Declining Teen Employment: Causes and Consequences*

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Abstract

Employment among high school students in the United States has fallen by 50 percent since the late 1990s. We provide causal evidence attributing the majority of this decline to crowding out by adults. To determine the consequences of this decline, we begin by estimating the effect of teenage employment on lifecycle wages. Among those who do not attend college, adolescents who worked earn significantly higher wages. We then develop a general equilibrium model in which teenagers allocate time between human capital accumulation on-the-job and in school, while adults choose between "teen" and "non-teen" occupations. Crowded-out teenagers suffer substantial income and welfare losses, though some substitute toward college, partially offsetting these effects. A decomposition exercise shows that minimum wages are central to transmitting rising adult competition into lower teen employment. Vocational training policies can mitigate these adverse effects for crowded-out teenagers.

JEL Codes: J24, O15, O33

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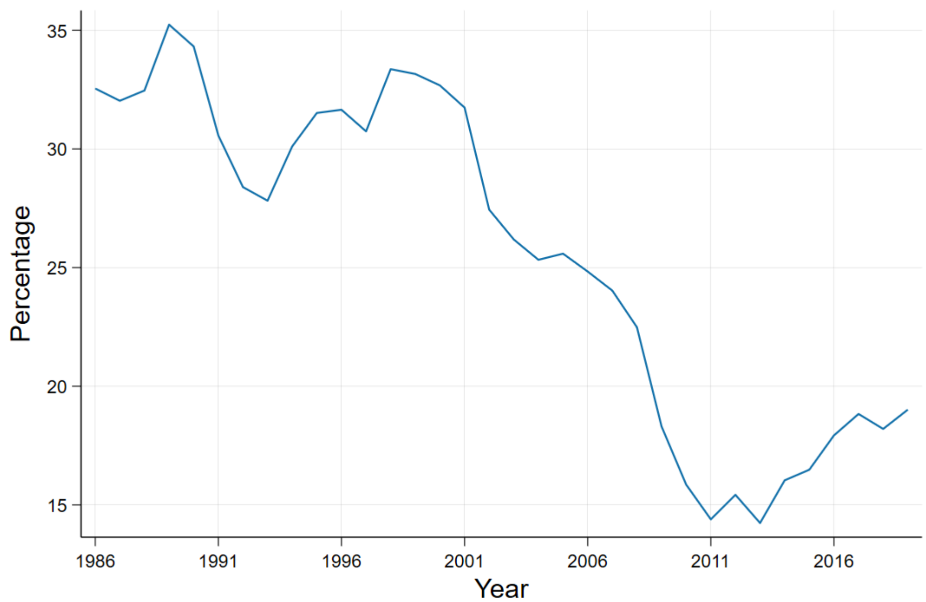
1 Introduction

Over the last 30 years, teen employment has declined by almost 50%. Historically, employment among teenagers enrolled in high school ranged between 30-40%, 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 15-18 year olds currently enrolled in high school.[1] This paper studies three aspects of this dramatic decline: (1) What are the underlying macroeconomic causes? (2) What are the implications for human capital accumulation and lifecycle earnings of teenagers? (3) How do minimum wage and education policies shape the effects of declining teen employment? We answer these research questions both empirically and quantitatively. The analysis combines reduced form identification with a quantitative general equilibrium framework, linking causal evidence from microdata to aggregate welfare and policy implications.

Figure 1: **Declining Teen Employment Rate**



Notes: This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined to be those with positive hours worked over the preceding week. We begin our sample in 1986 as the high school enrollment variable is not available prior to 1986. *Source*: Current Population Survey (CPS).

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

We begin the empirical analysis by presenting aggregate descriptive statistics that strongly suggest demand-side explanations, specifically the crowding out of teenagers by adults. We find that the number of adults working in occupations typically held by teenagers (e.g., retail, food service, and basic clerical work) increased sharply after 2000, while relative wages in these same occupations declined. This pattern implies greater competition for teen jobs originating from adults, rather than adults filling positions vacated by teenagers for supply-side reasons, such as substitution toward leisure activities (e.g. video games as in Aguiar et al., 2021), or stricter youth labor laws. Instead, we provide evidence that deteriorating adult labor market opportunities stemming from recessions, manufacturing decline, and job polarization have pushed adults into lower-skill service jobs.[2]

To further develop these results, we proceed to a more rigorous analysis to identify the causal effect of adult crowding out on the decline in teenage employment. We do so by exploiting geographic variation across U.S. commuting zones using data from the Census and the American Community Survey (ACS). Because ordinary least squares (OLS) estimates are likely biased, we employ an instrumental variables (IV) regression strategy.

Specifically, we construct Bartik-style instruments based on lagged occupational, age, and education compositions, which all follow a similar logic. At the national level, two post-2000 recessions, manufacturing decline and job polarization force some adults into less affected service jobs that were previously performed by teenagers. We use the fact that the occupations and demographics of adults most likely to transition into teen jobs are unequally distributed across U.S. commuting zones. The instrument exogeneity relies on the initial distributions being orthogonal to supply and other demand factors that could drive the changes in teenage employment. This allows us to identify the causal effects of adult crowding out on teenage employment. Across all specifications, the estimates reveal a large and significant negative effect of adult employment in teen jobs on teen employment. A back-of-the-envelope calculation implies that adult crowding out explains almost 60% of the total decline in teenage employment between 2000 and 2010. Moreover, increased adult presence in teen jobs depressed wages for both adults and teens, consistent with a demand-driven mechanism. To assess the full contribution of the underlying shocks that drive adults into teen jobs to the decline in teenage employment, incorporating all general equilibrium adjustments, we use our quantitative model.

Before moving to our quantitative model, we first determine the lifecycle wage returns to employment while in high school. Prior work such as Light (2001) and Ruhm (1997) finds

[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.

positive returns, while Hotz et al. (2002) or Ashworth et al. (2021) find none. We reconcile this discrepancy by documenting substantial heterogeneity in effects. Using geocoded National Longitudinal Survey of Youths (NLSY) data, we instrument for individual high-school work experience with local teen-employment rates, which are uncorrelated with unobserved individual abilities and preferences that might drive employment decisions and later-life income. We find that a one hour increase in average weekly hours worked is associated with 4% higher average wages over the lifecycle of workers who do not attend college, but no significant effect for those who do. Hence, teen work experience acts as an important form of on-the-job human capital accumulation for teenagers not college-bound. Combined with our first finding, this implies that teens are driven out of work that would give them considerable positive returns later in life.

Motivated by these findings, we develop a general equilibrium overlapping generations model. In the model teenagers differ in their ability to accumulate human capital through schooling, as in Ben-Porath (1967), or work experience in a learning-by-doing fashion. They then decide on the time spent on either activity. Adults choose between working in "adult" or "teen" occupations. A negative productivity shock to adult occupations, which captures the joint effects of recessions and structural change, drives adults into teenage occupations. This leads to the "crowding out" we identify in our empirical section. Importantly, crowding out interacts with existing labor market frictions. To capture this, the model includes a minimum wage, an important friction in the labor market for low-skill and particularly young workers (Neumark and Shirley, 2022; Clemens and Strain, 2025). Increased competition from adults reduces potential teenage wages, causing some to fall below the minimum wage and leading to unemployment.

Importantly, our model successfully captures the three essential elements identified in the data: (1) positive returns to teen employment, (2) adults increasing employment in teen occupations as a result of an aggregate shock, and (3) teens reducing employment as a result of adult crowding out. We discipline the parameters governing (1)-(3) by simulated method of moments to match our causal estimates on the returns to teen employment and crowding out of adults.

The calibrated model then allows us to quantify the aggregate contribution of the underlying shocks driving crowding out and to compute the aggregate changes in total output and the income distribution, taking into account full general equilibrium effects. It enables us to assess the income and welfare effects for a heterogeneous set of teenagers. To better understand the mechanisms that drive these changes, we are able to decompose (3) into separate channels through which the crowding out operates. Namely, current consumption, future earnings and college decision, and the minimum wage. Finally, guided by our model decompositions, we consider two main policy counterfactuals. We show the importance of frictions by comparing our baseline minimum wage economy with an economy without frictions and we introduce vocational schooling policies.

Overall, our model explains approximately 75% of the decline in teenage employment between 2000 and 2010. This is larger than the direct crowding out effect we isolate in the data, which is roughly 60% of the decline. The underlying productivity shock to adult occupations reduces all wages in general equilibrium beyond the direct crowding out effect, leading to an additional decline in teenage employment. In the model, we find that income and welfare losses are concentrated among teenagers who no longer allocate any of their time endowment toward employment. While the average lifetime income loss for all types of teenagers that worked in 2000 is approximately 6%, the negative effect for those who are no longer able to work is as large as 26%. This is mitigated for teens who successfully adjust their human capital investments towards schooling (and possibly college attendance). On aggregate, this implies rising income inequality and falling total output.

We then decompose the fall in teenage employment into its three channels. We find that changes in current teen wages play a small role in changing the incentives of teenagers to work, since the consumption they can afford from their own wages is only a small portion of the overall consumption that they receive from their parents. In contrast, the interaction of falling wages and a positive minimum wage accounts for almost half of the decline in teen employment. The other half is accounted for by changes in future relative wages that increase the returns to a college degree, which leads some teenagers to focus more on school and to supply less labor. As we have shown, it is especially the teenagers crowded out through frictions that are adversely affected. The fact that approximately half of the decline that we can explain is accounted for by the minimum wage then underscores the significance of the decline in teen employment and the importance of policy.

Guided by these results, we investigate how minimum wage and schooling policy shape the consequences of employment decline. To quantify the importance of the minimum wage friction, we solve an economy without it. Income and welfare losses are now only around half as large on average and almost all teenagers who do not work anymore now go to college. Finally, we simulate an optional vocational training program where some fraction of time spent in school can be used to accumulate human capital comparable to work experience. This policy is able to mitigate the welfare losses for less academically skilled teenagers. It gives teenagers who benefit the most from the practical work experience the opportunity to foster these skills even when employment options are reduced.

Prior work studying declining teen employment is surprisingly sparse. Aaronson et al.

(2006) discuss potential drivers for changes in the teen employment rate before the large trend break in 2000, without establishing causal effects. More recent work includes Smith (2012) and Neumark and Shupe (2019). Both papers focus on demand side factors. Smith (2012) argues that one factor contributing to this decline was increased competition from immigrants. Neumark and Shupe (2019) focuses on the effect of minimum wage *increases*.

While the analysis and findings of these two papers are complementary to our own, our approach differs in important ways. First, we focus on different time variation, and address the clear macroeconomic trend. Smith (2012) obtains identification through the pre-2000 period, and Neumark and Shupe (2019) exploit year by year changes without any relation to an initial period. We focus on variation stemming from the long run change. Second, these papers focus on specific individual explanations of the decline. While we also do so, our focus is to establish significant crowding out of teens by adults at a higher level, in order to motivate our quantitative framework. Finally, our paper is the first to study declining teenage employment in a quantitative general equilibrium model, allowing us to assess both the causes and consequences of this decline, decompose its mechanisms, and conduct policy analysis to rectify welfare losses.

More broadly, the 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 get crowded out of their first jobs when adults are pushed into competing 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 wages and employment among non-college workers. Finally, the model speaks to debates on minimum wages and vocational training (Neumark and Shirley, 2022; Dustmann and Schönberg, 2012) by quantifying which policies worsen or offset the welfare losses associated with declining teen employment.

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

2 Data

We combine information from three data sources: the Current Population Survey (CPS), the Census and American Community Survey (ACS), and the confidential geocoded versions of the National Longitudinal Surveys of Youth (NLSY).[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 Census and ACS for our regression analysis of the causes of the decline in teenage employment, given that this analysis requires larger samples. We use the confidential geocoded NLSY79 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, and the weekly Work History Data Files allow us to measure hours worked while enrolled in school. Further details on data sources are reported in *Appendix A*.

2.1 Sample Selection and Variable Definition

We keep the basic sample selection constant throughout all data sets whenever possible. All analysis for teenagers is for those aged 15-18 and currently enrolled in high school. In the baseline, we define an individual as employed if they report positive hours worked.[4] When we require earnings data, we focus on income from wages and salaries.

To investigate the crowding out of teenage workers by adults, we first define a "teen occupation". To do so we use the CPS-ASEC and begin by ranking all 4-digit census occupation codes by the share of all employed teenagers working in each occupation code for 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 a teen occupation. The list of top 20 occupations is stable over time and not affected by the employment changes after 2000.[6] This list of occupations captures approximately 75% of all employed teens. Cashiers is the highest-ranked occupation, employing approximately 15% of all teen workers, followed by food service and retail sales jobs.

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.

[3]The CPS, Census, and ACS data are made available by the Integrated Public Use Microdata Series.

[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 schemes of the Census Bureau 2010 occupation codes. See *Table D.6* in *Appendix D* for the complete list of occupations.

[6]*Appendix B.2* reports robustness checks with different time periods. *Appendix B.2* also reports robustness checks with alternative definitions of teen occupations. All our main results remain unchanged.

3 Empirical Analysis: Causes of Employment Decline

We start by presenting our empirical analysis, which we use both to motivate and to calibrate the quantitative model. This section investigates the causes underlying declining adolescent employment. The effects of teen employment on later-life earnings and employment outcomes are established 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 reduced supply of labor originating from teens, and demand-side factors would entail a reduced demand for teen labor originating from firms. 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.

We emphasize a demand-side explanation driven by adult workers crowding out teens, originating from some aggregate productivity shock. Adults crowd out teen labor when employment and earnings opportunities deteriorate elsewhere. A variety of shocks to specific adult workers have been studied for the period of interest, including job polarization, recessions, trade competition, and structural change. We confirm that these phenomena drive adults to take teen jobs.

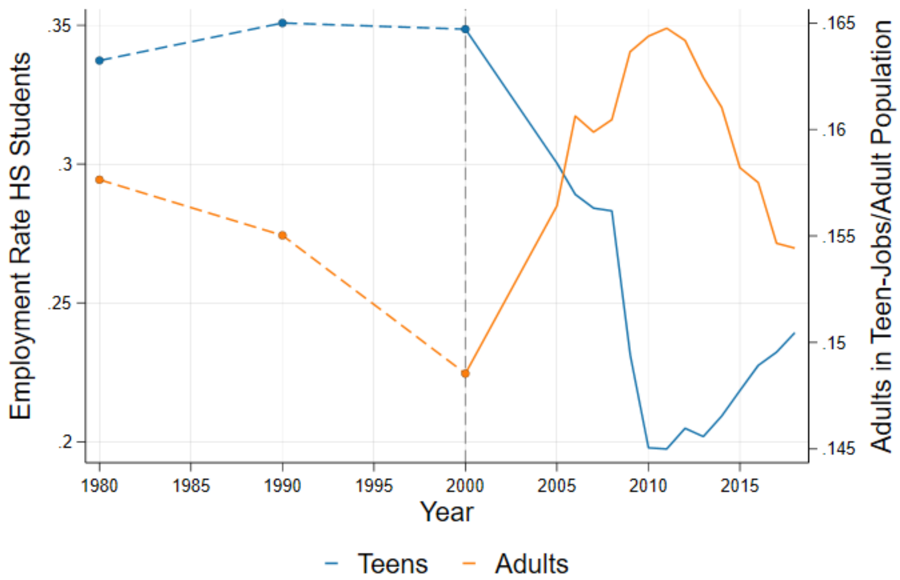
3.1 Descriptive Statistics

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 our instruments laid out 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 positions declines. Beginning in the early 2000s, there is a sharp trend break in both adults and teens employed in teen occupations. Adults cease leaving teen occupations and begin to enter them, while teens sharply begin to exit. This implies a marked substitution from teen to adult labor within teen occupations.

Figure 2: **Adults Entering Teen Occupation**



Notes: The left scale plots the employment rate of teenagers aged 15-18 and currently enrolled in high school. The right scale 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, not enrolled in high school or college. Employment is defined as positive hours worked in the preceding week. *Source*: Census and American Community Survey (ACS).

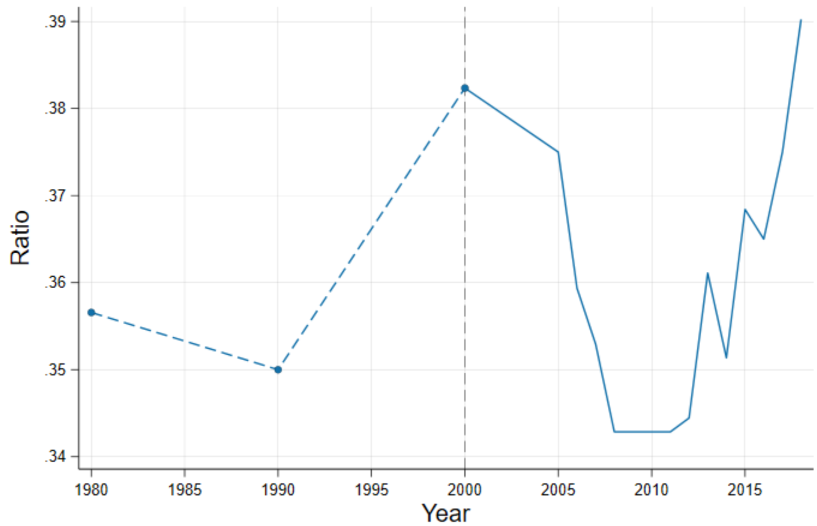
It is unclear whether the substitution from teen labor to adult labor stems from demand or supply factors. *Ceteris paribus*, a large supply shock generating *Figure 2* would require wages in teen occupations to be rising. *Figure 3* plots real median wages in teen occupations relative to real median 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.[7] This motivates further investigation of adult labor crowding out teens as the source of the decline, and rules out an explanation *primarily* driven by supply-side factors.

In *Appendix B.1*, we formalize this argument 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. The IV strategy mirrors the one discussed in *Section 3.2*.

We conclude this section with a brief discussion of possible supply-side explanations. The

[7] *Appendix D* conducts robustness analysis of *Figure 3* and provides additional earnings figures consistent with a demand shock.

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



Notes: This figure plots the ratio of median annual wages in teen occupations to those in non-teen occupations for ages 15 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*: Census and American Community Survey (ACS).

first set of explanations fall under changes in teen time use. Perhaps teens begin placing a higher value on leisure activities, with the commonly cited culprit being video games. The argument for video games overwhelmingly applies to male teenagers. *Figure D.2* shows that the decline in teen employment is equally pronounced for male and female teenagers. More generally, technological change might pull teens into college independently of any crowding out. We cannot differentiate this using aggregate data. Our causal regression strategy will ensure that our results are not confounded by such pull factors.

A second explanation is an income effect, whereby parents generally become wealthier over time. This could cause teens to not "need to" work. *Figure D.4* shows that the decline in teen employment is quite similar across different income levels, suggesting this is unlikely to be the case. Finally, a third explanation could be changes to restrictions on teen employment. Teen labor laws have been remarkably consistent across regions and over time, and we do not consider this as a factor explaining the decline in teen employment.

3.1.2 Determinants of Adult Crowing Out

In order to motivate our empirical strategy, we first present evidence for the notion that large economy-wide trends drive adult workers into teen occupations. We can then use the characteristics of those adults primarily exposed to these shocks to build instruments

Table 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 brackets. The dependent variable is the share of adults working in teen occupations. *Source*: American Community Survey (ACS).

that exploit the differential distribution of workers with these characteristics throughout the United States.

We start by focusing on changes in the employment rate to proxy for the effects of business cycle fluctuations (as in Yagan (2019)) and the manufacturing decline.[8] We use data from the American Community Survey (ACS) to investigate the effect of these demand factors (D) using commuting zone (c) and time (t) variation by estimating OLS regressions

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

Here, X controls for median income and demographics within commuting zones, and θ_t and ψ_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 (1) using the years 2000 and 2010, which is the period of the largest decline in teen employment.[9] *Table 1* shows that both factors are significant explanations for adults working in teen occupations. Commuting zones that experience negative employment shocks or a decline in manufacturing see more adults take up teen occupations.

Next, we investigate the characteristics of adults entering teen occupations and the types of occupations they come from. Both factors will be used to inform our IV regression analysis in *Section 3.2*. Starting with the occupations adults originate from, we use the linked monthly CPS data to observe transitions of adults in and out of teen occupations.

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

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

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 two 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 in the 1990-2000 and 2000-2010 periods. We take the difference of these two "net inflows" measures to obtain a *change* in flows into teen occupations. *Table 2* reports the occupations with the ten highest net inflows into teen occupations and the ten highest changes in net inflows into teen occupations.

The lists of occupations from which workers move into teen occupations are largely comprised 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, like farming, and positions affected by offshoring, such as sales workers. 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. In general, we observe that middle-aged (born 1955-1969) and college-educated workers are relatively more likely to enter teen occupations when transitioning from another position.

We hypothesize (and descriptive evidence confirms) that when faced with a common shock, older workers are more likely to transition into non-participation than middle-aged workers. Moreover, younger workers are more likely to retrain and switch career paths. We formalize this logic in *Section 3.2* with an IV regression analysis.

After 2000, adults working in teen occupations became more highly educated, as we document in *Figure D.21*. 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.[10] 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 a sharp rise in non-participation rates over this period among workers with lower 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. The same shocks affected those without a college education more severely, since they are unable to obtain employment *even in* teen occupations.

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

Table 2: **Top 10 Occupations with Largest Net Inflows into Teen Occupations**

Net Inflows (2000-2010)	Δ Net Inflows (1990-2000 & 2000-2010)
Mechanics	Admin support
Motor vehicle operators	Farmers
Sales supervisors	Misc. machine operators
Misc. machine operators	Printing machine operators
Health service	Health service
Admin support	Teachers
Sales, commodities	Sales supervisors
Teachers	Personal Service
Private household	Precision workers
Secretaries, typists	Mail distributors

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

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. To further investigate the degree to which adults competing with teenagers since 2000 have contributed to the decline in aggregate teen employment, we use cross-commuting-zone variation in an instrumental variables regression setting. Throughout this section, we use data from the Census and ACS. Our main relationship of interest is given by

$$\text{TeenEmpShare}_{c,t} = \beta \left(\frac{\text{Adults in Teen Jobs}}{\text{All Adults}} \right)_{c,t} + \gamma X_{c,t} + \phi_c + \theta_t + \epsilon_{c,t} \tag{2}$$

where $X_{c,t}$ is a vector of controls, ϕ_c are commuting zone fixed effects, and θ_t are time fixed effects. The dependent variable is the share of 15-18 year olds enrolled in high school who are employed. Given the fixed effects, we exploit commuting-zone-by-time variation to identify the coefficients of interest. A more natural formulation is given by the first-differenced equation

$$\Delta\text{TeenEmpShare}_{c,t} = \beta\Delta \left(\frac{\text{Adults in Teen Jobs}}{\text{All Adults}} \right)_{c,t} + \gamma \Delta X_{c,t} + \Delta\theta_t + \epsilon_{c,t} \tag{3}$$

There are two major biases that make estimating this equation using OLS infeasible. 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 (e.g., a change in the industrial composition of a region), then both teen employment and adults in teen occupations would move in the same direction. This biases 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 comes with 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 in the commuting zones,

$$z_{c,t} = \sum_{o} s_{o,c,t_0} g_{o,t} \tag{4}$$

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 in the period of interest, $g_{o,t}$.[11] These weights are calculated using flows of workers as discussed in *Section 3.1*. In practice, we choose the top 20 previous occupations of workers transitioning into teen occupations.[12] To minimize potential endogeneity, we use lagged occupational shares. That is, instead of using their shares in 2000, we use their shares in $t_0 = 1990$.

Demographic Instrument – We split the adult population by cohort and education. We then construct the instrument $z_{c,t}$ as either the share of all adults born between y_0 and y_T or the

[11] The shift term is thus the "Δ Net Into" in the second column of *Table 2*.

[12] We ensure that each occupation is not closely related to those defined as teen occupations.

share of all workers born between y_0 and y_T who have a college degree,

$$z_{c,t} = \sum_{a=y_0}^{y_T} s_{a,c,t_0} \tag{5}$$

where s_{a,c,t_0} is the share of adults in location c in the initial period t_0 who belong to demographic group a. Specifically, a refers to workers born in year y, or workers born in year y who have a college degree. We thus implicitly weight cohorts born between y_0 and y_T (with college degree) with a factor of 1 and all other cohorts with a factor of zero in the construction of the instrument. We discuss the details of which cohorts are used below. We again use lagged demographic shares from 1990. This reduces any concerns of 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 the changes in the share of adults in teen occupations.[13] The underlying national shocks are the two post-2000 recessions, the manufacturing decline, and job polarization. These shocks adversely affected workers in specific occupations and demographics.[14] Commuting zones that have high shares of these occupations and demographics are then more exposed to the national shocks, which provides the variation we exploit for identification.

Changes to the preferences of teenagers that are explained by national phenomena (e.g., video games) would be uncorrelated with our instrument. The same holds for national changes in the demand for teen occupation products, 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 forced into teenage occupations. This leads to lower income for these adults, which in turn could reduce local demand, negatively affecting teenage employment. To isolate the crowding out of adults from this second demand channel, we include the change in median income 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

[13] Although our demographic instruments are not technically Bartik instruments, the same identifying assumptions go through.

[14] We show in *Appendix B.3* that many occupations identified in *Section 3.1* saw falling employment and wages after 2000.

conditional on the inclusion of the additional controls.

Some of the negatively affected adults are also the parents of teenagers in our sample. Negative shocks to their income might drive their children to work more to compensate for the lost income. We address this concern by re-estimating our model, constructing our instrument only using adults without teenage children. Results are unchanged and reported in *Table B.4*.

Generally, by including several independent instruments, we reduce the concerns of any of these individual factors biasing our results. We show that the occupation instrument and the demographic instrument are largely uncorrelated and thus pick up different variation in *Appendix B.3.2*, where we also discuss additional tests that give confidence in the exogeneity of our instruments. We now turn to a discussion below 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, the employment opportunities in certain occupations are negatively affected by recessions, structural change, and routinization, pushing adult workers into teen occupations at a 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. We are more concerned that the initial employment share of certain occupations could predict changes in the demand for teen occupation products, which would again bias the coefficient positively. Insofar as this demand change is a change in demand for service goods in general, we again control for the change in manufacturing share.

Demographic Instrument – 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 changes in teen employment. While the age distribution is largely determined by birthrates 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 the conditions prior to the 1990s were orthogonal to the changes after 2000. They only matter for changes in teen employment post-2000 because certain demographic groups were exposed to nationally worsening 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. It would only threaten our identification if favorable economic conditions for college graduates before 1990 predict (expected) increasing demand for college graduates after 2000. This would lead to a change in teenagers' preferences for work. 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 larger teen employment and more adults in teen occupations. Thus β would be positively biased. Combined, a lower supply of teenage labor due to expected favorable conditions for college graduates and larger demand for teen occupations' products would bias β in opposite directions. Moreover, our results show very similar coefficients. Additionally, these would both imply rising wages for workers in teen occupations. However, as we show in *Section B.5*, 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 with regression equations in first differences. Our main interest lies in the rapid drop of teen employment after 2000. In our baseline, we use 10-year differences, starting from the initial period 2000. In the Census and ACS, teen employment falls from 35% to 20% over this time period. Identification comes from the differential exposure of different commuting zones to common shocks occurring in 2000. As described 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.

Since our treatment occurs in 2000, we regard the time before that as a pre-period. In *Appendix B.3*, we explore the correlation of our variables of interest between the pre- and post-period, as well as the change in variance. These correlations and changes in variance show that variation in changes in teen employment and adult share in teen occupations increases significantly after 2000, giving further support for the choice of initial period. There is also a weak negative correlation in the changes of 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. The other elements in $X_{c,t}$ are the median wage income, share of whites, share of teenagers, employment rate, and manufacturing share. In *Appendix B.3.1*, we show that including the minimum wage as a control does not alter our results and that *changes* in the minimum wage are insignificant in explaining the changes in teen employment over our time period.[15]

Lastly, we show in *Figure D.1* that, pre-2000, the share of adults working in teen occupations was continuously falling, with a trend reversal in 2000. Therefore, in our baseline we, normalize the change in adults working in teen occupations by its pre-2000 trend. We then calculate the change in the share of adults in teen occupations from 1990 to 2000 and subtract it from the change between 2000 and 2010. The non-normalized share of adults in teen occupations over all employed adults rose by 1.55 percentage points. The normalized share rose by 2.27 percentage points.

3.2.3 Results

We report our baseline results in *Table 3*. We estimate equation (3) for the change between 2010 (the lowest point of teen employment) and 2000.[16] We report the estimates of the elasticity of teen employment with respect to the adult share in teen occupations, β, and the other key controls. The full regression table and the first-stage regression can be found in *Appendix B.3*. For the previous occupation instrument, we choose the top 20 occupations with the largest change in net inflows into teen occupations between the 1990-2000 and 2000-2010 periods. The cohort instrument is constructed as the share of adults in a commuting zone in 1990 who were born between 1955 and 1969. These are individuals who turn 41-55 in 2010.[17] For the education instrument, we use the same cohorts, but only college-educated individuals.

We find a significant negative causal relationship between the share of all adults who work in teen occupations and the share of teenagers who are employed. Columns (1), (3), and (5) show the resulting elasticities when we do not normalize the change in adult share

[15] We explain in more detail in *Appendix B.3.1* how these results fit with the conclusions in Neumark and Shupe (2019).

[16] Our results are robust to averages across years after 2010. See *Appendix B.3* for details.

[17] Younger workers (those born after 1970) display similar transition dynamics. However, we are unable to use them in our regression due to using the lagged initial share. We show in *Appendix B.3* that when using the initial 2000 share, our regressions hold using the 1970-1980 cohorts as well.

Table 3: **Instrumental Variable Regression Results**

	(1)	(2)	(3)	(4)	(5)	(6)	OLS
AdultShare	-3.98	-3.48	-2.54	-3.08	-5.11	-3.78	-0.27
	(0.043)	(0.043)	(0.026)	(0.030)	(0.003)	(0.001)	(0.250)
Z_{Cohort}	Yes	Yes	No	No	No	No	No
$Z_{Education}$	No	No	Yes	Yes	No	No	No
$Z_{PreviousOcc}$	No	No	No	No	Yes	Yes	No
F-stat	9.77	5.66	22.41	10.80	19.27	21.64	-
1st stage coef.	0.051	0.058	0.104	0.061	0.013	0.018	-
Norm. Adults.	No	Yes	No	Yes	No	Yes	No
Observations	741	741	741	741	741	741	741

Notes: P-values shown in brackets. 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.

by its pre-trend. Coefficients are all of similar magnitude. The demographic instrument is relatively weak, and its F-stat is below the typical cutoff proposed in Staiger and Stock (1997). Comparing columns (1) and (3) alleviates those concerns. Restricting the instrument to college-educated workers increases the precision; however, the cohort instrument delivers a remarkably similar coefficient. This provides further confidence that the additional concerns to identification with the education instrument are minor.

Coefficients range from -2.54 to -5.11. Given the aggregate decline of teen employment of roughly 15 percentage points and the aggregate increase of adults in teen jobs in that same period of roughly 1.55 percentage points, a back-of-the-envelope calculation shows that adult crowding out explains between 26 and 53 percent of the decline.

Looking at the elasticities in columns (2), (4), and (6), we see again very similar estimates. Given that the regressor is larger, the coefficients are of comparable size to their counterparts in (1), (3), and (5). With the same back-of-the-envelope calculation, taking into account that the normalized share of adults increased by 2.27 percentage points, we can now explain between 47 and 57 percent of the decline in teen employment. In *Appendix B.3.2*, we confirm these results by estimating overidentified regressions that include several instruments together. This also allows us to run overidentification tests, which return large p-values, lending additional confidence to our instruments.

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

We now briefly turn to a discussion of the remaining regressors in (3). We are particularly interested in the effects of the employment rate and the manufacturing share, which are the same demand factors considered in (1). *Table B.3* reports the coefficients as well as the results from re-estimating (3) without the share of adults in teen occupations. *Table 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)-(6), we see that unemployment seems to have a negative effect on teenage employment, which mostly vanishes when including the adult share. Negative unemployment shocks (measured by the unemployment rate) drive adults into teen occupations, this crowds out teenagers but has no *direct* effect on teens. For the manufacturing decline, the same logic goes through, except that a direct effect remains. Less manufacturing 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 a higher demand for service products, which includes teen labor products.

4 Empirical Analysis: Returns to Teen Employment

We use the National Longitudinal Surveys of Youth (NLSY) to determine the lifecycle wage returns or "value-added" of teen employment. We put emphasis on the effects for adults who graduate high school but never attend college, but report results for all groups. Further details are 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% keep the same occupation within five years of graduating high school (4-digit occupation code level) and entering the labor force. *Figure D.22* plots the raw average annual wages over the lifecycle comparing students that worked in high school with those that did not. We demonstrate that working while attending high school *may* have important benefits both in earnings levels, but also growth. From *Figure D.23* there is a large and persistent difference in employment rates over the lifecycle for those who worked in high school versus those who did not.

The descriptive evidence provided here, 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 in the next section.

4.2 Instrumental Variable Regression Analysis

We now turn to the causal estimation of the return to teenage employment. We are interested in the effect of working during high school on future wages. To identify causal effects in the data, we address the endogeneity of the decision to work. This decision is influenced by unobservable abilities and preferences of teenagers. To overcome this problem, we again rely on an instrumental variable approach. Similarly to Light (2001) and Ruhm (1997), we exploit variation in local labor market conditions as an instrument. The most basic relationship of interest is then a variation of a Mincer regression that includes in-school work experience E^S, which stands in contrast to the years of schooling and post-schooling work experience of an individual. We are interested in the coefficient γ_1 from the regression

$$W_i = \gamma_0 + \gamma_1 E_i^S + \gamma_2 X_i + \epsilon_i \tag{6}$$

where W_i is the natural logarithm of average lifetime yearly wages.[18] γ_1 is likely biased if we estimate this with OLS. For example, individuals with higher ability or motivation for working might decide to work more during high school. Simultaneously, higher ability could lead to higher wages later in life, which would positively bias the coefficient of interest. To overcome potential biases with OLS, we instrument with the local employment rate of teenagers. We use restricted-access geocoded NLSY79 and NLSY97 data.

One of the reasons we chose this instrument is that it alleviates a typical shortcoming of IV strategies. As shown by Angrist et al. (2000), an IV regression allows identification of the local average treatment effect (LATE). This means we can only estimate the effect on students who change their behavior due to the instrument. However, this is precisely what we are interested in: the effect of falling employment opportunities for teenagers post-2000.

For our instrument to be valid, it must correlate with future wages only through its effect on the employment of a teenager. We acknowledge that there are concerns with this exclusion restriction. We include the average unemployment rates of the locations an adult works in during their life. We include this variable as there might be autocorrelation in the local economic conditions individuals face. Teenagers growing up in locations with favorable economic conditions could also live in stronger labor markets as adults, which would lead to our instrument being correlated with W_i. Including the unemployment rate controls for this. Our controls, X, also include the sex and race of individual teenagers, the Armed

[18]The NLSY allows us to create weekly employment histories. As explained in for individual i, and X_i is a set of individual and location controls. *Section 2*, these are aggregated at the annual level. For all jobs observed in a year, we then multiply the hourly wage by the total hours worked, which gives us a yearly wage income. We then average this over all observed years in the lifecycle. All periods without an observation are thus ignored.

Services Vocational Aptitude Battery (ASVAB or AFQT), and several controls for initial 1980 economic conditions in the geographic location.

A key assumption is that the average local teenage ability and motivation do not vary across regions. If they did, and if higher-ability teens work more, then higher local teenage employment would positively correlate with individual ability. To alleviate these concerns, we include 1980 local economic controls in our regression, including the median real wage and the share of college graduates. If a location has a higher share of high-ability or high-motivation individuals, it is reasonable to assume that this location would also see higher income and higher education levels.

4.2.1 Results

Columns (1)-(4) of *Table 4* show the estimates of our instrumental variables regression for individuals who graduate from high school and do not graduate from college. *Appendix B.6* presents the first-stage results. The returns to teen employment are given by "Avg. hours worked HS", which is the average weekly hours worked while in high school. We see a significant and positive effect of employment on later-life wages. As we add controls, the coefficient of interest ranges from 0.064 to 0.041. Our preferred specification is column (4), which predicts that a one-hour increase in average weekly hours worked while in high school is associated with 4.2% higher average wages over the lifecycle. We use this as a moment to identify the parameter governing returns to teen employment in our quantitative model.

Appendix B.6 reports additional results where the regression is broken up by age groupings. We find that returns to teen employment are the largest during the middle of the lifecycle, particularly ages 30-54. Although we can only observe individuals up to the age of 39, we also estimate our main regression using the NLSY97 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 a self-selection of lower-ability workers into teen employment.

Next, we estimate (6) for teenagers who do attend and graduate from college. Results are reported in Column (5). We find that high school work has no effect on later wages for this group of individuals. 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 go to college. Taking this into account can change the overall effect of teen employment. We therefore estimate (6) for all individuals and report results in column (6). Returns are still positive but slightly smaller than for only non-college-bound workers. In the quantitative section, we explicitly model the endogenous college decisions.

Table 4: **High School Employment and Life Time Wages**

	log average life time wages					
	(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 wages 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 brackets. 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 79 (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 enables us to quantify how aggregate shocks that drive adults into teen occupations contribute to the decline in teen employment and to compute the aggregate changes in total output and the income distribution, while accounting for general equilibrium effects. It also allows us to assess the income and welfare effects of adjusting to economic changes for a heterogeneous set of teenagers (depending on their ability). To better understand the mechanisms that drive empirical changes, we can use the model to decompose the decline into separate channels through which the crowding out operates: current consumption, future earnings and college decisions, and the minimum wage. Finally, guided by our model decompositions, we will consider policy counterfactuals geared toward adolescents adversely affected by adult crowding out.

5.1 Model Overview

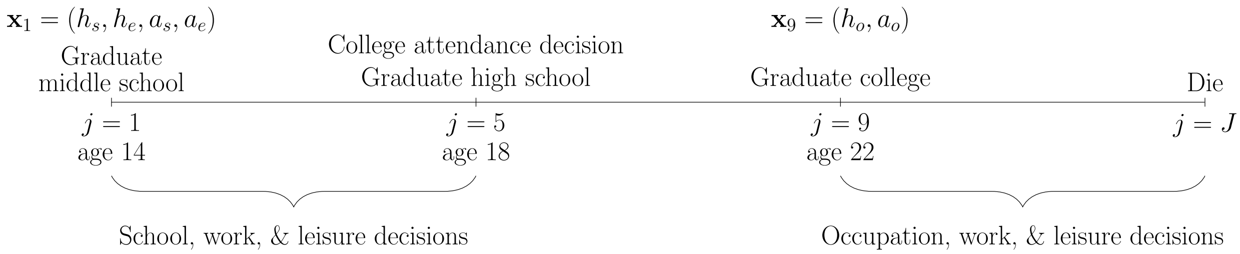
Time is discrete. Agents live for J biological years indexed by age j. One model period represents one year. The economy is populated by a continuum of J overlapping generations with a uniform demographic structure. Only steady states are considered, and so time subscripts are omitted throughout. We 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 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. The lifecycle before age 15 is not modeled. At the beginning of period one, agents differ heterogeneously with respect to: an employment ability a_e, a schooling ability a_s, and schooling human capital h_s. Initial working human capital h_e is homogeneous across agents and normalized to one.[19]

Over the next four periods, $j = 1$ to $j = 4$ (biological ages 15-18), 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 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.

[19]The Fair Labor Standards Act (FLSA) sets the minimum age for employment at 14 in the United States, with a few exceptions for acting, agriculture, or entirely parent-owned businesses.

Figure 4: **Lifecycle Timeline Summary**



At the beginning of period $j = 5$ (biological age 19), the agent graduates from high school.[20] The agent makes a one-off decision to attend college. If the agent attends college, they spend four years 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. 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 and make a labor-leisure decision. Human capital accumulates dynamically according to time spent working. At the beginning of each period, agents choose which occupation to work in. Adults live until period $j = J$, at which time 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, which are not perfect substitutes in production.

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

[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.

capital h_i accumulate according to,

$$h_i' = \epsilon_i' a_i (h_i n_i)^{\gamma_i} + h_i, \quad \text{for} \quad i \in \{s, e\} \tag{7}$$

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,

$$h_o = \left(\alpha h_s^\zeta + (1 - \alpha) h_e^\zeta\right)^{\frac{1}{\zeta}}. \tag{8}$$

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 (8). Adult ability is drawn from the normal distribution,

$$a_o \sim \mathcal{N}\left(\lambda a_s + (1 - \lambda) a_e, \sigma_a^2\right), \tag{9}$$

where λ represents the relative weight placed on schooling versus employment ability, and σ_a^2 is the variance of the ability draw. Adults then accumulate human capital via learning-by-doing, given the function,

$$h_o' = a_o (h_o n_o)^{\gamma_o} + (1 - \delta_o) h_o \tag{10}$$

where $n_o \in [0, 1]$ is time spent accumulating human capital/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.

5.3 Teenage Recursive Decision Problems

Problem for $1 \leq j \leq 4$*:* Given a teen occupation wage 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,

$$
\begin{aligned}
V^k(j, h_s, h_e, a_s, a_e) = \max_{c,z,n_s,n_e} &\Big\{ u\big(\bar{c} + c, z\big) + \beta \mathbb{E}_{\epsilon_s,\epsilon_e}\big[V^k(j', h_s', h_e', a_s, a_e)\big]\Big\} \\
\text{subject to,} & \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (11) \\
& c = \omega_l(\psi + \phi h_o) n_e \\
& h_i' = \epsilon_i' a_i (h_i n_i)^{\gamma_i} + h_i, \quad \text{for} \quad i \in \{s, e\} \\
& h_o = \big(\alpha h_s^{\zeta} + (1-\alpha) h_e^{\zeta}\big)^{\frac{1}{\zeta}} \\
& n_s \in [\bar{n}_s, 1], \quad n_e \in [0, \bar{n}_e], \quad z \in [0, 1] \\
& n_s + n_e + z = 1
\end{aligned}
$$

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.

Problems 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,

$$
\max \Big\{ \mathbb{E}_{a_o}\big[V^{hs}\big(j = 5, h_s, h_e, a_s, a_e\big)\big], \mathbb{E}_{a_o,\epsilon_s}\big[V^{u}\big(j = 5, h_s, h_e, a_s, a_e\big)\big] \Big\} \tag{12}
$$

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 (11) where the continuation value is given by equation (12) and the laws of motion are given by equations (8)-(9).

While in college, the agent spends their full time endowment accumulating schooling human capital ($n_s = 1$ in equation (7)) 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.[22] The state variables while in college are thus given by (h_s, a_s, a_e).

[22] This implies that upon entering the labor force, college graduates combine their accumulated h_s with the initial level of h_e according to (8). We interpret this as work experience during high school being essentially useless by the time college graduates enter the labor force. This also 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 Decision Problem

Given a wage $\omega \in \{\omega_l, \omega_s, \omega_m\}$, agents choose work time n_o, leisure time z, and consumption c, in order to solve,

$$
\begin{aligned}
V^o(j, h_o, a_o) &= \max_{c,z,n_o} \Big\{ u\big(c, z\big) + \beta V^o(j', h'_o, a_o) \Big\} \\
&\text{subject to,} \\
&\quad c = E(\omega, h_o) \\
&\quad h'_o = a_o(h_o n_o)^{\gamma_o} + (1 - \delta_o)h_o \\
&\quad z, n_o \in [0, 1] \\
&\quad n_o + z = 1
\end{aligned}
\tag{13}
$$

where $E(\omega, h_o)$ is earnings for a given occupation technology, wage, and human capital level, and will be discussed in *Section 5.4.1*.

5.4.1 Occupation Choice

For notational simplicity, problem (13) 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,

$$
w_l = \omega_l(\psi + \phi h_o) \tag{14}
$$

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 only use a fraction ϕ of their human capital, plus a fixed term ψ. The productivity of most teen occupations (e.g., cashiers) is largely independent of the person and consists of the worker being physically at work and performing simple tasks. We capture this with ψ. However, we do assume that there are productivity differences between workers, which capture both the ability of a worker (e.g., reliably showing up to work) and the more classical accumulation of skills that allow workers to complete the simple tasks more efficiently.

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,

$$h^*_{\{m,s\}} = \psi \frac{\omega_l}{\omega_{\{m,s\}} - \phi \omega_l}. \tag{15}$$

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 CES function $F(Y_l, Y_m, Y_s)$, given by,

$$Y = \left((A_l Y_l)^\nu + \theta \left[(A_m Y_m)^\sigma + (A_s Y_s)^\sigma \right]^{\frac{\nu}{\sigma}} \right)^{\frac{1}{\nu}} \tag{16}$$

Firms solve the profit maximization problem,

$$\max \; F(Y_l, Y_m, Y_s) - \omega_l Y_l - \omega_m Y_m - \omega_s Y_s \tag{17}$$

and the marginal product of each aggregate labor input $F_{\{Y_l, Y_m, Y_s\}}$ equates 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. Labor is aggregated according to,

$$Y_l = \int_0^{h^*_m} (\psi + \phi h^m_o) n_o d\tilde{\Phi} + \int_0^{h^*_s} (\psi + \phi h^s_o) n_o d\tilde{\Phi} + \int (\psi + \phi h_o) n_e d\Phi \tag{18}$$

$$Y_m = \int_{h^*_m}^{H_{max}} h^m_o n_o d\tilde{\Phi} \tag{19}$$

$$Y_s = \int_{h^*_s}^{H_{max}} h^s_o n_o d\tilde{\Phi}. \tag{20}$$

Here, $\Phi(j, h_s, h_e, a_s, a_e)$ is the share of teenagers with characteristics (j, h_s, h_e, a_s, a_e), and $\tilde{\Phi}(h_o, a_o)$ is the share of 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 if their total hourly wage is such that $w_l = \omega_l(\psi + \phi h_o) < w_{min}$. Teenagers with low human capital are then not allowed to work 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.

We investigate the importance of the minimum wage for our results by calibrating our benchmark economy with the minimum wage and then re-calibrating the model without it. We show in *Section 7* that the efficient model can also capture all features of teen labor supply dynamics described in *Section 3* and *Section 4*.

5.6 Equilibrium

Here, we summarize the equilibrium conditions of this economy. For the formal equilibrium definition, see *Appendix C*.

An equilibrium is a set of wages $\{\omega_l, \omega_m, \omega_s\}$, labor supply, schooling time and college decisions of teenagers g_{n_e}, g_{n_s},[23] labor supply decisions for adults g_{n_o}, occupational choices of adults $\{g_m, g_s\}$, and labor demands $\{Y_l, Y_m, Y_s\}$, such that,

1. Wages equal the marginal product of aggregate labor inputs $F_{\{Y_l, Y_m, Y_s\}}$.
2. Labor demand is consistent with the firms optimization problem (17).
3. Labor supply and college choices of teenagers are consistent with (11) and (12).
4. Labor choices for adults are consistent with (13) and occupational choices of adults are defined by (15).
5. The labor market clears according to (18)-(20).

[23]Given that in college agents supply their entire time endowment to schooling, choosing to attend college corresponds to $g_{n_s} = 1$.

6 Model Estimation

The main quantitative exercise involves choosing parameters for the model to match important cross-sectional and transitional moments of the U.S. data. One set of parameters is set exogenously. Conditional on the external parameters, the remaining parameters are then estimated by simulated method of moments to target the causal reduced form estimates of *Sections 3 and 4*. The estimated model is used to determine the distributional impacts of falling teen employment, to decompose the underlying causes, and to conduct policy analysis.

6.1 External Parameters

Agents spend four years in high school and then live as adults for an additional forty years, to the age of 59. This corresponds to $J = 40$. 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 income during ages they would typically have a teenage child. This fraction is taken from the large literature on adult consumption equivalence, with values typically 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 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 (see 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 13 hours per day (see Guvenen et al. (2014)). 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, $\bar{n}_s = {}^{(5\cdot 7)}/_{(7\cdot 13)} = 0.38$.

Variation in state teen labor laws is not substantial and typically conforms with 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 $\bar{n}_e = {}^{40}/_{91} = 0.44$. Empirically, 40 hours represents the 95$^{\text{th}}$ percentile of working teens in our ACS sample. Note that, since $\bar{n}_e < 1 - \bar{n}_s$ only $\bar{n}_e$ binds in the model. This follows from $n_s + n_e = 1$. Thus $n_e \leq 1 - \bar{n}_s$, but the calibrated values give us $n_e \leq \bar{n}_e < 1 - \bar{n}_s$.

In general, 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 is the case with 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.

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 20 parameters are chosen to minimize the distance between 41 moments, simulated by the model and empirical counterparts. Empirical moments are estimated from the Census, ACS, and NLSY. Steady state moments calculated using the Census are for the year 2000, with the exception of wage profiles where we pool the 1980, 1990, and 2000 Census 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*. Our baseline NLSY moments are all calculated using the NLSY79 and NLSY97. *Section 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,

$$u(c, z) = \ln(c) + \kappa \ln(z), \quad \text{for } \kappa \in \{\kappa_k, \kappa_o\} \tag{21}$$

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 the leisure parameter for teenagers, κ_k. Specifically, we target the share of total discretionary time that is spent on leisure activities. For details see *Section A.4*. Given that the curvature and depreciation of adult human capital is set exogenously, the choice of κ_o helps to match the wage profiles of adults as described below.

6.2.2 Initial Distributions

The initial distribution of human capital and ability depends on $\sigma_{a_e}, \sigma_{a_s}, \sigma_{h_s}, \mu_{a_e}, \mu_{a_s}$, and μ_{h_s}. To separately identify parameters governing the accumulation of schooling and working 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 credits taken and GPA, for each school year. We proceed to measure schooling human capital as the GPA-weighted stock of credits, h_s^{data}. It is assumed that $h_s^{model} = B \times h_s^{data}$, 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,

$$\log(h_s^{data}) = \alpha_{h_s} + \beta_{h_s} \times age + \epsilon_{hs} \tag{22}$$

We plot the profiles separately for children who subsequently attend college and those who do not in *Figure D.13*. 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. Similarly, we set μ_{h_s} to one.

6.2.3 Teens

The percentage of teens employed is estimated using the year 2000 Census and discussed extensively in *Section 3* and *Appendix A*. In the model, we consider any agent who allocates less than one hour of their time endowment towards employment (n_e) as not working. This is consistent with our empirical definition of working as those who worked at least one hour.

A central moment to our analysis is the returns to teen employment. We causally estimate this using geocoded NLSY data, as presented in *Section 4.2*. Using simulated data from the model we estimate the return by running the OLS regression,

$$\log(LFE_i) = \gamma_1^{model} sn_{e,i} + \gamma_2 a_{e,i} + \gamma_3 a_{s,i} + \gamma_4 h_{s,0,i} + \epsilon_i \tag{23}$$

where LFE is the average of lifetime earnings,[24] sn_e is the average hours worked while in high school (normalized to correspond to actual hours as measured in the empirical exercise), a_e is employment ability, a_s is schooling ability, and $h_{s,0}$ is initial schooling human capital. We compare γ_1^{model} to our causal estimate of γ_1 from the data.

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

[24] Earnings in the model correspond to yearly wages in the data.

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 wages. The difference is that h_s^{data} is only affected by γ_s. We can thus 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 (6) with h_s^{data} as the dependent variable, utilizing the same IV strategy (outlined above), i.e.

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

In the model we then estimate equation (23) with the dependent variable now h_s^{model}, i.e.

$$\log(h_s^{model}) = \delta_0^{model} + \delta_1^{model} sn_{e,i} + \delta_2 a_{e,i} + \delta_3 a_{s,i} + \delta_4 h_{s,0,i} + \epsilon_i$$

We finally match the coefficients δ_1 and δ_1^{model} .[25] Data regression results are reported in *Appendix C.3.1*. 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 (8) would be determined by the shares of h_s and h_e inputs in production. The smaller is α, the more h_e matters and will be used. 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 elasticity between schooling and work human capital ζ is pinned down by the wage ratio of workers with different human capital levels. Again, h_e is unobserved. In this case we can use the fact that some teenagers do not work at all during high school. For those individuals work human capital is homogeneous at $h_e = 1$, and equation (8) reduces to $h_o = \left(\alpha h_s^{\zeta} + (1-\alpha)\right)^{\frac{1}{\zeta}}$. All variation in wages then comes from h_s. The wage 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 wages on h_s in data and model.[26]

[25] Note, as seen *Figure D.13* schooling human capital growth is near linear. Our calibrated value of $\gamma_s = 0.95$ together with modest variation in n_s delivers effectively linear profiles.

[26] The exact specifications and regression results are in *Appendix C.3*.

6.2.4 College

The curvature of schooling human capital production in college, γ_c, 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 wage premium for young adults. Using Census data, we target the college wage 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. The college attainment rate is defined to be those with at least an associate's degree and above, again calculated from the Census.

6.2.5 Adults

The parameters λ and σ_{a_o} govern the mean and variance of the initial distribution of adult abilities. As is standard in the adult human capital accumulation literature, these parameters target wage growth profiles by college educated vs. non-college educated workers. We follow closely the method of Huggett et al. (2011) and Lee and Seshadri (2019) when constructing these wage profiles. Using pooled 1980, 1990, and 2000, Census samples, we run the regression,

$$\log(E_{i,a,t}) = S_s + A_a + T_t + S_s A_a + S_s T_t + \epsilon_{i,a,t} \tag{24}$$

where, $E_{i,a,t}$ is total wage earnings of individual i in year t. S_s is the schooling effect, A_a the age effects, and T_t the time effects. The interaction terms are used to identify wage profiles separately for those with and without a college education. The coefficients are then estimated for each education-age category to produce the wage profiles plotted in *Figure D.25*.

The parameters ψ and ϕ define the human capital level of those who work in teen occupations. This in turn defines a cutoff for those who work in teen vs. non-teen occupations, and hence governs the percentage of adults working in teen occupations by age. *Figure D.24* plots the percentage of adults employed in teen occupations by education status.

6.2.6 Production

The productivity parameters A_l, A_m, A_s, and θ, govern income and employment shares in the initial steady state. We normalize θ to one. 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 such that the share of adults taking up teenage occupations matches the data. We calibrate this to a second steady state, ignoring the transition of the economy. The elasticity between teen and adult jobs, ν, then translates the change of adults in teen occupations 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. 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. This corresponds to the empirical exercise in *Section 3*. We use the counterfactual, steady state where we only vary the amount of adults in teen occupations and match the resulting wage changes to the coefficient from the causal wage regression in (29).

Finally, we look at the "crowding out" of teen workers. We define the model change in teen employment coefficient as,

$$\frac{(\% \text{ teen work})_3 - (\% \text{ teen work})_1}{(\text{adults in teen occ.})_2 - (\text{adults in teen occ.})_1} \tag{25}$$

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 (6) of *Table 3*, i.e. the occupation instrument with normalized change in adult employment. The occupation instrument is the most natural, as we replicate it in the model. We use the normalized change in adult share since we assume the model to be in steady state initially and abstract from changes in the overall demand for teenage occupations. This elasticity 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 elasticity of teen labor supply to price changes is determined by a large set of parameters, which operate through the aforementioned mechanisms. In the case of current consumption, $\bar{c}$ and the curvature of the utility function are important. Additionally, the college decision (and hence future consumption) plays an important role in determining this elasticity. Therefore, the curvature of college human capital production, γ_c, is also important for pinning down this elasticity.

6.2.7 Minimum Wage

We calibrate the size of the minimum wage relative to the average wage of teenagers in accordance with the data. 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 assume the minimum wage to be fixed at its 2000 level. This purposely ignores changes in the minimum wage, since we are interested in the interaction of adult crowding out with the *level* of the minimum wage. Changes to the minimum wage can potentially explain an additional part of the teenage employment decline. Extending the model in this direction is left for future research.

6.3 Model Fit

This section reports moments estimated in the data and model counterparts. The model parameterization matches well the most important features of the data: positive returns to teen employment, adults increasing employment in teen occupations as a result of an aggregate shock, and teens sharply reducing employment as a result of inflowing adult workers. The model closely matches moments including the percent of teens working, college attendance rate, and percent of adults working in teen occupations. We are also able to calibrate the shock to θ so that the model accurately generates the influx of adult workers into teen occupations.

7 Quantitative Results

This section discusses the quantitative dynamics of the model solution, both with and without minimum wages, and then concludes with a policy analysis. In all sections, we compare the benchmark model to what we refer to as the "counterfactual" economy and the "new steady state" economy.

The economy is calibrated to the initial period pre-fall (pre-2000) in teen employment. The second steady state post-fall (post-2010) in teen employment is obtained by re-solving the model with the sole difference being a negative shock to the productivity of adult labor, θ. This captures some aggregate shock in the data that induced adults (both college and non-college educated) to take up teen occupations over the 2000 to 2010 period. As discussed above in *Section 6.2* we calibrate the shock size to match the increase in adults employed in teen occupations observed in the data for this 2000 to 2010 period.

We obtain the counterfactual economy using the following procedure. First, we solve the benchmark model calibrated to the pre-2000 period. We then solve for the new steady state economy, as described above. To obtain the counterfactual economy, we calculate what wages would be if adults were employed in teen occupations, as in the second steady state. Holding all else (including θ) fixed at the initial steady state level, we then recompute outcomes. Again, see *Section 6.2* for more details. We solve for the counterfactual economy

Table 5: **Model Fit – ACS Moments**

Moment	**Data**	**Model**
Teens		
Decline regression coefficient	-3.78	-3.79
% teens working	0.349	0.348
Average hours worked for working	20.1	20.2
Adults		
% working in teen occ.	0.116	0.153
% with college degree	0.402	0.406
% working in teen occ. – college	0.049	0.054
% working in teen occ. – non-college	0.186	0.189
Δ in adults working teen occ.	0.022	0.021
Wages		
College/non-college, all adult	1.92	1.60
College/non-college, non-teen occ. all adult	1.85	1.81
College/non-college, 24-29	1.49	1.31
Non-teen occ./teen occ.	1.79	1.95
Adult/teen, teen occ.	3.78	3.98
Wage regression	-7.83	-6.78
Minimum Wage/Avg. Teen wage	0.78	0.73

Notes: The columns compare the model to the data for selected targeted moments. All steady state moments in this table are taken from the 2000 year American Community Survey (ACS). Transitional moments are calculated using the 2000 and 2010 ACS.

Table 6: **Model Fit – NLSY Moments**

Moment	**Data**	**Model**
Teens		
Returns to employment on wages	0.041	0.053
Returns to schooling on grades	-0.047	-0.035
% Growth of h_s^{data}, grade 9-12	338	321
Returns to h_s^{data}	0.24	0.31
SD($h_s^{data}(Grade8)$)/Mean($h_s^{data}(Grade8)$)	0.80	0.85
Average hours worked, non-college	15.2	16.1

Notes: The columns compare the model to the data for selected targeted moments. *Source*: NLSY79 and NLSY97.

in order to isolate the effects of adults "crowding out" teen workers. We can then investigate the results and mechanisms of the crowding out in isolation, before moving to the analysis of the full general equilibrium effects in the new steady state.

7.1 Consequences of Declining Teen Employment

This section discusses the new steady state and counterfactual economy, where we compare the results for the baseline minimum wage economy with the frictionless economy. We begin by discussing model mechanisms and then turn to a quantitative analysis of the income and welfare effects.

Under the counterfactual economy, teen occupation wages fall by roughly 14% while adult occupation (college and non-college) wages are largely unaffected (changes by less than 0.5%). Looking at the post-fall steady state in the minimum wage economy, teen employment falls to around 24%. The model can thus explain the majority (75%) of the observed fall to around 20% in 2010. In the counterfactual economy that isolates the crowding out, the teen employment rate falls to 27% to match the causal elasticity, we can see that taking into account the general equilibrium adjustments to the underlying shocks further increases the decline in teen employment. This follows since the underlying productivity shock to adult occupations reduces all wages in general equilibrium. This includes teenage wages which fall additionally beyond the direct crowding out effect.

Next, we quantify the changes in lifetime income for different types of workers. We classify workers by their initial state vector, (a_e, a_s, h_s), and compare workers with the same state vectors across steady states. We consider changes for: (1) those who were teen workers in the first steady state and are any type of agent in the second (*workers*), (2) those who were teen workers in the first steady state and are still workers in the second steady state (*still workers*), (3) those who were teen workers in the first steady state and are no longer workers in the second steady state (*no longer workers*), and (4) those who are not teen workers in either steady state (*never workers*). We then translate these income changes into welfare changes by calculating the consumption equivalent variation. Results for the minimum wage economy are in *Table 7*, where we focus on the counterfactual economy to isolate the consequences of the direct crowding out.

As expected, *never workers* experience essentially no income and welfare changes in the counterfactual economy. For those who still work, *still workers*, we observe losses of roughly 3% of their lifetime income. This is due to reduced hours and therefore human capital accumulation. Types of teenagers that used to work in high school, but are now unable to do so lose a significant amount of income. A large share of these teens are bounded by the

Table 7: **Income and Welfare Changes in Counterfactual Economy**

	Workers	**Still Workers**	**No Longer Workers**	**Never Workers**
Change life time income	-0.057	-0.026	-0.260	-0.002
Change welfare	-0.044	-0.031	-0.152	-0.001

Notes: This table gives the percentage changes in life time adult income and welfare for different types of teenagers.

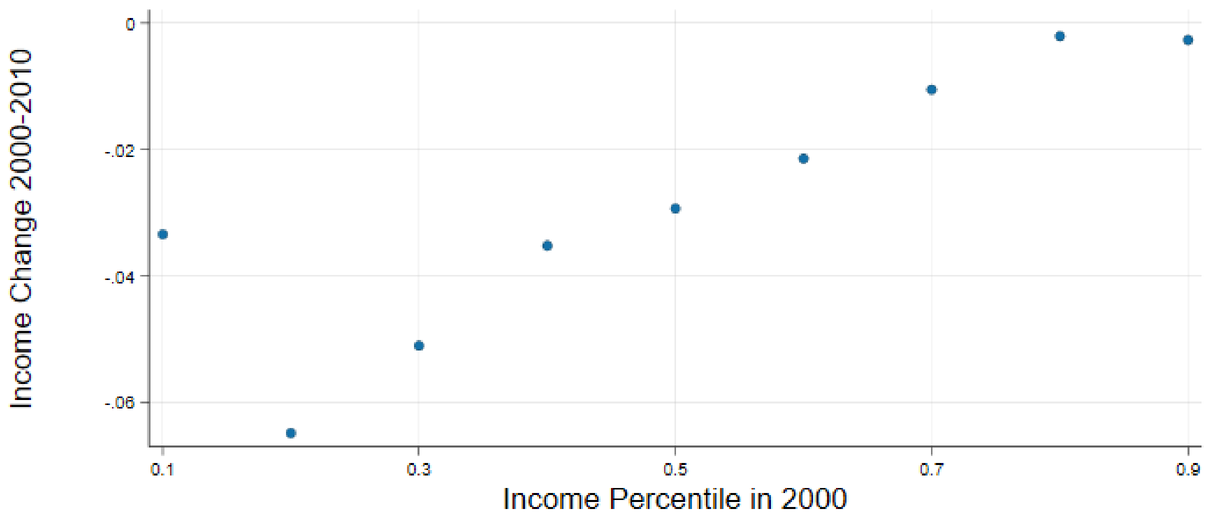
minimum wage. This leads to income losses of 26% on average. In total, if we consider all teenagers who would have been *workers*, we see an income loss of 6%.

This matters for the aggregate economy. Fewer working hours and lower human capital accumulation imply a 5% reduction in total output. We plot the changes of lifetime income by income percentile in the first steady state to assess the effects of the decline in teen employment on the income distribution. We find that low-skill workers in the 20th percentile incur the largest income losses. Those are the workers that benefit the most from work experience and are most likely to be crowded out due to the minimum wage. The income losses are then decreasing in the income percentile of workers. The lowest-skilled workers lose less as they are already not working in the first steady state. Ultimately, this implies that inequality rises. We compute the P90/P10 ratio, the wage income of the 90th percentile divided by the wage income of the 10th percentile. It increases by 2.2%, from 5.09 to 5.20 between the initial steady state and the counterfactual economy.[27] The income share of the top tenth percentile even rises by 5.2%. In contrast, the wage premium of college workers over non-college workers decreases by 2.8%. This is driven by the increased college attendance of lower-skill workers. In fact, the college enrollment rate increases by 4.7%. The increase in overall inequality, the reduction in the college wage premium, and the rise in college attendance can also be observed in the data over the same period.

Teen employment falls for three main reasons. First, the counterfactual economy induces a larger percentage of teens to attend college as the relative returns to college attendance increase. This comes from the fact that a much smaller share of college-educated workers work in teen occupations. However, the decline is also partially driven by those who do not attend college, as this group also reduces employment while in high school. Partly, this is driven by uncertainty in the model, agents cannot perfectly predict whether they will go to college. Additionally, lower wages imply less current consumption which teens can afford from their hours worked, causing a reduction in work effort. Finally, the minimum wage is

[27] The model P90/P10 ratio is below its data counterpart. We do not target the overall wage dispersion in the model estimation. It is nevertheless useful to observe that income inequality rises in the model.

Figure 5: **Income Change by Percentile**



Notes: This figure plots the change in lifetime income between 2000 and 2010 by income percentile in the first steady state.

binding for some. A small number of teenagers who are not working in the initial steady state do so because they would earn below the minimum wage and thus cannot work. This number increases in the counterfactual economy by 8 percentage points, leading to crowding out of teenagers who would otherwise optimally work. Among teens who continue to work, those with the highest working ability a_e remain, as reflected in the increase in average working ability.

7.1.1 Decomposition of the Model Mechanisms

To formalize the above discussion, we decompose the fall in teenage employment into its three mechanisms. Negative pressure on current wages reduces the current consumption teenagers can afford from their hours worked and increases the share of teenagers directly affected by the minimum wage. Negative pressure on future wages of teen occupations increases the incentive to attain a college degree, which reduces the return to teen employment.

The relative strength of these mechanisms cannot be calculated in the data for three reasons. First, we are missing large-scale consumption data for teens, which is necessary to quantify the importance of current consumption. Second, to estimate the effect of adult crowding out on college attainment, we require panel data. To use local variation in the share of adults in teen occupations, we must know the share of college graduates who *lived*

Table 8: **Decomposition Results**

Moment	**(1)**	**(2)**	**(3)**
Counterfactual teen employment	0.27	0.28	0.31
Decline regression coefficient	-3.78	-3.42	-1.68
Percentage Contribution	100	0.90	0.44

Notes: This table gives the decomposition of the decline in teen employment and the decline elasticity. Column (1) gives the original moments keeping all channels. Column (2) turns off the current consumption channel and column (3) additionally turns of the minimum wage channel. Percentage Contributions are the sequential shares of turning an additional channel off.

in commuting zones with a high share of adults in teen occupations while the teens attended high school. Using only local variation in college attainment excludes all individuals who move into different commuting zones for college and/or later employment. While we do not have the data to fully quantify this channel, we find some evidence of adult crowding out leading to increased college enrollment. We are able to estimate the effect of adult crowding out on college enrollment of 19-year-olds after 2005 and find a significant positive relationship. More details are reported in *Appendix B.4*.

Third, while Neumark and Shupe (2019) identify the effects of *changes* in the minimum wage on teen employment, our point is a different one. It is how the minimum wage interacts with increased competition from adults. Conditional on the amount of adults coming into teenage occupations, the importance of the minimum wage for crowding out teenagers depends on the distribution of human capital around the point where the minimum wage binds. If there are many individuals earning slightly above the minimum wage before the increased competition through adults, then the wage decrease induced by adults will crowd out many teenagers. Importantly, this effect does not necessarily depend on the size of the minimum wage, but on the distribution of teenage human capital. Given limited data, it is difficult to establish enough local variation in teenage human capital, conditional on the size of the increase in adults.

However, we are able to use our calibrated model to decompose these channels. For each case, we solve the model in the initial steady state and our counterfactual economy that isolates the direct effect of adult crowding out. We then sequentially turn off each mechanism to assess its relative importance. First, to ignore the effect of current consumption, we set ω_l (in the budget constraints of teenagers, equation (11)) to its initial steady state level. 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 $\omega_l(\phi + \psi h_o) < w_{min}$ using ω_l from the initial steady state. Finally, the effect of future wages is turned off by setting all future wages in the adult problem to their initial steady state values.

Results – We show the results of the decomposition exercise as described above in *Table 8*.[28] The third row reports the percentage contribution of sequentially turning one additional channel off. Only a fraction of teenagers choose to work for current consumption and thus almost none change their behavior because of it. Only 10% of the model decline operates through this margin. The other two mechanisms are of approximately equal importance and thus each account for roughly 45% of the decline. Teenagers reduce working hours optimally to achieve higher education, but are also prevented from attaining working hours through frictions, in this case the minimum wage. The latter matters most for welfare, as teens who are prevented from working lose important human capital accumulation opportunities.

7.2 Policy Analysis

In this section we investigate the importance of the minimum wage in amplifying the negative effects of lost employment opportunities for teenagers. We then discuss a possible schooling policy intervention that can help those teens who are adversely affected by crowding out.
Minimum Wage Policy – We start by comparing our benchmark economy with an economy without a minimum wage. To do so, we keep all parameter values as in the baseline economy but set the minimum wage to zero. Here, only the first two channels operate. Teenagers change their schooling behavior and can enjoy less current consumption from their employment. In line with our decomposition exercise, teen employment now only falls by around half of the baseline fall to around 30%. This leads to significantly lower income losses for teen workers as can be seen in *Table 9*. Losses are less than half of the baseline economy. Part of this change is due to the smaller decline in teen employment. To isolate how much the minimum wage affects the *consequences* of the decline, we analyze a second counterfactual. We re-calibrate the model without the minimum wage to fit all moments as in the baseline economy.

Parameter values and model fit for the re-calibrated model without the minimum wage are in *Appendix D.1*. To match the decline in teen employment, the re-calibrated model now features lower costs and higher returns to attending college. This incentivizes more teenagers to go to college in response to adult crowding out. This distinction becomes important when we look at the consequences for lifecycle income and welfare for affected teenagers.

[28] We also go through the other permutations of the order of turning off the different mechanisms. Results are very similar.

Table 9: **Income Changes without the Minimum Wage**

Change lifetime income	**Baseline**	**No Minimum Wage**	**Re-calibrated**
for teen workers	-0.057	-0.024	-0.035
for low-skill non-teen workers	-0.021	-0.046	-0.043

Comparing the income effects, we still see substantial differences to the baseline. Now, all the teenagers that are *no longer workers* have adjusted by going to college and thus have significantly lower income and welfare losses. In the baseline economy with a minimum wage, this group consisted largely of teenagers bound by the minimum wage. Instead, many of the teens that were bounded by the minimum wage, are now *still workers*. Average income losses for all workers are now 3.5%. This is still significantly smaller than in the baseline economy and closer to the economy where we removed the minimum wage without re-calibrating. Together, these results underscore that the minimum wage amplifies both the crowding out itself and the consequences of it.

While removing the minimum wage positively affects teenagers that benefit from early work experience, it reduces wages for everyone else. Especially adults that are negatively affected by the shock to adult occupations benefit from the existence of the minimum wage. We can show this in the model by looking at the income changes for non-college-educated adults that did not work in the first steady state. These adults do not benefit from the removal of the minimum wage, since they would not have worked in the first steady state anyway, but they are hurt by the lower wages as adults. To fully assess this trade-off, we would have to solve the transition path of our economy, since this would allow us to calculate the effects for workers that were already adults in 2000.

Schooling Policy – Next, we consider a policy exercise to mimic vocational schooling, where we allow some fraction ξ of time spent on schooling to instead increase employment human capital. In particular, equation (7) becomes

$$h'_e = \epsilon' a_e (h_e(n_e + \xi n_s))^{\gamma_e} + h_e \tag{26}$$

$$h'_s = \epsilon' a_s (h_s(1 - \xi) n_s)^{\gamma_s} + h_s \tag{27}$$

In equilibrium, it will be optimal for some types of agents to complete vocational training. In particular, those who are constrained by how much they are able to work will benefit from this policy. However, those who optimally do not work will never choose to attend vocational training, as they benefit most from academic schooling.

Compared to the benchmark model, the rise in adults working in teen occupations is very similar, however, the fall in teen employment is now smaller. This follows from fewer teenagers working in the initial steady state, given that schooling can give similar benefits for human capital accumulation. This shrinks the pool of teenagers at the minimum wage margin when the competition from adult labor rises, which leads to less crowding-out. Income and welfare now fall by less for those who are *still workers* and *no longer workers*. Their losses are reduced by roughly two-thirds. Welfare is mostly unaffected for other types of agents, as prices are affected similarly and these types of agents simply do not choose to participate in vocational schooling.

8 Conclusion

Teen employment declined markedly over the last 30 years. We provide new evidence on why this occurred, what it implies for human capital and welfare, and how policy can shape outcomes, by combining causal reduced form identification with a quantitative general equilibrium model.

Empirically, we use an instrumental variables strategy to causally identify two key points. First, the decline in teen employment is mainly caused by adults crowding out teen labor. We can explain around 60% of the aggregate decline in teen employment with the aggregate number of adults taking up teen jobs between 2000 and 2010. Adults are driven into teen jobs by negative productivity shocks affecting adult occupations, including job polarization, successive recessions, and structural change. Second, working in high school has large positive life cycle returns for teenagers who do not attend college. An additional average weekly hour is associated with approximately 4% higher average lifetime earnings, with no effect for future college graduates. We use these estimates to discipline key model parameters via simulated method of moments.

Quantitatively, the overlapping-generations lifecycle model with human capital accumulation and occupational choice matches three core data patterns: (1) positive returns to teen employment; (2) adults' increased employment in teen occupations following an aggregate productivity shock; and (3) teens' reduced employment in response. The consequences of the decline in teen employment are sizable. On average prior teen workers lose 6% of life time income, while losses for those not able to work anymore reach 26%. Because these losses are concentrated among lower skill workers, overall income inequality increases. A decomposition attributes around half of the decline the model can account for to the minimum wage, which amplifies the negative effects of adult crowding out. Solving a counterfactual economy without the minimum wage, we show that income losses for workers that rely on early work experience are more than halved. The remaining half of the decline in teen employment is accounted for by teenagers that focus more time on schooling in order to go to college. Our policy analysis simulates an optional vocational training program, which is successful in substantially reducing welfare losses for the most adversely affected teenagers.

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Online Appendix

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 (ASEC) supplement sample for exposition of our main trends. We use linked monthly CPS data for identifying transitions in and out of teen occupations. All analysis for teenagers is for those aged 15-18 and currently enrolled in high school. We begin our descriptive statistics in 1986, when the high school enrollment variable first becomes available. Demographic variables are given at the date of the interview. The necessary employment variables are also recorded at the date of the interview. We use information on the occupation and the employment status. In our baseline, we define employment as positive hours worked in the preceding week, but supplement this measure with direct questions on the employment status. When plotting wages in *Figure 3* we have to rely on the income variable that is recorded for the previous calendar year. We supplement this with the variable that gives last years' occupation. We otherwise do not condition on other demographics in this figure.

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 those who transition through unemployment, *if* the most recent occupation before unemployment was a non-teen occupation. The linked CPS data consists of two four-month waves per individual. We do not consider transitions across the two waves and only those within the four-month observation window. We aggregate 4-digit Census occupation codes into 81 broader categories following the natural aggregation provided by the IPUMS CPS classification scheme. We exclude all top 20 teen occupations that we defined previously on a 4-digit level and consider the 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 collects a 5% sample of the U.S. population through 2000, with the subsequent American Community Survey (ACS), which collects a yearly 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 analysis 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 for those aged 15-18 and currently enrolled in high school. Demographics and employment variables again refer to the time of the survey. Income variables are given for the last 12 months. In our wage regression, we thus assume that the reported income corresponds to the current occupation.

A.3 National Longitudinal Surveys of Youths

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 a longer lifecycle 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, observable 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, where we assign 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 summer, and to observe how many hours teenagers work while enrolled in school.

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

A.4 American Time Use Survey

We require information on the time spent in school, in the labor market and enjoying leisure for teenagers in order to estimate all of our model parameters. We thus additionally employ the American Time Use Survey. We use the variables representing the major activity categories in the ATUS activity coding lexicon as made available by IPUMS. Specifically, we chose the activity category “Working and Work-related Activities” to proxy for time spent working, the activity category “Educational activities” to represent time spend on schooling and the categories “Socializing, relaxing, and leisure” together with “Sports, exercise, and recreation” to be 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 chose 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 Robustness

B.1 Teen Employment

Our baseline sample is defined over those aged 15 to 18 that are currently enrolled in high school. *Figures D.2-D.4* show that the decline in teen employment holds across alternative demographic samples. In particular, defining teen employment to be 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 as positive employment hours during the preceding week. See *Figures D.5-D.9* with alternative definitions. Our result of declining teen employment is not sensitive to the alternative definitions. We also show that the decline holds for summer employment and employment not during the summer in *Figure D.10*. *Figure D.11* shows that we obtain a similar result when using the ACS as opposed to the CPS.

We used Organisation for Economic Co-operation and Development (OECD) data to show that this is not an American specific phenomenon. *Figure D.12* plots teen employment rates across several countries, and the OECD average.

B.2 Teen Occupations

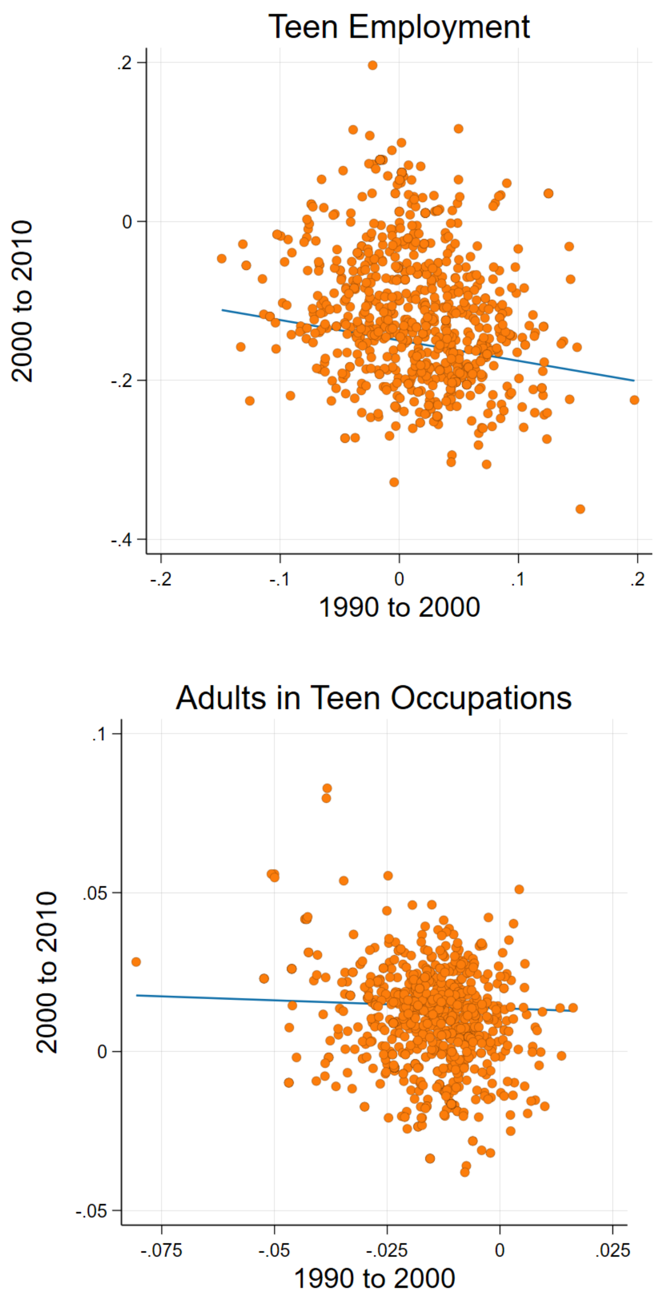
The list of teen occupations is generated for those aged 15-18 that report positive hours worked in the previous week.

Table D.6 reports the top 20 occupations used to define a teen occupation. The analysis in *Section 3* remains unchanged if we instead use the top 15 or top 30 occupations.

In order to provide consistent trending over time it is necessary to be consistent with the definition of a teen occupation. For this reason, we average top occupations over the 1986-2019 period inclusive. The top 20 occupations consistently represent between 73%-75% of total teen employment over this period. This occupations list is stable across time with all occupations inside the top ten present over the entire time period. The largest outliers that appear between 1986-1991 and drop out thereafter are "Pumping Station Operators" and "Driver/Sales Workers and Truck Drivers" which are ranked 13^{th} and 15^{th} for this period, respectively. The largest outliers that are not included before for the 2016-2019 period are "Athletes, Coaches, Umpires, and Related Workers" and "Law enforcement workers, nec" which are ranked 17^{th} and 19^{th} for this period, respectively. None of these occupations are present on the averaged list.

B.3 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.

Table B.1: **Instrumental Variable First Stage**

	AdultShare					
	(1)	(2)	(3)	(4)	(5)	(6)
Z_{Cohort}	0.051	0.058				
	(0.002)	(0.018)				
$Z_{Education}$			0.104	0.068		
			(0.000)	(0.000)		
$Z_{PreviousOcc}$					0.0132	0.0178
					(0.000)	(0.000)
$TeenEmp._{t-1}$	0.001	0.078	0.01	0.083	-0.005	0.071
	(0.903)	(0.000)	(0.313)	(0.000)	(0.636)	(0.000)
$MedianWage$	0.28	-0.49	0.44	-0.42	0.21	0.54
	(0.356)	(0.266)	(0.164)	(0.315)	(0.476)	(0.187)
$Emp.Rate$	-0.14	-0.14	-0.16	-0.15	-0.15	-0.16
	(0.000)	(0.003)	(0.000)	(0.001)	(0.000)	(0.000)
$WhiteShare$	-0.05	-0.03	-0.019	0.00	-0.028	0.001
	(0.001)	(0.154)	(0.263)	(0.99)	(0.083)	(0.961)
$TeenShare$	-0.025	-0.35	-0.106	-0.40	0.073	-0.23
	(0.790)	(0.001)	(0.225)	(0.000)	(0.402)	(0.022)
$Manufacturing$	-0.087	0.029	-0.11	0.02	-0.06	0.05
	(0.001)	(0.431)	(0.000)	(0.623)	(0.012)	(0.101)
$Constant$	-0.012	-0.006	-0.002	0.007	-0.02	-0.022
	(0.066)	(0.473)	(0.269)	(0.012)	(0.001)	(0.009)
F-stat	9.77	5.66	22.47	10.80	19.27	21.64
Norm. Adults.	No	Yes	No	Yes	No	Yes
Observations	741	741	741	741	741	741

Table B.2: P-values shown in brackets. Wages in 10,000. *Source*: American Community Survey (ACS).

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

	(1)	(2)	(3)	(4)	(5)	(6)	OLS	No Adults
$AdultShare$	-3.98	-3.48	-2.54	-3.08	-5.11	-3.78	-0.27	
	(0.043)	(0.043)	(0.026)	(0.030)	(0.003)	(0.001)	(0.250)	
$TeenEmp._{t-1}$	-0.307	-0.04	-0.30	-0.067	-0.31	-0.018	-0.28	-0.28
	(0.000)	(0.786)	(0.000)	(0.563)	(0.000)	(0.850)	(0.000)	(0.000)
$MedianWage$	0.86	0.57	0.84	0.59	0.86	0.49	0.81	0.81
	(0.000)	(0.011)	(0.000)	(0.002)	(0.000)	(0.005)	(0.000)	(0.000)
$Emp.Rate$	0.42	0.488	0.58	0.35	0.28	0.45	0.85	0.89
	(0.177)	(0.078)	(0.014)	(0.033)	(0.374)	(0.060)	(0.000)	(0.000)
$WhiteShare$	-0.17	-0.06	-0.11	-0.05	-0.218	-0.069	-0.00	0.01
	(0.232)	(0.537)	(0.258)	(0.567)	(0.107)	(0.514)	(0.966)	(0.988)
$TeenShare$	-0.44	-1.56	-0.49	-1.45	-0.399	-1.64	-0.57	-0.58
	(0.456)	(0.028)	(0.321)	(0.022)	(0.528)	(0.017)	(0.177)	(0.166)
$Manufacturing$	-0.66	-0.21	-0.56	-0.22	-0.734	-0.189	-0.41	-0.39
	(0.002)	(0.315)	(0.000)	(0.231)	(0.001)	(0.307)	(0.005)	(0.007)
$Constant$	-0.05	-0.03	-0.06	-0.03	-0.04	-0.02	-0.08	-0.08
	(0.003)	(0.305)	(0.000)	(0.152)	(0.003)	(0.258)	(0.000)	(0.000)
Z_{Cohort}	Yes	Yes	No	No	No	No	No	No
$Z_{Education}$	No	No	Yes	Yes	No	No	No	No
$Z_{PreviousOcc}$	No	No	No	No	Yes	Yes	No	No
Norm. Adults.	No	Yes	No	Yes	No	Yes	No	No
Observations	741	741	741	741	741	741	741	741

Notes: P-values shown in brackets. Dependent variable in all columns is the teen employment share. *Source*: American Community Survey (ACS).

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

	(1)	(2)	(3)	(4)	(5)	(6)
AdultShare	-3.78	-4.07	-3.34	-3.66	-3.85	-3.86
	(0.028)	(0.019)	(0.032)	(0.016)	(0.011)	(0.009)
Z_{Cohort}	Yes	Yes	No	No	No	No
$Z_{Education}$	No	No	Yes	Yes	No	No
$Z_{PreviousOcc}$	No	No	No	No	Yes	Yes
F-stat	11.79	11.89	14.03	16.07	18.64	12.24
1st stage coef.	0.035	0.048	0.045	0.053	0.013	0.013
Norm. Adults	No	No	No	No	No	No
Omit Parents	Yes	No	Yes	No	Yes	No
Observations	741	741	741	741	741	741

Notes: P-values shown in brackets. 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. Given an initial share of 2000 it is no longer feasible to also report regressions using the normalized change. In order to employ a more direct comparison to main results we also now include cohorts born between 1970 and 1979. *Source*: American Community Survey (ACS).

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

	(1)	(2)	(3)	(4)
	2000-(2011,12,13)	2000-(2011,12,13)	2000-(2015,16,17)	2000-(2015,16,17)
AdultShare	-4.77	-3.07	-3.61	-1.79
	(0.013)	(0.003)	(0.095)	(0.048)
$Z_{PreviousOcc}$	Yes	Yes	Yes	Yes
F-stat	14.27	16.97	7.00	18.89
1st stage coef.	0.009	0.014	0.007	0.015
Norm. Adults	No	Yes	No	Yes
Observations	741	741	741	741

Notes: P-values shown in brackets. Columns (1) and (2) give coefficient for the fall in teen employment between 2000 and the years 2011, 2012 and 2013 pooled. Columns (3) and (4) for the years 2015,2016 and 2017 pooled. *Source*: American Community Survey (ACS).

B.3.1 Minimum Wage Changes

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

Here, we utilize the same minimum wage data as Neumark and Shupe (2019), that is the higher of the state and federal minimum wage and assign this value to each commuting zone. We calculate the average minimum wage weighted by population 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 started rising in 2005, five years after the beginning of the sharp drop in teen employment. Also, while the levels of the minimum wage differ between states, we do not find large variation in the changes of the minimum wage between 2000 and 2010. As we show in *Table B.8*, these changes furthermore do not correlate with our instruments, which gives us additional confidence that we are identifying a channel independent of 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 of the negative pressure on teen wages due to adults crowding out and the existence of a positive minimum wage is immensely important in explaining the magnitude of the employment decline. While our current work thus focuses on the *level* of the minimum wage, we will include the *changes* in future work on the topic.

B.3.2 Plausibility of Instrument Exogeneity

Although there is no formal test to establish the exogeneity of our instruments, we can give supporting evidence that we are identifying causal effects in our exercise. Since our instruments follow a Bartik-style logic, we follow the suggestions 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.6* show that estimating overidentified IV regressions delivers remarkably similar coefficients. The regressions return large p-values for the overidentification J-Tests, lending

Table B.6: **Overidentification Tests**

	(1)	(2)	(3)	(4)
$AdultShare$	-4.42	-3.74	-3.33	-3.59
	(0.001)	(0.000)	(0.004)	(0.001)
Z_{Cohort}	Yes	Yes	No	No
$Z_{Education}$	No	No	Yes	Yes
$Z_{PreviousOcc}$	Yes	Yes	Yes	Yes
F-stat	13.74	12.11	15.64	12.13
J-Test p-value	0.41	0.91	0.052	0.63
Norm. Adults	No	Yes	No	Yes
Observations	741	741	741	741

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

Table B.7: **Correlation Between Instruments**

	$Z_{PreviousOcc}$	Z_{Cohort}	$Z_{Education}$
$Z_{PreviousOcc}$	1	-0.08	0.12
Z_{Cohort}	-0.08	1	0.74
$Z_{Education}$	0.12	0.74	1

Source: American Community Survey

confidence to our instruments. The tests are meaningful as our occupation instrument is only weakly correlated with the demographic instruments. The instruments thus pick up different variation in the data.

Next, we investigate if our instruments are correlated with the additional controls. Positive correlations could be a worry if these regressors were correlated with other unobserved factors that explain *changes* in teen employment. We can see that the controls only explain a small share of the variation in the instrument. Importantly, the minimum wage is uncorrelated with our instruments, which further confirms that the relationship between adults in teen jobs and teen employment that we identify is independent of any changes in the minimum wage. Across all instruments, the only control that is always significant is the median income in a commuting zone. Given that we control for other measures of local economic conditions, we think that median income is a sufficient statistic for the remaining changes in economic activity within a commuting zone. As intended, this then absorbs additional demand factors and gives us a clean identification of the direct crowding out effect.

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

	$Z_{PreviousOcc}$	Z_{Cohort}	$Z_{Education}$
Median Wage	1.59	0.57	0.53
	(0.000)	(0.000)	(0.000)
Emp. Rate	0.53	-0.12	-0.20
	(0.591)	(0.485)	(0.169)
Share White	0.14	-0.16	-0.05
	(0.480)	(0.000)	(0.001)
Share Teens	9.01	1.45	-0.26
	(0.000)	(0.000)	(0.372)
Share Manufact.	-0.08	-0.13	-0.16
	(0.665)	(0.005)	(0.000)
Minimum Wage	-0.01	0.02	0.01
	(0.782)	(0.059)	(0.405)
R^2	0.27	0.29	0.36

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

B.4 Adult Crowding out on the College Enrollment of Teenagers

Throughout the paper, we emphasize that one channel through which adult crowding out operates is that it increases the relative return to going to college for some teenagers. This is because workers with a college degree hardly work in the negatively affected teen occupations. As explained in *Section 7.1.1*, without panel data, it is not possible to quantify this channel directly in the data, since one has to know the location in which an individual of college age lived while being in high school. We are able to give some supporting evidence of increased college enrollment in this section. This is possible, because from 2005 onward, the ACS reports the location of last year's residence of individuals. We can thus compute for 19-year-olds the amount of adults in teen jobs in the commuting zone they lived in while being 18 and thus most likely still in high school. We thus estimate

$$\Delta\text{Coll. Enrollment}_{c_{t-1},t} = \beta\Delta\left(\frac{\text{Adults in Teen Jobs}}{\text{All Adults}}\right)_{c_{t-1},t-1} + \gamma\Delta X_{c_{t-1},t} + \epsilon_{c_{t-1},t} \qquad (28)$$

for 19-year-olds, where all controls are measured in the previous year and the previous year's location. We estimate this equation for the changes between the years 2005 -2010, 2005-2012 and 2005-2015. We find consistently a positive effect, which aligns with the theory

Table B.9: **Differing Terminal Year**

	$t = 2010$	$t = 2012$	$t = 2015$
Adults in Teen Jobs	0.602	0.413	0.515
	(0.042)	(0.055)	(0.039)
Observations	741	741	741

Notes: P-values shown in brackets. *Source*: American Community Survey.

Table B.10: **Wage Regression Results**

	(1)	(2)	(3)	(4)
	$TeenWages$	$TeenWages$	$AdultWages$	$AdultWages$
$AdultShare$	-6.03	-4.46	-7.83	-5.80
	(0.002)	(0.001)	(0.049)	(0.038)
$Z_{PreviousOcc}$	Yes	Yes	Yes	Yes
Norm. Adults.	No	Yes	No	Yes
Observations	741	741	741	741

Notes: P-values shown in brackets. Wages in \$10,000. *Source*: American Community Survey (ACS).

and the quantitative results of this paper. Interpreting the size of the coefficient, a back of the envelope calculation reveals that we can explain around 10% of the aggregate increase in the college enrollment rate of 19-year-olds between 2000 and 2005.

B.5 Effect on Wages

In *Section 3.1* we argue that the fall in teenage employment and increase in the share of adults in teen occupations is 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 (3) with wages in teen occupations on the left-hand side

$$\Delta \text{TeenOccWages}_{c,t} = \beta \Delta \left(\frac{\text{Adults in Teen Jobs}}{\text{All Adults}} \right)_{c,t} + \gamma \Delta X_{c,t} + \Delta \theta_t + \epsilon_{c,t}. \qquad (29)$$

We estimate (29) separately for teenagers and adults to reduce effects of compositional change. We measure the median yearly wage of all workers employed in teen occupations (teens or adults) that report non-zero 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 findings that it is adults crowding out teenagers that leads to the fall in teen employment instead of adults taking up vacated jobs.

The average increase in the share of adults in teen occupations is 1.5 percentage points and the pre-period normalized share rose by 2.2 percentage points (see Figure 2). The average increase causes a reduction in yearly income of $900-$1,000 for teenagers and $1,200-$1,300 for adults. This is sizable, given that average median income in 2000 was around $3,000 for teenagers and $16,000 for adults. The large difference in these earnings is due to adults working significantly more hours per person. We thus see a reduction in teenage wages by around one-third.

To further interpret the size of the wage and employment changes, we can compute the implied extensive margin labor supply elasticity. We combine the estimated changes in teen employment due to crowding out from *Table 3* of around 8% with the baseline level of employment of 35%, which implies a change in employment of around 20%. We repeat the same exercise for wages, which gives a change of roughly 33%. Dividing the change in employment by the change in wages gives an implied extensive margin labor supply elasticity of 0.7. This is larger than the elasticities usually found for adults, as reported in, for example, Chetty (2012). We will elaborate in more detail why teenagers react so strongly to wage changes in *Sections 5* and *7*. Here, we preface the quantitative results and give some intuition. Firstly, teenagers usually earn lower hourly wages than adults, even within low-skill service jobs. This implies that more teenagers are at the minimum wage margin and as wages fall, the implied wages of many teenagers fall below the minimum wage. These individuals cannot then be employed and leave the labor market. Additionally, teenagers rely less on labor income for their expenses and have other activities to turn to, they can for example spend more time on schooling to avoid the worse-paying service jobs also in the future.

B.6 Life Cycle Wage Returns Regression Analysis

Table B.11: **First-Stage for Wage 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)	(0.32)
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 wage 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 brackets. Columns (1)-(4) are for those who graduate high school and do not graduate college. Column (5) is for college graduate. Column (6) is for all workers. *Source*: NLSY79

Table B.12: **First-Stage for Wage 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 wage 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)	(0000)
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 brackets. 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*: NLSY79.

Table B.13: **Second-Stage for Wage Returns Regressions by Age Group**

	log of average wages							
	(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 wage 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)	(0002)	(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 brackets. 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*: NLSY79.

Table B.14: **First-Stage for Wage 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 wage 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 brackets. Columns (1) is for all ages. Columns (2)-(4) are for age groups 20-24, 25-29, and 30-34, respectively. *Source*: NLSY97.

Table B.15: **Second-Stage for Wage Returns Regressions with NLSY97**

	log of average wages			
	(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 wage 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 brackets. Columns (1) is for all ages. Columns (2)-(4) are for age groups 20-24, 25-29, and 30-34, respectively. *Source*: NLSY97.

Table B.16: **Ordinary Least Squares for Wage Returns Regressions**

	log avg. lifetime wages			
	(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 wage 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 brackets. *Source*: NLSY79.

Appendix C Model

C.1 Equilibrium Definition

Let $\Phi_j(h_s, h_e, a_s, a_e)$ be the share of teenagers at age j with states (h_s, h_e, a_s, a_e) and let $\tilde{\Phi}_j(h_o, a_o)$ be the share of adults at age j with states (a_o, h_o).

Definition: A stationary recursive competitive equilibrium in this economy is, value functions for teenagers $\{V^k, V^{hs}, V^u\}$, and for adults $\{V^o\}$ policy functions for teenagers $\{g_{n_e}, g_{n_s}\}$, and for adults $\{g_{n_o}, g_m, g_s\}$, labor demands of firms $\{Y_l, Y_m, Y_s\}$, wages $\{\omega_l, \omega_m, \omega_s\}$, and measures $\Phi_j(h_s, h_e, a_s, a_e)$ and $\tilde{\Phi}(h_o, a_o)$ such that,

1. Given wages, value functions $\{V^k, V^{hs}, V^u\}$ solve the dynamic problems (11) and (12) and $\{g_{n_e}, g_{n_s}\}$ are the associated policy functions.
2. Wages are equal to the marginal product of aggregate labor inputs $F_{\{Y_l,Y_m,Y_s\}}$.
3. Labor demand is consistent with the firms optimization problem (17).
4. Given wages, value function $\{V^o\}$ solve dynamic problem (13) and $\{g_{n_o}\}$ is the associated policy function. Policy functions $\{g_m, g_s\}$ can be summarized by cut-off values (15) which define the occupational choice.
5. The labor market clears according to (18)-(20).
6. The measures $\Phi_j(h_s, h_e, a_s, a_e)$ and $\tilde{\Phi}_j(h_o, a_o)$, and wages are stationary.

C.2 Computation

The dynamic programming problem for teens is solved by backward induction, beginning with terminal conditions $\mathbb{E}_{a_o,\epsilon_o}\big[V^{hs}\big(j=5, h_s, h_e, a_s, a_e\big)\big]$ and $\mathbb{E}_{a_o,\epsilon_s,\epsilon_o}\big[V^{u}\big(j=5, h_s, h_e, a_s, a_e\big)\big]$, which summarize the continuation values of adults. Adult continuation values are calculated in a first step, using a similar computational method.

For all periods, a uniform rectangular grid is set over the continuous state variables (h_e, h_s). The initial distribution over states (a_e, a_s, h_s) and the distributions for market luck shocks ϵ are discretized using the equal-mass approach of Kennan (2006). We interpolate using cubic splines over next period's value functions. We solve for policy functions g_{n_e} and g_{n_s} (the leisure decision is then implied) using a modified Nelder-Mead to allow for rectangular box constraints. To simulate moments from the model, we take our vector of internally calibrated parameters Θ and solve the model to obtain all decision rules. We then simulate $N = 1{,}000{,}000$ agents. We first simulate cross-sectional moments and then resolve and simulate the model to calculate transitional moments.

To calibrate the model, we define the loss function to be minimized as $\mathcal{L}(\Theta) = \big(m(\Theta) - \hat{m}\big)'\mathbf{W}\big(m(\Theta) - \hat{m}\big)$, where $m(\Theta)$ is the vector of model-simulated moments, $\hat{m}$ is the vector of data-equivalent moments, and $\mathbf{W}$ is a weighting matrix. We set the weighting matrix to the identity matrix. Computationally, we use the TikTak global optimization method from Arnoud et al. (2019) using 10,000 starting points and Nelder-Mead as the local optimizer over 50 points.

C.3 Calibration

C.3.1 Returns to Schooling Human Capital

To calibrate ζ in the model. We use the fact that equation (8) reduces to

$$h_o = \left(\left(\alpha h_s^{\zeta} + (1-\alpha)\right)^{\frac{1}{\zeta}}\right)$$

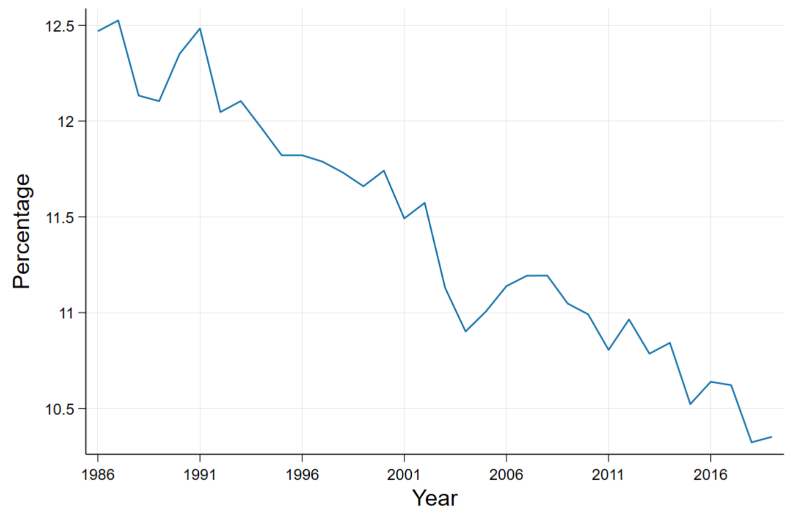
for teenagers that never work. We thus regress wages of recent high school graduates that do not attend college on their accumulated h_s^{data}.[29] Practically, we select all 19 year old workers that never work during high school and do not attend college. We further restrict the sample to observations with positive wages and full time employment (i.e. 40 hours) at age 19. Finally, we drop observations without a full transcript history. We run a simple OLS regression that also includes dummies for sex and race. To better interpret the coefficient, we normalize h_s^{data} to be between 0 and 1. The coefficient of interest is 0.238 with a p-value of 0.015. We then estimate the same regression with simulated data from the model and match the coefficients.

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

Appendix D Additional Figures and Tables

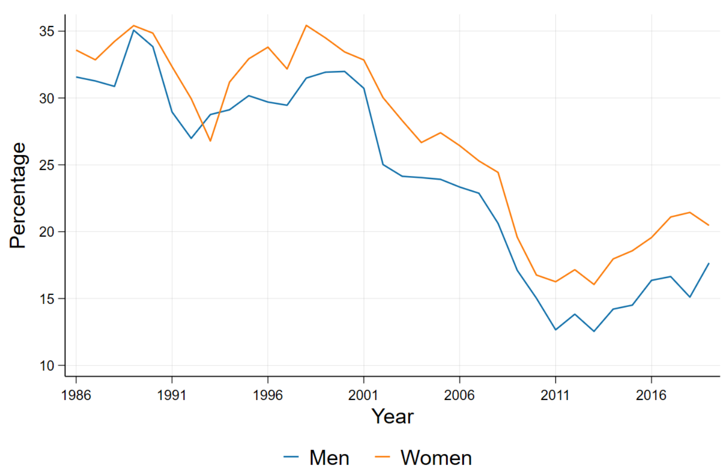
D.1 No Minimum Wage Model Calibration

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



Notes: This figure plots the total number of individuals (age 15 and older) employed in teen occupations, relative to total population size. *Source*: Current Population Survey (CPS).

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



Notes: This figure plots the employment rate for 15-18 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).

Table D.1: **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 wage 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 brackets. *Source*: NLSY97

Table D.2: **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 wage 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 brackets. *Source*: NLSY97

Table D.3: **Internally Calibrated Parameters (no minimum wage)**

Parameter	**Value**	**Description**
Initial distributions		
σ_{a_e}	1.2	Employment ability variance
σ_{a_s}	1.1	Schooling ability variance
σ_{h_s}	0.73	Initial schooling human capital variance
μ_{a_e}	0.0	Employment ability mean
μ_{a_s}	-1.1	Schooling ability mean
Teens		
γ_e	0.80	Working human capital production
γ_s	0.94	Schooling human capital production
α	0.85	CES human capital aggregator share
ζ	0.76	CES human capital aggregator elasticity
College		
γ_c	0.51	College human capital production
$\bar{c}_u$	1.2	Fixed college consumption
Adults		
λ	0.49	Share of schooling ability
σ_{a_o}	0.04	Variance of adult ability
ψ	2.8	Fixed human capital, teen occupations
ϕ	0.51	Fraction human capital, teen occupations
Production		
ν	0.46	Production CES elasticity
A_l	0.07	Production CES productivity
A_m	0.39	Production CES productivity
A_s	1.2	Production CES productivity
θ shock	0.10	Percent shock to adult productivity

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

Table D.4: **Model Fit – ACS Moments (no minimum wage)**

Moment	**Data**	**Model**
Teens		
Decline regression coefficient	-3.78	-3.76
% teens working	0.349	0.351
Average hours worked for working	20.1	22.0
Adults		
% working in teen occ.	0.116	0.119
% with college degree	0.402	0.406
% working in teen occ. – college	0.049	0.059
% working in teen occ. – non-college	0.186	0.134
Δ in adults working teen occ.	0.022	0.021
Wages		
College/non-college, all adult	1.92	1.61
College/non-college, non-teen occ. all adult	1.85	1.74
College/non-college, 24-29	1.49	1.71
Non-teen occ./teen occ.	1.79	1.89
Adult/teen, teen occ.	3.78	3.90
Wage regression	-7.83	-8.30

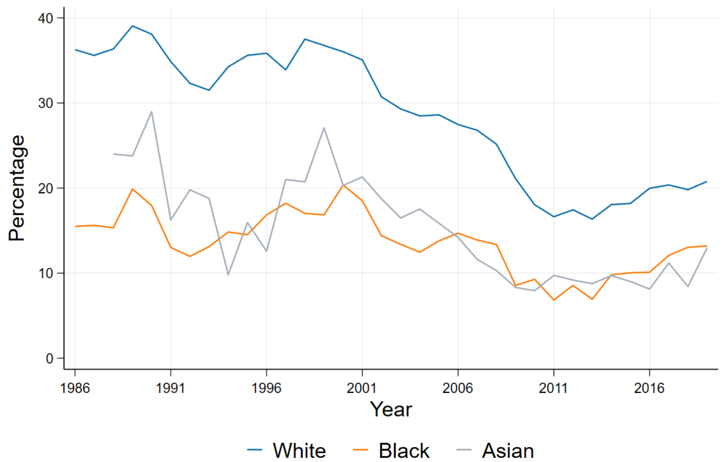
Notes: The columns compare the model to the data for selected targeted moments. All steady state moments in this table are taken from the 2000 year American Community Survey (ACS). Transitional moments are calculated using the 2000 and 2010 ACS.

Table D.5: **Model Fit – NLSY Moments (no minimum wage)**

Moment	**Data**	**Model**
Teens		
Returns to employment on wages	0.041	0.054
Returns to schooling on grades	-0.047	-0.034
% Growth of h_s^{data}, grade 9-12	338	321
Returns to h_s^{data}	0.24	0.29
SD(h_s^{data}(Grade8))/Mean(h_s^{data}(Grade8))	0.80	0.75
Average hours worked, non-college	15.2	16.5

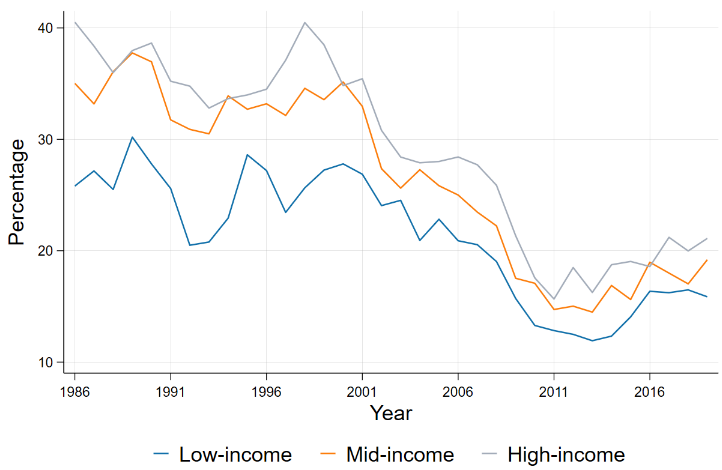
Notes: The columns compare the model to the data for selected targeted moments. *Source*: NLSY79 and NLSY97.

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



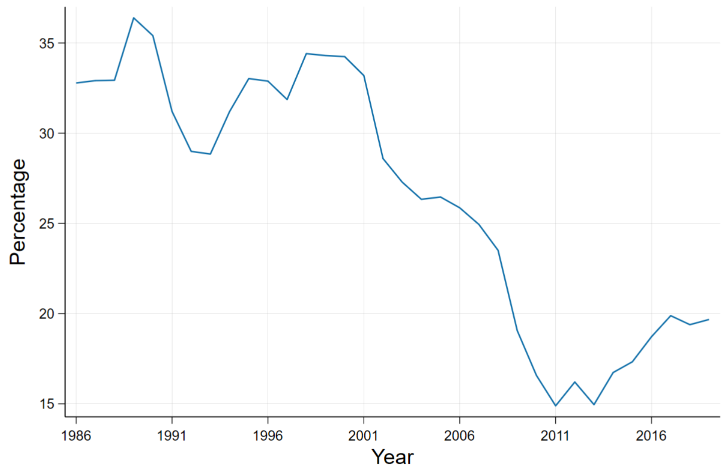
Notes: This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined to be those with positive hours worked over the preceding week. *Source*: Current Population Survey (CPS).

Figure D.4: **Teen Employment Decline by Parental Income**



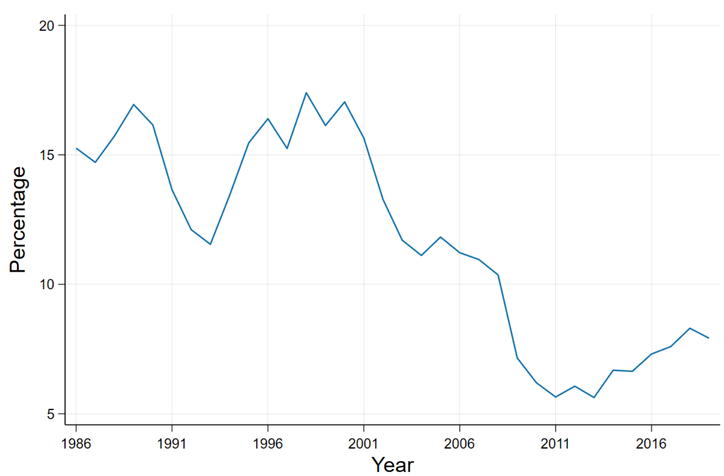
Notes: This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined to be those with positive hours worked over the preceding week.*Source*: Current Population Survey (CPS).

Figure D.5: **Teen Employment Decline – Employment Indicator**



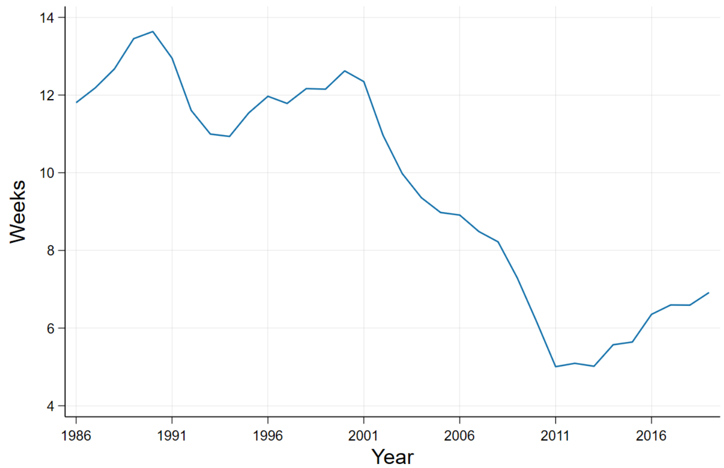
Notes: This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined using the indicator variable for employment status. *Source*: Current Population Survey (CPS).

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



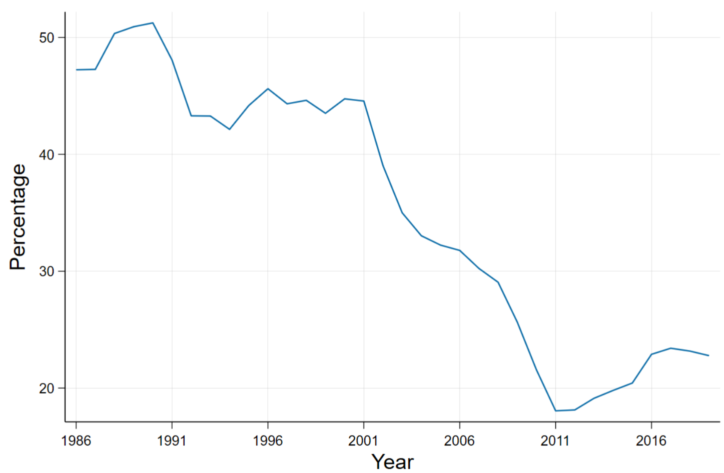
Notes: This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined as those working greater than 15 hours per week . *Source*: Current Population Survey (CPS).

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



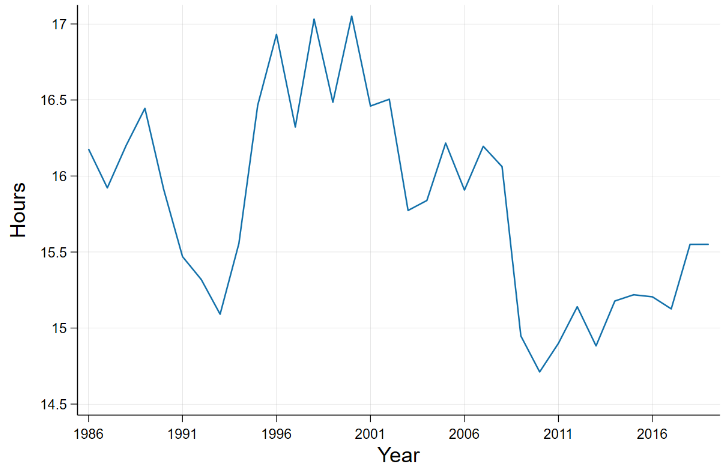
Notes: This figure plots the average weeks worked for 15-18 year olds currently enrolled in high school. *Source*: Current Population Survey (CPS).

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



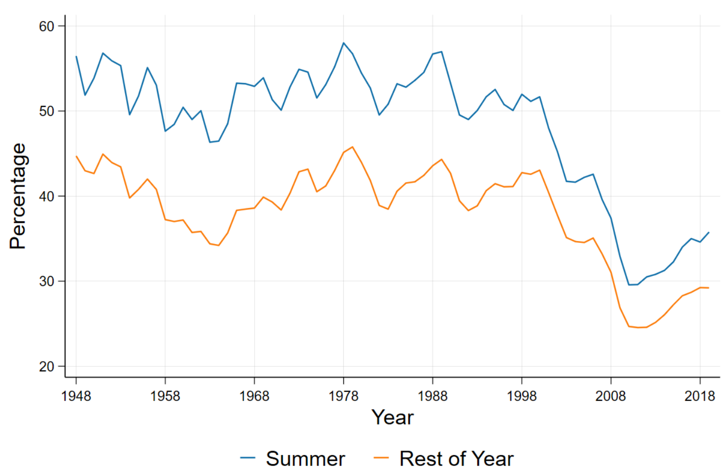
Notes: This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined as positive usual hours worked per week. *Source*: Current Population Survey (CPS).

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



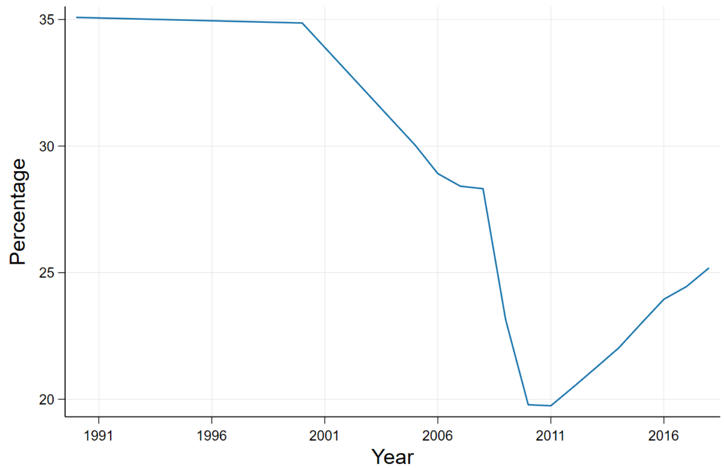
Notes: This figure plots the average hours worked for employed 15-18 year olds currently enrolled in high school. *Source*: Current Population Survey (CPS).

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



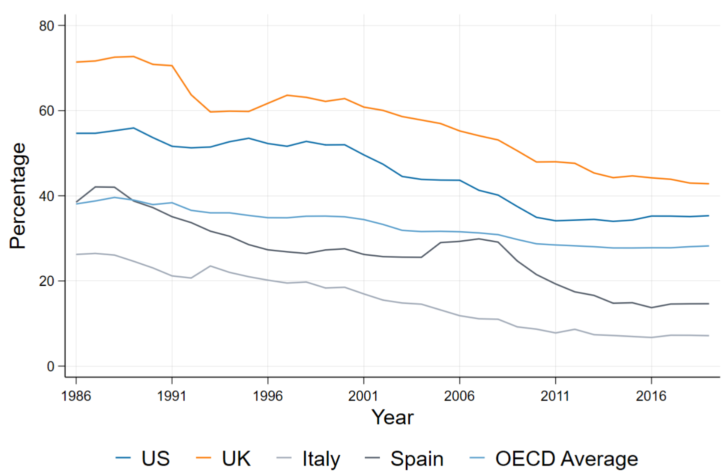
Notes: This figure plots the employment to population ratio for 16-19 year olds. *Source*: Bureau of Labor Statistics (BLS).

Figure D.11: **Teen Employment Decline – ACS**



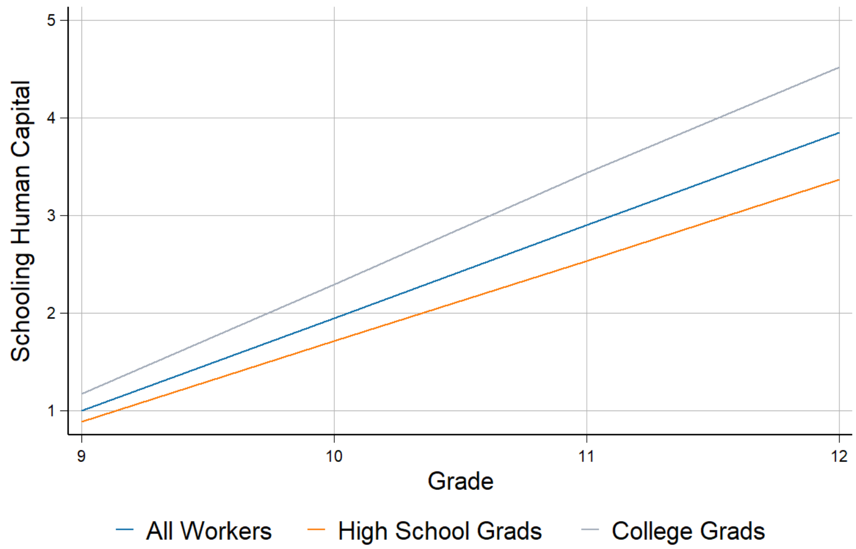
Notes: This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined as positive hours worked last week. *Source*: American Community Survey (ACS).

Figure D.12: **Teen Employment Decline – Across Countries**



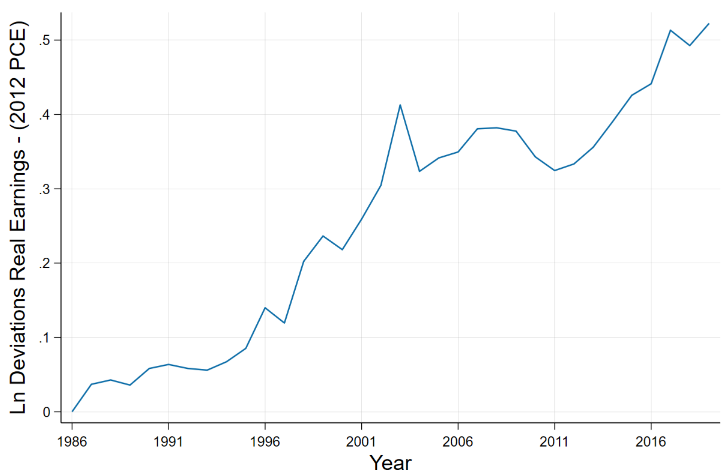
Notes: This figure plots the employment to population ratio for 16-19 year olds. *Source*: Economic Co-operation and Development (OECD) tables.

Figure D.13: **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*: NLSY97.

Figure D.14: **Mean Wages in Teen Occupations**



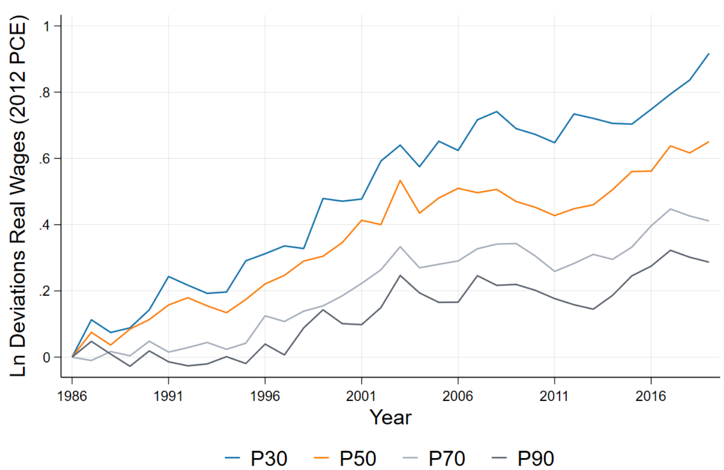
Notes: This figure plots mean wages in teen occupations for ages 15 and older. Zero earnings reported are dropped and 98th percentile and above wages are winsorized. Real wages are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: Current Population Survey (CPS).

Table D.6: **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
Telemarketeters
Stock Clerks and Order Fillers
Receptionists and Information Clerks
Grounds Maintenance Workers
Host and Hostesses, Restaurant, Lounge, and Coffee Shop
Construction Laborers
Cleaners of Vehicles and Equipment
First-Line Supervisors of Food Preparation and Serving Workers

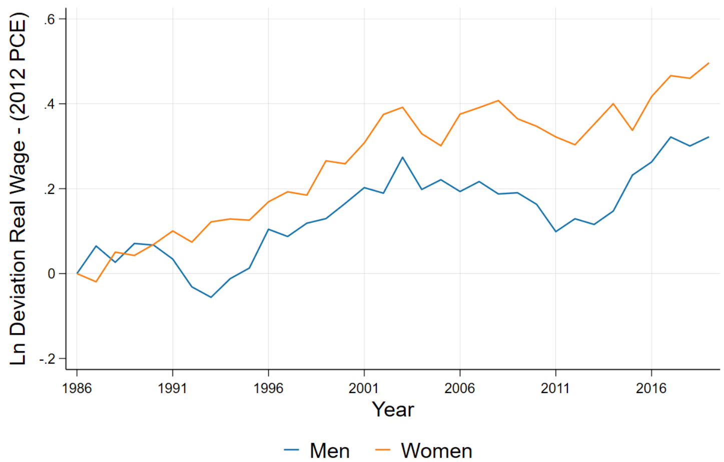
Notes: This table reports the top 20 teen occupations that are aggregated to define a teen occupation. *Source*: Current Population Survey (CPS).

Figure D.15: **Percentiles of Wages in Teen Occupations**



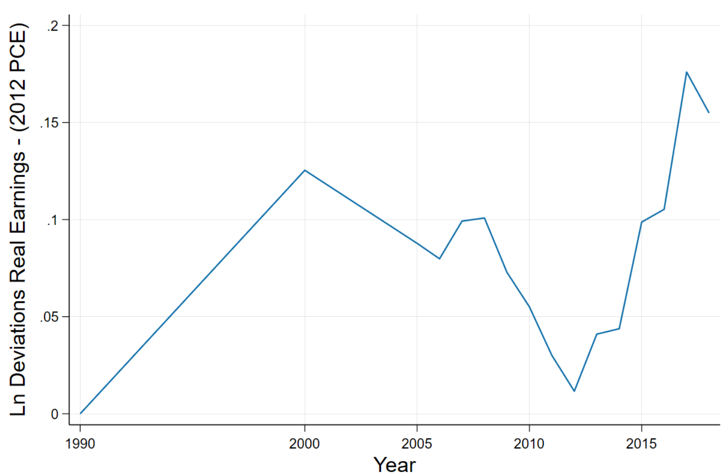
Notes: This figure plots certain percentile wages in teen occupations for ages 15 and older. Zero earnings reported are dropped and 98th percentile and above wages are winsorized. Real wages are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: Current Population Survey (CPS).

Figure D.16: **Median Wages in Teen Occupations by Gender**



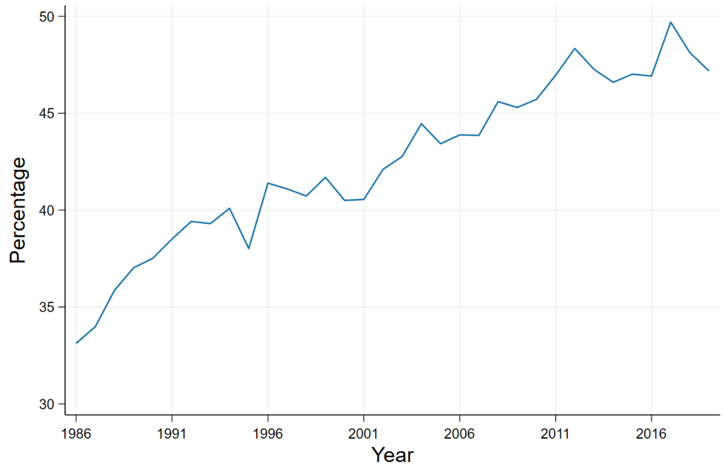
*Notes:*This figure plots median wages in teen occupations for ages 19 and older, not enrolled in an academic institution. Zero earnings reported are dropped and 98th percentile and above wages are winsorized. Real wagess are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: Current Population Survey (CPS).

Figure D.17: **Median Wages in Teen Occupations – ACS**



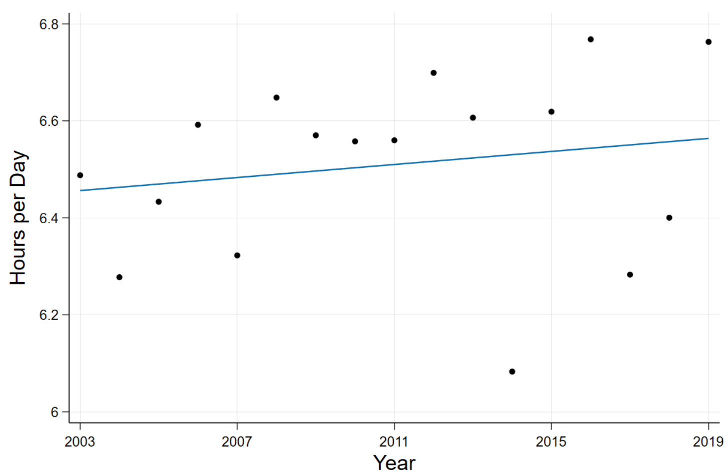
Notes: This figure plots median wages in teen occupations for ages 15 and older. Zero earnings reported are dropped and 98th percentile and above wages are winsorized. Real wages are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: American Community Survey (ACS).

Figure D.18: **College Enrollment**



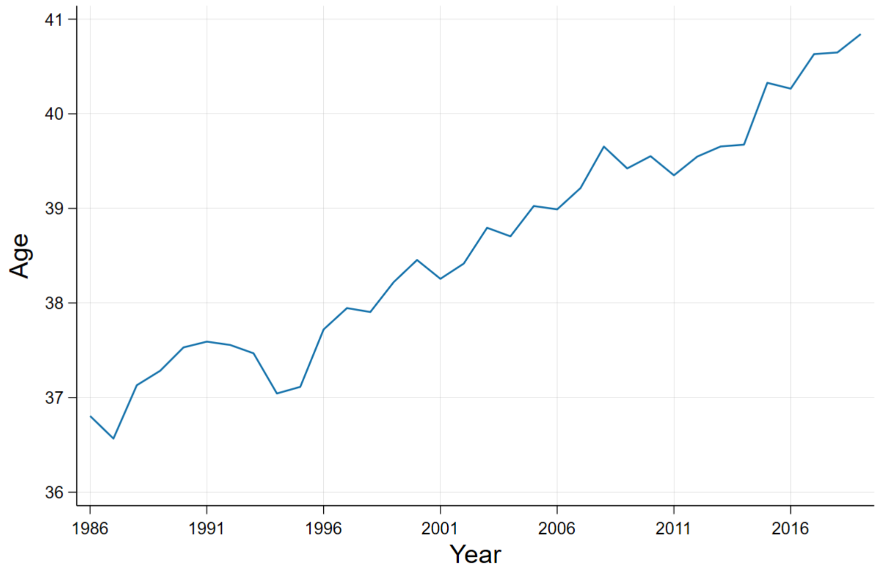
Notes: This figure plots the percentage of those aged 19-22 currently enrolled part-time or full-time in college. *Source*: Current Population Survey (CPS).

Figure D.19: **Schooling Time Use**



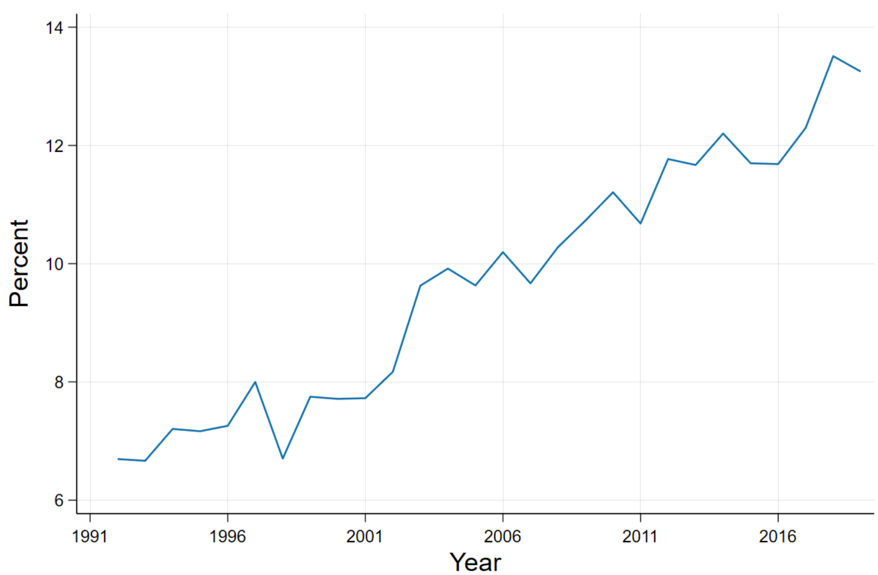
Notes: This figure plots average daily time spent on schooling activities. *Source*: American Time Use Survey (ATUS).

Figure D.20: **Average Age of Adults in Teen Occupations**



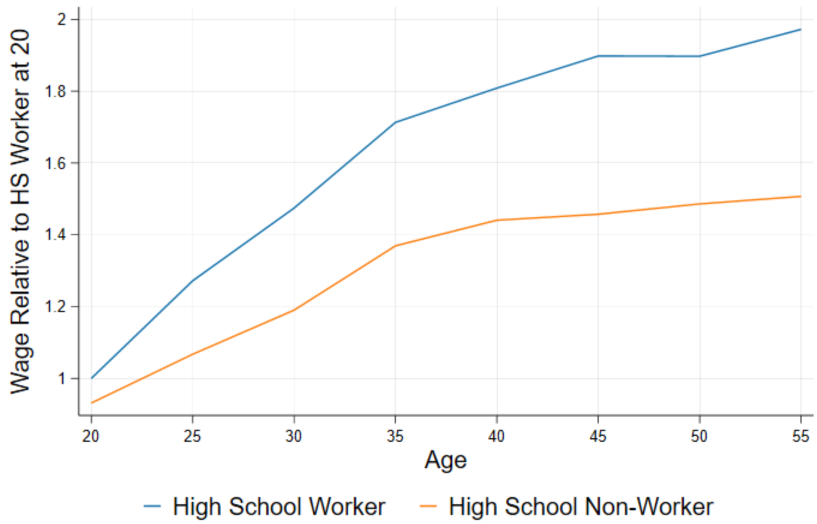
Notes: This figure plots the average adults of adults 19 and older, not enrolled in an academic institution, who are employed in a teen occupation. *Source*: Population Survey (CPS).

Figure D.21: **College Attainment of Adults in Teen Occupations**



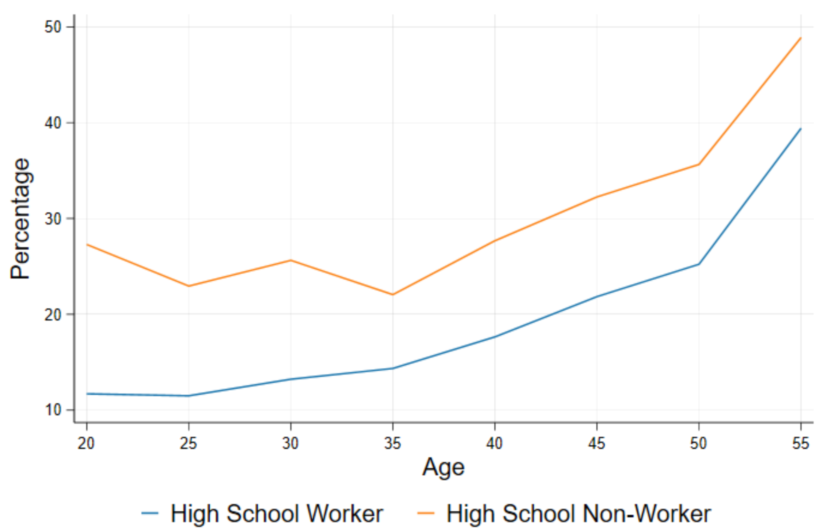
Notes: This figure plots the percentage adults 19 and older, not enrolled in an academic institution, who are employed in a teen occupation and have at least a Bachelor's degree. *Source*: Current Population Survey (CPS).

Figure D.22: **Lifecycle Wages by High School Work Status**



Notes: This figure plots real annual wages 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. Wages are indexed to wages of a 20 year old who worked while in high school. Real wages are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: National Longitudinal Surveys of Youth 1979 (NLSY79).

Figure D.23: **Lifecycle Labor Force Participation by High School Work Status**



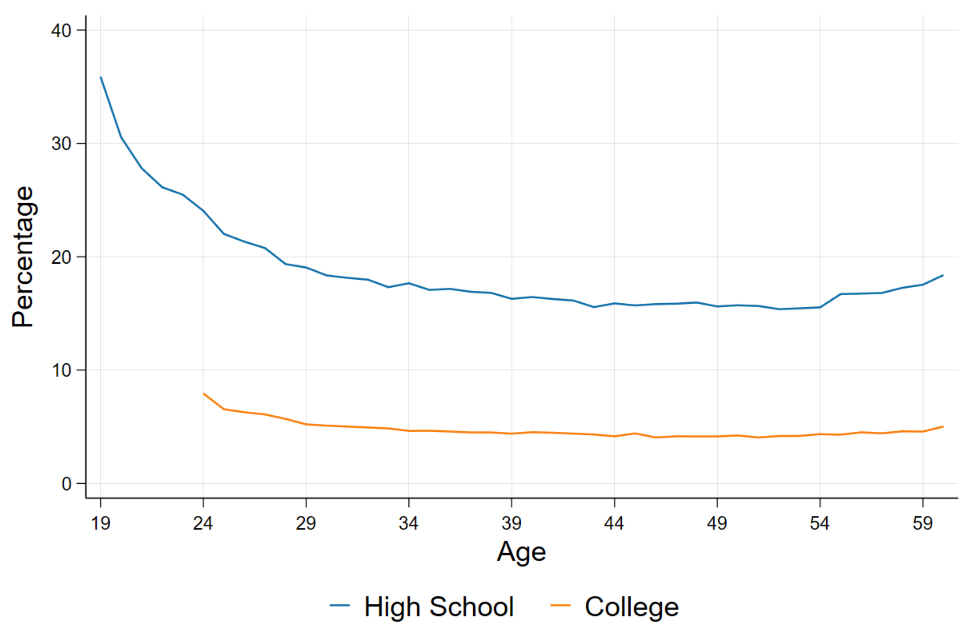
Notes: This figure plots the non-participation rate from ages 20-55, for high school graduates who never attended college, split by those who worked while in high school and those who did not. *Source*: National Longitudinal Surveys of Youth 1979 (NLSY79).

Table D.7: **Externally Calibrated Parameters**

Parameter	**Description**	**Value**	**Source**
Preferences			
J	Model periods	44	Biological life 15-58
β	Discount factor	0.95	Standard
χ	Relative risk aversion	1.0	Log utility
Teens			
$\bar{c}$	Teen fixed consumption	0.35	Literature
σ_ϵ	Luck shocks	0.05	Literature
$\bar{n}_e$	Max hours working	0.44	Teen labor laws
$\bar{n}_s$	Min hours schooling	0.38	Standard schooling day
Adults			
γ_o	Adult human capital curvature	0.30	Literature
δ_o	Adult human capital depreciation	0.05	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.

Figure D.24: **Data Lifecycle Employment in Teen Occupations by Education**



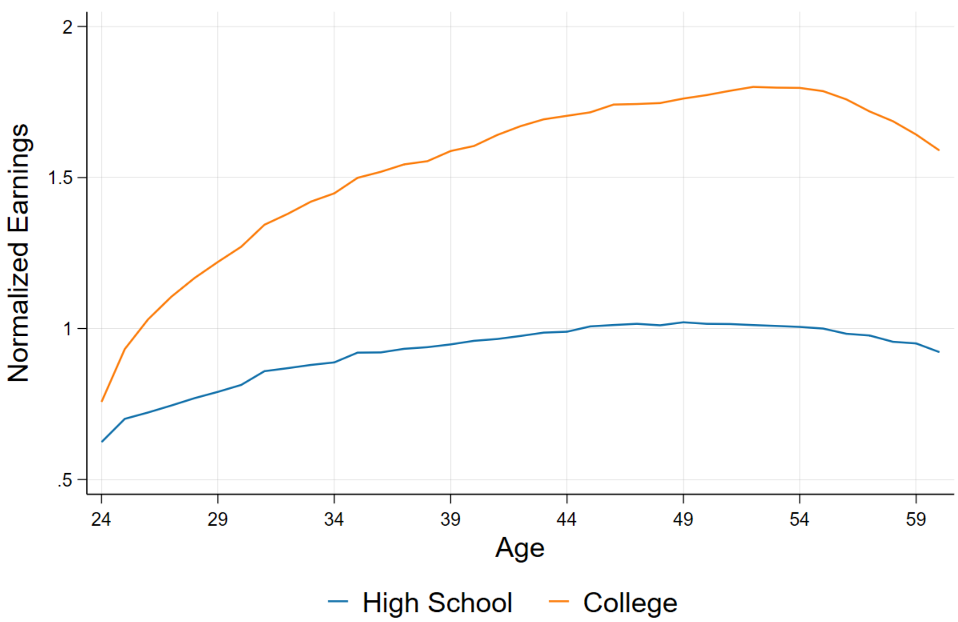
Notes: This figure plots the percentage of adults employed in a teen occupation, by adult age and education type from the data. *Source*: 2000 Census.

Table D.8: **Internally Calibrated Parameters**

Parameter	Value	Description
Initial distributions		
σ_{a_e}	1.3	Employment ability variance
σ_{a_s}	1.1	Schooling ability variance
σ_{h_s}	1.3	Initial schooling human capital variance
μ_{a_e}	-0.32	Employment ability mean
μ_{a_s}	-1.2	Schooling ability mean
Teens		
κ_k	0.21	Preference over leisure
γ_e	0.78	Working human capital production
γ_s	0.94	Schooling human capital production
α	0.85	CES human capital aggregator share
ζ	0.75	CES human capital aggregator elasticity
College		
γ_c	0.51	College human capital production
$\bar{c}_u$	2.3	Fixed college consumption
Adults		
κ_o	1.98	Preference over leisure
λ	0.47	Share of schooling ability
σ_{a_o}	0.05	Variance of adult ability
ψ	4.9	Fixed human capital, teen occupations
ϕ	0.52	Fraction human capital, teen occupations
Production		
ν	0.6	Production CES elasticity
A_l	0.07	Production CES productivity
A_m	0.39	Production CES productivity
A_s	1.0	Production CES productivity
θ Shock	0.10	Percent shock to adult productivity
w_{min}	8.5	Minimum Wage

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

Figure D.25: **Data Lifecycle Wage Profiles by Education**



Notes: This figure plots data average wage profiles by highschool and college education. High school earnings at age 55 are normalized to one. *Source*: 1980, 1990, and 2000 Census.