adults into teen occupations. Importantly, the model replicates three essential features of the data. First, teen employment has positive returns for non-college graduates. Second, adults increase employment in teen occupations in response to an aggregate shock. Third, teens reduce employment in response to adult crowding out. We identify the parameters governing these dynamics using simulated method of moments, targeting our causal estimates of the returns to teen employment and adult crowding out.

The quantitative analysis delivers three main results. First, adult crowding out reduces teenage employment through three channels. Increased competition from adults lowers the potential wage of some teenagers below the minimum wage, pushing them into unemployment. This minimum-wage channel is the largest, accounting for 53% of the decline in teen employment generated by crowding out. Among teenagers whose potential wages remain above the minimum wage, lower wages reduce the current consumption return to work and induce lower labor supply, accounting for 27% of the decline. Lastly, changes in future wages increase the incentive to attend college, accounting for 20% of the decline in teen employment. We also show that alternative explanations for the post-2000 decline, including increases in the minimum wage, stronger preferences for leisure, and a rising college premium, cannot simultaneously reproduce the observed decline in teen employment, increase in adult employment in teen occupations, and decline in relative teen-job wages.

Second, this reallocation of adults into teen occupations has persistent and highly unequal consequences. College enrollment increases by 6.5 percentage points, as some teenagers respond to diminished employment opportunities by investing more in schooling and attending college. For teenagers who do not make this adjustment, however, lost work experience reduces employment human capital upon entering adulthood and lowers earnings throughout the lifecycle. As a result, the P75-to-P25 ratio of lifetime earnings rises by 0.4%, driven almost entirely by lower earnings at the bottom of the distribution. Aggregate lifetime welfare falls by 0.7%, with losses of 0.8% among those who worked as teenagers and 1.2% among non-college adults. Thus, the teenagers most harmed by crowding out are those for whom work experience is most valuable and who have the weakest schooling alternative.

Third, we evaluate two policies aimed at mitigating reductions in employment opportunities and human capital accumulation caused by adult crowding out. A lower age-specific minimum wage raises teenage employment by 12.2 percentage points and increases aggregate welfare by 0.3%. An optional career and technical education policy, which allows students to accumulate employment human capital through school, generates similar aggregate welfare gains but produces a much smaller increase in employment. The policies therefore operate through different margins. The teen minimum wage is more effective at restoring access to employment and generates larger gains for teen workers and non-college adults, while career and technical education provides an alternative means of accumulating employment human capital for teenagers who remain unable to work. Neither policy unambiguously dominates the other, but both highlight the same finding: policies that preserve or replace access to work experience can successfully mitigate the persistent welfare costs of adults crowding out teenagers and the resulting decline in teen employment.

Prior work studying the decline in teen employment is surprisingly sparse. Aaronson et al. (2006) discuss potential drivers of changes in teen employment rates prior to the large trend break in 2000, without establishing causal effects. Work studying the post-2000 decline includes Smith (2012), who studies increased competition from immigrants, and Neumark and Shupe (2019), who examine the effects of minimum wage increases. Our approach is complementary but differs by focusing on the long-run macroeconomic decline in teen employment and the role of adult crowding out.

Our paper is also the first to study declining teenage employment in a quantitative macro setting, allowing us to assess both the causes and consequences of this decline, decompose its mechanisms, and conduct policy analysis to address welfare losses. The model can therefore speak to debates on minimum wages and vocational training (Dustmann and Schönberg, 2012; Neumark and Shirley, 2022). While a large literature studies the contemporaneous employment effects of minimum wages, our analysis emphasizes their dynamic consequences for young workers, who are disproportionately exposed to the minimum wage.

More broadly, this paper relates to several larger literatures. First, it builds on research documenting how technological change, trade exposure, and recessions have displaced middle-skill adults into low-wage service work (Autor et al., 2003; Acemoglu and Autor, 2011; Autor et al., 2013; Foote and Ryan, 2015; Yagan, 2019). We show that this reallocation has important spillovers for younger workers, as they are crowded out of their first jobs when adults directly compete with them. Second, the paper contributes to work on early human capital accumulation and labor market entry. Prior research finds that initial labor market conditions at entry have long-run effects on earnings and employment rates (Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016; Schwandt and Wachter, 2019).

We extend this perspective by showing that losing access to work even during high school has persistent consequences for earnings and employment among non-college workers. This mechanism provides a novel view on the broader decline in labor market attachment and earnings among young workers. While existing work studies deteriorating employment outcomes among young workers (Heathcote et al., 2020; Aguiar et al., 2021), our results point to a large lifecycle and cross-generation channel.

Taken together, our results connect these literatures by showing how well-documented changes in adult labor markets can have persistent general equilibrium effects on younger workers. As adults displaced by technological change, trade exposure, and recessions move into lower-skill service occupations, they crowd teenagers out of their first jobs and reduce opportunities to accumulate employment human capital. More broadly, we show that teenage employment is not simply a source of contemporaneous earnings. For many non-college workers, early employment is an investment in human capital, so deteriorating labor market opportunities can have persistent consequences for earnings, inequality, and welfare that begin well before adulthood and persist into later life. This provides a lifecycle and cross-generation link between the forces reshaping adult labor markets and the worsening of outcomes among young adults.

The remainder of this paper is organized as follows. *Section 2* discusses the datasets and sample selection. Our main empirical results are in *Section 3* and *Section 4*. *Section 5* lays out our quantitative framework and *Section 6* discusses the quantitative estimation strategy. *Section 7* reports the model results and policy exercises. *Section 8* concludes.

2 Data

We combine three main data sources: the Current Population Survey (CPS), the Census and American Community Survey (ACS), and the confidential geocoded version of the National

Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97).[3] We primarily use CPS data to compute descriptive statistics on teenage employment and to define "teen occupations," one of our key variables. We use the ACS for our regression analysis determining the causes of declining teen employment, as this analysis requires a larger sample size. We use the confidential geocoded NLSY to estimate the lifecycle earnings returns to teenage employment and to discipline the structural model. The geocoded version provides county-of-residence identifiers needed for our instrumental variables strategy, while the weekly Work History Data Files allow us to measure hours worked while enrolled in school. Further details on the data sources are reported in *Appendix A*.

2.1 Sample Selection and Variable Definition

We keep the baseline sample selection constant across datasets whenever possible. All analysis of teenagers using the ACS or CPS is restricted to those aged 16-18 and currently enrolled in high school. When using the NLSY, we extend this age range to high school students aged 15-18. In our baseline, we define an individual as employed if they report positive hours worked.[4] For earnings data, we use wages and salaries.

To investigate the crowding out of teenage workers by adults, we first define "teen occupations." To do so, we use the CPS and begin by ranking all four-digit ACS occupation codes by the share of all employed teenagers working in each occupation over the 1986-2019 period.[5] Hence, the ranking is based on how much a given occupation contributes to total teen employment. We call the top 20 occupation codes "teen occupations." The list of top 20 occupations is stable over time and is not affected by the employment changes after 2000. This list of occupations captures approximately 75% of all employed teenagers. Cashier is the highest-ranked occupation, employing approximately 15% of all teen workers, followed by food service and retail sales.

Our empirical approach relies on geographic variation. For a consistent and economically meaningful unit of observation, we follow Autor et al. (2013) and aggregate data to the commuting-zone (CZ) level. *Appendix A* reports additional details of the sample selection and data sources.

[3]The CPS, Census, and ACS data are made available by the Integrated Public Use Microdata Series (IPUMS). We combine the decennial Census, which provides a 5% sample of the U.S. population through 2000, with the subsequent American Community Survey (ACS), which provides an annual 1% sample from 2005 onward. For brevity, we refer to the combined Census and ACS data as the ACS throughout the remainder of the paper.

[4]We show that our results are robust to other employment definitions.

[5]We use the consistent occupational codes provided by IPUMS that follow the classification scheme from the 2010 ACS occupation codes. See *Table F.1* in *Appendix F* for the complete list of occupations.

3 Empirical Analysis: Causes of Employment Decline

We start by presenting our empirical analysis, which we use both to motivate and calibrate the quantitative model. This section investigates the causes of declining teen employment. The effects of teen employment on later-life earnings and employment outcomes are examined in *Section 4*. In both sections, we begin with motivating descriptive statistics. We then turn to an analysis using instrumental variables (IV) regressions to establish causality for our main mechanisms and moments of interest. *Appendix B* reports robustness analyses.

The decline in teen employment could be the result of supply-side and/or demand-side factors. Supply-side explanations would entail a reduction in the supply of labor by teens, while demand-side explanations would entail a reduction in firms' demand for teen labor. We argue that the aggregate descriptive statistics are at odds with an entirely supply-driven explanation. However, we also discuss the details and validity of specific supply-side explanations at the end of this section.

We emphasize a demand-side explanation driven by adult workers crowding out teens in response to an aggregate productivity shock. Adults crowd out teen labor when employment opportunities and wages deteriorate elsewhere. A variety of shocks affecting adult workers have been studied over the period of interest, including job polarization, recessions, trade competition, and structural change (Autor and Dorn, 2013; Foote and Ryan, 2015; Yagan, 2019). We confirm that these phenomena in fact drive adults into teen jobs.

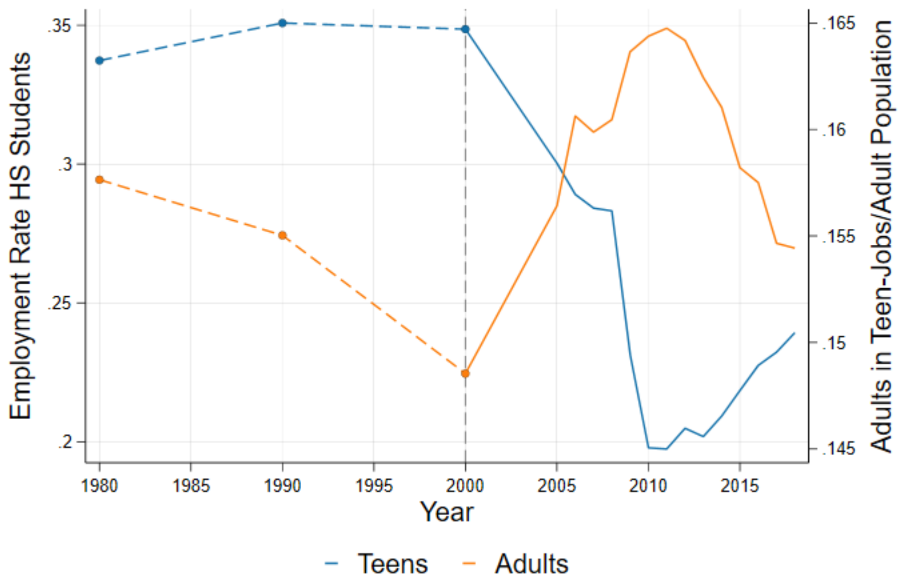
3.1 Descriptive Statistics

We use descriptive statistics to motivate our focus on demand-side explanations in the empirical exercise below. To identify the contribution of these demand-side factors to the decline in teenage employment, we then rely on instrumental variables. In this section, we present data that support the construction of the instruments described in *Section 3.2*.

3.1.1 Adults Crowding Out Teen Labor

Figure 2 plots the teen employment rate and the share of adults employed in teen occupations relative to the adult population. Prior to 2000, teen employment in teen occupations is relatively flat, while adult employment in teen occupations declines. Beginning in the early 2000s, there is a sharp trend break in the employment of both adults and teens in teen occupations. Adults cease leaving teen occupations and begin to enter them, while teens begin to exit sharply. This implies a marked substitution of adult for teen labor within teen occupations.

Figure 2: **Adults Entering Teen Occupations**

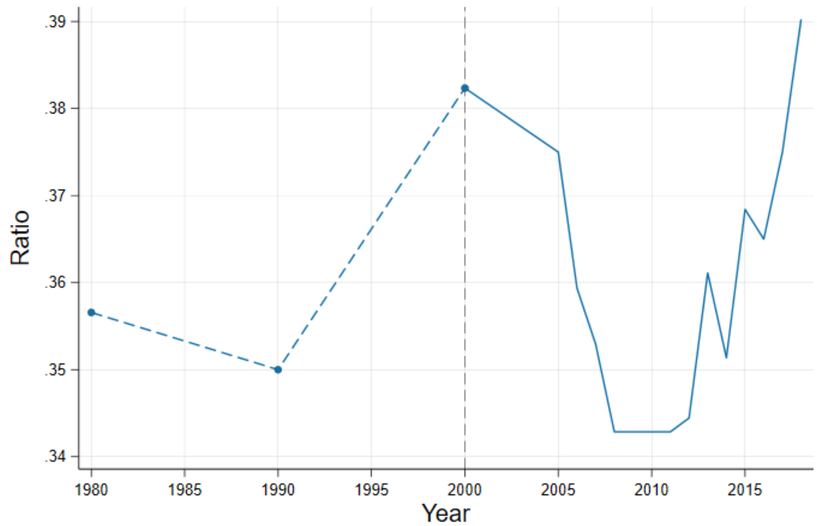


Notes: The left axis plots the employment rate of teenagers aged 16-18 and currently enrolled in high school. The right axis plots the share of adults working in teen occupations as a fraction of the total adult population. The adult population is defined as individuals aged 19 and older who are not enrolled in high school or college. Employment is defined as positive hours worked in the preceding week. *Source:* American Community Survey (ACS).

It is unclear whether the substitution from teen labor to adult labor stems from demand or supply factors. *Ceteris paribus*, a large supply shock generating the pattern in *Figure 2* would require wages in teen occupations to be rising. *Figure 3* plots real median wages in teen occupations relative to real median wages in non-teen occupations. This ratio increases until the early 2000s, then flattens and even falls until the early 2010s. This period coincides precisely with the influx of adult workers, and the ratio only begins to rise again when adult workers start to leave teen occupations in the early 2010s. This motivates further investigation of adult labor crowding out teen labor as a source of the decline and rules out an explanation *primarily* driven by supply-side factors. In *Section 3.3*, we formalize this using an IV regression analysis and causally show that an increase in the share of adults in teen occupations has a significant negative effect on wages within teen occupations.

Several supply-side explanations could also contribute to the aggregate decline in teen employment, including changes in preferences for leisure, rising parental income, or greater

Figure 3: **Ratio of Wages in Teen Occupations to Non-teen Occupations**



Notes: This figure plots the ratio of median annual earnings in teen occupations to those in non-teen occupations for individuals aged 16 and older. Reported zero earnings are dropped, and wages at the 98th percentile and above are winsorized. Real wages are calculated using the 2012 personal consumption expenditures (PCE) price index. *Source:* American Community Survey (ACS).

incentives to invest in schooling.[6] The aggregate evidence alone cannot fully distinguish these explanations from adult crowding out. However, our IV analysis exploits predetermined geographic differences in exposure to adult entry into teen occupations to identify the causal effect of adult crowding out on teen employment.

3.1.2 Characteristics of Adults Entering Teen Jobs

Our empirical strategy builds on the idea that large economy-wide trends drive specific adult workers into teen occupations. These trends include the decline in manufacturing employment, the routinization of work, and the successive recessions after 2000. We present evidence of these mechanisms in *Appendix B.3*. However, we remain agnostic about the exact nature of these shocks and instead focus on the types of workers who enter teen occupations after 2000.

We specifically focus on the demographic characteristics of adults entering teen occupations and the types of occupations they originate from. Both factors will be used to inform our IV regression analysis in *Section 3.2*. To identify the occupations from which adults

[6] For example, Aguiar et al. (2021) emphasize increased leisure, particularly video gaming among young men. However, *Figure E.2* shows similar declines in employment among male and female teenagers, while *Figure E.4* shows similar declines across household earnings groups. Teen labor laws have also remained quite stable across regions and over time.

originate, we use the linked monthly CPS data to observe transitions of adults into and out of teen occupations. First, we consider occupations with the highest inflows into teen occupations. For example, we count all movements from farming into a teen occupation and all movements from a teen occupation into farming. We subtract the latter from the former and call this difference "net inflows into teen occupations" from farming. We then calculate these net inflows into teen occupations for each non-teen occupation over the 1990-2000 and 2000-2010 periods. We take the difference between these two "net inflows" measures to obtain a *change* in net inflows into teen occupations. *Table 1* reports the occupations with the ten highest changes in net inflows into teen occupations.[7]

The list of occupations from which workers move into teen occupations is largely composed of middle-skill occupations. These occupations include both manual and non-manual positions affected by job polarization, such as machine operators and administrative support. We also see positions that have clearly been affected by structural change, such as farming.[8] We use these occupations to inform our IV regressions in the next section.

The two most important demographic characteristics of adults entering teen occupations are age and education. As with occupations, we calculate the age and education groups that saw the largest changes in net inflows into teen occupations. We find that it is largely middle-aged workers (born between 1950 and 1965) who contribute to the rise in adult employment in teen occupations. When faced with a common shock, older workers are more likely to transition into non-participation than middle-aged workers (Chan and Huff Stevens, 2001; Coile and Levine, 2011). Younger workers, on the other hand, are more likely to retrain and switch occupations (Topel and Ward, 1992; Wachter and Bender, 2006). We formalize this logic in *Section 3.2* with an IV regression analysis.

We also find that after 2000, adults working in teen occupations became more highly educated, as we document in *Figure F.4*. While the majority of workers transitioning into teen jobs continue to be those without a college degree, the share of college-educated workers in these positions has risen markedly relative to the pre-2000 period. Prior to 2000, college-educated workers were essentially absent from teenage occupations; this is no longer the case.[9] Although initially surprising, this pattern is consistent with a large body of literature (see Binder and Bound (2019) and Abraham and Kearney (2020) for reviews) documenting

[7] We use changes in net flows to correct for normal lifecycle movements into and out of teen occupations.

[8] Only Health Diagnostic and Health Service occupations experienced steady growth over our period of interest. If we separately look at net inflows in the 1990-2000 and 2000-2010 periods, we see that their ranking in our list is driven by relatively large net *outflows* in the 1990-2000 period. This means that many workers transitioned from teen jobs into health professional jobs before 2000 and then this movement stopped after 2000.

[9] The rise in college attainment among workers in teen occupations holds when controlling for birth cohort.

Table 1: **Top 10 Origin Occupations by Increase in Net Flows into Teen Occupations**

Δ Net Inflows (1990-2000 & 2000-2010)
Admin Support
Farmers
Records Processing
Machine Operators
Printing Machine Operators
Health Diagnosing
Personal Service
Health Service
Teachers
Precision Workers

Notes: This table reports the top ten non-teen occupations in which adults are employed before switching into teen occupations. We calculate inflows net of outflows and report the changes in these net flows. We count those directly entering teen occupations and those who move through unemployment spells, *if* their most recent occupation before unemployment was a non-teen occupation. *Source:* Linked monthly Current Population Survey (CPS).

a sharp rise in non-participation rates over this period among workers with lower levels of education, particularly males. We argue that the shocks affecting these occupations were severe enough to displace a sizable share of college-educated workers as well.

3.2 Instrumental Variable Regression Analysis

The descriptive statistics presented in *Section 3.1* suggest that crowding out of teenagers by adult workers is an important explanation for the decline in teen employment. Using the ACS, we further investigate the extent to which adult competition has contributed to the post-2000 decline in aggregate teen employment, exploiting cross-commuting-zone variation in an instrumental variables regression. Our main relationship of interest is given by,

$$\Delta \text{TeenEmpShare}_{c,t} = \beta \Delta \left(\frac{\text{Adults in Teen Jobs}}{\text{All Adults}} \right)_{c,t} + \gamma \Delta X_{c,t} + \epsilon_{c,t} \tag{1}$$

where $X_{c,t}$ is a vector of controls. The dependent variable is the share of 16-18 year-olds enrolled in high school who are employed. We identify β from cross-commuting-zone variation in changes between 2000 and 2010.

There are two major sources of bias when estimating this equation using OLS. First, if teenagers decide to stop working for reasons unrelated to the labor market (e.g., a change in preferences for leisure), adults would naturally take up some of those positions. This would bias β negatively. While the behavior of wages in teen occupations shows that such supply explanations cannot be the main driver of the observed changes, they could still partly affect the estimates. Second, if the demand for the output of teen occupations changes, then both teen employment and adult employment in teen occupations would move in the same direction. This would bias β positively.

To identify the causal relationship of interest, we rely on an instrumental variables strategy. We use the descriptive statistics presented above to inform our construction of three complementary instruments. We build a Bartik-style instrument that relies on variation in the occupational distribution within commuting zones. Similarly, we use the observation that the increase in adults in teen occupations is accompanied by an increase in older and college-educated adults, and we exploit this demographic variation within commuting zones. As in Goldsmith-Pinkham et al. (2020), identification in both cases comes from the initial distribution of either demographics or occupations.

Previous Occupation Instrument – We construct a Bartik-style instrument, $z_{c,t}$, using the occupational distribution within commuting zones,

$$z_{c,t} = \sum_{o} s_{o,c,t_0} g_{o,t} \tag{2}$$

where s_{o,c,t_0} are the initial employment shares of each occupation o in commuting zone c in the initial period t_0. We then weight each of these shares by the national change in net inflows into teen employment from occupation o over the period of interest, $g_{o,t}$.[10] These weights are calculated using flows of workers, as discussed in *Section 3.1*. In practice, we use the top 20 previous occupations of workers transitioning into teen occupations.[11] To minimize potential endogeneity, we use lagged occupational shares. That is, instead of using shares in 2000, we use shares in $t_0 = 1990$.

Demographic Instruments – We proceed similarly for our demographic instruments. We split the adult population by birth cohort. We then construct the instrument $z_{c,t}$ as the share of all adults born between y_0 and y_T, weighted by each cohort's change in net inflows into teen jobs between 2000 and 2010,

$$z_{c,t} = \sum_{a=y_0}^{y_T} s_{a,c,t_0} g_{a,t} \tag{3}$$

where s_{a,c,t_0} is the share of adults in location c in the initial period t_0 who belong to birth

[10]The shift term is thus the "Δ Net Inflows" in *Table 1*.

[11]We ensure that none of these occupations are closely related to those defined as teen occupations.

cohort a. The weights $g_{a,t}$ are then calculated in the same way as the weights $g_{o,t}$ for the occupation instrument. We calculate each cohort's net inflows into teen jobs between 2000 and 2010 from the CPS and then subtract the net inflows between 1990 and 2000 for birth cohorts ten years older. This last step eliminates age effects. Finally, since we observe that relatively more college-educated workers enter teen jobs, we construct our third instrument as above, restricting it to college-educated adults only. For both demographic instruments, we again use lagged demographic shares from 1990. This reduces any concerns about individuals moving into and out of commuting zones endogenously.

3.2.1 Instrument Exogeneity

As discussed in Goldsmith-Pinkham et al. (2020), the identifying assumption we make is that the initial shares s_{o,c,t_0} and s_{a,c,t_0} are uncorrelated with the *changes* in teen employment except through their correlation with changes in the share of adults in teen occupations. The underlying national shocks are the two post-2000 recessions, the decline in manufacturing employment, and job polarization. These shocks adversely affected workers in specific occupations and demographic groups. Commuting zones with high shares of workers in these occupations and demographic groups are then more exposed to the national shocks, which provides the variation we exploit for identification.

Changes in the preferences of teenagers that are driven by national phenomena (e.g., video games) would be uncorrelated with our instrument. The same holds for national changes in the demand for the output of teen occupations, such as structural change toward service goods. To control for local exposure to structural change, we include the change in the manufacturing share as a regressor in X. Our instrument builds on initial shares of adults who are adversely affected and therefore pushed into teen occupations. This leads to lower earnings for these adults, which in turn could reduce local demand, negatively affecting teen employment. To isolate the crowding out of teenagers by adults from this second demand channel, we include the change in median earnings in a commuting zone as a control in X. Including these regressors means that additional local demand effects are absorbed and that β therefore identifies the direct crowding-out effect. The exclusion restriction of our instruments holds conditional on the inclusion of these additional controls.

A portion of the negatively affected adults are also parents of teenagers in our sample. Negative shocks to their earnings might drive their children to work more to compensate for the lost earnings. We address this by also constructing our instrument using only adults without teenage children. The results are unchanged and are reported in *Table B.4*.

Finally, by including several independent instruments, we reduce concerns that any individual factor biases our results. We show that the occupation and demographic instruments are largely uncorrelated and thus capture different sources of variation in *Appendix B.4.2*, where we also discuss additional tests that provide support for the exogeneity of our instruments. We now turn to a discussion of instrument-specific exogeneity concerns.

Previous Occupation Instrument – We assume that the initial distribution of occupations does not directly affect changes in teen employment. Rather, employment opportunities in certain occupations are negatively affected by recessions, structural change, and routinization, pushing adult workers into teen occupations at the national level. The occupational structure of adult workers is again most likely uncorrelated with any changes in teenagers' preferences for work. The logic of the instrument builds on some medium-skill occupations being negatively affected by macroeconomic shocks. This might directly change the returns to a college degree and thus threaten identification. However, the set of occupations that we exploit with this instrument is only a small subset of all medium-skill occupations. The shares are thus measured relative to all other medium-skill occupations. It is therefore unlikely that a higher share of these occupations predicts changes in the return to a college degree. In *Appendix B.4.2*, we aggregate occupations into coarser groups and find that our instrument is uncorrelated with changes in employment shares in all middle-skill job groups.[12] It is also uncorrelated with employment shares in routine jobs and all jobs in the manufacturing industry. A second concern is that the initial employment share of certain occupations could predict changes in the demand for the output of teen occupations, which would again bias the coefficient positively. In *Appendix B.4.2*, we show that our instrument is uncorrelated with changes in the aggregate employment share in the service industry. Furthermore, we find that our instrument is uncorrelated with employment changes in most occupation groups that include teen occupations.[13] A potential concern is that our instruments predict demand changes specific to teen occupations. However, teen occupations constitute only a small subset of broader service, sales, administrative, and manufacturing support jobs, and our instruments are unrelated to changes in demand across these broader categories. It is therefore unlikely that the instruments capture demand shocks affecting only the particular occupations in which teenagers work. Nonetheless, as an additional precaution, we include changes in the manufacturing share in our regression.

Demographic Instruments – For the demographic instruments, a similar logic holds. Our hypothesis is that there is no direct effect of the distribution of age and education on future

[12] Operators, Fabricators, and Laborers; Precision Production, Craft, and Repair Occupations; Farming, Forestry, and Fishing Occupations; Service Occupations; Technical, Sales, and Administrative Support Occupations.

[13] Operators, Fabricators, and Laborers; Service Occupations.

changes in teen employment. While the age distribution is largely determined by birth rates and past migration patterns (from inside and outside the U.S.), the distribution of college and high school degrees is mainly driven by past enrollment (and some past migration). Certainly, migration and school attendance decisions are endogenous to the economic conditions in each commuting zone. However, we assume that conditions prior to the 1990s were orthogonal to changes after 2000. They only matter for changes in teen employment post-2000 because certain demographic groups were exposed to worsening national labor market conditions, which may have driven them into teenage occupations.

There is no clear reason for the age distribution of adults, together with the past economic conditions that led to it, to affect changes in teenagers' preferences for work. By contrast, a larger college share is likely indicative of higher demand for high-skill workers. This might influence the *level* of teenage labor, as teenagers might focus more on schooling and less on work in order to increase their chances of going to college. However, it would only threaten our identification if favorable economic conditions for college graduates before 1990 predicted stronger (expected) demand for college graduates after 2000. This would lead to a change in teenagers' preferences for work. We do not find any significant relationship between our education instrument and the change in the employment share of high-skill jobs.[14] An additional threat to identification comes from different demographic groups having different demands for products produced by teen labor. In particular, the demand for service goods rises over the lifecycle (Cravino et al., 2019). In this case, a larger share of older workers would imply higher teen employment and more adults in teen occupations. Thus, β would be positively biased. We do not find that larger employment shares in service occupations predict larger values of our cohort instrument. Additionally, a lower supply of teenage labor due to expected favorable conditions for college graduates and greater demand for products produced by teen occupations would bias β in opposite directions. However, our results show very similar coefficients. These two channels would also imply rising wages for workers in teen occupations. However, as we show in *Section 3.3*, wages for teens and adults in teen occupations are significantly reduced by increased adult shares.

3.2.2 Implementation

We exploit within-commuting-zone time variation using regression equations in first differences. Our main interest lies in the sharp drop in teen employment after 2000. In our baseline, we use 10-year differences, starting from the initial period of 2000. In the ACS, teen employment falls from 35% to 20% over this period. Identification comes from the differential exposure of commuting zones to common shocks occurring after 2000. As described

[14] Managerial and Professional Specialty Occupations.

in Goldsmith-Pinkham et al. (2020), this is akin to a difference-in-differences setting. Hence, we focus on a different source of time variation than Smith (2012) and Neumark and Shupe (2019). The former obtains identification through the pre-2000 period, while the latter exploits year-by-year changes without any relation to an initial period. We focus on variation stemming from the long-run change.

The elements in $X_{c,t}$ are median earnings, the share of whites, the share of teenagers, the unemployment rate, and the manufacturing share. In *Appendix B.4.1*, we show that controlling for the minimum wage does not alter our results and that changes in the minimum wage do not significantly explain changes in teen employment over this period.[15] We additionally show in *Figure F.1* that, prior to 2000, the share of adults working in teen occupations was continuously falling, with a trend reversal in 2000. Therefore, we also include the lagged change in adults in teen occupations from 1990 to 2000.

Since 2000 marks the beginning of our treatment period, the period before 2000 is the pre-period. In *Appendix B.4*, we explore the correlation of our variables of interest between the pre- and post-periods, as well as the change in variance. These correlations and changes in variance show that variation in changes in teen employment and the adult share in teen occupations increases significantly after 2000, providing further support for the choice of initial period. There is also a weak negative correlation in the changes in our variables of interest between the two periods. We therefore include the pre-period change in teen employment in each commuting zone as a regressor to control for any changes induced by mean reversion or other pre-2000 trends. We compare specifications with and without this pre-period change and find very similar results.

3.2.3 Results

We report our baseline results in *Table 2*. We estimate equation (1) for the change between 2010 (the lowest point of teen employment) and 2000.[16] We report the estimated crowding-out coefficient, β, along with the other key controls. The full regression table and the first-stage regression can be found in *Appendix B.4*. For the previous occupation instrument, we choose the top 20 occupations with the largest changes in net inflows into teen occupations between the 1990-2000 and 2000-2010 periods. The cohort instrument uses all adults who are at least 25 years old in 1990.

We find a significant negative relationship between the share of all adults who work in teen occupations and the share of teenagers who are employed. The coefficients are all of similar magnitude. The cohort instrument is relatively weak, and its F-statistic is below the

[15] *Appendix B.4.1* also discusses in more detail how these results relate to Neumark and Shupe (2019).

[16] Our results are robust to other years after 2010. See *Appendix B.4* for details.

Table 2: **Instrumental Variable Regression Results**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	OLS
$AdultShare$	-4.74	-2.67	-3.57	-3.24	-7.33	-4.41	-4.12	-4.22	-0.23
	(.089)	(.052)	(.009)	(.010)	(.056)	(.011)	(.006)	(.005)	(.315)
Z_{Cohort}	Yes	No	No	No	Yes	No	No	No	No
$Z_{Education}$	No	Yes	No	Yes	No	Yes	No	Yes	No
$Z_{PreviousOcc}$	No	No	Yes	Yes	No	No	Yes	Yes	No
F-stat	6.57	10.80	19.67	12.09	5.31	15.70	18.85	11.63	–
Lag teen emp.	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	741	741	741	741	741	741	741	741	741

Notes: P-values shown in parentheses. Dependent variable in all columns is the teen employment share. $AdultShare$ is the share of adults employed in teen occupations as a fraction of all adults. Columns (5), (6), (7) and (8) control for the change in teen employment between 1990 and 2000. *Source:* American Community Survey (ACS).

typical cutoff proposed in Staiger and Stock (1997). Restricting the cohort instrument to college-educated workers increases precision; however, the unrestricted cohort instrument delivers a similar coefficient. This provides further confidence that the additional identification concerns associated with the education instrument are minor.

The coefficients for the education and occupation instruments range from -2.67 to -4.41. Given the aggregate decline in teen employment of roughly 15 percentage points and the aggregate increase in the share of adults in teen jobs over the same period of roughly 2.14 percentage points, a back-of-the-envelope calculation shows that adult crowding out explains between 38 and 63% of the decline. In *Appendix B.4.2*, we confirm these results by conducting the recommended tests from Goldsmith-Pinkham et al. (2020) and by running overidentification tests, which return large p-values, lending additional confidence to our instruments.

Comparing our coefficients with the OLS estimates, we see that OLS is positively biased. Co-movements of teen employment and the employment share of adults in teen occupations due to changes in demand for the output of these occupations appear to be an important factor.

We now briefly turn to a discussion of the remaining regressors in (1). We are particularly interested in the effects of the unemployment rate and the manufacturing share, which are the same demand factors considered in equation (B.1) in *Appendix B.3*. *Table B.3* reports the coefficients, as well as the results from re-estimating (1) without the share of adults in teen occupations. *Table B.1* shows that increasing unemployment rates and declining manufacturing employment significantly increase the share of adults in teen occupations.

Comparing the last column in *Table B.3* with columns (1)-(8), we see that unemployment seems to have a negative effect on teenage employment, which mostly vanishes when including the adult share. Adverse labor market shocks (measured by the unemployment rate) drive adults into teen occupations, which crowd out teenagers but have no *direct* effect on teens. For the decline in manufacturing, the same logic applies, except that a direct effect remains. Declining manufacturing employment increases the number of adults in teen occupations, which again crowds out teens, but it also directly increases teen employment. We hypothesize that this direct effect of manufacturing proxies for structural change toward higher demand for service products, including those produced by teen labor.

We close this section by reemphasizing that our results are not driven by a specific group of teenagers. As mentioned above, *Figures E.2, E.3,* and *E.4* show that teen employment falls similarly for teens of different sexes, races, and parental earnings levels, even though employment levels in 2000 differ. We confirm this here by re-estimating (1) separately for the teenage population split by these demographic characteristics, and we find that we can explain very similar relative declines in employment.

3.3 Effect on Wages

In *Section 3.1*, we argue that the fall in teenage employment and the increase in the share of adults in teen occupations are accompanied by a fall in wages for these workers. Going beyond what we can observe from aggregate time series data, we estimate a version of (1) with wages in teen occupations on the left-hand side,

$$\Delta \log \text{TeenOccWages}_{c,t} = \beta \Delta \left(\frac{\text{Adults in Teen Jobs}}{\text{All Adults}} \right)_{c,t} + \gamma \Delta X_{c,t} + \epsilon_{c,t} \tag{4}$$

We estimate (4) separately for teenagers and adults to reduce the effects of compositional change. We measure the median annual wage of all workers employed in teen occupations (teens or adults) who report nonzero wages in the year of interest.

We find significant negative effects of an increased share of adults in teen occupations on wages within these occupations, for both teenagers and adults. This supports our finding that adults crowding out teenagers leads to the fall in teen employment, rather than adults taking up vacated jobs. The average increase in the share of adults in teen occupations is 0.02. This implies that average adult crowding out reduces teen wages by around 21%. Average adult wages decline by 8%.

To interpret the magnitude of these changes, we compute an implied extensive-margin labor supply elasticity. The roughly ten-percentage-point decline in teen employment due

Table 3: **Wage Regression Results**

	(1)	OLS	(3)	OLS
	$TeenWages$	$TeenWages$	$AdultWages$	$AdultWages$
$AdultShare$	-10.44	1.35	-3.84	-0.62
	(0.024)	(0.112)	(0.016)	(0.066)
$Z_{PreviousOcc}$	Yes	–	Yes	–
$Z_{Education}$	Yes	–	Yes	–
Observations	741	741	741	741

Notes: P-values shown in parentheses. *Source:* American Community Survey (ACS).

to crowding out in *Table 2*, relative to a baseline employment rate of 35%, implies a decline of approximately 25%. Combined with the roughly 20% decline in wages, this gives an implied elasticity of 1.2, which is larger than estimates typically found for adults (e.g., Chetty (2012)). Two features help explain the stronger response among teenagers. First, teenagers earn relatively low wages and are therefore more exposed to the minimum wage. As wages fall, the potential wages of some teenagers fall below the minimum wage, pricing them out of employment. Second, teenagers rely less on labor earnings for consumption and have alternative uses of their time, particularly schooling.

4 Empirical Analysis: Returns to Teen Employment

We use the National Longitudinal Surveys of Youth (NLSY) to determine the lifecycle earnings returns, or "value added", of teen employment. We emphasize the effects for adults who graduate from high school but never attend college, but report results for all groups. Further details are provided in *Appendix B.6*.

4.1 Descriptive Statistics

The effects of working while in high school are experienced immediately for nearly a quarter of teens entering the labor market. Of those who worked while enrolled in high school and do not attend college, 22% remain in the same occupation within five years of graduating from high school and entering the labor force (at the 4-digit occupation code level). *Figure F.6* plots raw average annual earnings over the lifecycle for students who worked in high school compared with those who did not. *Figure F.7* shows a large and persistent difference in employment rates over the lifecycle between those who worked in high school and those who did not. Taken together, these patterns suggest that high school employment may represent an early stage of labor market attachment rather than simply a source of contemporaneous earnings, with differences persisting well into adulthood.

However, this descriptive evidence does not prove that there are positive causal effects of working while in high school. It could also be that selection explains the observed differences. We therefore move to an IV regression setting.

4.2 Instrumental Variable Regression Analysis

We estimate the causal effect of working during high school on future earnings using a Mincer-style regression,

$$W_i = \gamma_0 + \gamma_1 E_i^S + \gamma_2 X_i + \epsilon_i \tag{5}$$

where W_i is the natural logarithm of average lifetime annual earnings, E_i^S is in-school work experience, and X_i includes years of schooling, post-school work experience, and other individual and location controls.[17] Because unobserved ability or motivation may raise both high school employment and later earnings, OLS estimates of γ_1 may be biased. Following Light (2001) and Ruhm (1997), we instrument E_i^S with the local teen employment rate using restricted-access geocoded NLSY79 and NLSY97 data.

This instrument alleviates a typical shortcoming of IV strategies. An IV regression identifies the local average treatment effect (LATE) (Angrist et al., 2000), meaning that we estimate the effect only for students who change their behavior in response to the instrument. However, this is precisely the group relevant for studying the effects of declining teen employment opportunities after 2000.[18]

The exclusion restriction requires that local teen employment affect future earnings only through an individual's high school employment. To address persistence in local economic conditions, we control for the average unemployment rate in the locations where an individual works over adulthood. The controls X_i also include sex, race, the Armed Services Vocational Aptitude Battery (ASVAB/AFQT), and 1980 local economic conditions.[19]

[17] The NLSY provides weekly employment histories. Individual and location controls are aggregated to the annual level. We calculate annual earnings by multiplying hourly wages by total hours worked and average earnings across observed years, omitting years without observations.

[18] In estimating the quantitative model, we replicate this logic by matching the returns for teenagers who *change* their behavior in response to economic conditions.

[19] The AFQT is a composite of four ASVAB subtests. We use the NLSY79 AFQT score and the comparable NLSY97 math-verbal percentile score constructed from the same subtests, referring to both as the AFQT for simplicity.

4.2.1 Results

Columns (1)-(4) of *Table 4* show the estimates from our instrumental variables regression for individuals who graduate high school but do not graduate from college. *Appendix B.6* presents the first-stage results. The returns to teen employment are captured by "Avg. hours worked HS," which measures average weekly hours worked while in high school. We find a significant and positive effect of employment on later-life earnings. As we add controls, the coefficient of interest ranges from 0.064 to 0.041. Our preferred specification is column (4), which implies that a one-hour increase in average weekly hours worked while in high school is associated with 4.1% higher average earnings over the lifecycle. Or alternatively, a one-standard-deviation increase in average weekly hours worked increases lifetime earnings by 1%. We use this estimate as a moment to identify the parameter governing returns to teen employment in our quantitative model.

Appendix B.6 reports additional results in which the regression is estimated separately by age group. We find that the returns to teen employment are largest during the middle of the lifecycle, particularly at ages 30-54. The persistence of these returns into middle age indicates that the benefits of teen employment extend well beyond initial labor market entry.

The NLSY97 allows us to observe individuals only up to age 39, however, we also estimate our main regression using this sample and find a coefficient of similar magnitude. Finally, *Appendix B.6* also reports the OLS regression, which estimates a coefficient of 0.013 in our preferred specification. This indicates that the OLS estimate is negatively biased, suggesting negative selection of lower-ability workers into teen employment.

Next, we estimate equation (5) for individuals who attend and graduate from college. Results are reported in column (5). We find that high school work has no effect on later earnings for this group. This is not surprising, as higher-skill college-educated jobs are likely to be poorly matched with the set of skills teens develop on the job while working in high school. Finally, working while in high school can potentially affect the decision or ability to attend college. Taking this into account can change the overall effect of teen employment. We therefore estimate equation (5) for all individuals and report the results in column (6). Returns remain positive but are slightly smaller than for non-college-bound workers. In the quantitative section, we explicitly model the endogenous college decision.

Combined with the evidence in *Section 3*, these estimates establish a lifecycle channel through which changes in adult labor markets propagate to younger workers. When adult reallocation crowds teenagers out of employment, affected non-college workers lose an opportunity to accumulate human capital that raises earnings well into adulthood.

Table 4: **High School Employment and Lifetime Earnings**

	log average lifetime earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. hours worked HS	0.064	0.057	0.051	0.041	0.007	0.036
	(0.000)	(0.000)	(0.000)	(0.003)	(0.808)	(0.006)
Sex		−0.122	−0.130	−0.145	−0.236	−0.146
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White		−0.141	−0.157	−0.121	−0.103	−0.127
		(0.000)	(0.000)	(0.000)	(0.034)	(0.000)
Black		−0.084	−0.113	−0.109	−0.104	−0.080
		(0.000)	(0.000)	(0.000)	(0.052)	(0.001)
AFQT score		0.011	0.021	0.015	0.017	0.012
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. life unemp. rate			−0.018	−0.008	0.001	−0.009
			(0.000)	(0.067)	(0.893)	(0.023)
Median real earnings 1980				−0.000	−0.000	−0.000
				(0.094)	(0.998)	(0.087)
% white 1980				−0.234	−0.027	−0.250
				(0.011)	(0.883)	(0.004)
Teen share 1980				−4.919	−4.255	−4.662
				(0.000)	(0.085)	(0.000)
% col. deg. 1980				1.675	0.590	1.551
				(0.000)	(0.262)	(0.000)
Intercept	2.496	2.530	2.683	3.085	3.287	3.059
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F-stat	152.53	101.30	98.98	54.65	11.50	66.08
Observations	3,118	3,057	3,056	3,056	1,163	4,219

Notes: P-values shown in parentheses. Columns (1)-(4) are for those who graduate high school and do not graduate college. Column (5) is for college graduates. Column (6) is for all workers.
Source: Geocoded National Longitudinal Surveys of Youth 1979 (NLSY79).

5 Quantitative Model

Our empirical analysis allows us to identify the direct effect of adult crowding out on the decline in teenage employment and to quantify to what extent this reduces the average teenager's lifetime income. We now extend our analysis by developing a dynamic overlapping generations general equilibrium model, which allows us to go beyond this reduced-form evidence. The framework links changing conditions in adult labor markets to teenage labor markets through wages and employment, while the lifecycle structure endogenously propagates these effects across cohorts as changes in teenage human capital accumulation and college choices shape outcomes when those teenagers enter adulthood.

The framework allows us to go beyond the empirical evidence in several ways. First, we use the model to quantify how aggregate shocks that drive adults into teen occupations contribute to the decline in teen employment and to decompose the decline into the separate channels through which crowding out operates: current consumption, future earnings and college decisions, and the minimum wage. Second, we quantify the consequences for aggregate output, the income distribution, and welfare, accounting for general equilibrium effects and heterogeneity across teenagers of different abilities. Finally, guided by these results, we evaluate policy counterfactuals aimed at mitigating the consequences of adult crowding out for teenagers.

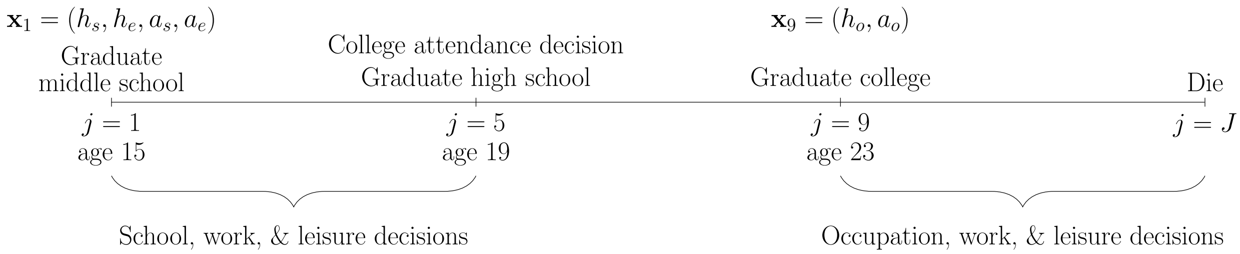
5.1 Model Overview

Time is discrete. Agents live for J model periods indexed by age j, with one model period representing one year. The economy is populated by a continuum of J overlapping generations with a uniform demographic structure. Only steady states are considered, and so time subscripts are omitted throughout. We use "prime" notation to denote the next period in an agent's lifecycle and omit j subscripts where it does not cause ambiguity. Period utility is over consumption c and leisure z, and is denoted by $u(c, z)$.

Figure 4 summarizes the phases of an agent's lifecycle. The lifecycle of an agent begins at $j = 1$ (biological age 15), having just graduated from middle school and entered grade 9. The lifecycle before age 15 is not modeled. At the beginning of period one, agents differ with respect to an employment ability a_e, a schooling ability a_s, and schooling human capital h_s. Initial employment human capital h_e is homogeneous across agents and normalized to one.

Over the next four periods, $j = 1$ to $j = 4$ (biological ages 15-18), corresponding to grades 9 through 12, the agent is enrolled in high school. Agents are endowed with one unit of time in each period and divide their time between schooling and employment human

Figure 4: **Model Lifecycle Timeline Summary**



capital accumulation and leisure. Both schooling and work raise human capital, and so we combine a Ben-Porath-style model with a learning-by-doing framework.

At the beginning of period $j = 5$ (biological age 19), the agent graduates from high school and makes a one-time decision to attend college.[20] If the agent attends college, they spend periods $j = 5$ through $j = 8$ (biological ages 19-22) accumulating schooling human capital and lose the employment human capital accumulated during high school.[21] Agents use schooling ability to accumulate human capital full time while in college.

If the agent decides not to attend college, they immediately enter the workforce at $j = 5$. Agents who attend college enter the workforce at $j = 9$ (biological age 23), after completing four periods of college. Agents enter the workforce with an adult ability a_o and human capital h_o, which is formed by combining the two types of teenage human capital. Adults are endowed with one unit of time, make a labor-leisure choice, and dynamically accumulate human capital. At the beginning of each period, agents choose which occupation to work in. Agents work until period $j = J$, when exogenous death/retirement is imposed.

The model is developed in general equilibrium, with a representative firm combining aggregate teenage and adult labor services to produce one consumption good. Adult labor services are a combination of college and non-college workers, and are imperfect substitutes.

5.2 Human Capital and Ability

5.2.1 Teenagers

While enrolled in high school, agents accumulate two types of human capital. Schooling human capital h_s accumulates with time spent in school and studying. Employment human capital h_e accumulates with time spent supplying labor to the market. Both types of human capital h_i accumulate according to,

[20] High school graduation rates are over 93% in the United States.

[21] *Section 4.2* shows that this is an empirically motivated assumption, as teen employment does not increase lifetime earnings for those who attend and graduate from college.

$$h_i' = \epsilon_i'\big(a_i(h_i n_i)^{\gamma_i} + h_i\big), \quad \text{for} \quad i \in \{s, e\} \tag{6}$$

where $n_i \in [0,1]$ is time spent accumulating human capital, ϵ_i' is a luck shock, and $\gamma_i \in (0,1)$ is the elasticity of human capital production with respect to investment. The luck shock is drawn from an i.i.d. log-normal distribution with mean 1 and variance σ_ϵ^2.

An agent must spend a minimum of $\bar{n}_s$ time accumulating schooling human capital. This captures both the time they are physically present in high school and some minimum study time needed to graduate. Teenagers may spend at most $\bar{n}_e$ time employed while in high school. This represents child labor laws, which limit the amount of time a teenager may work. When working, teens use both their schooling and employment human capital, which are aggregated according to the constant elasticity of substitution (CES) aggregator,

$$h_o = \big(\alpha h_s^\zeta + (1-\alpha) h_e^\zeta\big)^{\frac{1}{\zeta}} \tag{7}$$

The share parameter is given by α, and the elasticity of substitution between the two types of human capital is given by $\eta = \frac{1}{1-\zeta}$.

5.2.2 Adults

The distinction between schooling and employment human capital does not exist for adult workers. The two types of child human capital and ability are transformed into one adult human capital and ability upon entering the workforce. Initial adult human capital is formed with the same aggregate of schooling and employment human capital given in equation (7). Adult ability is log-normally distributed according to,

$$\log a_o \sim \mathcal{N}\big(\mu_{a_o} + \lambda(\log a_s - \mu_{a_s}) + (1-\lambda)(\log a_e - \mu_{a_e}),\ \sigma_{a_o}^2\big) \tag{8}$$

where μ_{a_s} and μ_{a_e} denote the means of log schooling and employment ability, μ_{a_o} governs the mean of adult ability, λ governs the strength of selection on schooling versus employment ability, and $\sigma_{a_o}^2$ is the variance of the ability draw.[22] Adults then accumulate human capital via learning-by-doing, given the function,

$$h_o' = a_o(h_o n_o)^{\gamma_o} + (1-\delta_o) h_o \tag{9}$$

where $n_o \in [0,1]$ is time spent working, γ_o is the elasticity of human capital production with respect to investment, and $\delta_o \in [0,1]$ is the period depreciation rate of human capital.

[22]We discuss this specific specification further in *Section 6.2.5* when calibrating the model.

5.3 Teenage Recursive Problems

Problem for $1 \le j \le 4$*:* Given a teen occupation skill-price ω_l, agents choose time investment in schooling n_s, time investment in employment n_e, leisure z, and consumption c, in order to solve,

$$\begin{aligned} V^k(j, h_s, h_e, a_s, a_e) = & \max_{c,z,n_s,n_e} \Big\{ u\big(\bar{c} + c, z\big) + \beta \mathbb{E}_{\epsilon_s,\epsilon_e} \big[V^k(j', h_s', h_e', a_s, a_e) \big] \Big\} \\ & \text{subject to,} \\ & c = \omega_l(\psi + \phi h_o) n_e \\ & h_i' = \epsilon_i' \big(a_i (h_i n_i)^{\gamma_i} + h_i \big), \quad \text{for} \quad i \in \{s, e\} \\ & h_o = \big(\alpha h_s^{\zeta} + (1-\alpha) h_e^{\zeta} \big)^{\frac{1}{\zeta}} \\ & n_s \in [\bar{n}_s, 1], \quad n_e \in [0, \bar{n}_e], \quad z \in [0, 1] \\ & n_s + n_e + z = 1 \end{aligned} \tag{10}$$

where $\bar{c}$ is some consumption provided by parents, and β is the time discount factor. We discuss the interpretation of ψ and ϕ in *Section 5.4.1* below. Throughout, skill-price means the price/wage per efficiency unit of labor.

Problem for $j = 5$*:* Upon graduating high school, an agent's state is characterized by (h_s, h_e, a_s, a_e). The agent begins period $j = 5$ with a decision to attend college or not, by solving,

$$\max \Big\{ \mathbb{E}_{a_o} \big[V^{hs}\big(j = 5, h_s, h_e, a_s, a_e\big) \big], \mathbb{E}_{a_o,\epsilon_s} \big[V^{u}\big(j = 5, h_s, a_s, a_e\big) \big] \Big\} \tag{11}$$

where V^{hs} and V^u denote the maximum possible continuation value of not attending college and attending college, respectively. Note that the agent chooses to attend college, or not, before the realization of adult ability, a_o. We omit an explicit reformulation of equation (10) where the continuation value is given by equation (11) and the laws of motion are given by equations (7)-(8).

While in college, the agent spends their full time endowment accumulating schooling human capital ($n_s = 1$ in equation (6)) and consumes a fixed amount $\bar{c}_u$. Workers who choose to go to college lose all their h_e accumulated during high school, reverting it to the initial level.[23] The state variables while in college are thus given by (h_s, a_s, a_e).

[23]This abstracts from any work experience during college. Our empirical analysis in *Section 4.2* confirms this assumption where we estimate zero returns to teen employment for those who later graduate from college.

5.4 Adult Recursive Problem

Given a skill-price $\omega \in \{\omega_l, \omega_m, \omega_s\}$, adult agents of education type $E \in \{m, s\}$ choose work time n_o, leisure time z, and consumption c, in order to solve,

$$\begin{aligned} V_E^o(j, h_o, a_o) = \max_{c,z,n_o} & \Big\{ u\big(c, z\big) + \beta V_E^o(j', h_o', a_o) \Big\} \\ \text{subject to,} & \\ & c = \mathcal{E}(\omega_i, h_o, n_o), \quad \text{for} \quad i \in \{l, m, s\} \\ & h_o' = a_o(h_o n_o)^{\gamma_o} + (1 - \delta_o)h_o \\ & z, n_o \in [0, 1] \\ & n_o + z = 1 \end{aligned} \tag{12}$$

where $\mathcal{E}(\omega_i, h_o, n_o)$ is earnings for a given occupation technology, skill-price, and human capital level, and will be discussed below in *Section 5.4.1*.

5.4.1 Occupation Choice

For notational simplicity, problem (12) describes the dynamic human capital accumulation/leisure decisions, omitting the occupation choice faced by adults at the very beginning of each period. Adults decide whether to work in teenage occupations (l) or adult occupations. We denote adult occupations of non-college graduates by m and those of college graduates by s. Workers are paid competitive hourly wages, $w_m = \omega_m h_o$ for adults without a college degree and $w_s = \omega_s h_o$ for workers with a college degree. Adults who work in teen occupations (and teenagers) earn the hourly wage,[24]

$$w_l = \omega_l(\psi + \phi h_o) \tag{13}$$

The marginal product of a worker in an adult occupation corresponds to the adult's human capital. In teen occupations, we assume that workers can use only a fraction ϕ of their human capital, plus a fixed term ψ. The productivity of workers in most teen occupations depends largely on the worker simply being physically present at work. We capture this with ψ, but also allow for productivity differences between workers. These differences reflect both worker ability (e.g., reliably showing up to work) and the more traditional accumulation of skills that allows workers to complete simple tasks more efficiently.

[24] Period earnings $\mathcal{E}(\omega, h_o, n_o)$ from problem (12) are given by $\mathcal{E}_m = \omega_m h_o n_o$, $\mathcal{E}_s = \omega_s h_o n_o$, and $\mathcal{E}_l = \omega_l(\psi + \phi h_o)n_o$.

Mathematically, this formulation allows us to characterize occupational choice by a cutoff for adult human capital h_o. This cutoff is independent of the labor/leisure decision. Workers below $h^*_{\{m,s\}}$ supply their labor in teen occupations, and workers above supply their labor in adult occupations. The cutoff value is given by,

$$h^*_{\{m,s\}} = \psi \frac{\omega_l}{\omega_{\{m,s\}} - \phi\omega_l} \tag{14}$$

where in practice we restrict parameters and equilibrium prices such that $\omega_{\{m,s\}} > \phi\omega_l$, ensuring a unique positive occupational cutoff.

5.5 Firms

Production is performed by a representative firm, which combines labor inputs from workers in teenage occupations, adults in non-college occupations, and adults in college occupations according to the nested constant elasticity of substitution (CES) function $F(Y_l, Y_m, Y_s)$,

$$Y = \left((A_l Y_l)^\nu + \theta \left[(A_m Y_m)^\sigma + (A_s Y_s)^\sigma \right]^{\frac{\nu}{\sigma}} \right)^{\frac{1}{\nu}} \tag{15}$$

Firms solve the profit maximization problem,

$$\max_{Y_l, Y_m, Y_s} \left\{ F(Y_l, Y_m, Y_s) - \omega_l Y_l - \omega_m Y_m - \omega_s Y_s \right\} \tag{16}$$

and the marginal product of each aggregate labor input $F_{\{Y_l, Y_m, Y_s\}}$ equals equilibrium skill-prices $\omega_{\{l,m,s\}}$. Here, A_l, A_m, A_s are standard productivity parameters, while θ measures adult occupation productivity relative to teenage occupation productivity. We solve the model for two values of θ, assuming a negative, unanticipated shock to θ that implies a second steady state with more adults in teen occupations and fewer teenagers working. The change in θ proxies for all underlying macroeconomic changes that drive adults into teen jobs, such as recessions and job polarization.[25] Labor is aggregated according to,

$$Y_l = \int_0^{h^*_m} (\psi + \phi h^m_o) n_o d\tilde{\Phi}_m + \int_0^{h^*_s} (\psi + \phi h^s_o) n_o d\tilde{\Phi}_s + \int_0^{H^k_{max}} (\psi + \phi h_o) n_e d\Phi \tag{17}$$

$$Y_m = \int_{h^*_m}^{H^o_{max}} h^m_o n_o d\tilde{\Phi}_m \tag{18}$$

[25] *Section 7.1.1* contrasts this mechanism with alternative explanations for the decline in teen employment that we deliberately abstract from in this baseline model. We show that a host of alternative forces are counterfactual to the data and do a poor job of capturing the dynamics of declining teen employment.

$$Y_s = \int_{h_s^*}^{H_{max}^o} h_o^s n_o d\tilde{\Phi}_s \tag{19}$$

where $\Phi(j, h_s, h_e, a_s, a_e)$ is the share of teenagers with characteristics (j, h_s, h_e, a_s, a_e), and $\tilde{\Phi}_s(j, h_o, a_o)$ and $\tilde{\Phi}_m(j, h_o, a_o)$ are the shares of college and non-college adults with human capital level h_o and ability a_o. Together with the optimal labor supply of teenagers n_e and adults n_o, this closes the labor market.

5.5.1 Minimum Wage

The minimum wage may play an important role in the ability of young workers to supply their labor, as demonstrated in ample empirical work (Neumark and Shirley, 2022; Clemens and Strain, 2025). In the efficient model laid out so far, crowding out of teenagers works through downward pressure on the current and future wages of teens, causing an optimal reduction in working hours. We now introduce a minimum wage in the economy. For teens, the minimum wage w_{min} binds when their potential hourly wage satisfies $w_l = \omega_l(\psi + \phi h_o) < w_{min}$. These teenagers cannot be employed and must set $n_e = 0$. As adults with higher human capital take up teenage occupations, w_l falls, which increases the share of teens for whom the minimum wage binds. The number of teens that are crowded out by the minimum wage depends on the mass of teens whose human capital is “slightly” above the cutoff value in the original steady state.

5.6 Equilibrium

Here, we summarize the equilibrium conditions of this economy. For the formal equilibrium definition, see *Appendix C*. A stationary competitive equilibrium in this economy is a set of skill-prices $\{\omega_l, \omega_m, \omega_s\}$, teen schooling and employment supply $\{g_{n_e}, g_{n_s}\}$ and college attendance choice g_u, adult labor supply g_{n_o} and occupation choices $\{h_m^*, h_s^*\}$, and labor demands $\{Y_l, Y_m, Y_s\}$, such that

1. Skill-prices are consistent with the firm optimization over technology (16).
2. Labor supply and college choices of teenagers are consistent with (10) and (11).
3. Labor choices for adults are consistent with (12) and occupational choices of adults are given by (14).
4. The labor market clears according to (17)-(19).

6 Model Estimation

The empirical analysis established that adult crowding out causally reduces teen employment and that teen employment increases lifecycle earnings of non-college graduates. However, the reduced-form evidence cannot determine the mechanisms through which the decline operates, its macroeconomic and welfare consequences, or how policy can address the decline in teen employment. Answering these questions is the purpose of the quantitative model, which allows us to decompose the mechanisms behind the decline, trace consequences that unfold over the lifecycle and across the earnings distribution, and evaluate counterfactual policies.

To do so, we must first estimate the quantitative model. The estimation has two main objectives. First, discipline the model to reproduce the U.S. economy prior to the decline in teen employment. This includes teen work and schooling choices, human capital accumulation, college attendance, adult occupational choices, and lifecycle earnings dynamics. We treat the year 2000 as this initial steady state. Second, discipline how the U.S. economy responds to the reallocation of adults into teenage occupations. We use changes between 2000 and 2010 and our causal estimates of the effects of adult competition on teenage earnings and employment to identify the forces governing this response.[26]

More specifically, we choose one set of parameters externally using empirical estimates for the U.S. economy and from the literature, in *Section 6.1*. Conditional on these parameters, we jointly choose the remaining parameters in *Section 6.2* to minimize the distance between model-generated moments and their empirical counterparts. We use the causal estimates of declining teen employment from adult crowding out in *Section 3.2* and the returns to working while in high school in *Section 4.2* to discipline key parameters governing the model's central mechanisms. *Appendix D* reports additional details on the calibration procedure, construction of the model equivalent moments, and robustness exercises.

6.1 External Parameters

Agents spend four years in high school and then remain in the model for an additional 45 years, through age 59. Thus, the full modeled adult lifecycle consists of $J = 45$ periods. We choose a standard value of 0.95 for β, the time discount factor.

Teen fixed consumption provided by parents, $\bar{c}$, is expressed as a fraction of average adult earnings at the ages when teenagers are typically present in the household. This fraction is taken from the large literature on adult consumption equivalence, with values typically

[26]We perform a robustness analysis and show that the results are not sensitive to the choice of 2010 as the second steady-state year.

falling in the range of 0.2-0.5 (Browning, 1992; Apps and Rees, 2001; Browning and Ejrnæs, 2009). We take the midpoint of 0.35.

The variance of luck shocks σ_ϵ^2 is set to 0.05 in order to smooth corner solutions and generate random variation for our model regressions. The value chosen is in line with estimates for adult human capital accumulation (Lee and Seshadri, 2019).

Next, we set the constraints on minimum time devoted to schooling human capital accumulation $\bar{n}_s$, and maximum time devoted to employment human capital accumulation $\bar{n}_e$. We take the discretionary time endowment of an individual to be 11.5 hours per day, which we show in *Appendix A.4* is the average time teenagers spent on school, work, and leisure activities. The 2003-2004 Schools and Staffing Survey (SASS) reports average time spent per day in school of 6.64 hours. Correspondingly we set the minimum amount of time a student must spend in order to finish high school to 7 hours per day. Hence, $\bar{n}_s = {}^{(5 \cdot 7)}/_{(7 \cdot 11.5)} = 0.43$.

Cross-state variation in teen labor laws is small and typically conforms to the federal limit of 18 hours per week when school is in session and the individual is under the age of 16. Otherwise, federal law does not limit hours worked for those older than 16, or when school is not in session for those under 16. However, most states choose to limit the amount those aged 16 and 17 may work to 40 hours per week, and limit the times of day teens may work while school is in session. Therefore, we choose to set the upper bound using a full-time work week of 40 hours and thus $\bar{n}_e = {}^{40}/_{7 \cdot 11.5} = 0.50$. Empirically, 40 hours represents the 95^{th} percentile of working teens in our ACS sample.

The two parameters governing the learning-by-doing accumulation of adult human capital γ_o and δ_o are not well identified in the data. Additionally, there is not a standard method for estimation in the literature, as there is for corresponding parameters in a Ben-Porath style model. We take these parameters as 0.30 and 0.02, from Blandin (2018), which presents an in-depth discussion of their estimation and robustness.[27]

Finally, the CES parameter between adult college educated and non-college educated labor is set to $\sigma = 0.31 = (1 - 1/1.44)$ in accordance with the elasticity of substitution estimates in Katz and Murphy (1992) and Heckman et al. (1998).

6.2 Internal Parameters

The remaining 23 parameters are chosen to minimize the distance between 26 model-generated moments and their empirical counterparts. Empirical moments are estimated from the ACS

[27] Our main results are not sensitive to the choice of γ_o and δ_o, and the model does well in matching average lifecycle growth for college and non-college labor. In general, lifecycle profiles are not the focus of this analysis. We simply need an accurate way to capture continuation values for teenagers making forward-looking decisions.

and NLSY. Steady-state moments calculated using the ACS are for the year 2000, with the exception of earnings profiles where we pool the 1980, 1990, and 2000 ACS to account for time effects. Transitional moments using the ACS are calculated by comparing the years 2000 and 2010. This is in line with our empirical analysis presented in *Section 3*. *Appendix A* reports additional details of the method and sample selection used to calculate our empirical moments. Several of our moments are regression coefficients in the data, which we match by estimating comparable regressions on simulated model data.

6.2.1 Preferences

We parameterize the period utility function as,

$$u(c, z) = \ln(c) + \kappa \ln(z), \quad \text{for } \kappa \in \{\kappa_k, \kappa_o\} \tag{20}$$

where κ_k is preference over leisure for teenagers, and κ_o preference over leisure for adults. We use data from the American Time Use Survey to pin down the leisure parameter for both teenagers and adults. Specifically, we target the share of total discretionary time that is spent on leisure activities. For details see *Appendix A.4*.

6.2.2 Initial Distributions

Initial employment ability, schooling ability, and schooling human capital are log-normally distributed, with their distributions governed by $\sigma_{a_e}, \sigma_{a_s}, \sigma_{h_s}, \mu_{a_e}, \mu_{a_s}$, and μ_{h_s}. To separately identify parameters governing the accumulation of schooling and employment human capital, we need a measure of schooling human capital. To this end, we use transcript data from the NLSY. For each student we observe the yearly credits taken and GPA. We then measure schooling human capital as the GPA-weighted stock of credits, h_s^{data}. It is assumed that $h_s^{model} = B \cdot h_s^{data}$, with B some constant scaling factor. Given that our model begins with grade 9, we use grade-8 credits and GPA variance to discipline σ_{h_s}. We then calculate schooling human capital profiles as,

$$\log(h_s^{data}) = \alpha_{h_s} + \beta_{h_s} age + \epsilon_{hs} \tag{21}$$

We plot the profiles separately for children who subsequently attend college and those who do not in *Figure F.5*. The average growth rate of h_s^{data} and the employment share of teenagers identify μ_{a_e} and μ_{a_s}. We normalize initial employment human capital to one for all agents and similarly set μ_{h_s} to one.

6.2.3 Teens

A central moment to our analysis is the return to teen employment. We causally estimate this return using geocoded NLSY data, as discussed in *Section 4.2*. We replicate this empirical exercise in the model through an indirect inference procedure designed to match the data estimate as closely as possible. Specifically, we induce small changes in the teen skill-prices and re-solve teenagers' employment, schooling, and leisure choices, allowing both hours worked and the set of teenagers who work to adjust. We then construct the model analogue of our IV estimate as the ratio of the resulting change in adult earnings to the change in teen employment time. As in the data, this identifies the return to work for teenagers whose employment decisions respond to changes in economic conditions, while also allowing endogenous changes in schooling and college attendance. Formal details of this procedure are provided in *Appendix D.1*.

The two parameters which most sharply affect the returns to teen employment and the teen employment rate are the curvature of employment human capital production, γ_e, and the elasticity of substitution between school and employment human capital, ζ. We describe how ζ is determined by a separate moment below, leaving the returns to teen employment to identify γ_e.

The curvature of schooling human capital, γ_s, directly governs returns to schooling investment on schooling human capital (i.e., the return to not working on h_s^{data}). The logic is similar to the effect of γ_e on earnings. The difference is that h_s^{data} is only affected by γ_s. Hence, we can identify γ_s by estimating the returns of working on schooling human capital in the data and the model. In practice, we estimate the effect of the sum of hours worked during high school on schooling human capital at graduation. In the data we estimate a version of equation (5) with h_s^{data} as the dependent variable, utilizing the same IV strategy as *Section 4.2*,

$$\log(h_s^{data}) = \delta_0 + \delta_1 E_i^S + \delta_2 X_i + \epsilon_i$$

We use the same procedure in the model as that for the returns to teen employment on earnings. Empirical regression results are reported in *Appendix D.2*. More hours worked during high school have a negative and significant causal effect on schooling human capital acquired.

The share parameter α that governs the relative weight on schooling human capital versus employment human capital in (7) is determined by the shares of h_s and h_e inputs in production. A smaller value of α places greater weight on employment human capital in the adult human-capital aggregator and thereby increases the incentive to accumulate h_e. However, we do not observe h_e directly. Instead, the intensive margin of teen employment

n_e works as a proxy for the employment human capital stock. These moments are taken from the NLSY79.

The CES parameter ζ, which determines the elasticity of substitution between schooling and employment human capital, is pinned down by the earnings ratio of workers with different human capital levels. Again, h_e is unobserved and so we use n_e as a proxy in the data and model. Conditional on time spent working, all variation in earnings then comes from h_s. The earnings ratio of workers with different h_s then identifies ζ. In practice, we use workers that just graduated high school and entered the labor market. We then estimate ζ by using a simple OLS of initial earnings on h_s in the data and model. The exact specifications and regression results are in *Appendix D*.

We need a measure of the propensity to work conditional on the future decision to go to college or not. Since there are no future earnings gains from teenage work experience for anyone who goes to college, the difference in work hours between college and non-college bound teens plays a crucial role in determining how teenagers adjust to the changes in the economy. Since our model abstracts from important determinants of hours worked, in particular parents' earnings, race, and sex, we use the data from the NLSY to regress average hours worked during high school on a dummy that indicates whether an individual completes at least an associate's degree and demographic controls, including parents' earnings, race, and sex. We then match the difference in hours worked between college- and non-college-bound teenagers in the model to the estimated coefficient on the college dummy in the data. Finally, the percentage of teens employed is estimated using the year 2000 ACS and discussed extensively in *Section 3* and *Appendix A*.

6.2.4 College

The curvature of schooling human capital production in college, γ_u, directly affects the amount of human capital that those graduating college enter the labor force with. Hence, it is most closely identified by the college earnings premium for young adults. Using ACS data, we target the college earnings premium observed for 24-29 year-olds with the model equivalent. Fixed consumption while in college $\bar{c}_u$ largely affects the college attainment rate (Gong et al., 2019). The college attainment rate is defined as the share of individuals with an associate's degree and above, again calculated from the ACS.

6.2.5 Adults

The parameters μ_{a_o}, λ, and σ_{a_o} jointly govern the level, selection, and dispersion of the adult ability distribution. We orthogonalize the level of adult ability from its dependence on childhood abilities by specifying the distribution in equation (8), so that μ_{a_o} governs the mean of adult ability while λ governs the strength of selection on schooling versus employment ability. Because the childhood abilities enter in deviation form, the selection parameter shifts ability symmetrically around the mean without altering its level, which allows μ_{a_o} and λ to be identified separately in estimation.

As is standard in the adult human capital accumulation literature, we target these parameters using earnings growth profiles for college-educated versus non-college-educated workers, with μ_{a_o} shifting the overall level of the profiles, λ governing the divergence between the college and non-college profiles, and σ_{a_o} governing the dispersion of adult earnings. The variances of the childhood ability distributions, σ_{a_s} and σ_{a_e}, together with the variance of initial schooling human capital σ_{h_s}, are in turn disciplined by the cross-sectional dispersion of teen and adult earnings, since they determine how much heterogeneity agents carry into their schooling, work, and college decisions. We use pooled 1980, 1990, and 2000 Census samples and closely follow Lagakos et al. (2018) to construct earnings profiles.

The parameters ψ and ϕ define the level of human capital for those who work in teen occupations. This then defines a cutoff separating those who work in teen versus non-teen occupations, and hence governs the share of adults working in teen occupations by age. *Figure F.8* plots the share of adults employed in teen occupations by education status. Additionally, ψ and ϕ jointly determine the spread of earnings within teen occupations. When ψ is large relative to ϕ, own human capital plays a smaller role in earnings, compressing the within-occupation earnings distribution.

6.2.6 Production

The productivity parameters A_l, A_m, A_s, and θ govern earnings and employment shares in the initial steady state. We normalize θ to one. The initial productivity parameters A_l, A_m, and A_s are disciplined by employment shares and relative earnings across teen, non-college, and college occupations in the initial steady state.

The remaining parameters to identify are ν and the shock to θ. The shock to θ is the sole *exogenous* driver inducing a change in our economy. We calibrate the shock to θ so that the share of adults taking up teen occupations matches the data. We use this shock to calibrate a second steady state. The elasticity of substitution between college and non-college adult labor is $1/(1-\sigma)$, while the elasticity of substitution between teen labor and the adult labor composite is $1/(1-\nu)$. The parameter ν therefore governs how changes in adult employment in teen occupations translate into wage changes. To isolate the effect of adults on wages, we first simulate the following three economies: (1) we solve the benchmark model, (2) we solve for the new steady state, with all parameters held fixed except for a negative shock to θ, and (3) taking adult employment levels from (2), we calculate prices and simulate the partial equilibrium response, keeping all else fixed at (1), including θ. In this way, we can focus on the effects of adults taking up teen occupations without conflating them with other equilibrium effects of the productivity shock. We use the counterfactual steady state in which we vary only the number of adults in teen occupations and match the resulting wage changes to the coefficient from the causal earnings regression in (4), which corresponds to the empirical exercise in *Section 3*.

Then, to examine the "crowding out" of teen workers, we define the model-implied teen employment coefficient as,

$$\frac{(\%\text{ teen work})_3 - (\%\text{ teen work})_1}{(\text{adults in teen occ.})_2 - (\text{adults in teen occ.})_1} \tag{22}$$

where subscripts refer to moments from economies (1)-(3). We calibrate this to our causal estimates of the effect of adult crowding out on teenage employment. We target the coefficient in column (7) of *Table 2*, i.e., the occupation instrument and controlling for the lagged change in teen employment. The occupation instrument is the most natural, as we replicate it in the model. We control for the lagged change in teen employment (and the lagged change in the number of adults in teen jobs) since we assume the model to be in steady state initially. This coefficient is determined by the effect of the change of adults in teen occupations on wages and the reaction of teens to these wage changes. The former is governed by the production parameters, especially ν, as explained above.

The second component, the elasticity of teenage employment to wage changes, is not governed by a specific parameter but instead reflects three margins discussed above. First, lower current wages reduce the consumption return to working, with the strength of this response governed primarily by parental consumption, $\bar{c}$, and preferences for leisure, κ_k. Second, wage changes alter the relative returns to accumulating employment and schooling human capital and, through future wages, the incentive to attend college. These margins depend on the human capital production parameters γ_e, γ_s, α, and ζ, as well as the parameters governing the college decision, particularly γ_u and $\bar{c}_u$. Third, lower wages increase the share of teenagers for whom the minimum wage binds, with the magnitude of this response depending on the distribution of teen wages around the minimum wage, governed in part by ψ, ϕ, and the distribution of teenage human capital. Hence, conditional on the wage transmission ν (disciplined separately by the causal earnings regression) matching the crowding-out coefficient in column (7) of *Table 2* is an overidentification exercise where the model must reproduce the reduced-form effect of adult entry on teen employment as the product of two independently identified pieces.

6.2.7 Minimum Wage

We calibrate the minimum wage relative to the average wage of teenagers. Following Autor et al. (2008) we use the real federal minimum wage in 2000. Vogel (2023) shows that the federal minimum wage is approximately equal to a weighted average of the max of federal and state minimum wages until 2000. We intentionally hold the minimum wage fixed at its 2000 level in the baseline to isolate the interaction of adult crowding out with the *level* of the minimum wage. In *Section 7.1.1*, we separately quantify how much of the observed decline in teen employment can be explained by an increasing minimum wage.

6.3 Model Fit

Before turning to our quantitative analysis we verify that the model accurately fits key features of the U.S. economy. *Tables 5 and 6* report the model-generated moments compared to empirical counterparts. *Appendix D* reports additional details of the calibration procedure and how specific model moments are calculated.

The model does well at matching the key moments in the data, including the causal estimates from *Sections 3* and *4*. Among the teenage labor-supply moments, a notable discrepancy is average hours worked by all teenagers, where the model produces 175 versus 230 hours in the data. In general, the model can match either average hours worked or the gap in hours between college- and non-college-bound teenagers.

This tension arises because the data show no earnings returns to teen employment for college graduates, which we impose in the model. In the model, these teenagers work only because employment raises current consumption or because of idiosyncratic risk over human capital accumulation. In the data, they may also work for reasons absent from the model, such as parental pressure, social considerations, or preferences for working. Capturing these motives would require additional preference heterogeneity that is difficult to identify. Instead, in *Appendix D.4* we show that our main results are robust to an alternative calibration that exactly matches average hours worked while overshooting the gap in hours between college- and non-college-bound teenagers.

7 Quantitative Results

In this section, we use the quantitative model to present three sets of results on declining teen employment. First, *Section 7.1* decomposes the mechanisms through which declining teen employment occurs and shows that competing hypotheses cannot account for the observed decline. Second, *Section 7.2* explores the macroeconomic, distributional, and welfare effects

Table 5: **Model Fit – ACS Moments**

Moment	**Model**	**Data**
Teens		
Decline regression coefficient	−5.0	−4.1
Share teens working	0.41	0.35
Average hours worked, all teens	175	230
P90 to P10 earnings ratio	9.5	9.7
Schooling-time share	0.58	0.58
Adults		
Share working in teen occ.	0.14	0.11
Share with college degree	0.42	0.40
Share working in teen occ. – college	0.01	0.05
Share working in teen occ. – non-college	0.24	0.18
Δ in adults working teen occ.	0.02	0.02
College lifetime earnings growth	0.82	0.82
Non-college lifetime earnings growth	0.58	0.55
Variance lifetime earnings	0.50	0.50
Leisure rate	0.33	0.20
Earnings		
College/non-college, all adult	1.64	1.68
College/non-college, 24-29	1.45	1.47
Non-teen occ./teen occ.	2.01	1.68
Adult/teen, teen occ.	4.3	5.3
Earnings regression	−10.4	−10.4
Minimum wage/avg. teen wage	0.82	0.81

Notes: The columns compare the model to the data for selected targeted moments. *Source:* Leisure share moments are taken from the American Time Use Survey (ATUS). Earnings profiles use the 1980, 1990, and 2000 American Community Survey (ACS). All remaining steady-state moments in this table are taken from the 2000 ACS. Transitional moments are calculated using the 2000 and 2010 ACS.

Table 6: **Model Fit – NLSY Moments**

Moment	**Model**	**Data**
Teens		
Returns to employment on earnings	0.04	0.04
Returns to employment on h_s	-0.06	-0.05
% Growth of h_s^{data}, grade 9-12	355	320
Returns to h_s^{data}	0.04	0.03
SD($h_s^{data}(Grade\ 8)$)/Mean($h_s^{data}(Grade\ 8)$)	0.80	0.80
College to non-college hours regression	-144	-134

Notes: The columns compare the model to the data for selected targeted moments. *Source:* National Longitudinal Surveys of Youth 1979 and 1997 (NLSY79) and (NLSY97).

of declining teen employment. Third, *Section 7.3* conducts two policy exercises aimed at improving welfare for those teens crowded out of the labor market by adult workers.

Throughout the results section, we refer to three steady states across which we compare results. Steady state one (SS1) is the benchmark calibrated U.S. economy in 2000. Steady state two (SS2) is the steady-state economy in 2010, in which the adult-occupation productivity, θ, is changed while all else is held constant at SS1 levels. For steady state three (SS3), we take adult employment levels from SS2, calculate prices, and simulate partial-equilibrium decisions while keeping all else (including θ) fixed at SS1 levels. This counterfactual economy allows us to isolate the effects of adults crowding out teens from the productivity shock effects present in SS2.[28]

7.1 Causes of Declining Teen Employment

We begin by investigating the mechanisms through which teen employment declines. Downward pressure on current wages reduces the consumption that teenagers can afford from their labor income and increases the share of teenagers directly affected by the minimum wage. Downward pressure on the future wages of workers in teen occupations increases the incentive to attain a college degree, thereby reducing the return to teen employment.

The relative strength of these mechanisms cannot be calculated from the data for three reasons. First, we lack large-scale consumption data for teens, which are necessary to quantify the importance of current consumption. Second, estimating the effect of adult crowding out on college attainment requires panel data. To use local variation in the share of adults

[28]Strictly speaking, SS3 is a counterfactual allocation and is not a steady-state equilibrium. For expositional simplicity, we refer to SS3 as a steady state throughout the remainder of the paper.

Table 7: **Decomposition of Decline in Teen Employment from Adult Crowding Out**

Current Consumption	**Minimum Wage**	**Schooling**
27%	53%	20%

Notes: This table reports a decomposition of teen employment decline between current consumption, minimum wages, and schooling choices or future consumption. Numbers are averaged over the six possible sequential permutations, turning each channel off, one at a time.

employed in teen occupations, we must know the share of college graduates who lived in commuting zones with a high share of adults in teen occupations while they attended high school. Using only local variation in college attainment excludes all individuals who move to different commuting zones for college and/or later employment.[29]

Third, while Neumark and Shupe (2019) identify the effects of *changes* in the minimum wage on teen employment, our point is different. The minimum wage interacts with increased competition from adults. Conditional on the number of adults entering teen occupations, the importance of the minimum wage in crowding out teenagers depends on the distribution of human capital around the threshold at which the minimum wage binds. If many individuals earn slightly above the minimum wage before the increase in competition from adults, then the wage decline induced by this competition will crowd out many teenagers. Importantly, this effect does not depend on the level of the minimum wage, but rather on the distribution of teenage human capital. Given limited data, it is difficult to identify sufficient local variation in teenage human capital, conditional on the magnitude of the increase in adult employment.

However, we are able to use our calibrated model to decompose the effects of these channels. For each case, we solve the model in the initial steady state and our counterfactual economy (SS3) that isolates the direct effect of adult crowding out. We then sequentially turn off each mechanism to assess its relative importance.[30]

Table 7 reports the results of this decomposition exercise, where contributions are averaged across the six possible sequential permutations. Current consumption accounts for 27%

[29]Although we do not have the data required to fully quantify this channel, we find some evidence that adult crowding out leads to increased college enrollment. We are able to estimate the effect of adult crowding out on college enrollment among 19-year-olds after 2005 and find a significant positive relationship. Further details are reported in *Appendix B.5*.

[30]To ignore the effect of current consumption, we set ω_l (in the budget constraints of teenagers, equation (10)) to its initial steady state level (SS1). As a result, only the minimum wage and future wages change the behavior of teens. Second, to turn off the effect of the minimum wage, we calculate the cutoff $\omega_l(\psi + \phi h_o) < w_{min}$ using ω_l from the initial steady state (SS1). Finally, the effect of future wages is turned off by setting all future wages in the adult problem to their initial steady state (SS1) values.

of the decline in teen employment, while future wages and college choice account for 20%. The minimum wage plays the largest role in transmitting the effects of a productivity shock to declining teen employment, explaining roughly half, or 53%, of the decline.

The three channels differ in kind, not only in magnitude. Current consumption and schooling operate on the intensive margin. A lower teen wage reduces the marginal value of an hour worked, and teenagers respond by reallocating time toward school and leisure at a rate governed by the curvature of the human capital production functions, and relative to both employment and schooling abilities. The minimum wage, on the other hand, is an extensive mechanism. A teenager whose productivity places them just above the minimum wage before adults enter loses their job entirely once competition from adults pushes wages down, however small that decline may be. The size of the resulting displacement depends on the estimated teen wage schedule. Because the fixed component of teen productivity, ψ, is large relative to the component that varies with accumulated human capital, ϕ, teenage wages are compressed, and a given proportional decline in ω_l moves a large mass of teenagers across the threshold at once.[31] Had teen productivity been more dispersed, the same decline would have displaced far fewer of them and the minimum wage share would have fallen accordingly. This is the sense in which our mechanism concerns the interaction between the minimum wage and adult crowding out, rather than the level of the minimum wage itself.

The decomposition also implies that the teenagers who stop working are drawn from opposite ends of the ability distribution. The minimum wage rations out teenagers with the least human capital (and typically lowest abilities), who are closest to the threshold. The schooling channel removes teenagers with the highest schooling ability, who are on the margin of college and for whom the decline in the return to work experience tips the attainment decision. The two groups leave employment for very different reasons. Those in the second group reallocate time toward a more productive investment and gain in lifetime earnings. Those in the first group are rationed out, losing both current earnings and the work experience that would have raised their adult wages, with no offsetting investment. Roughly half of the decline in teen employment is therefore "involuntary" in a well-defined sense, which is what makes the aggregate decline consequential for macroeconomic and policy considerations, rather than just a change in how teenagers allocate their time.

7.1.1 Alternative Forces

We now consider alternative shocks, beyond the shock to labor productivity in adult occupations, θ, that we deliberately abstract from in our baseline. First, we showed that the

[31] Recall from the calibration that these parameters ψ and ϕ are partially identified by the spread of teen wages in the data.

existence of a positive and constant minimum wage plays an important role in the decline in teen employment. In reality, however, the average minimum wage in the U.S. increased by approximately 10% between 2000 and 2010. We solve an alternative economy in which, instead of introducing a negative shock to adult occupation productivity, θ, we increase the minimum wage by 10%. We find that teen employment falls by 5.4 percentage points. This is much smaller than the full 10 percentage point decline captured by our baseline model with a shock to θ. Furthermore, the share of adults working in teen jobs rises by a negligible amount. With a combined shock to θ and a 10% increase in the minimum wage, teen employment falls by an additional 6.5 percentage points relative to the benchmark model. When solving the model with an increase in the minimum wage alone, wages in teen jobs relative to those in non-teen jobs increase by 0.1%. This is counterfactual, as the data show a decrease in teen-job wages of roughly 10%, consistent with our baseline results with a shock to θ. We interpret this finding as indicating that the increase in the minimum wage can explain a portion of the decline in teen employment but cannot be the main explanation.

Our empirical and quantitative results focus on the change in demand for teen jobs being the main driver behind the employment decline. However, the model allows us to contrast this with a change in the supply of teen labor, as a possible explanation for declining teen employment. To this end, we now increase the preference for leisure κ_k in the 2010 steady state, leaving everything else at its 2000 value. Since we cannot observe changes in preferences in the data, we solve for the change in κ_k which produces the same decline in teen employment as in the benchmark model and data. This increases κ_k by a factor of approximately two. The resulting equilibrium features a small increase in the number of adults in teen jobs but essentially no change in the relative wages of workers in teen occupations, which again contradicts the data.

Another competing hypothesis is that an increase in the college wage premium may have induced teenagers to substitute away from working time and towards schooling time, as the value of a college degree increased. While the large run-up in the college wage premium mainly occurred from 1980 through 2000, we find that it still rose from 1.68 to 1.75 for the 2000 to 2010 period. As with the change in leisure preference, we solve for college labor productivity A_s which induces the increase in the college wage ratio seen in the data. College attendance rises by a small amount of 3.2%, however teen employment also rises by 17.4% which is counterfactual to the data.[32]

[32] Teen employment rises through two channels from the general equilibrium increase in the teen skill-price. First, because skilled and unskilled labor are complementary in production, the increase in A_s raises the teen skill-price while the nominal minimum wage remains fixed. Second, because current consumption plays a small role in teen employment decisions, the income effect is small and the substitution effect dominates, increasing hours on the intensive margin.

7.2 Consequences of Declining Teen Employment

With a better understanding of the mechanisms through which declining teen employment operates, we now turn to an analysis of both the macroeconomic and distributional consequences of declining teen employment. A central feature of these results is that the effects of adult labor market reallocation propagate across stages of the lifecycle and generations, altering teenagers' human capital accumulation and their subsequent outcomes in adulthood. *Section 7.2.1* looks at how inequality and a set of macro moments change due to adults crowding out teen labor.[33] *Section 7.2.2* performs a welfare analysis of the effect of adults crowding out teen labor. Throughout this section, we compare SS1 and SS3 in order to analyze the isolated effect of adults crowding out teen employment.

7.2.1 Distributional

Table 8, row one, shows that under SS3, college enrollment rises by 15.6%, or 6.5 percentage points relative to the benchmark economy. The main force driving this increase is that many of the teens crowded out of the labor force substitute toward college attendance. That is, teenagers with low-to-middle schooling and employment ability choose to work in the initial steady state, SS1. However, in SS3, they are no longer able to work and now find it more valuable to spend time acquiring schooling human capital and subsequently attending college. This effect is strong enough to counteract the reduction in the college skill-price premium, which causes a mechanical substitution away from college attainment. The college skill-price ω_s rises by 0.2%, and the non-college skill-price rises by 0.7%.[34]

The falling gap between the college and non-college skill-prices also mechanically contributes to the 1.9% decrease in the college earnings premium shown in row two of *Table 8*. The college skill premium also falls as the rise in the number of college graduates decreases the average earnings of those working with a college degree. Teenagers who switch to college attendance after being crowded out of teen employment have lower schooling ability and earn less over their lifecycle. *Ceteris paribus*, this lowers the college earnings premium.

More than offsetting the decline in the college skill premium is the stark decline in the average earnings of teenagers who are crowded out of the labor force and do not reallocate to college. This causes the P75-to-P25 earnings ratio to rise by 0.4%. Overall, among teens who worked in SS1, employment human capital upon graduation from high school falls by 1.9% (or 1.0% on average for all teens). This reduction persists into adulthood through lower earnings. Among individuals who do not attend college in either SS1 or SS3, lifetime

[33] In *Appendix C.3.1* we also discuss changes in aggregate output.

[34] Recall, by skill-prices we are referring to wage/price per efficiency unit of labor.

Table 8: **Distributional and Equilibrium Effects of Adult Crowding Out**

Moment	**% Change**
College enrollment	+15.6
College earnings premium	−1.9
P75-to-P25 ratio lifetime earnings	+0.4
Entering h_e	−1.0
Teen occupation skill-price, ω_l	−6.4
Non-college occupation skill-price, ω_m	+0.7
College occupation skill-price, ω_s	+0.2

Notes: This table reports changes in selected model moments between the initial calibrated steady state (SS1), and the counterfactual steady state which isolates the effects of adults crowding out teenagers (SS3).

earnings fall by 1.2%. Thus, even holding college attainment fixed, the loss of employment opportunities during high school leaves affected workers with less human capital and lower earnings throughout their adult lifecycle. The increase in earnings inequality is therefore almost entirely driven by falling 25$^{\text{th}}$-percentile earnings among adults who were crowded out of the labor force as teenagers and were unable to accumulate employment human capital or adjust toward college attendance. Earnings for those at the 75$^{\text{th}}$ percentile, on the other hand, are largely unaffected by adult crowding out, as these are high-schooling-ability agents who attend college in both SS1 and SS3.

This is the key lifecycle and cross-generational propagation mechanism in the model. A shock that initially reallocates existing adults across occupations changes the human capital accumulated by teenagers and, in turn, the earnings distribution of those individuals after they enter adulthood. Thus, the consequences of changing adult labor market opportunities extend beyond the workers initially affected and shape the labor market outcomes of younger workers into later life.

7.2.2 Welfare

Table 9 reports realized consumption-equivalent (CE) welfare changes between the benchmark calibrated equilibrium (SS1) and the counterfactual economy that isolates the effect of adult crowding out (SS3). Welfare is reported for those who did and did not work during high school and for those who did and did not obtain a college degree. Because these are endogenous outcomes that can change in SS3, we fix the groupings in SS1.

Those who worked as teenagers in SS1 see a 0.8% decline in welfare. The vast majority

Table 9: **Welfare Effects of Adult Crowding Out**

Grouping	**Δ Welfare %**
Worked as teenager	-0.8
Did not work as teenager	-0.4
Non-college graduate	-1.2
College graduate	$+0.1$
Whole economy	-0.7

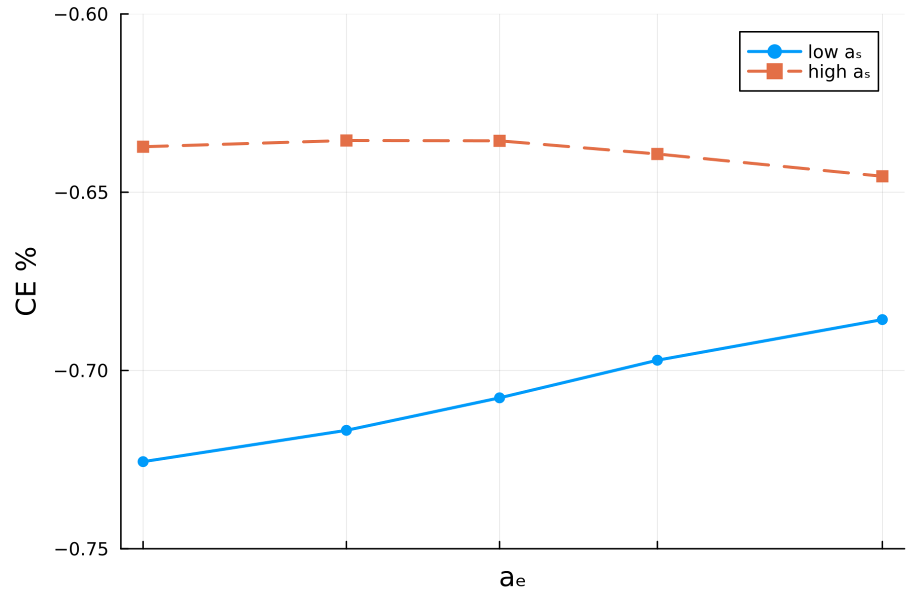
Notes: This table reports the realized welfare change between the benchmark calibrated equilibrium (SS1), and the counterfactual economy which isolates the effect of adult crowding out (SS3). Groupings are fixed in SS1.

of this welfare decline is driven by lost human capital accumulation due to adult crowding out, rather than by lost consumption during the teenage years or a lower teen-occupation skill-price. The welfare of teens who did not work during high school falls by 0.4%. Most of these teenagers go on to obtain a college degree, so the welfare loss is driven in part by the decline in the relative college skill-price premium. The welfare of non-college adults falls by 1.2%, while that of college adults rises by 0.1%. Many non-college adults are former teen workers who lose human capital accumulation opportunities. Additionally, many switch into teen occupations and earn lower wages permanently. Welfare in the economy as a whole falls by 0.7%. Importantly, the incidence of adult crowding out is not confined to teenage years. The largest welfare losses arise among non-college adults because reduced access to work during high school changes the human capital with which these workers enter adulthood.

Figure 5 examines heterogeneity in the welfare effects of adult crowding out by plotting welfare changes between SS1 and SS3 across schooling ability, a_s, and employment ability, a_e. Schooling human capital, h_s, is held at its median level. Welfare *losses* decline with employment ability among individuals with low schooling ability. Those with high employment ability are typically workers and do not attend college. Among those with high employment ability, fewer agents are crowded out by adult workers, as they are able to accumulate sufficient employment human capital, h_e. On the other hand, welfare losses are flat for those with high schooling ability. Teen workers who also have high schooling ability have a better outside option and can more easily substitute toward schooling human capital accumulation and/or college attendance. This is consistent with *Section 7.2.1*, where the increase in inequality was driven by large losses among agents at the bottom of the skill distribution.

Taken together, these two sets of results in *Section 7.2* show that the general equilibrium effects of changing adult labor market opportunities extend beyond the adults initially

Figure 5: **Welfare Effects of Adult Crowding Out by Schooling and Employment Ability**



Notes: This figure plots realized lifetime welfare changes between SS1 and SS3 for the benchmark calibrated economy, broken down by high and low schooling ability a_s and employment ability a_e. This figure is shown for a median level of initial schooling human capital h_s.

affected. By crowding teenagers out of employment, adult reallocation changes early human capital accumulation and college choices, with consequences for productivity, earnings inequality, and welfare that persist after those teenagers enter adulthood. The effects of shocks to adult labor markets can therefore begin shaping the next generation of workers well before they reach adulthood.

7.3 Policy Analysis

We now turn to a policy analysis in which we examine two policies designed to mitigate the lifetime welfare losses of teenagers crowded out by adult workers. In the preceding section, we analyzed differences between SS1 and SS3 in order to isolate the effects of adults crowding out teenagers. Here, the relevant analysis is the effect of policies on the observed 2010 equilibrium, SS2. Hence, our welfare analysis in this section compares realized welfare in the 2010 steady state (SS2) with and without the policy intervention.

7.3.1 Minimum Wage

The decomposition analysis in *Section 7.1* showed that the minimum wage is an important factor in explaining the effects of adults crowding out teen labor. Hence, alternative minimum wage policies are a natural candidate for reducing the negative effects on teens crowded out of the labor force. Teen minimum wage policies vary significantly across states. Nine states, such as Michigan and Colorado, have specific age-based subminimum wage policies in place.[35] In seven of these nine states, the policy is to pay workers under the age of 18 a wage equal to 85% of the adult minimum wage.

In *Table 10*, we compare our baseline 2010 steady state with the alternative-policy 2010 steady state. The number of college graduates decreases, and the college skill-price increases under this policy. This increases the welfare of college graduates and agents who did not work as teenagers by 0.3% and 0.2%, respectively.

Lifetime welfare of teen workers and non-college graduates rises by 0.4% and 0.4%, respectively. Teen employment rises by 12.2 percentage points. That is, teen employment declines by 12.2 percentage points less between SS1 and SS2 than in the benchmark economy. Introducing a lower teen-specific minimum wage positively affects agents who benefit from early work experience but reduces skill-prices for everyone else as a result of the increase in teen labor supply. However, teens now graduate from high school with higher human capital and earn more over their lifecycle, increasing welfare overall.

However, non-college agents who do not work during high school under either the original or the lower minimum wage (i.e., the lowest-skilled teenagers) benefit in adulthood from the higher minimum wage in SS2 that keeps teenagers out of the labor force. The minimum wage essentially "protects" very low-skill workers from the negative effects of the θ shock. For this set of agents, who are most adversely affected by the shock, welfare rises by only 0.02%, driven by a slight change in skill-prices.

Note that we are comparing steady states. Hence, this discussion is for illustrative purposes. We would have to solve for the transition path of our economy to fully assess this trade-off, since doing so would allow us to calculate the effects on workers who were already adults in 2000.

7.3.2 Career and Technical Education

An alternative method through which policymakers can alleviate the negative effects of lost work experience for teenagers crowded out by adults is career and technical education

[35] The remaining state teen minimum wage policies broadly fall into three categories. First, states such as California and New York have no youth subminimum wage, and teens earn the same minimum wage as adults. Second, states such as Georgia and Texas do not consider teenagers to be "employees", so the teen minimum wage defaults to the federal youth minimum wage of $4.25 established by the Fair Labor Standards Act (FLSA). Third, states such as Minnesota and Nebraska have a youth "training" wage that pays teens a subminimum wage for, typically, the first 90 days of employment or in specific occupations, such as camp counselors or lifeguards.

Table 10: **Welfare Changes in SS2 Under Minimum Wage Policy**

Grouping	**Δ Welfare %**
Worked as teenager	+0.4
Did not work as teenager	+0.2
Non-college graduate	+0.4
College graduate	+0.3
Whole economy	+0.3

Notes: This table reports the realized welfare change under a teen minimum wage policy at 85% of adult minimum wage. Welfare changes are reported for the counterfactual economy with a shock to θ, (SS2).

(CTE).[36,37] We model a CTE program in which students may voluntarily enroll at any time during high school. While enrolled in a CTE program, high school students devote a fraction $\xi \in (0, 1]$ of their schooling time to accumulating work-related human capital rather than schooling human capital. That is, if agents choose to enroll in the CTE program, their effective schooling and working time choices are given by $(1-\xi)n_s$ and $n_e+\xi n_s$, respectively. Teens are not paid for vocational training time. We analyze a CTE policy with $\xi = 0.15$. Welfare changes for SS2 are reported in *Table 11*.[38]

Under the CTE policy, there is a 1.0% increase in teen employment relative to SS2 without vocational training. This increase is driven by two forces. First, many teens who were crowded out by adults because the minimum wage prevents them from accessing the labor market are now able to accumulate enough human capital through vocational training to access the labor market. Second, given the new human capital production technology, the relative benefits of accumulating employment human capital increase, and it is optimal for many teens to "specialize" by attending CTE schooling and working.

In particular, there is a 1.2% decrease in teen leisure, and teens allocate significantly more time to CTE schooling and work. This increases employment human capital at graduation. That is, CTE raises average employment human capital by allowing teens to work more and by directly increasing employment human capital for those enrolled in the CTE program, even if they are still unable to work. Together, welfare rises by 0.1% for those who worked

[36]Career and technical education (CTE) is also commonly referred to as "vocational schooling."

[37]During most of the twentieth century, CTE availability steadily declined, plateauing in the late 1990s. The reasons for this shift away from CTE involve a complex set of political, racial, and economic factors that are well beyond the scope of this paper. However, a detailed study of vocational training is an important avenue for future research that could be pursued through the lens of our quantitative framework.

[38]The current federal definition of a "CTE concentrator" program requires 10-15% of instructional time (at least two courses) to be devoted to vocational training. We choose this as our vocational policy.

Table 11: **Welfare Changes in SS2 Under CTE Policy**

Grouping	**Δ Welfare %**
Worked as teenager	+0.1
Did not work as teenager	+0.4
Non-college graduate	+0.2
College graduate	+0.3
Whole economy	+0.3

Notes: This table reports the realized welfare change under a voluntary CTE schooling policy, where 15% of schooling time is spent accumulating employment human capital. Welfare changes are reported for the counterfactual economy with a shock to θ, (SS2).

as teenagers and by 0.2% for non-college adults. The CTE policy also reduces the college attainment rate by 0.9%. This decline in college attainment raises the college skill-price, increasing welfare by 0.3% for college-educated agents and by 0.4% for those who did not work in high school.

However, the welfare of those who attended college in the benchmark economy but no longer attend under the CTE policy falls by 0.03%. These agents have both low employment ability, a_e, and low schooling ability, a_s. In the benchmark economy, they were unable to work as teenagers and attended college to increase their human capital upon entering the workforce. However, many of these individuals subsequently worked in teen occupations for much of their adult lives. Under the CTE policy, they are now able to increase their employment human capital, h_e, but they still work in teen occupations after graduating from high school. The increase in the number of teens working and the increase in employment human capital cause a corresponding decline in teen-occupation skill-prices. Hence, among those who switch out of college and work in teen occupations for most of their lives, welfare barely changes. That is, the policy increases welfare for all groups in the economy except teen-occupation "lifers." These teen-occupation "lifers" tend to be those who attended college in the benchmark equilibrium but not under the CTE policy.

7.3.3 Discussion

Taken together, the two policies generate similar aggregate welfare gains but operate through different margins. The teen minimum wage directly relaxes the constraint preventing teens from working and therefore produces a much larger increase in teen employment. As a result, it generates larger welfare gains for those who worked as teenagers and for non-college adults, the groups for whom employment experience has the largest return. CTE instead provides a substitute method of accumulating employment human capital for teenagers who have limited access to the labor market. It therefore produces a substantially smaller employment response, but allows teenagers to partially replace the human capital that would otherwise have been accumulated through work.

Consequently, neither policy unambiguously dominates the other. If the objective is to restore employment opportunities and offset the losses among teenagers who would otherwise work and subsequently enter the non-college labor market, the teen minimum wage is more effective in our quantitative exercises. CTE, however, generates larger welfare gains for those who did not work during high school by providing an alternative source of employment human capital. Both policies also have difficulty fully protecting the lowest-skill workers. Under the teen minimum wage, those who remain unable to work, experience little welfare improvement. Under CTE, some marginal college attendees switch out of college and subsequently spend much of their careers in teen occupations, leaving their welfare essentially unchanged.

8 Conclusion

Little is known about the causes or consequences of the dramatic 50% decline in teen employment since 2000. We provide new evidence on why this decline occurred, what it implies for human capital and welfare, and how policy can shape outcomes. We do so by combining causal reduced-form identification with a quantitative model.

Empirically, we use an instrumental variables strategy to causally establish two results. First, adult crowding out of teen labor accounts for more than 50% of the aggregate decline. Adults were driven into teen occupations for a variety of reasons, including job polarization, successive recessions, and structural change. Second, working in high school has large positive lifecycle returns for teenagers who do not attend college. A one-standard-deviation increase in average weekly hours worked increases lifetime earnings by 1%.

These empirical results discipline our quantitative lifecycle model with human capital accumulation and occupational choice. Teenagers allocate time between schooling, work experience, and leisure, while adults choose between teen and adult occupations. Aggregate shocks that worsen opportunities in adult occupations reallocate adults toward teen jobs, generating the crowding out observed in the data. The model allows us to go beyond our empirical evidence in three ways: (1) decomposing the underlying mechanisms, (2) quantifying the aggregate and distributional consequences, and (3) evaluating policy interventions.

Adult crowding out reduces teen employment through three distinct channels. The largest is the minimum-wage channel, which accounts for 53% of the decline generated by crowding out as competition pushes some teenagers' potential wages below the minimum wage. Lower current returns to work account for a further 27%, while stronger schooling incentives account for the remaining 20%. These mechanisms generate heterogeneous responses. Some teenagers substitute toward schooling and college, with college enrollment increasing by 6.5 percentage points. Others lose access to work without making this adjustment and enter adulthood with less employment human capital and experience lower lifetime earnings. As a result, crowding out increases earnings inequality and reduces aggregate welfare by 0.7%, with the largest welfare losses concentrated among non-college workers.

Our policy experiments show that these losses are partially mitigated by either preserving access to teenage employment or providing an alternative means of accumulating employment human capital. A lower teen-specific minimum wage substantially restores teen employment, while career and technical education allows teenagers to accumulate work-related human capital through school. Both policies raise aggregate welfare by 0.3%, although they benefit different groups and operate through different margins.

More broadly, our results show that teenage employment is not simply a source of contemporaneous earnings. For many non-college workers, early employment is an investment in human capital, and so changes in access to work during high school can have persistent consequences for earnings, inequality, and welfare throughout the adult lifecycle. Our findings therefore suggest that the long-run effects of deteriorating labor market opportunities can begin well before adulthood.

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Appendix A Datasets and Sample Selection

A.1 Current Population Survey

We use annual Current Population Survey (CPS) data from the Annual Social and Economic Supplement (ASEC) to present our main trends. We use linked monthly CPS data to identify transitions in and out of teen occupations. All analysis for teenagers is restricted to those aged 16-18 and currently enrolled in high school. Demographic and employment variables are recorded at the time of the interview. We use information on occupation and employment status. In our baseline, we define employment as a positive response to the direct question on employment status.

A.1.1 Teen Employment Transitions

We employ the basic monthly CPS sample for this exercise. All variables of interest are given for the month of the survey. We define transitions into and out of teen occupations for the sample of adults aged 19-79 who are not enrolled in an academic program. We consider transitions directly from non-teen occupations to teen occupations, as well as transitions through unemployment, *if* the most recent occupation before unemployment was a non-teen occupation. The linked CPS data consist of two four-month waves per individual. We consider only transitions within each four-month observation window and do not consider transitions across the two waves. We aggregate 4-digit ACS occupation codes into 81 broader categories following the natural aggregation provided by the IPUMS CPS classification scheme. We exclude the top 20 teen occupations defined previously at the 4-digit level and consider transitions from the broader occupation categories into those 4-digit teen occupations.

A.2 Census and American Community Survey

We combine the decennial Census, which provides a 5% sample of the U.S. population through 2000, with the subsequent American Community Survey (ACS), which provides an annual 1% sample from 2005 onward. We use the 1990 and 2000 Census samples and all ACS samples between 2005 and 2019. We use the ACS for all regression analyses establishing the crowding out of teen workers by adults in *Section 3*. We also verify all aggregate trends in the CPS using the ACS. All analysis for teenagers is restricted to those aged 16-18 and currently enrolled in high school. Demographic and employment variables again refer to the time of the survey. Earnings variables are given for the preceding 12 months. In our earnings regression, we thus assume that the reported earnings correspond to the current occupation.

A.3 National Longitudinal Surveys of Youth

The NLSY79 follows individuals who were 14-22 years of age on January 1, 1979, and the NLSY97 follows individuals who were 12-16 years of age as of December 31, 1996. Our baseline results are based on the NLSY79, since it provides longer lifecycle coverage and covers a period before the decline in teenage employment. We use public-access NLSY79 and NLSY97 data linked to restricted-access geocoded NLSY variables at the county level; the geocoded version, obtained from the Bureau of Labor Statistics, provides the county-of-residence identifiers needed for our instrumental variables strategy. We link counties to commuting zones using the crosswalks provided in Autor et al. (2013). The NLSY contains detailed information on schooling, employment, and earnings, observed on a weekly basis using the Work History Data Files. We construct yearly panels following Guvenen et al. (2020), except that we define years according to the academic calendar, assigning the summer months to the subsequent school year. This allows us to capture employment transitions that occur at the end of high school, typically during the summer, and to observe how many hours teenagers work while enrolled in school.

We adopt variable definitions consistent with the ACS. To construct annual earnings comparable to the ACS, we multiply the hourly wage for each occupation an individual worked in during a specific year by the exact number of hours worked in that occupation over the same period. Since the ACS includes tips, bonuses, and commissions in its earnings variable, the resulting NLSY earnings measure differs slightly from the ACS measure.

A.4 American Time Use Survey

We require information on the time teenagers spend in school, in the labor market, and on leisure in order to estimate all of our model parameters. We therefore also employ the American Time Use Survey (ATUS). We use the variables representing the major activity categories in the ATUS activity coding lexicon as made available by IPUMS. Specifically, we choose the activity category "Working and Work-related Activities" to proxy for time spent working, the activity category "Educational activities" to represent time spent on schooling, and the categories "Socializing, relaxing, and leisure" together with "Sports, exercise, and recreation" to represent leisure. We then assume that these activities make up the total time budget of an individual. We apply the same sample selection as in the other data sets and choose the year 2003, which is the first year in the data set, as our baseline. For teenagers, our selected activities account for 11.5 hours per day on average.

Appendix B Empirical Robustness

B.1 Teen Employment

Our baseline sample is defined as those aged 16 to 18 who are currently enrolled in high school. *Figures E.2-E.4* show that the decline in teen employment holds across alternative sample definitions. In particular, when we define the sample to include all teens, regardless of enrollment status, we obtain similar results and are able to present a trend further back in time.

For our baseline analysis, teen employment is defined by a positive answer to the direct questions on employment status. See *Figures E.1-E.9* for alternative definitions. Our finding of declining teen employment is not sensitive to these alternative definitions. We also show that the decline holds for both summer and non-summer employment in *Figure E.10*. *Figure 2* shows that we obtain a similar result when using the ACS rather than the CPS.

We use Organization for Economic Co-operation and Development (OECD) data to show that this phenomenon is not specific to the United States. *Figure F.2* plots teen employment rates across several advanced economies and the OECD average.

B.2 Teen Occupations

The list of teen occupations is generated for those aged 16-18 who report positive hours worked in the previous week. *Table F.1* reports the top 20 occupations used to define teen occupations. The results in *Section 3* remain unchanged if we instead use the top 15 or top 30 occupations.

In order to provide consistent trends over time, it is necessary to maintain a consistent definition of a teen occupation. For this reason, we average the top occupations over the 1986-2019 period, inclusive. The top 20 occupations consistently represent between 73% and 75% of total teen employment over this period. This occupation list is stable over time, with all occupations in the top ten present throughout the entire period. The largest exceptions that appear between 1986 and 1991 and drop out thereafter are "Pumping Station Operators" and "Driver/Sales Workers and Truck Drivers," which are ranked 13$^{\text{th}}$ and 15$^{\text{th}}$ over this period, respectively. The largest exceptions that appear only in the 2016-2019 period are "Athletes, Coaches, Umpires, and Related Workers" and "Law enforcement workers, nec," which are ranked 17$^{\text{th}}$ and 19$^{\text{th}}$ over this period, respectively. None of these occupations are present in the averaged list.

B.3 Factors Driving Adults into Teen Occupations

In order to motivate our empirical strategy, we first present evidence that large economy-wide trends drive adult workers into teen occupations. We then use the characteristics of those adults most exposed to these shocks to build instruments that exploit their differential distribution across commuting zones.

We start by focusing on the employment rate as a proxy for business cycle fluctuations (as in Yagan (2019)) and on the decline in manufacturing.[39] We use data from the American Community Survey (ACS) to investigate the effects of these demand factors (D), exploiting commuting zone (c) and time (t) variation by estimating OLS regressions

$$\left(\frac{\text{Adults in Teen Jobs}}{\text{All Adults}}\right)_{c,t} = \alpha D_{c,t} + \gamma X_{c,t} + \theta_t + \phi_c + \epsilon_{c,t} \tag{B.1}$$

where, X includes controls for median earnings and demographics within commuting zones, and θ_t and ϕ_c are time and commuting zone fixed effects. The variable of interest, $D_{c,t}$, is either the total employment rate or the manufacturing employment share. We estimate (B.1) using the years 2000 and 2010, the period of the largest decline in teen employment.[40] *Table B.1* shows that both factors significantly explain adult employment in teen occupations. Commuting zones that experience negative employment shocks or a decline in manufacturing see more adults take up teen occupations.

Table B.1: **Demand Factor Regression Results**

	(1)	(2)
Employment	-0.12	
	(0.000)	
Manufacturing		-0.064
		(0.015)
Observations	741	741

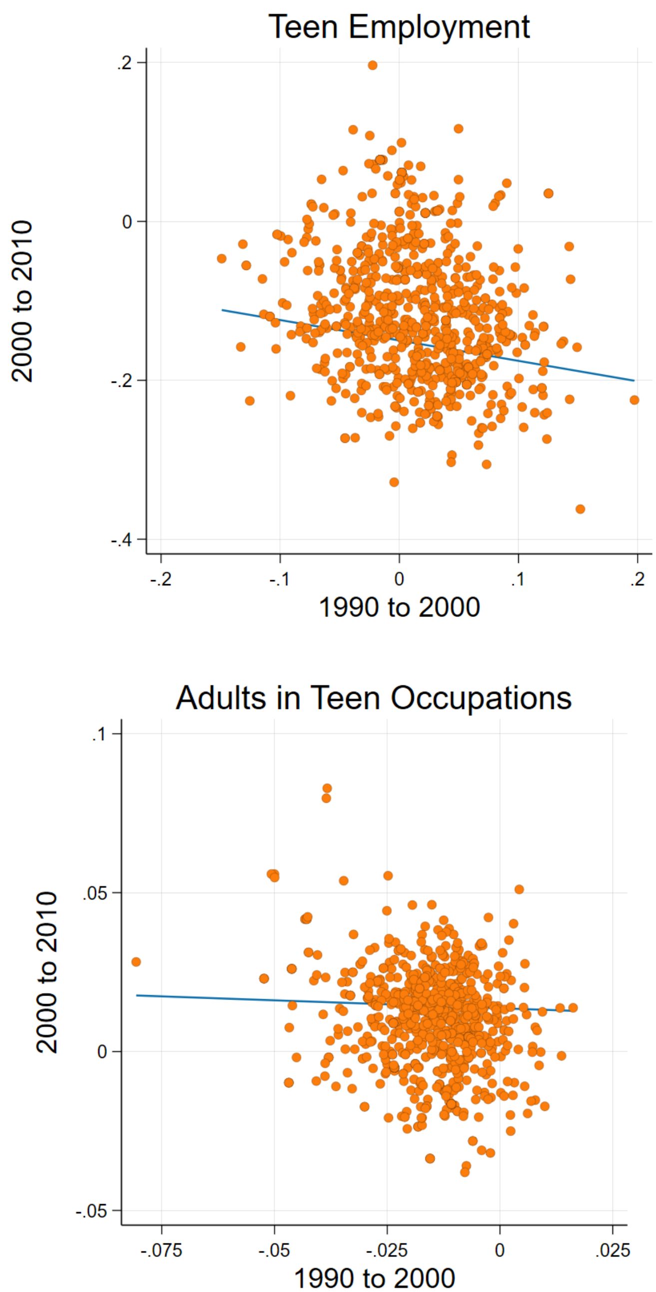
Notes: P-values shown in parentheses. The dependent variable is the share of adults working in teen occupations. *Source*: American Community Survey (ACS).

[39] We experimented with the inclusion of a "China shock" from Autor et al. (2013). However, controlling for manufacturing absorbs the effects of increased trade competition from China.

[40] The qualitative relationship is robust to including more years. We discuss the time variation we exploit in detail in *Section 3.2*.

B.4 Employment Decline Regression Analysis

Figure B.1: **Pre- and Post-Period Correlation**



Notes: Each dot represents one commuting zone. The x-axis plots the change of the variable between 1990 and 2000 and the y-axis the change between 2000 and 2010. The line plots the weighted correlation between pre- and post-period. *Source:* American Community Survey (ACS).

Table B.2: **First-Stage Regression Results**

	Adult Share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Z_{Cohort}	0.015				0.015			
	(0.011)				(0.021)			
$Z_{Education}$		0.140		0.081		0.142		0.081
		(0.000)		(0.022)		(0.000)		(0.027)
$Z_{PreviousOcc}$			0.011	0.009			0.011	0.009
			(0.000)	(0.002)			(0.000)	(0.002)
$TeenEmp_{t-1}$					-0.007	0.001	-0.007	-0.000
					(0.558)	(0.907)	(0.521)	(0.996)
$AdultShare_{t-1}$	-0.070	-0.101	-0.082	-0.099	-0.085	-0.098	-0.098	-0.099
	(0.453)	(0.230)	(0.252)	(0.180)	(0.360)	(0.269)	(0.202)	(0.205)
$MedianWage$	0.004	0.005	0.003	0.005	0.004	0.005	0.003	0.005
	(0.218)	(0.120)	(0.264)	(0.116)	(0.230)	(0.118)	(0.268)	(0.115)
$EmpRate$	-0.134	-0.151	-0.164	-0.171	-0.132	-0.152	-0.162	-0.171
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$WhiteShare$	-0.055	-0.030	-0.024	-0.021	-0.056	-0.030	-0.025	-0.021
	(0.001)	(0.095)	(0.138)	(0.214)	(0.001)	(0.097)	(0.112)	(0.215)
$TeenShare$	0.065	-0.010	0.077	0.025	0.057	-0.009	0.068	0.025
	(0.472)	(0.915)	(0.366)	(0.789)	(0.525)	(0.923)	(0.428)	(0.790)
$Manufacturing$	-0.098	-0.124	-0.081	-0.110	-0.101	-0.124	-0.085	-0.110
	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
$Constant$	-0.007	-0.002	-0.017	-0.017	-0.006	-0.002	-0.017	-0.017
	(0.312)	(0.416)	(0.001)	(0.001)	(0.358)	(0.411)	(0.001)	(0.001)
F-stat	5.66	10.80	19.67	12.09	5.30	15.70	18.85	11.63
Observations	741	741	741	741	741	741	741	741

Notes: P-values are shown in parentheses. The dependent variable is the adult employment share in teen occupations. All specifications include the controls used in the corresponding second-stage regression. *Source:* American Community Survey (ACS).

Table B.3: **Instrumental Variable Regression Full Results**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	OLS	No Adults
$Adult\ Share$	-4.738	-2.669	-3.571	-3.244	-7.332	-4.405	-4.124	-4.222	-0.231	
	(0.089)	(0.052)	(0.009)	(0.007)	(0.056)	(0.011)	(0.006)	(0.002)	(0.318)	
$TeenEmp_{t-1}$					-0.322	-0.284	-0.281	-0.282	-0.231	-0.228
					(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$AdultShare_{t-1}$	0.989	1.120	1.063	1.083	0.063	0.338	0.364	0.355	0.730	0.751
	(0.055)	(0.005)	(0.025)	(0.015)	(0.929)	(0.536)	(0.506)	(0.513)	(0.008)	(0.006)
$MedianWage$	0.084	0.080	0.082	0.081	0.088	0.083	0.083	0.083	0.076	0.076
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Emp.Rate$	0.272	0.523	0.413	0.453	0.020	0.368	0.402	0.390	0.865	0.893
	(0.502)	(0.045)	(0.126)	(0.075)	(0.970)	(0.241)	(0.160)	(0.168)	(0.000)	(0.000)
$WhiteShare$	-0.141	-0.049	-0.089	-0.075	-0.316	-0.179	-0.166	-0.171	0.016	0.027
	(0.410)	(0.611)	(0.379)	(0.438)	(0.202)	(0.180)	(0.148)	(0.142)	(0.807)	(0.677)
$TeenShare$	-0.154	-0.323	-0.249	-0.276	-0.340	-0.533	-0.551	-0.545	-0.808	-0.823
	(0.819)	(0.519)	(0.629)	(0.587)	(0.701)	(0.387)	(0.324)	(0.345)	(0.061)	(0.056)
$Manufacturing$	-0.472	-0.329	-0.391	-0.369	-0.875	-0.646	-0.624	-0.632	-0.319	-0.301
	(0.059)	(0.045)	(0.026)	(0.026)	(0.018)	(0.001)	(0.002)	(0.001)	(0.029)	(0.039)
$Constant$	-0.035	-0.049	-0.043	-0.045	-0.030	-0.048	-0.050	-0.050	-0.075	-0.077
	(0.171)	(0.000)	(0.000)	(0.000)	(0.402)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Z_{Cohort}	Yes	No	No	No	Yes	No	No	No	No	No
$Z_{Education}$	No	Yes	No	Yes	No	Yes	No	Yes	No	No
$Z_{PreviousOcc}$	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Lag teen emp.	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	741	741	741	741	741	741	741	741	741	741

Notes: P-values are shown in parentheses. The dependent variable in all columns is the teen employment share. Earnings are in units of 10,000. *Source:* American Community Survey (ACS).

Table B.4: **Employment Decline Regressions, Omitting Parents**

	(1)	(2)	(3)
$AdultShare$	-0.72	-3.92	-4.15
	(0.511)	(0.019)	(0.008)
Z_{Cohort}	Yes	No	No
$Z_{Education}$	No	Yes	No
$Z_{PreviousOcc}$	No	No	Yes
F-stat	10.90	13.58	13.37
Lag Teen Emp.	Yes	Yes	Yes
Omit Parents	Yes	Yes	Yes
Observations	741	741	741

Notes: P-values shown in parentheses. This table reports robustness excluding parents. To do so, we must use initial shares in 2000 *not* 1990, since parent status is only observed from 2000 onward. *Source:* American Community Survey (ACS).

Table B.5: **Different Time Changes**

	2009	2010	2011	2012	2013	2014
$AdultShare$	-5.37	-4.12	-6.83	-2.27	-1.86	-3.33
	(0.046)	(0.006)	(0.075)	(0.113)	(0.293)	(0.099)
$Z_{PreviousOcc}$	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	7.83	18.85	4.96	14.85	8.24	7.32
Lag Teen Emp.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	741	741	741	741	741	741

Notes: P-values shown in parentheses. Dependent variable in all columns is the teen employment share. *AdultShare* is the share of adults employed in teen occupations as a fraction of all adults. *Source:* American Community Survey (ACS).

B.4.1 Minimum Wage Changes

We investigate whether changes in the minimum wage can help explain the decline in teen employment. Indeed, Neumark and Shupe (2019) find that changes in state minimum wages explain a significant part of the variation in teen employment rates between 1989 and 2015. The authors use state-year variation to identify their coefficients and include the share of immigrants as a measure of competition for teen jobs in their regression. In contrast, we use the 10-year change and variation at the commuting zone level for identification. Our measure of adults in teen jobs then quantifies the total competition faced by teenagers, including immigrants who actually take up teen work.

Here, we use the same minimum wage data as Neumark and Shupe (2019), (the higher of the state and federal minimum wage) for each commuting zone. We calculate the population-weighted average minimum wage for commuting zones that span more than one state. In contrast to Neumark and Shupe (2019), we find that changes in the minimum wage are not significant in explaining the change in teen employment from 2000 to 2010. This seems sensible, as the average minimum wage in the U.S. only began rising in 2005, five years after the beginning of the sharp drop in teen employment. Also, while the levels of the minimum wage differ across states, we do not find large variation in changes in the minimum wage between 2000 and 2010. As we show in *Table B.9*, these changes also do not correlate with our instruments, giving us additional confidence that we are identifying a channel independent of changes in the minimum wage.

Finally, we view our results not as contradicting Neumark and Shupe (2019) but as complementary. Our quantitative model exercise shows that the interaction between the negative pressure on teen wages due to adult crowding out and the existence of a minimum wage is quantitatively important in explaining the magnitude of the employment decline.

Table B.6: **Instrumental Variable Regression with Minimum Wage**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	OLS	No Adults
$Adult\ Share$	-4.574	-2.622	-3.620	-3.230	-7.167	-4.420	-4.336	-4.367	-0.250	
	(0.077)	(0.047)	(0.009)	(0.008)	(0.051)	(0.012)	(0.006)	(0.003)	(0.278)	
$Minimum\ Wage$	0.075	0.042	0.059	0.052	0.234	0.173	0.171	0.171	0.080	0.075
	(0.521)	(0.620)	(0.520)	(0.553)	(0.165)	(0.141)	(0.111)	(0.118)	(0.343)	(0.380)
$TeenEmp_{t-1}$					-0.365	-0.318	-0.316	-0.317	-0.247	-0.242
					(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$AdultShare_{t-1}$	1.021	1.135	1.077	1.099	0.039	0.307	0.316	0.313	0.714	0.739
	(0.042)	(0.004)	(0.023)	(0.012)	(0.955)	(0.572)	(0.572)	(0.568)	(0.009)	(0.007)
$MedianWage$	0.085	0.081	0.083	0.082	0.091	0.086	0.086	0.086	0.077	0.077
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Emp.Rate$	0.286	0.526	0.403	0.451	0.032	0.361	0.371	0.367	0.860	0.890
	(0.460)	(0.042)	(0.141)	(0.078)	(0.950)	(0.264)	(0.213)	(0.212)	(0.000)	(0.000)
$WhiteShare$	-0.141	-0.051	-0.097	-0.079	-0.338	-0.202	-0.198	-0.199	0.005	0.018
	(0.402)	(0.600)	(0.351)	(0.420)	(0.182)	(0.152)	(0.101)	(0.104)	(0.935)	(0.779)
$TeenShare$	-0.179	-0.333	-0.254	-0.285	-0.442	-0.599	-0.604	-0.602	-0.838	-0.852
	(0.782)	(0.500)	(0.624)	(0.574)	(0.593)	(0.315)	(0.280)	(0.292)	(0.049)	(0.045)
$Manufacturing$	-0.456	-0.322	-0.391	-0.364	-0.877	-0.658	-0.651	-0.654	-0.326	-0.306
	(0.049)	(0.042)	(0.026)	(0.025)	(0.015)	(0.001)	(0.002)	(0.001)	(0.026)	(0.036)
$Constant$	-0.061	-0.064	-0.063	-0.063	-0.111	-0.108	-0.107	-0.107	-0.103	-0.102
	(0.072)	(0.017)	(0.040)	(0.029)	(0.013)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Z_{Cohort}	Yes	No	No	No	Yes	No	No	No	No	No
$Z_{Education}$	No	Yes	No	Yes	No	Yes	No	Yes	No	No
$Z_{PreviousOcc}$	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Lag teen emp.	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	741	741	741	741	741	741	741	741	741	741

Notes: P-values are shown in parentheses. The dependent variable in all columns is the teen employment share. Earnings are in units of 10,000. *Source:* American Community Survey (ACS).

Table B.7: **Overidentification Tests**

	(1)	(2)	(3)	(4)	(5)	(6)
$AdultShare$	-3.73	-4.52	-3.24	-4.22	-3.26	-4.24
	(0.003)	(0.001)	(0.007)	(0.002)	(0.007)	(0.002)
Z_{Cohort}	Yes	Yes	No	No	Yes	Yes
$Z_{Education}$	No	No	Yes	Yes	Yes	Yes
$Z_{PreviousOcc}$	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	14.46	13.49	12.09	11.64	9.97	9.44
J-Test p-value	0.68	0.34	0.50	0.86	0.30	0.42
Lag Teen Emp.	No	Yes	No	Yes	No	Yes
Observations	741	741	741	741	741	741

Notes: P-values shown in parentheses. *Source:* American Community Survey (ACS).

B.4.2 Plausibility of Instrument Exogeneity

Although there is no formal test to establish the exogeneity of our instruments, we can provide supporting evidence for a causal interpretation of our estimates. Since our instruments follow a Bartik-style logic, we follow the recommendations in Goldsmith-Pinkham et al. (2020). First, since we have several instruments, we can run overidentification tests by including different combinations of our instruments jointly in the regressions. Results in *Table B.7* show that the overidentified IV regressions deliver remarkably similar coefficients. The regressions return large p-values for the overidentification J-tests, lending support to the validity of our instruments. These tests are meaningful because our occupation instrument is only weakly correlated with the demographic instruments. The instruments thus pick up distinct variation in the data.

Next, we investigate whether our instruments are correlated with the controls. Such correlations could be a concern if these regressors were correlated with other unobserved factors that explain *changes* in teen employment. We can see that the controls explain a small share of the variation in the instruments. Importantly, the minimum wage is uncorrelated with our instruments, providing further support that the relationship between adults in teen jobs and teen employment that we identify is independent of changes in the minimum wage. Across all instruments, the only control that is always significant is the overall employment rate in a commuting zone. Given that we control for other measures of local economic conditions, the employment rate is a sufficient statistic for the remaining changes in economic activity within a commuting zone. Controlling for the employment rate therefore absorbs additional demand factors and provides clean identification of the direct crowding-out effect.

Table B.8: **Correlation Between Instruments**

	$Z_{PreviousOcc}$	Z_{Cohort}	$Z_{Education}$
$Z_{PreviousOcc}$	1.0	0.11	0.28
Z_{Cohort}	0.11	1.0	0.60
$Z_{Education}$	0.28	0.60	1.0

Notes: This table shows the correlation between each instrument for decline in teen employment regressions. *Source:* American Community Survey (ACS).

Next, we calculate the Rotemberg weights as recommended in Goldsmith-Pinkham et al. (2020). The largest weight is on Admin Support occupations, one of the key cognitive middle-skill jobs that suffered from routinization. The same is true for Records Processing workers.

While higher-skilled than the previous occupations, Managerial Related occupations saw a reduction in employment in our period of interest, with employment falling by 3.5% from the onset of the 2008 recession through 2010. Finally, Health Service occupations experienced steady growth in our period of interest, but it seemingly became harder to transition from teen jobs into those occupations as better-trained workers increasingly took up these jobs after 2000. The share of workers with a college degree in health service occupations rose by 23% between 2000 and 2010. This, in turn, has the same effect of driving more lower-skilled adult workers into teen jobs. Looking at the demographic instruments, we find that it is mostly cohorts born between 1950 and 1965 that drive the first-stage correlation, precisely those middle-aged workers who have the largest net inflows into teen jobs.

We then use these results to investigate the correlation between our explanatory variables and each of the occupations and demographic groups with the largest Rotemberg weights. We find results very similar to those for the aggregated instruments. Finally, we experiment with re-estimating our IV regressions, leaving out each of the top shares from the instrument construction. Leaving out Admin Support occupations is the only omission that weakens the first stage enough to reduce the F-statistic below 10, although the second-stage coefficient remains of similar magnitude. We can remove each of the other shares without affecting the results. Thus, we conclude that our results do not depend on any one occupation or demographic group, although Admin Support workers seem to play an important role.

Table B.9: **Correlation Between Controls and Instruments**

	$Z_{PreviousOcc}$	Z_{Cohort}	$Z_{Education}$
Median Earnings	-0.08	-0.10	-0.01
	(0.284)	(0.003)	(0.010)
Emp. Rate	3.05	0.80	0.12
	(0.000)	(0.011)	(0.002)
Share White	-1.34	0.88	-0.02
	(0.000)	(0.000)	(0.434)
Share Teens	-1.46	0.05	0.41
	(0.389)	(0.944)	(0.000)
Share Manufact.	-1.85	1.87	0.16
	(0.217)	(0.002)	(0.085)
Share Service	0.60	1.49	0.18
	(0.716)	(0.013)	(0.055)
Share Routine Jobs.	-0.36	0.95	-0.03
	(0.544)	(0.000)	(0.411)
Occ. Group 1	0.20	-0.78	-0.04
	(0.919)	(0.255)	(0.718)
Occ. Group 2	-3.66	-3.40	-0.61
	(0.071)	(0.000)	(0.000)
Occ. Group 3	1.34	-1.21	0.05
	(0.511)	(0.064)	(0.587)
Occ. Group 4	0.07	1.53	0.52
	(0.972)	(0.067)	(0.000)
Occ. Group 5	1.33	-0.92	0.19
	(0.337)	(0.123)	(0.050)
Occ. Group 6	4.03	0.01	0.27
	(0.022)	(0.985)	(0.008)
Minimum Wage	0.27	-0.44	-0.04
	(0.386)	(0.001)	(0.267)
R^2	0.23	0.39	0.56

Notes: P-values shown in parentheses. Occ. Group 1 are Managerial and Professional Specialty Occupations. Occ. Group 2 are Technical, Sales, and Administrative Support Occupations. Occ. Group 3 are Service Occupations. Occ. Group 4 are Farming, Forestry, and Fishing Occupations. Occ. Group 5 are Precision Production, Craft, and Repair Occupations. Occ. Group 6 are Operators, Fabricators, and Laborers. *Source:* American Community Survey (ACS).

Table B.10: **Rotemberg Weights – Occupation Instrument**

Occupation	Rotemberg Weight
Administrative Support	0.656
Managerial Related	0.226
Records Processing	0.079
Health Service	0.068

Source: American Community Survey (ACS).

Table B.11: **Top Rotemberg Correlations**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Median Earnings	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.121)	(0.034)	(0.041)	(0.311)	(0.012)	(0.019)	(0.058)	(0.000)	(0.000)	(0.227)
Emp. Rate	0.05	0.03	0.01	0.04	0.05	0.03	0.04	0.15	0.41	0.23
	(0.005)	(0.197)	(0.014)	(0.001)	(0.009)	(0.001)	(0.002)	(0.025)	(0.004)	(0.085)
Share White	-0.00	-0.00	0.00	-0.04	-0.01	-0.01	-0.01	0.09	0.30	0.35
	(0.662)	(0.829)	(0.835)	(0.000)	(0.617)	(0.423)	(0.299)	(0.001)	(0.000)	(0.000)
Share Teens	0.18	0.32	0.05	-0.17	0.10	0.13	0.20	-0.79	-0.39	1.04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.041)	(0.000)	(0.000)	(0.000)	(0.219)	(0.005)
Share Manufact.	0.01	0.07	0.01	-0.13	0.09	0.03	0.04	0.24	0.59	0.81
	(0.863)	(0.242)	(0.234)	(0.002)	(0.048)	(0.340)	(0.175)	(0.035)	(0.033)	(0.002)
Share Service	-0.01	0.04	0.00	-0.07	0.08	0.04	0.06	0.14	0.42	0.72
	(0.863)	(0.430)	(0.960)	(0.048)	(0.075)	(0.152)	(0.045)	(0.252)	(0.102)	(0.003)
Share Routine Jobs	-0.01	0.03	0.00	-0.06	-0.03	-0.00	-0.00	0.08	0.52	0.40
	(0.423)	(0.348)	(0.356)	(0.001)	(0.135)	(0.905)	(0.694)	(0.073)	(0.000)	(0.001)
Occ. Group 1	0.02	0.02	0.01	0.04	-0.02	-0.01	-0.02	0.04	-0.05	-0.52
	(0.688)	(0.700)	(0.381)	(0.261)	(0.735)	(0.839)	(0.665)	(0.788)	(0.867)	(0.089)
Occ. Group 2	-0.09	-0.33	-0.04	0.16	-0.27	-0.15	-0.18	-0.45	-1.26	-1.63
	(0.076)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
Occ. Group 3	0.07	0.07	0.03	0.10	0.02	0.03	0.02	-0.12	-0.36	-0.56
	(0.205)	(0.246)	(0.032)	(0.070)	(0.765)	(0.351)	(0.517)	(0.344)	(0.218)	(0.034)
Occ. Group 4	0.19	0.31	0.06	-0.03	0.22	0.15	0.16	-0.06	0.69	0.63
	(0.000)	(0.000)	(0.000)	(0.475)	(0.000)	(0.000)	(0.000)	(0.699)	(0.060)	(0.085)
Occ. Group 5	0.06	0.10	0.01	0.09	0.10	0.06	0.04	-0.02	-0.24	-0.52
	(0.125)	(0.050)	(0.358)	(0.007)	(0.027)	(0.026)	(0.179)	(0.861)	(0.403)	(0.035)
Occ. Group 6	0.11	0.18	0.02	0.12	0.12	0.09	0.07	0.07	0.25	-0.31
	(0.012)	(0.002)	(0.060)	(0.007)	(0.016)	(0.002)	(0.023)	(0.572)	(0.360)	(0.246)
Minimum Wage	-0.00	-0.02	0.00	0.01	-0.02	-0.01	-0.00	-0.10	-0.20	-0.13
	(0.870)	(0.215)	(0.320)	(0.278)	(0.205)	(0.122)	(0.838)	(0.006)	(0.001)	(0.018)
R^2	0.41	0.58	0.43	0.36	0.53	0.56	0.56	0.27	0.39	0.38

Notes: P-values shown in parentheses. Columns (1) to (4) use each of the top four Rotemberg occupation shares as dependent variables. The remaining columns use the share of people in a commuting zone born between 1950 and 1955, then 1955 and 1960, and then 1960 and 1965, as dependent variables, where columns (5)-(7) restrict those shares to college educated adults, and columns (8)-(10) use all adults, in accordance with the education and age instrument. Occupation groups are defined as in *Table B.9*. *Source:* American Community Survey (ACS).

Table B.12: **IV Results Excluding Individual Instrument Components**

	Admin support excluded	Management related excluded	Records processing excluded	Health service excluded
Adult Share	-4.122	-4.008	-4.211	-4.913
	(0.095)	(0.018)	(0.007)	(0.002)
Lag teen emp.	-0.281	-0.279	-0.282	-0.291
	(0.001)	(0.000)	(0.000)	(0.001)
Lag adult share	0.365	0.375	0.356	0.290
	(0.516)	(0.497)	(0.524)	(0.633)
Median Earnings	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Emp. Rate	0.402	0.416	0.391	0.308
	(0.266)	(0.167)	(0.183)	(0.319)
Share White	-0.166	-0.161	-0.170	-0.203
	(0.276)	(0.168)	(0.148)	(0.110)
Share Teens	-0.551	-0.559	-0.545	-0.499
	(0.316)	(0.307)	(0.333)	(0.414)
Share Manufact.	-0.624	-0.615	-0.631	-0.686
	(0.014)	(0.004)	(0.002)	(0.001)
Constant	-0.050	-0.051	-0.050	-0.045
	(0.010)	(0.000)	(0.000)	(0.002)
F-stat	8.69	13.95	17.48	19.50
Observations	741	741	741	741

Notes: Each column excludes the indicated occupation's component from the previous-occupation instrument. P-values in parentheses. *Source:* American Community Survey (ACS).

B.5 Adult Crowding Out and Teen College Enrollment

Throughout the paper, we show that one channel through which adult crowding out operates is by increasing the relative return to attending college for a subset of teenagers. This is because workers with a college degree have a much smaller probability of working in a negatively affected teen occupation. As discussed in *Section 7.1*, without panel data, it is not possible to empirically quantify this channel directly, since we must know the location in which an individual of college age lived while in high school. We are able to provide some supporting evidence of increased college enrollment in this section. This is possible because, from 2005 onward, the ACS reports individuals' location of residence in the previous year. We can therefore compute, for 19-year-olds, the share of adults in teen jobs in the commuting zone in which they lived at age 18, when they were most likely still in high school. Letting the previous year's commuting zone of residence be c_{-1}, we then estimate,

$$\Delta\text{Col. Enrollment}_{c_{-1},t} = \beta\Delta\left(\frac{\text{Adults in Teen Jobs}}{\text{All Adults}}\right)_{c_{-1},t-1} + \gamma\Delta X_{c_{-1},t-1} + \epsilon_{c_{-1},t} \quad \text{(B.2)}$$

for 19-year-olds, where all controls are measured in the previous year and at the previous year's location. Since we can only estimate this equation from 2005 onward, we include the college enrollment rate of 19-year-olds in 2005 as a control to adjust for changes that occurred between 2000 and 2005. We then employ the same IV strategy as in our baseline regressions and report results using the occupation instrument. We estimate the relationship for changes between 2005 and 2010 and between 2005 and 2015. We find significant positive effects for both periods. Given the coefficients, the average increase in adults in teen jobs between 2005 and 2010 leads to an increase in the college enrollment rate of around five percentage points, which corresponds to around half a standard deviation of local changes in the enrollment rate observed between 2005 and 2010. We interpret these results as some evidence that increased competition from adults for low-skill jobs leads to increased college attendance, as predicted by the model. Further interpretation should be treated with caution, since our measure captures enrollment in any type of college, i.e., 4-year and 2-year colleges. This does not directly provide evidence on the number of individuals completing a college degree.

Table B.13: **Change in College Enrollment of 19-Year-olds**

	$t = 2010$	$t = 2015$
Adults in Teen Jobs	6.14	8.94
	(0.022)	(0.001)
F-stat	17.29	20.62
Observations	741	741

Notes: P-values shown in parentheses. *Source:* American Community Survey (ACS).

B.6 Lifecycle Earnings Returns Regression Analysis

Table B.14: **First-Stage for Earnings Returns Regressions**

	Avg. hours worked HS					
	(1)	(2)	(3)	(4)	(5)	(6)
Teen emp. rate 1980	11.795	9.829	9.812	11.009	8.640	10.471
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Sex		-1.269	-1.269	-1.271	-1.447	-1.238
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White		0.403	0.399	0.443	0.515	0.406
		(0.041)	(0.048)	(0.032)	(0.248)	(0.320)
Black		-0.475	-0.480	-0.589	-0.791	-0.559
		(0.024)	(0.028)	(0.012)	(0.118)	(0.009)
AFQT score		0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.870)	(0.000)
Avg. life unemp. rate			-0.003	0.015	0.006	0.004
			(0.937)	(0.723)	(0.941)	(0.915)
Median real earnings 1980				-0.000	-0.000	-0.000
				(0.664)	(0.557)	(0.418)
% white 1980				-1.965	-0.446	-1.654
				(0.059)	(0.815)	(0.071)
% teen share 1980				-1.306	16.701	2.707
				(0.919)	(0.476)	(0.811)
% col. deg. 1980				1.400	-1.116	0.995
				(0.628)	(0.832)	(0.695)
Intercept	-0.325	0.213	0.242	1.496	2.015	1.375
	(0.311)	(0.564)	(0.639)	(0.405)	(0.522)	(0.380)
F-stat	152.53	101.30	98.98	54.65	11.50	66.08
Observations	3,118	3,057	3,056	3,056	1,163	4,219

Notes: P-values shown in parentheses. Columns (1)-(4) are for those who graduate high school and do not graduate college. Column (5) is for college graduates. Column (6) is for all workers. *Source:* National Longitudinal Surveys of Youth 1979 (NLSY79).

Table B.15: **First-Stage for Earnings Returns Regressions by Age Group**

	Avg. Hours worked HS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Teen emp. rate 1980	10.126	11.357	11.458	12.075	11.890	13.620	11.624	10.813
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median real earnings 1980	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.546)	(0.671)	(0.424)	(0.343)	(0.759)	(0.627)	(0.984)	(0.781)
% white 1980	-2.235	-2.775	-2.484	-2.655	-3.193	-2.032	-0.658	-1.539
	(0.032)	(0.011)	(0.028)	(0.024)	(0.007)	(0.104)	(0.603)	(0.345)
Teen share 1980	4.270	1.162	-6.176	0.073	-1.147	-5.042	2.083	-7.439
	(0.736)	(0.931)	(0.654)	(0.996)	(0.936)	(0.736)	(0.891)	(0.696)
% col. deg. 1980	2.261	3.075	1.544	3.029	1.389	-0.018	1.316	-1.153
	(0.447)	(0.304)	(0.628)	(0.358)	(0.682)	(0.996)	(0.719)	(0.798)
Sex	-1.315	-1.236	-1.185	-1.258	-1.123	-1.286	-1.401	-1.272
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.417	0.459	0.426	0.519	0.641	0.322	0.382	0.328
	(0.037)	(0.031)	(0.059)	(0.026)	(0.006)	(0.178)	(0.126)	(0.303)
Black	-0.595	-0.603	-0.581	-0.567	-0.619	-0.707	-0.576	-0.991
	(0.009)	(0.013)	(0.022)	(0.027)	(0.016)	(0.008)	(0.038)	(0.005)
AFQT score	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. unemp. rate 20-24	0.010							
	(0.730)							
Avg. unemp. rate 25-29		0.072						
		(0.072)						
Avg. unemp. rate 30-34			0.020					
			(0.576)					
Avg. unemp. rate 35-39				0.016				
				(0.618)				
Avg. unemp. rate 40-44					0.053			
					(0.302)			
Avg. unemp. rate 45-49						-0.085		
						(0.013)		
Avg. unemp. rate 50-54							-0.016	
							(0.743)	
Avg. unemp. rate 55-59								-0.071
								(0.424)
Intercept	1.467	1.276	2.284	1.631	1.989	2.340	0.147	2.659
	(0.400)	(0.485)	(0.237)	(0.399)	(0.318)	(0.271)	(0.946)	(0.313)
F-stat	46.96	53.49	48.72	52.15	47.48	57.27	40.25	21.38
Observations	3,121	2,876	2,531	2,351	2,088	1,949	1,765	1,092

Notes: P-values shown in parentheses. Columns are for age groups (inclusive) 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, and 55-59, respectively. *Source:* National Longitudinal Surveys of Youth 1979 (NLSY79).

Table B.16: **Second-Stage for Earnings Returns Regressions by Age Group**

	log of average earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. hours worked HS	-0.000	0.009	0.029	0.030	0.061	0.055	0.031	0.011
	(0.979)	(0.454)	(0.040)	(0.003)	(0.000)	(0.001)	(0.102)	(0.658)
Median real earnings 1980	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.284)	(0.376)	(0.897)	(0.381)	(0.217)	(0.281)	(0.284)
% white 1980	-0.203	-0.178	-0.278	-0.290	-0.191	-0.383	-0.510	-0.487
	(0.019)	(0.025)	(0.004)	(0.189)	(0.115)	(0.004)	(0.000)	(0.006)
Teen share 1980	-0.246	-5.248	-3.435	-4.672	-4.092	-5.272	-4.011	-5.083
	(0.841)	(0.000)	(0.011)	(0.012)	(0.016)	(0.003)	(0.028)	(0.023)
% col. deg. 1980	1.019	1.472	1.525	1.333	1.403	1.162	1.607	1.811
	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.006)	(0.000)	(0.001)
Sex	-0.215	-0.187	-0.161	-0.171	-0.163	-0.133	-0.150	-0.186
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	-0.046	-0.059	-0.030	-0.052	-0.077	-0.068	-0.038	-0.033
	(0.024)	(0.002)	(0.203)	(0.035)	(0.013)	(0.021)	(0.225)	(0.401)
Black	-0.115	-0.134	-0.112	-0.128	-0.088	-0.081	-0.089	-0.131
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.015)	(0.010)	(0.007)
AFQT score	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. unemp. rate 20-24	-0.012							
	(0.000)							
Avg. unemp. rate 25-29		-0.013						
		(0.000)						
Avg. unemp. rate 30-34			0.007					
			(0.041)					
Avg. unemp. rate 35-39				-0.002				
				(0.007)				
Avg. unemp. rate 40-44					-0.009			
					(0.135)			
Avg. unemp. rate 45-49						-0.008		
						(0.070)		
Avg. unemp. rate 50-54							-0.008	
							(0.154)	
Avg. unemp. rate 55-59								-0.012
								(0.266)
Intercept	2.352	2.914	2.731	2.954	3.056	3.366	3.353	3.551
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F-stat	46.96	53.49	48.72	52.15	47.48	57.27	40.25	21.38
Observations	3,121	2,876	2,531	2,351	2,088	1,949	1,765	1,092

Notes: P-values shown in parentheses. Columns are for age groups (inclusive) 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, and 55-59, respectively. *Source:* National Longitudinal Surveys of Youth 1979 (NLSY79).

Table B.17: **First-Stage for Earnings Returns Regressions with NLSY97**

	Avg. hours worked HS			
	(1)	(2)	(3)	(4)
Teen emp. rate 2000	8.880	8.415	9.352	10.431
	(0.002)	(0.002)	(0.002)	(0.001)
Median real earnings 2000	-0.000	-0.000	-0.000	-0.000
	(0.450)	(0.248)	(0.148)	(0.365)
% white 2000	0.455	0.535	0.212	0.337
	(0.746)	(0.684)	(0.884)	(0.831)
Emp. rate 2000	34.536	31.060	41.735	21.279
	(0.006)	(0.008)	(0.001)	(0.115)
Teen share 2000	55.474	48.693	64.611	31.804
	(0.008)	(0.011)	(0.003)	(0.171)
Col. deg. 2000	0.308	0.674	2.401	0.010
	(0.912)	(0.794)	(0.400)	(0.997)
Sex	-0.440	-0.470	-0.432	-0.357
	(0.014)	(0.006)	(0.020)	(0.077)
White	0.808	0.744	0.188	0.806
	(0.415)	(0.417)	(0.864)	(0.460)
Black	0.065	-0.031	-0.587	0.198
	(0.948)	(0.973)	(0.597)	(0.858)
Hispanic	0.559	0.458	-0.073	0.606
	(0.579)	(0.623)	(0.948)	(0.584)
AFQT score	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Avg. life unemp. rate	-0.016			
	(0.789)			
Avg. unemp. rate 20-24		-0.099		
		(0.135)		
Avg. unemp. rate 25-29			0.067	
			(0.167)	
Avg. unemp. rate 30-34				-0.213
				(0.001)
Intercept	-35.068	-30.772	-42.382	-19.996
	(0.005)	(0.007)	(0.001)	(0.130)
F-stat	9.56	9.85	10.00	10.67
Observations	3,424	3,710	3,236	2,798

Notes: P-values shown in parentheses. Column (1) is for all ages. Columns (2)-(4) are for age groups 20-24, 25-29, and 30-34, respectively. *Source:* National Longitudinal Surveys of Youth 1997 (NLSY97).

Table B.18: **Second-Stage for Earnings Returns Regressions with NLSY97**

	log of average earnings			
	(1)	(2)	(3)	(4)
Avg. hours worked HS	0.036	0.042	0.016	0.024
	(0.144)	(0.192)	(0.470)	(0.303)
Median real earnings 2000	0.000	0.000	0.000	0.000
	(0.496)	(0.062)	(0.733)	(0.306)
% white 2000	-0.334	-0.054	-0.237	-0.257
	(0.003)	(0.710)	(0.023)	(0.040)
Emp. rate 2000	-2.628	-4.790	-1.711	-2.919
	(0.101)	(0.014)	(0.289)	(0.003)
Teen share 2000	-1.360	-4.590	-1.863	-2.057
	(0.576)	(0.110)	(0.443)	(0.903)
% col. deg. 2000	0.847	0.728	0.835	0.714
	(0.000)	(0.005)	(0.000)	(0.002)
Sex	-0.177	-0.189	-0.175	-0.197
	(0.000)	(0.000)	(0.000)	(0.000)
White	-0.024	0.072	-0.147	0.080
	(0.752)	(0.452)	(0.054)	(0.341)
Black	-0.133	0.044	-0.266	-0.053
	(0.080)	(0.630)	(0.001)	(0.524)
Hispanic	-0.030	0.098	-0.143	0.077
	(0.694)	(0.306)	(0.065)	(0.360)
AFQT	0.000	0.000	0.000	0.000
	(0.031)	(0.873)	(0.007)	(0.000)
Avg. life unemp. rate	0.000			
	(0.976)			
Avg. unemp. rate 20-24		0.004		
		(0.585)		
Avg. unemp. rate 25-29			-0.000	
			(0.976)	
Avg. unemp. rate 30-34				-0.006
				(0.382)
Intercept	5.092	6.656	4.382	5.271
	(0.002)	(0.001)	(0.007)	(0.000)
F-stat	9.56	9.85	10.00	10.67
Observations	3,424	3,710	3,236	2,798

Notes: P-values shown in parentheses. Column (1) is for all ages. Columns (2)-(4) are for age groups 20-24, 25-29, and 30-34, respectively. *Source:* National Longitudinal Surveys of Youth 1997 (NLSY97).

Table B.19: **Ordinary Least Squares for Earnings Returns Regressions**

	log avg. lifetime earnings			
	(1)	(2)	(3)	(4)
Avg. hours worked HS	0.023	0.015	0.015	0.013
	(0.000)	(0.000)	(0.000)	(0.000)
Sex		-0.174	-0.175	-0.180
		(0.000)	(0.000)	(0.000)
White		-0.110	-0.131	-0.105
		(0.000)	(0.000)	(0.000)
Black		-0.100	-0.127	-0.124
		(0.000)	(0.000)	(0.000)
AFQT score		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Avg. life unemp. rate			-0.010	-0.008
			(0.000)	(0.059)
Median real earnings 1980				0.000
				(0.500)
% white 1980				-0.170
				(0.042)
% teen share 1980				-4.385
				(0.000)
% col. deg. 1980				1.710
				(0.000)
Intercept	2.636	2.651	2.802	3.029
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,923	3,796	3,794	3,056

Notes: P-values shown in parentheses. *Source:* National Longitudinal Surveys of Youth 1979 (NLSY79).

Appendix C Quantitative Model

C.1 Equilibrium Definition

A high school agent has state $\mathbf{s} = (h_s, h_e, a_s, a_e) \in \mathcal{S}^{hs} \equiv \mathbb{R}^4_{++}$, a college agent has state $(h_s, a_s, a_e) \in \mathcal{S}^u \equiv \mathbb{R}^3_{++}$, and an adult has state $\mathbf{x} = (h_o, a_o) \in \mathcal{S}^o \equiv \mathbb{R}^2_{++}$. Partition age into high school $\mathcal{J}^{hs} = \{1, 2, 3, 4\}$, college $\mathcal{J}^u = \{5, 6, 7, 8\}$, non-college working $\mathcal{J}^m = \{5, \ldots, J\}$, and college working $\mathcal{J}^s = \{9, \ldots, J\}$, with the college attendance decision occurring at the beginning of $j = 5$. A cohort of measure $1/J$ enters each period distributed according to a fixed entry measure Λ over $\mathcal{S}^{hs}$.

Let Φ_j be the measure of high school agents at age $j \in \mathcal{J}^{hs}$ on $\mathcal{S}^{hs}$. Let Ψ_j be the measure of college students at age $j \in \mathcal{J}^u$ on $\mathcal{S}^u$. Let $\tilde{\Phi}^m_j$ and $\tilde{\Phi}^s_j$ be the measures of non-college and college adults at ages $j \in \mathcal{J}^m$ and $j \in \mathcal{J}^s$, respectively, on $\mathcal{S}^o$. Let $g_u : \mathcal{S}^{hs} \to \{0, 1\}$ denote the college attendance policy (with $g_u = 1$ for attendance). Collect all measures as $\Omega = \big(\{\Phi_j\}, \{\Psi_j\}, \{\tilde{\Phi}^m_j\}, \{\tilde{\Phi}^s_j\}\big)$.

A stationary recursive competitive equilibrium is, value functions for teenagers $\{V^k, V^{hs}, V^u\}$, and adults $\{V^o_m, V^o_s\}$, policy functions for teenagers $\{g_{n_e}, g_{n_s}, g_u\}$, and adults $\{g_{n_o}, g_m, g_s\}$, firm labor demands $\{Y_l, Y_m, Y_s\}$, skill-prices $\{\omega_l, \omega_m, \omega_s\}$, and measures Ω such that,

1. Given skill-prices, value functions $\{V^k, V^{hs}, V^u\}$ solve the dynamic problems (10) and (11) and $\{g_{n_e}, g_{n_s}, g_u\}$ are the associated policy functions.

2. Skill-prices are equal to marginal products of aggregate labor inputs, $\frac{\partial F}{\partial Y_l}, \frac{\partial F}{\partial Y_m}, \frac{\partial F}{\partial Y_s}$.

3. Labor demand is consistent with the firm's optimization problem (16).

4. Given skill-prices, value functions $\{V^o_m, V^o_s\}$ solves dynamic problem (12) and $\{g_{n_o}\}$ is the associated policy function. Policy functions $\{g_m, g_s\}$ can be summarized by cut-off values (14) which define the occupational choice.

5. The labor market clears according to (17)-(19).

6. Given policies and skill-prices, Ω is generated from the entry cohort Λ under the laws of motion. Teenage states evolve by (6). At $j = 5$ the cohort splits by g_u into college students $\{\Psi_j\}$ and non-college adults. Adult ability is drawn on entry from (8), with human capital evolving by (12).

7. The entry cohort Λ, measures Ω, and skill-prices $\{\omega_l, \omega_m, \omega_s\}$ are stationary.

C.2 Computation

The adult dynamic program is solved by backward induction from the terminal conditions $V_m^o(j_o = 46, h_o, a_o) = 0$ and $V_s^o(j_o = 46, h_o, a_o) = 0$. Iterating backward to the first adult period and integrating over adult ability a_o and the labor-market luck shocks ϵ yields $\mathbb{E}_{a_o,\epsilon_o}\left[V^{hs}(j = 5, h_s, h_e, a_s, a_e)\right]$ and $\mathbb{E}_{a_o,\epsilon_s,\epsilon_o}\left[V^{u}(j = 5, h_s, h_e, a_s, a_e)\right]$, which summarize the continuation values that enter the teen problem. The college attendance decision is made at the end of the teen phase by comparing these two continuation values.

For all periods, we use a logarithmically spaced rectangular grid over the continuous state variables (h_e, h_s), rebuilt at each parameter evaluation so that it spans the range of states reachable under the current parameters. The initial distribution over states (a_e, a_s, h_s) and the distributions of the labor-market luck shocks ϵ are discretized on equal-probability quantile nodes following Kennan (2006). We interpolate next-period value functions using monotone (shape-preserving) piecewise cubic Hermite interpolation with a tensor-product extension to two dimensions. We use a shape-preserving scheme rather than an unconstrained cubic spline because the value function has kinks at two boundaries: the minimum wage threshold, and the college-attendance boundary. We preserve both kinks by interpolating the value function separately on each side of the relevant boundary and applying the threshold or the maximum at each integration node, so that the expectation is never taken through a smoothed kink.

At each state, we solve the interior problem and all relevant boundary problems, including voluntary nonemployment among teenagers whose productivity exceeds the minimum-wage threshold. The interior branch is solved by first evaluating the objective on a coarse grid to locate the basin of the optimum and then polishing with a Nelder-Mead search on a logistic reparametrization of (n_e, z) that enforces the box and simplex constraints. The constrained branch reduces to a one-dimensional search over leisure, which we solve using Brent's method. The policy functions g_{n_e} and g_z are stored, and the schooling decision is implied by $n_s = 1 - n_e - z$.

To simulate moments from the model, we take our vector of internally calibrated parameters Ξ and solve for the general equilibrium, defined as a fixed point in the skill-price vector $\omega = (\omega_l, \omega_m, \omega_s)$. Given the equilibrium decision rules, we simulate $N = 250{,}000$ agents. We first simulate cross-sectional moments and then re-solve and re-simulate the model to compute transitional moments, holding everything else fixed and applying a shock to θ. Baseline and counterfactual simulations share common random numbers, so that differenced moments reflect changes in behavior rather than sampling variation. The results are unchanged when increasing N.

To calibrate the model, we define the loss function to be minimized as $\mathcal{L}(\Xi) = \big(m(\Xi) - \hat{m}\big)'\mathbf{W}\big(m(\Xi) - \hat{m}\big)$, where $m(\Xi)$ is the vector of model-simulated moments, $\hat{m}$ is the vector of data-equivalent moments, and $\mathbf{W}$ is a weighting matrix. All empirical and model-generated moments are normalized to lie on the unit interval, $[0, 1]$, before computing the estimation objective, so that differences in units and scale do not mechanically affect their relative weight. We set the weighting matrix to the identity matrix. Computationally, we use the TikTak global optimization method from Arnoud et al. (2019), with 25,000 starting points and Nelder-Mead as the local optimizer over 100 points.

C.3 Additional Results

C.3.1 Output

In addition to distributional changes, the crowding out of teen workers by adults affects aggregate output. To quantify the mechanisms underlying the 1.48% increase in aggregate output between SS1 and SS3, *Table C.1* decomposes the output difference into six mechanisms: schooling and employment human capital at labor force entry, current teen labor input, college attendance and the associated lifecycle reallocation, adult occupational reallocation, and adult labor supply and on-the-job human capital accumulation. SS1 and SS3 share the same productivity parameter θ, and so the decomposition contains no direct productivity effect. For each mechanism, we combine its SS1 or SS3 value with alternative combinations of the remaining mechanisms, reconstruct individual lifecycle paths, aggregate effective labor supplied to teen, non-college, and college occupations, and evaluate output using the common production technology.[41] For example, to isolate the effect of changing high school graduates' initial employment human capital, h_e, we replace each individual's SS1 value of h_e with their SS3 value while holding skill prices, all other decision rules, and entering schooling human capital fixed. The new value of h_e changes initial adult human capital for individuals who do not attend college. The fixed policy functions are then evaluated at this altered state.

The increase in output is driven primarily by the college-choice response. Changes in college choices increase output by 3.12%, more than twice the total increase in output between SS1 and SS3. As teenagers face fewer opportunities to work and accumulate employment human capital, the non-college path becomes less attractive and additional teenagers attend college. Although these individuals forgo four periods of market production, college

[41] The contribution of each mechanism depends on the values of the other mechanisms. We evaluate all $2^6 = 64$ subsets and use these to compute the average marginal contribution of each mechanism across all possible orderings.

raises their schooling human capital. For the marginal individuals whose choices change, the resulting increase in post-college effective labor is sufficiently large to outweigh both the production forgone while enrolled and the reduction in non-college labor. Importantly, this increase in output is a quantitative result rather than a mechanical consequence of higher college attainment. It depends on the relative supplies of college and non-college labor and on the calibrated productivity and substitution parameters. With sufficiently small productivity gains from college or sufficiently large losses of non-college labor and production while enrolled, higher college attainment could instead reduce aggregate output.

Several other mechanisms offset this increase in output. Most significantly, adult occupational reallocation reduces output by 1.51%. The SS3 wage schedule induces more adults to work in teen occupations rather than in college or non-college adult occupations. This reallocation is costly, as adult human capital enters effective labor directly in college and non-college occupations, whereas only $\psi + \phi h_o$ units of human capital are used in production in teen occupations. Adults who move into teen jobs therefore use their accumulated human capital less intensively and simultaneously reduce labor supplied to the college or non-college sectors. A slight offset to this decline comes from changes in adult labor-leisure choices, which increase output by 0.1%. Many non-college agents enter employment with lower human capital and hence lower earnings. These agents respond by substituting away from leisure and toward labor supply and human capital production.

The reduction in teen work also lowers output through two additional channels. Lower current teen labor directly reduces output by 0.29%. More importantly, crowding out has a persistent effect beyond teenage years, limiting opportunities to accumulate employment human capital while in high school. The resulting reduction in h_e at adult entry lowers output by a further 0.18%. Thus, the loss of teen employment reduces production both contemporaneously and through lower subsequent worker productivity. That is, shocks originating in the adult labor market can affect aggregate production with a delay by changing the human capital with which today's teenagers enter the adult labor market. These losses are partially offset by greater accumulation of schooling human capital, with higher entering h_s raising output by 0.24%, as some teenagers crowded out of employment reallocate time toward schooling.

Table C.1: **Output Decomposition between SS1 and SS3**

Mechanism	**%Δ in Output from SS1**
Entering h_s	+0.24
Entering h_e	−0.18
Teen labor/leisure choice	−0.29
College choice	+3.12
Occupation choice	−1.51
Adult labor/leisure choice	+0.10
Total	+1.48

Notes: This table decomposes the change in output between the initial calibrated steady state (SS1) and the steady state isolating adult crowding out (SS3). Rows (1) and (2) capture changes in schooling and employment human capital, respectively, at adult entry. Row (3) captures changes in current teen labor input. Row (4) captures changes in college choices and the associated lifecycle allocation of labor. Row (5) captures the reallocation of adults across teen, non-college, and college occupations. Row (6) captures changes in adult labor supply and subsequent on-the-job human capital accumulation. Contributions are averaged over the $2^6 = 64$ possible subsets.

Appendix D Quantitative Calibration

D.1 Returns to Teen Employment Time

A central moment in our analysis is the return to teen employment. We causally estimate this return using geocoded NLSY data, as presented in *Section 4.2*. Our empirical strategy identifies the returns to working for teenagers whose behavior changes in response to economic conditions. We replicate this exercise in the model.

We perturb the low-skill price ω_l, which anchors the teen skill-price $\omega_l(\psi+\phi h)$, symmetrically by $\pm 1\%$ around its baseline equilibrium value, holding the non-teen skill-prices ω_m and ω_s fixed.[42] This is a partial-equilibrium experiment in which we re-solve only the teen problem, so teenagers re-optimize their employment time n_e and reallocate their residual time freely between schooling n_s and leisure z, while the adult continuation values and the adult leisure policy are held at their baseline values. Using identical ability draws, initial human capital, and shock paths across the up and down perturbations, we estimate the return to teen employment as the Wald ratio of the reduced-form earnings response to the first-stage hours response,

$$\hat{\beta}^{\text{IV}}_{\text{work}} = \frac{\mathbb{E}\left[\ln E \mid \omega_l^{+}\right] - \mathbb{E}\left[\ln E \mid \omega_l^{-}\right]}{\mathbb{E}\left[N_e \mid \omega_l^{+}\right] - \mathbb{E}\left[N_e \mid \omega_l^{-}\right]} \tag{D.3}$$

where $N_e = \sum_{j=1}^{4} n_{e,j}$ is cumulative teen work time, $\ln E$ is log average adult earnings, and $\mathbb{E}[\cdot]$ denotes the mean over the non-college sample.

This design mirrors our empirical IV in identifying the return for teenagers whose behavior changes with economic conditions. Raising ω_l relaxes the minimum wage eligibility screen $\omega_l(\psi+\phi h) \geq \bar{w}$, so the perturbation moves teen employment along both the intensive margin (hours) and the extensive margin (which teenagers work at all). The marginal entrants have lower working ability, so the average ability of working teens falls and the estimand recovers a local average return for these compliers, as in the empirical estimate.

D.2 Returns to Teen Schooling Time

The curvature parameter for schooling human capital, γ_s, directly governs the returns to schooling investment in terms of h_s^{data} (i.e., the effect of not working on h_s^{data}). The logic is similar to the effect of γ_e on earnings. The difference is that h_s^{data} is affected only by γ_s. Hence, we can identify γ_s by estimating the effect of working on schooling human capital

[42] The moment is unchanged under alternative perturbation sizes.

in the data and the model. In practice, we estimate the effect of the sum of hours worked during high school on schooling human capital at graduation. In the data, we estimate a version of equation (5) with h_s^{data} as the dependent variable, using the same IV strategy outlined in *Section 4.2*,

$$\log(h_s^{data}) = \delta_0 + \delta_1 E_i^S + \delta_2 X_i + \epsilon_i \tag{D.4}$$

Regression results are reported in *Tables F.2* and *F.3*. In the model, we estimate equation (5) with h_s^{model} as the dependent variable, using the same strategy as *Appendix D.1*.

D.3 Returns to Schooling Human Capital

To calibrate ζ in the model, we use equation (7),

$$h_o = \left(\alpha h_s^{\zeta} + (1-\alpha) h_e^{\zeta}\right)^{\frac{1}{\zeta}} \tag{D.5}$$

We regress the earnings of recent high school graduates who do not attend college on their accumulated h_s^{data}.[43] In practice, we select all 19-year-olds who do not attend college. We further restrict the sample to observations with positive earnings and full-time employment (i.e., 40 hours) at age 19. Finally, we drop observations without a complete transcript history. We run a simple OLS regression that also includes indicators for sex and race. To facilitate interpretation of the coefficient, we use the logarithm of both earnings and h_s^{data}. The coefficient of interest is 0.025, with a p-value of 0.074. We then estimate the same regression using simulated data from the model and match the coefficient.

D.4 Model Fit Robustness

Many parameters affect average hours worked by teenagers and the gap in hours worked between college and non-college graduates. However, because the alternative parameter available to jointly match these two moments is also preference based, and the teen leisure parameter κ_k cleanly changes these two moments while keeping the others unchanged, we vary κ_k in this robustness exercise. Lowering κ_k by 25.2% and holding all other parameters fixed produces an exact match of 230 for average hours worked by all teens, but overshoots the gap between college and non-college graduates, with a regression coefficient of -176 versus -134. *Tables F.6* and *F.7* report deviations for all moments. *Table D.1* shows that welfare results are quite similar across the two calibrations.

[43] As described in *Section 6*, h_s^{data} is the cumulative GPA-weighted sum of credits for each student.

Table D.1: **Welfare Changes between SS1 and SS3 – Robustness Analysis**

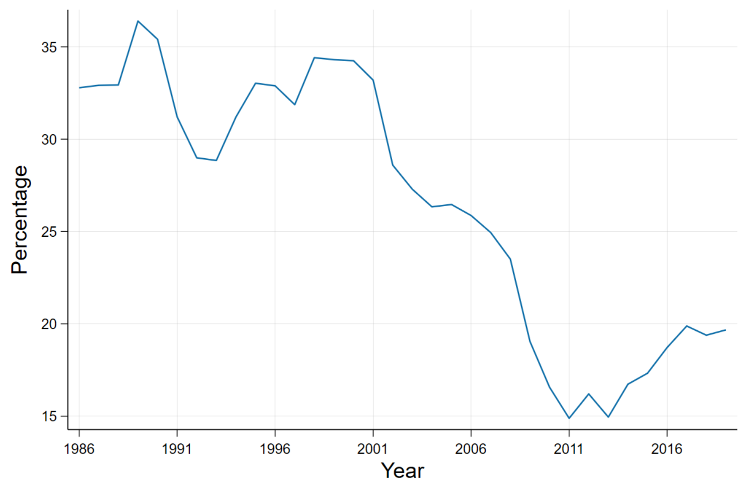
Grouping	**Δ Welfare – Robustness**	**Δ Welfare – Benchmark**
Worked as teenager	-0.810	-0.804
Did not work as teenager	-0.244	-0.407
Non-college graduate	-1.163	-1.223
College graduate	$+0.071$	$+0.126$
Whole economy	-0.643	-0.655

Notes: This table reports the realized welfare change between the benchmark calibrated equilibrium (SS1), and the counterfactual economy which isolates the effect of adult crowding out (SS3). Groupings are fixed in SS1. Welfare changes are reported for the benchmark calibrated economy, and a robustness check which exactly matched average hours worked for all teenagers.

Appendix E Figures of Teen Employment Decline

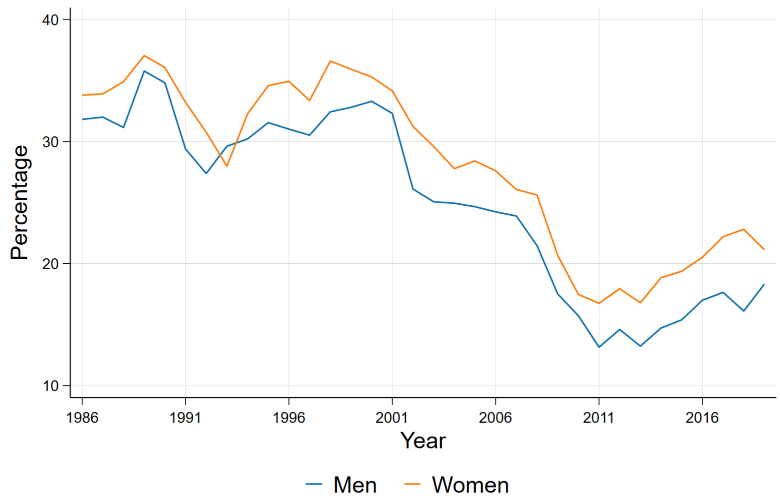
The figures in this appendix document the decline in teen employment across demographic groups and under alternative definitions of employment. Unlike *Figure 1*, these figures restrict the sample to teenagers aged 16-18 who are enrolled in high school, consistent with our main empirical specifications. Because the enrollment variable is available only from 1986 onward, we begin these figures in 1986.

Figure E.1: **Teen Employment Decline**



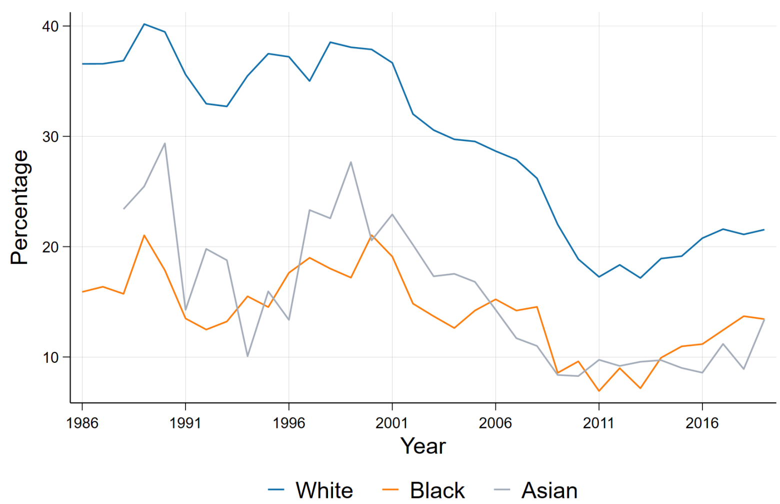
Notes: This figure plots the employment rate for 16-18 year-olds currently enrolled in high school. Employment is defined using the indicator variable for employment status. *Source:* Current Population Survey (CPS).

Figure E.2: **Teen Employment Decline by Gender**



Notes: This figure plots the employment rate for 16-18 year-olds currently enrolled in high school. Employment is defined to be those with positive hours worked over the preceding week. *Source:* Current Population Survey (CPS).

Figure E.3: **Teen Employment Decline by Race**

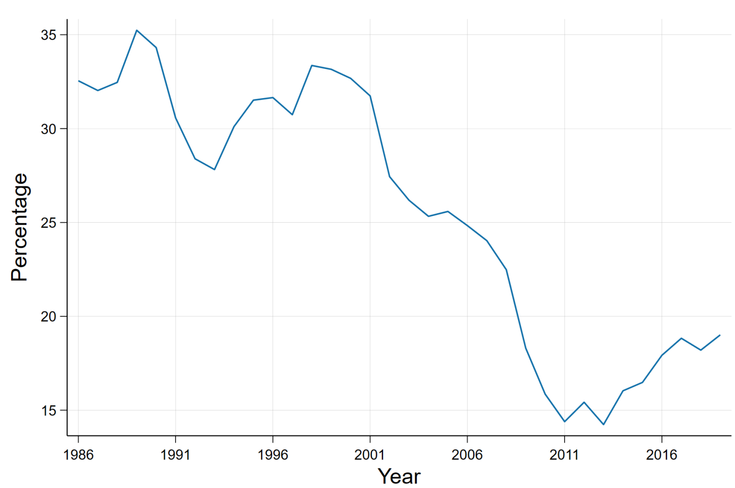


Notes: This figure plots the employment rate for 16-18 year-olds currently enrolled in high school. Employment is defined to be those with positive hours worked over the preceding week. *Source:* Current Population Survey (CPS).

Figure E.4: **Teen Employment Decline by Parental Earnings**

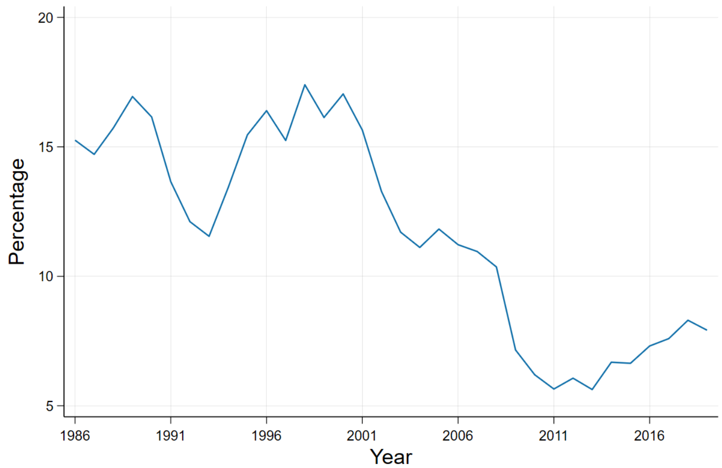
Notes: This figure plots the employment rate for 16-18 year-olds currently enrolled in high school. Employment is defined to be those with positive hours worked over the preceding week. *Source:* Current Population Survey (CPS).

Figure E.5: **Teen Employment Decline – Hours**



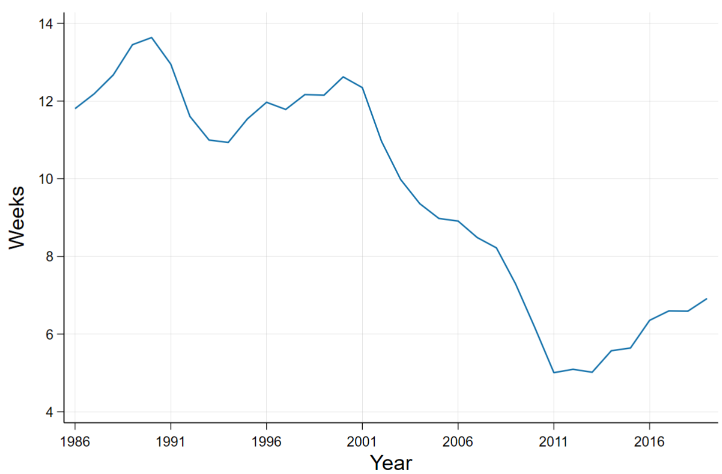
Notes: This figure plots the employment rate for 16-18 year-olds currently enrolled in high school. Employment is defined as those working positive hours. *Source:* Current Population Survey (CPS).

Figure E.6: **Teen Employment Decline – High Hours**



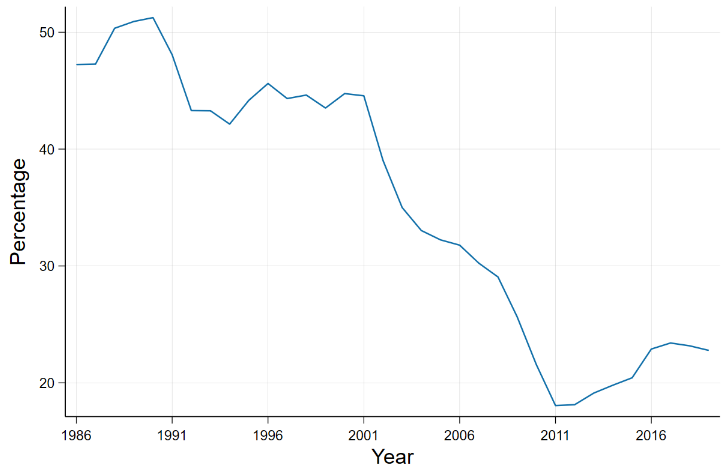
Notes: This figure plots the employment rate for 16-18 year-olds currently enrolled in high school. Employment is defined as those working greater than 15 hours per week. *Source:* Current Population Survey (CPS).

Figure E.7: **Teen Employment Decline – Average Weeks Worked**



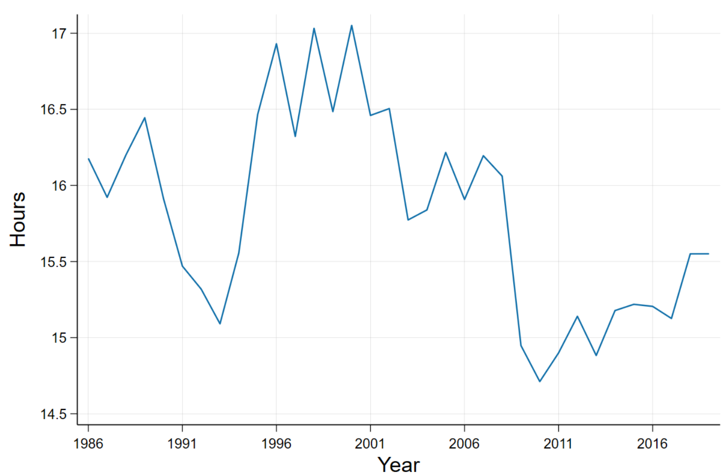
Notes: This figure plots the average weeks worked for 16-18 year-olds currently enrolled in high school. *Source:* Current Population Survey (CPS).

Figure E.8: **Teen Employment Decline – Usual Hours**



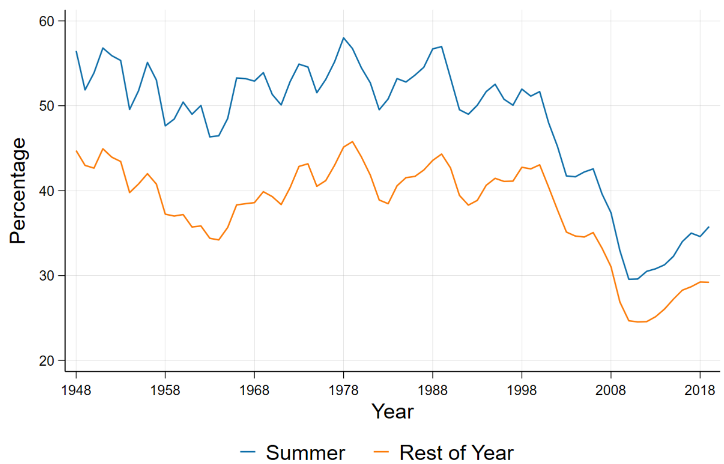
Notes: This figure plots the employment rate for 16-18 year-olds currently enrolled in high school. Employment is defined as positive usual hours worked per week. *Source:* Current Population Survey (CPS).

Figure E.9: **Teen Employment Decline – Average Hours of Workers**



Notes: This figure plots the average hours worked for employed 16-18 year-olds currently enrolled in high school. *Source:* Current Population Survey (CPS).

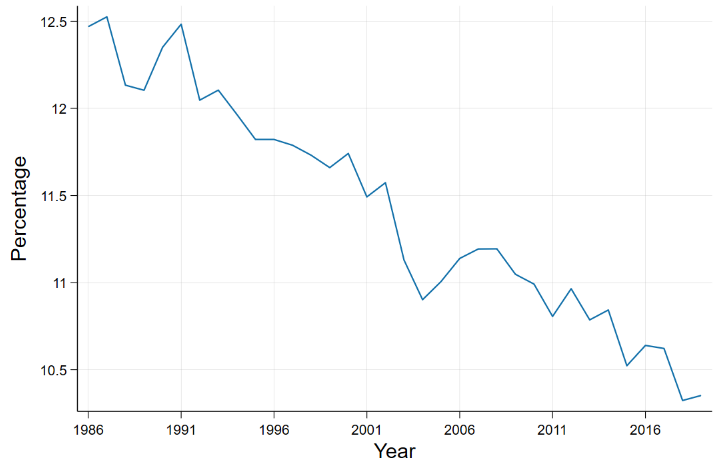
Figure E.10: **Teen Employment Decline – Summer vs. Rest of Year**



Notes: This figure plots the employment to population ratio for 16-19 year-olds. *Source:* Bureau of Labor Statistics (BLS).

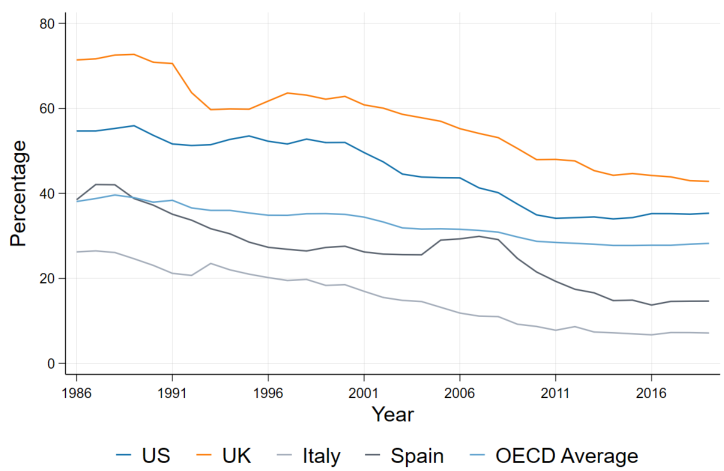
Appendix F Additional Figures and Tables

Figure F.1: **Total Teen Occupations to Population Ratio**



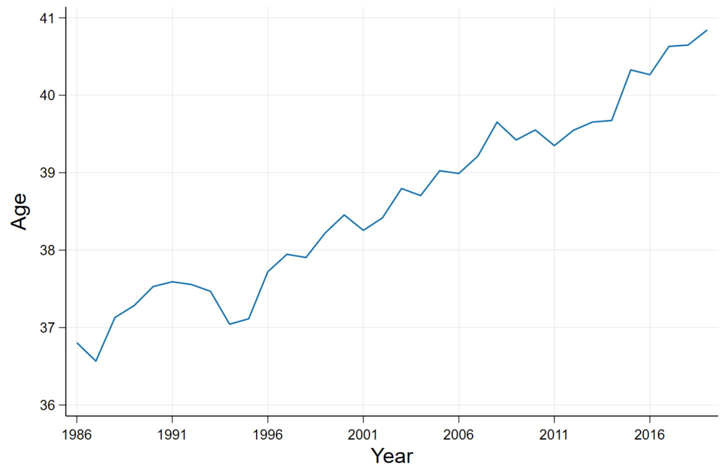
Notes: This figure plots the total number of individuals (age 16 and older) employed in teen occupations, relative to total population size. *Source:* Current Population Survey (CPS).

Figure F.2: **Teen Employment Decline – Across Countries**



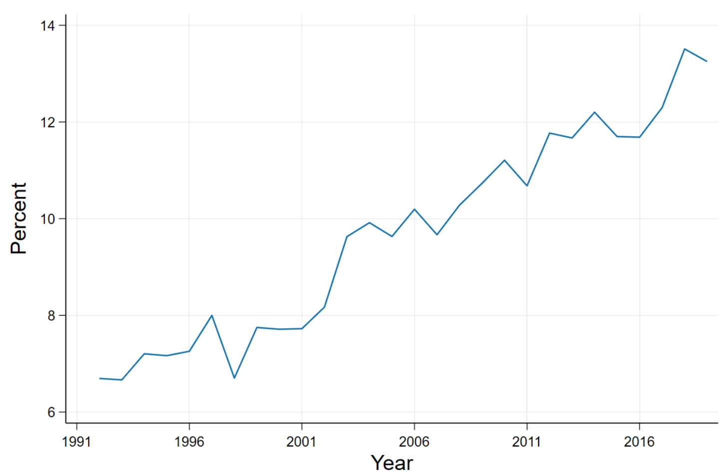
Notes: This figure plots the employment to population ratio for 16-19 year-olds. *Source:* Organization for Economic Co-operation and Development (OECD) tables.

Figure F.3: **Average Age of Adults in Teen Occupations**



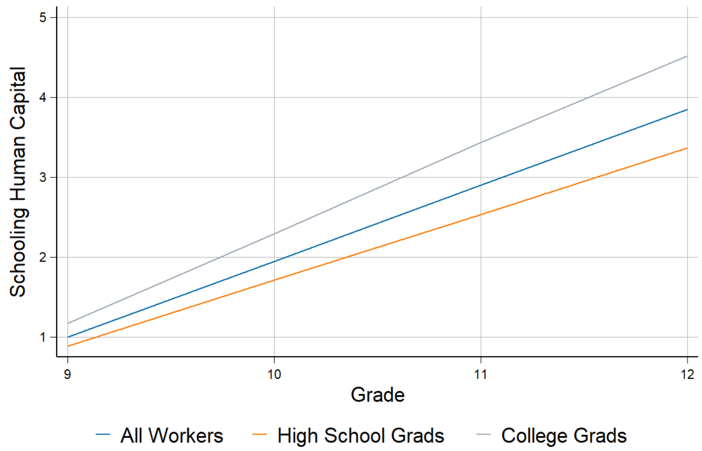
Notes: This figure plots the average age of adults 19 and older, not enrolled in an academic institution, who are employed in a teen occupation. *Source:* Current Population Survey (CPS).

Figure F.4: **College Attainment of Adults in Teen Occupations**



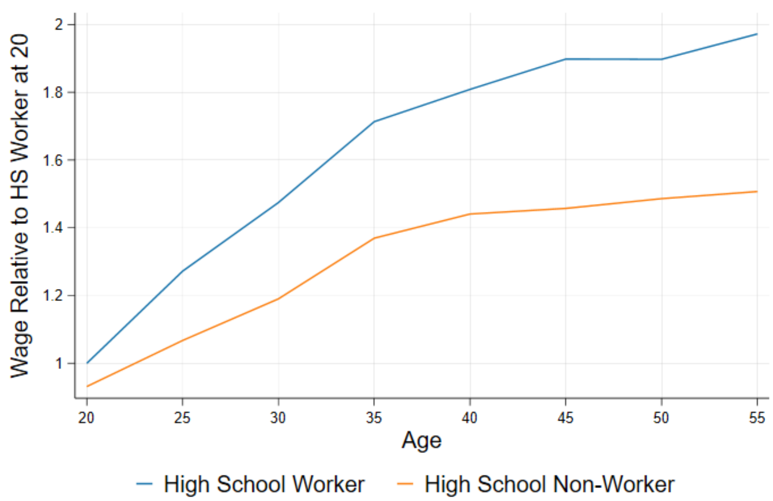
Notes: This figure plots the percentage of adults 19 and older, not enrolled in an academic institution, who are employed in a teen occupation and have at least a Bachelor's degree. *Source:* Current Population Survey (CPS).

Figure F.5: **Teen Schooling Human Capital Profiles**



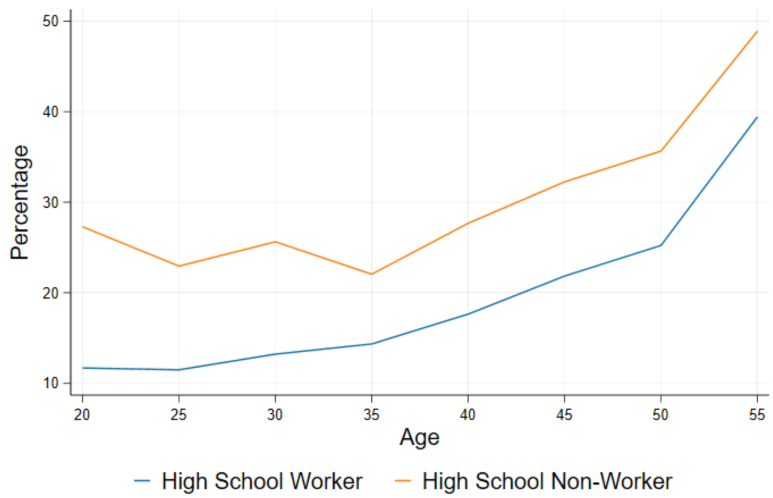
Notes: Schooling human capital is calculated as the cumulative GPA weighted total credits received during high school. The graph plots the average profile by grade, where we normalize the human capital for all workers in grade 9 to 1. *Source:* National Longitudinal Surveys of Youth 1997 (NLSY97).

Figure F.6: **Lifecycle Earnings by High School Work Status**



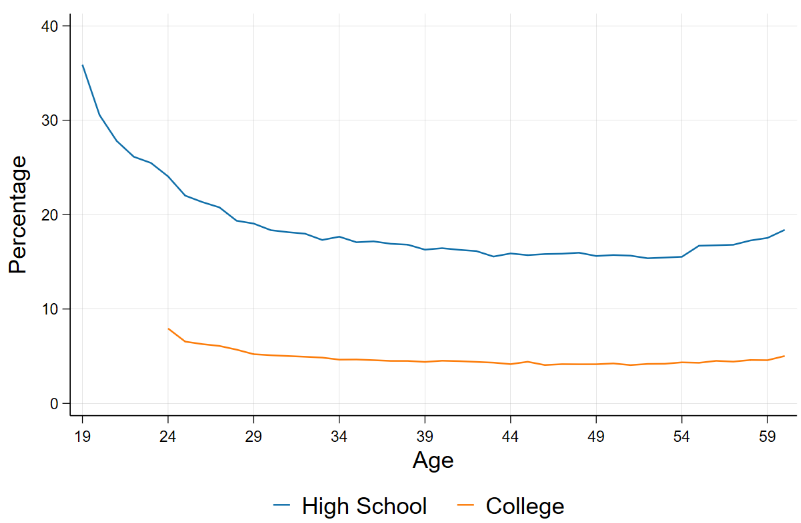
Notes: This figure plots real annual earnings from ages 20-55, for high school graduates who never attended college, split by those who worked while in high school and those who did not. Earnings are indexed to earnings of a 20-year-old who worked while in high school. Real earnings are calculated using the 2012 personal consumption expenditures (PCE) price index. *Source:* National Longitudinal Surveys of Youth 1979 (NLSY79).

Figure F.7: **Lifecycle Labor Force Non-participation by High School Work Status**



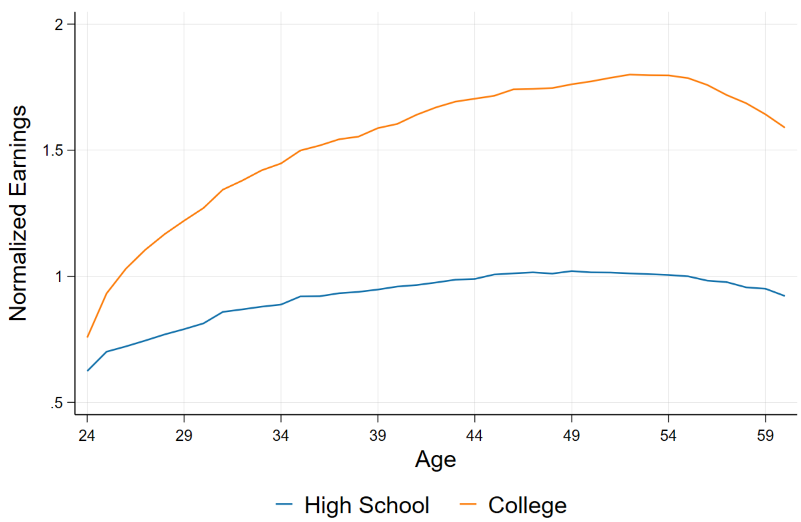
Notes: This figure plots the non-participation rate from ages 20-55, for high school graduates who never attended college, split by those who worked while in high school and those who did not. *Source:* National Longitudinal Surveys of Youth 1979 (NLSY79).

Figure F.8: **Data Lifecycle Employment in Teen Occupations by Education**



Notes: This figure plots the percentage of adults employed in a teen occupation, by adult age and education type from the data. *Source:* 2000 American Community Survey (ACS).

Figure F.9: **Data Lifecycle Earnings Profiles by Education**



Notes: This figure plots data average earnings profiles by high school and college education. High school earnings at age 55 are normalized to one. *Source:* 1980, 1990, and 2000 American Community Survey (ACS).

Table F.1: **Teen Occupations**

Cashiers
Laborers and Freight, Stock, and Material Movers, Hand
Chefs and Cooks
Food preparation and serving related workers, nec
Waiters and Waitresses
Childcare Workers
Counter Attendant, Cafeteria, Food Concession, and Coffee Shop
Retail Salespersons
Janitors and Building Cleaners
Agricultural workers, nec
Sales and Related Workers, All Other
Food Preparation Workers
Telemarketers
Stock Clerks and Order Fillers
Receptionists and Information Clerks
Grounds Maintenance Workers
Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
Construction Laborers
Cleaners of Vehicles and Equipment
First-Line Supervisors of Food Preparation and Serving Workers

Notes: This table reports the top 20 teen occupations that are aggregated to define a teen occupation. *Source:* Current Population Survey (CPS).

Table F.2: **First-Stage Schooling Human Capital Regressions**

	Avg. hours worked HS		
	(1)	(2)	(3)
Teen emp. rate 2000	9.353	9.423	5.332
	(0.000)	(0.000)	(0.005)
Sex	-0.382	-0.385	-0.386
	(0.013)	(0.012)	(0.012)
White	0.756	0.744	0.651
	(0.378)	(0.386)	(0.448)
Black	0.117	0.121	0.014
	(0.892)	(0.889)	(0.987)
Hispanic	0.292	0.297	0.202
	(0.738)	(0.733)	(0.818)
AFQT score	0.000	0.000	0.000
	(0.086)	(0.070)	(0.058)
% col. deg. 2000		-1.592	-2.104
		(0.189)	(0.343)
Median real earnings 2000			0.000
			(0.691)
% white 2000			0.602
			(0.620)
Emp. rate 2000			23.665
			(0.013)
Teen share 2000			32.466
			(0.066)
Intercept	0.621	0.945	-22.415
	(0.504)	(0.326)	(0.014)
F-stat	86.81	87.94	15.12
Observations	3,096	3,096	3,096

Notes: P-values shown in parentheses. *Source:* National Longitudinal Surveys of Youth 1997 (NLSY97).

Table F.3: **Second-Stage Schooling Human Capital Regressions**

	GPA weighted HS credits		
	(1)	(2)	(3)
Avg. hours worked HS	-0.013	-0.013	-0.047
	(0.020)	(0.022)	(0.040)
Sex	0.079	0.078	0.065
	(0.000)	(0.000)	(0.000)
White	0.080	0.079	0.096
	(0.075)	(0.076)	(0.134)
Black	0.037	0.037	0.031
	(0.413)	(0.411)	(0.612)
Hispanic	0.038	0.038	0.042
	(0.399)	(0.397)	(0.504)
AFQT score	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
% col. deg. 2000		-0.061	-0.214
		(0.335)	(0.242)
Median real earnings 2000			0.000
			(0.755)
% white 2000			0.057
			(0.573)
Emp. rate 2000			1.773
			(0.158)
Teen share 2000			1.241
			(0.504)
Intercept	0.310	0.323	-1.307
	(0.000)	(0.000)	(0.278)
F-stat	86.81	87.94	15.12
Observations	3,096	3,096	3,096

Notes: P-values shown in parentheses. *Source:* National Longitudinal Surveys of Youth 1997 (NLSY97).

Table F.4: **Externally Calibrated Parameters**

Parameter	**Description**	**Value**	**Source**
Preferences			
J	Model periods	45	Biological life 15-59
β	Discount factor	0.95	Standard
Teens			
$\bar{c}$	Teen fixed consumption	0.35	Literature
σ_ϵ^2	Luck shocks	0.05	Literature
$\bar{n}_e$	Max hours working	0.50	Teen labor laws
$\bar{n}_s$	Min hours schooling	0.43	Standard schooling day
Adults			
γ_o	Adult human capital curvature	0.30	Literature
δ_o	Adult human capital depreciation	0.02	Literature
Production			
σ	College/non-college CES parameter	0.31	Literature

Notes: This table gives model parameters, a brief description of their role, the externally calibrated value, and the source.

Table F.5: **Internally Calibrated Parameters**

Parameter	**Value**	**Description**
Initial distributions		
$\sigma^2_{a_e}$	0.0601	Employment ability variance
$\sigma^2_{a_s}$	0.0202	Schooling ability variance
$\sigma^2_{h_s}$	1.04	Initial schooling human capital variance
μ_{a_e}	-3.69	Employment ability mean
μ_{a_s}	0.197	Schooling ability mean
Teens		
κ_k	0.218	Preference over leisure
γ_e	0.0845	Working human capital production
γ_s	0.673	Schooling human capital production
α	0.217	CES human capital aggregator share
ζ	0.0345	CES human capital aggregator elasticity
College		
γ_u	0.447	College human capital production
$\bar{c}_u$	0.0461	Fixed college consumption
Adults		
κ_o	2.26	Preference over leisure
μ_{a_o}	-1.94	Adult mean level shifter
$\sigma^2_{a_o}$	0.0543	Variance of adult ability
λ	0.946	Share of schooling ability
ψ	0.454	Fixed human capital, teen occupations
ϕ	0.586	Fraction human capital, teen occupations
Production		
ν	0.586	Production CES elasticity
A_l	0.462	Production CES productivity
A_m	0.289	Production CES productivity
θ Shock	0.0876	Percent shock to adult productivity
w_{min}	3.23	Minimum Wage

Notes: This table gives model parameters, the internally calibrated value, and a brief description of their role.

Table F.6: **Model Moment Deviations – ACS**

Moment	**% Deviation**
Teens	
Decline regression coefficient	+8.3
Share teens working	+11.7
Average hours worked, all teens	+30.8
P90 to P10 earnings ratio	+2.1
Schooling-time share	+10.6
Adults	
Share working in teen occ.	−1.9
Share with college degree	−0.4
Share working in teen occ. – college	+0.0
Share working in teen occ. – non-college	−2.2
Δ in adults working teen occ.	+6.2
College lifetime earnings growth	−0.65
Non-college lifetime earnings growth	−0.54
Leisure rate	−0.04
Earnings	
College/non-college, all adult	+0.4
College/non-college, 24-29	+0.6
Non-teen occ./teen occ.	+0.2
Adult/teen, teen occ.	−17.0
Earnings regression	−22.1
Minimum wage/avg. Teen wage	+0.4

Notes: This table reports the model moment deviations between the benchmark calibration and robustness analysis in *Appendix D.4*.

Table F.7: **Model Moment Deviations – NLSY**

Moment	**% Deviation**
Teens	
Returns to employment on earnings	−25.8
Returns to schooling on grades	+8.7
% Growth of h_s^{data}, grade 9-12	+5.6
Returns to employment on h_s	−1.3
SD($h_s^{data}(Grade8)$)/Mean($h_s^{data}(Grade8)$)	−1.3
College to non-college hours regression	−21.9

Notes: This table reports the model moment deviations between the benchmark calibration and robustness analysis in *Appendix D.4*.