# Declining Teen Employment: Causes and Consequences*

Jacob Wright† Alex Wurdinger‡

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**Abstract**

Teen employment in the United States has fallen by more than 50% over the last 30 years. We provide causal evidence attributing the majority of this decline to crowding out by adults. To determine the macroeconomic consequences of this decline, we begin by causally estimating the returns to teen employment. We find that teens who worked while in high school and did not attend university earn significantly higher wages and face lower unemployment rates later in life. Next, we develop a general equilibrium model and calibrate it to match our causal estimates. The model features adolescents choosing between accumulating human capital on-the-job or in school, and adults choosing teen vs. non-teen occupations. Using this framework, we simulate a shock to adult occupations that displaces teen workers. Teens crowded out by adults experience significant welfare losses, mostly due to a loss of work experience. Increased college attendance mitigates these negative effects. A decomposition exercise reveals that minimum wage levels play a key role in transmitting the impact of increased adult competition into falling teen employment. Finally, we show that education policies, such as optional vocational training are effective at reducing adverse effects for teens who have been crowded out of the labor market.

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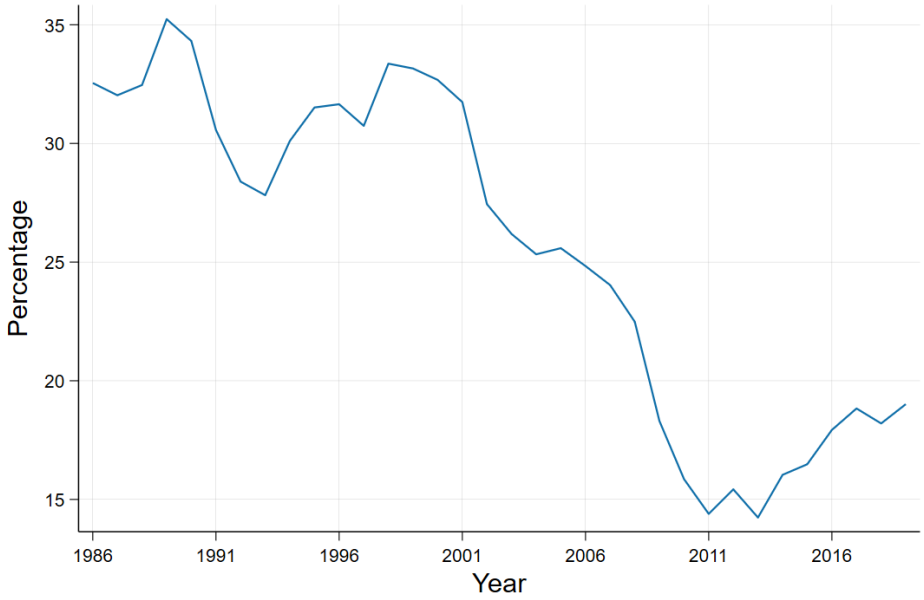
†University of Minnesota (email: wrig0974@umn.edu).

‡University of Minnesota (email: wurdi004@umn.edu).

# 1 Introduction

Over the last 30 years, teen employment has declined by over 50%. Adolescent employment historically ranged between 35-45%. Beginning in the late 1990s and early 2000s, there was a stark break from trend and teen employment fell below 15% by 2010. Today, this rate hovers around 20%. *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 lifecycle earnings dynamics and individual welfare? (3) How do education and minimum wage policies interact with and mitigate adverse effects of declining teen employment? We answer these research questions both empirically and quantitatively.

Figure 1: **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 2.1* discusses *Figure 1* in more detail. *Appendix B.1* reports extensive robustness analysis and discusses additional details.

We investigate the potential impact of various supply side and demand side factors on the decline in teen employment. Possible supply side explanations include; a substitution towards leisure activities (e.g. video games), or stricter teen labor laws. Demand side factors entail reduced employer demand for teen labor, such as increased competition from adult workers.

We begin our empirical analysis by presenting aggregate descriptive statistics as a first step in disentangling supply and demand forces. We provide evidence refuting a supply driven explanation of declining teen employment. We find that the share of adults working in occupations usually performed by teenagers increased significantly after 2000, while relative wages decreased in these same occupations. This implies greater competition for teen jobs originating from adults, rather than adults taking up jobs vacated by teenagers for supply side reasons.

Motivated by our descriptive statistics, we proceed to a more rigorous analysis to identify how the displacement of teenagers by adult labor contributed to the decline. We do so by exploiting geographic variation within the U.S. using data from the Census and American Community Survey (ACS). To mitigate biased estimates from endogeneity issues with ordinary least squares (OLS) we employ an instrumental variables (IV) regression strategy.

We instrument for adults in teen occupations using three separate Bartik-style instruments, all of which produce remarkably similar estimates. First, we observe that relatively more middle-aged and college educated adults enter teen occupations after 2000. Hence, we develop our first two instruments by exploiting lagged age and education demographic variation within commuting zones. Second, using linked Current Population Survey (CPS) data, we identify which occupations adults originate from, when moving into teen occupations. This is used to inform an instrument that relies on variation in the lagged occupational distribution within commuting zones.

Our results show that adults crowding out adolescents is an important factor explaining the decline in teen employment. A back-of-the-envelope calculation suggests rising adult

employment in teen occupations explains up to half of the decline. We use this result to inform our second main empirical exercise; determining the returns, or value-added, to employment while in high school.

For this analysis, we use geocoded National Longitudinal Survey of Youths (NLSY) data and instrument for teen employment with local economic conditions. Specifically, the aggregate employment share of teenagers. Our results show that teen employment has significant effects on wages throughout the lifecycle for workers who do not obtain a college degree. For college educated workers we find no returns to employment while in high school.

The quantitative portion of this paper is motivated by these two key empirical findings: (1) the teen employment decline is largely due to crowding out by adult workers and (2) employment while in high school has important benefits for later life earnings. The first finding implies teens "would like to" work, but are unable. The second suggests that this inability to work has considerable effects on later life outcomes. One and two combined motivate a policy analysis to mitigate adverse effects (welfare losses) for teens crowded out of the labor force.

To this end, we develop a general equilibrium, overlapping generations model. The model features a teenage problem where agents dynamically accumulate two types of human capital. One type accumulates á la Ben-Porath (1967) and we call it schooling human capital. The other accumulates in a learning-by-doing style and we call it employment human capital. Schooling and employment human capital play the central role in determining which agents choose to attend college, and later lifecycle earnings dynamics. Once the agent enters the workforce they work in either adult or teenage occupations. In the latter, they compete with teenagers.

In the model, a negative productivity shock to adult occupations is the sole exogenous driver of adult workers into teenage occupations, leading to the "crowding out" we identify in our empirical section. In our baseline efficient model, this affects teen choices through current wages (consumption), and by increasing the relative value of attending college. In

reality, there exist labor market frictions where teenagers that would optimally work are no longer able to do so. To capture this, we extend the model to include a minimum wage. Increased competition from adults reduces teenagers' potential wages, causing some to fall below the minimum wage and subsequently leading to unemployment.

Together our empirical and quantitative work allows us to discipline a variety of novel parameter estimates. Our model is simple, yet successfully captures the three essential elements identified in the data, which are critical for addressing our research questions: (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 use our causal estimate on the returns to teen employment and crowding out of adults to discipline parameters governing (1)-(3). In addition to policy analysis, our model is also able to decompose (3) into separate channels through which the aggregate productivity shock operates. Namely, current consumption, future earnings/college decision, and the minimum wage.

Our model experiments compare the pre-fall (pre-2000) steady state with the post-fall (post-2010) steady state. The post-fall steady state is generated with a negative shock to the productivity of non-teen labor. In the efficient model we find that welfare losses are largest for those who cannot adjust away from teen-employment. Whereas teens who successfully adjust their human capital investments towards schooling (and possibly college attendance) are less adversely affected. In the model with frictions, agents who cannot work, but would otherwise optimally do so, see the largest decreases in welfare.

Our policy analysis simulates an optional vocational training where some fraction of time spent accumulating schooling human capital also increases employment human capital. This policy is able to minimize the welfare losses for certain teen demographics.

Finally, we disentangle how the aggregate productivity shock interacts with model mechanisms, and decompose their contribution to falling teen employment. We find that changes in current teen wages play a small role, as teens are generally not working for the purpose of

current consumption. Our preliminary calibration suggests the role of future consumption and minimum wage are important and of similar magnitude.

Prior work studying declining teen employment is surprisingly sparse and 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.

Quantitatively, our paper is the first to study declining adolescent employment. A quantitative analysis allows us to extend the existing literature along several important dimensions. Without a quantitative model, we are unable to determine the effects of declining teen employment on teenage human capital accumulation dynamics and the full distribution of later life adult earnings. Moreover, we are able to use our general equilibrium framework to determine the macroeconomic implications of declining teen labor on a host of important moments, such as inequality or the college wage premium. Additionally, we are also the first paper able to conduct a policy analysis and attempt to rectify the welfare losses associated with declining teen labor. Finally, while we causally identify the strength of overall crowding out in the data, the same is not possible for the three mechanisms (current consumption, future consumption, and minimum wage) through which the aggregate productivity shock interacts. Our quantitative model allows us to do so.

The remainder of this paper proceeds as follows. *Section 2* begins by establishing our

main empirical results. *Section 3* lays out the framework for our quantitative analysis and *Section 4* discusses our calibration and identification strategy. *Section 5* reports the results of our counterfactual and policy exercises. *Section 6* concludes.

# 2 Empirical Evidence

This section presents our empirical analysis used to both motivate and calibrate the quantitative model. *Section 2.1* investigates the causes underlying the decline in teen labor. *Section 2.2* establishes the effects of teen employment on later life earnings and employment outcomes. 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 A* reports additional details of the sample selection, and methodology for both the descriptive statistics and regression analysis. *Appendix B* reports robustness analysis.

## 2.1 Decline in Teen Employment

The decline in teen employment could be a result of either supply and/or demand side factors. Supply side 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 details and the validity of specific supply side explanations.

We emphasize a demand side explanation driven by adult workers crowding out teens and originating from some aggregate productivity shock. Adults crowd out teen labor when the employment and earnings opportunities deteriorate elsewhere. A variety of shocks to specific adult workers have been studied for the period of interest, including, skill-biased technical change (SBTC), recessions, trade competition, and structural change. We begin by abstracting from these underlying shocks, and then discuss them each more explicitly at

the end of the section.

### 2.1.1 Descriptive Statistics

We use descriptive statistics to first explain declines in teen employment and then motivate our instrumental variables analysis.

To begin investigating the crowding out of teenage workers by adults, we must first define what is a "teen occupation". To do so we use the Current Population Survey (CPS) and begin by ranking all 4-digit occupation codes by the percent of teenagers inside the occupation code for the 1986-2019 period.[2] We call the top 20 occupation codes a teen occupation.[3] This list of occupations represents approximately 75% of all employed teens. Cashiers is the highest ranked occupation with 15% of all employed teens working as a cashier. Food services and retail sales services represent the bulk of the remaining occupations.

#### 2.1.1.1 Adults Crowding out Teen Labor

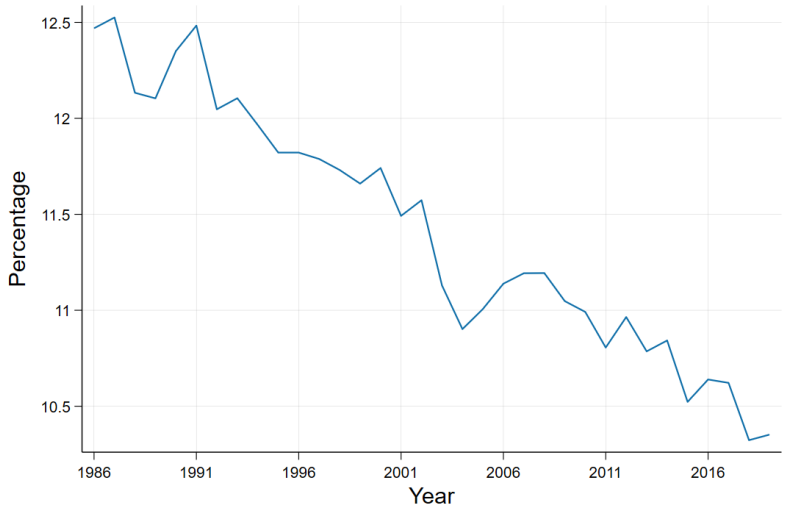
*Figure 2* plots the number of teen occupations relative to total population. Teen occupations have consistently declined over time, falling roughly 2 percentage points over the 1986-2019 period. The causes of this decline is beyond the scope of this paper. We present the trend here for illustrative purposes as it is important to note for our argument, that the total number of teen occupations in the economy is not constant over time. That is, we present our logic assuming that other aggregate moments can be "de-trended" by this constant decline in teen occupations.

*Figure 3* plots the total number of adults employed in teen occupations relative to the adult population. *Figure 4* plots the total number of teenagers employed in teen occupations relative to the teen population. Prior to 2000, teen employment in teen occupations is relatively flat, while adult employment in teen positions falls, driving the constant downward

[2]See *Table E.1* in *Appendix E* for the complete list of occupations.

[3]The list of top 20 occupations is quite stable overtime, however, *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.

Figure 2: **Total Teen Occupations to Population Ratio**



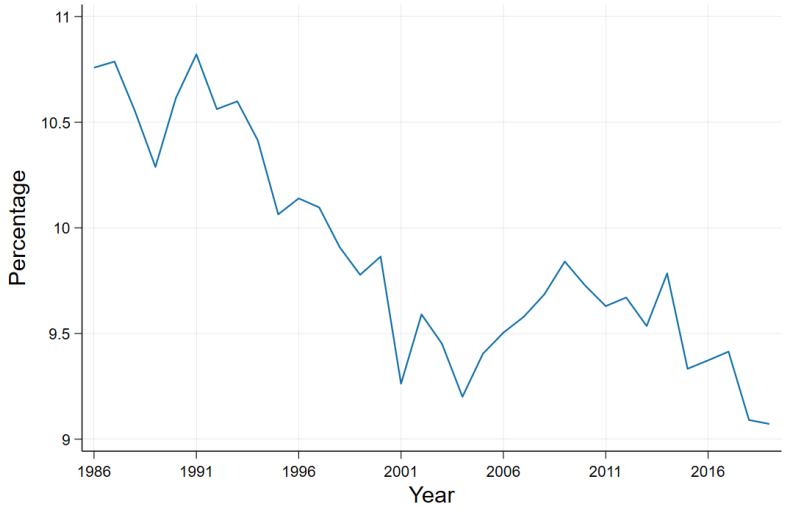

*Notes:* This figure plots the total number of individuals (age 15 and older) employed in teen occupations, relative to total population size. *Source*: Current Population Survey (CPS).

trend in teen occupations. 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, while teens sharply begin to exit. Recalling, the overall declining trend in the number of teen occupations, this implies a stark substitution from teen to adult labor inside teen occupations.

On the surface, it is yet unclear whether the substitution from teen labor to adult labor stems from demand or supply factors. *Ceteris paribus* a large supply shock generating *Figures 2-4* would require wages in teen occupations to be rising. *Figure 5* plots real median earnings in teen occupations relative to real median earnings in non-teen occupations. This ratio increases until the early 2000s and begins to flatten and even fall until the early 2010s. While this period coincides precisely with the influx of adult workers, the ratio only begins to rise again when adult workers start to leave teen occupations in the early 2010s.[4] This provides motivation to further investigate adult labor crowding out teens as the source of the decline. This evidence also rules out an explanation primarily driven by supply side factors.

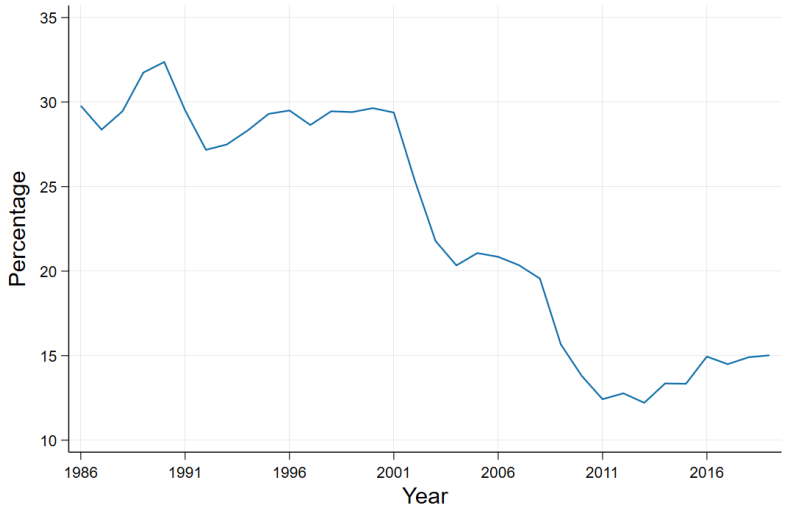
[4] *Appendix E* conducts robustness analysis of *Figure 5* as well as providing additional earnings figures consistent with a demand shock.

Figure 3: **Total Adults Employed in Teen Occupations Relative to Adult Population**



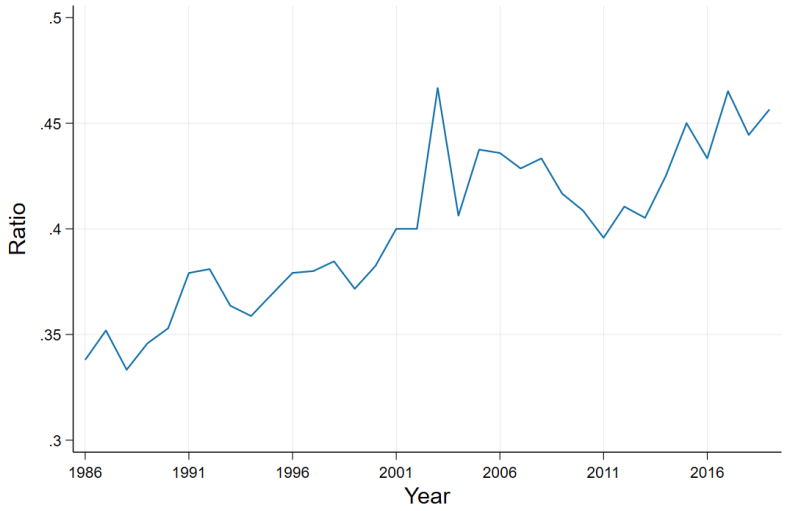

*Notes:* This figure plots the total number of adults, age 19 and older, not enrolled in high school or college, employed in teen occupations, relative to total adult population size. *Source*: Current Population Survey (CPS).

Figure 4: **Total Teens Employed in Teen Occupations Relative to Teen Population**




*Notes:* This figure plots the total number of teens, age 15-18, currently enrolled in high school, employed in teen occupations, relative to total teen population size. *Source*: Current Population Survey (CPS).

Figure 5: **Median Adult Earnings in Teen Occupations to Non-teen Occupations**




*Notes:* This figure plots the ratio median earnings in teen occupations to non-teen occupations for ages 15 and older. Zero earnings reported are dropped and 98th percentile and above earnings are Winsorized. Real earnings are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: Current Population Survery (CPS).

Before turning to our causal estimates, we more closely investigate the possible causes of inflowing adult workers into teen occupations using an OLS regression analysis. 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.[5] 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,

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

Here, $X$ controls for median income and demographics within commuting zones, and $\theta_t$ and $\psi_c$ are time and commuting zone fixed effects. We estimate (1) using the years 2000 and 2010, which is the time period of the largest decline in teen employment.[6] *Table 1* shows that

[5]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.

[6]The qualitative relationship is robust to including more years. We discuss the time variation we exploit in detail in *Section 2.1.2*

Table 1: **Demand Factor Regression Results**

| | *AdultShare.* |
|---|---|
| *Employment* | -0.12 |
| | (0.000) |
| *Manufacturing* | -0.064 |
| | (0.015) |
| Controls | Yes |
| Fixed Effects | Yes |
| Observations | 741 |

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

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 teenage employment.

We conclude this section with a brief discussion of possible supply side explanations. The 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 adolescents. *Figure E.1* shows that the decline in teen employment is equally pronounced for male and female teenagers. As explained in the introduction, the influx of adults into teen occupations partly drives teenagers to increase their education in order to avoid those occupations in the future. Generally, technological change might pull teens into college independently from any crowding out. We cannot differentiate this using aggregate data. Our causal regression strategy will ensure that our results are not confounded by the latter pull factors.

A second explanation is that of an income effect, where parents generally become wealthier over time. This could cause teens to not "need to" work. *Figure E.3* 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 time and

we do not consider this as a factor explaining the decline in teen employment.

#### 2.1.1.2 Motivating Instrumental Variables

We now turn to the characteristics of adults entering teen occupations and which types of occupations they enter from. Both factors will be used to inform our IV-regression analysis in *Section 2.1.2*. The two most important demographic characteristics of adults entering teen occupations are age and education status. 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 some 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. See *Appendix B.1* for details. We formalize this logic in *Section 2.1.2* with an IV-regression analysis.

Over time, those working in teen occupations have become more highly educated, and those transitioning into teen occupations are more likely to have a college degree.[7] While initially surprising, there is a large body of literature (see Binder and Bound (2019) or Abraham and Kearney (2020) for a review) demonstrating non-participation rates rising dramatically through our period of interest for lower education (particularity male) workers. We suggest that a common shock will "hit harder" those without a college education as they are unable to obtain any employment, even in teen occupations. Our first two IV-regressions in *Section 2.1.2* use these types of mechanisms.

We now turn to an analysis of which occupations adults moving into teen occupations are originating from, using the linked monthly CPS data to observe transitions of adults in and out of teen occupations. First, we consider occupations with the highest inflows into teen occupations. For example, we count all movements from farming, into a teen occupation,

[7] A rise in college attainment in teen occupations holds, even when controlling for cohort of birth.

Table 2: **Origin Non-teen Occupations Switching into Teen Occupations**

| Net Into (2001-2010) | Δ Net Into (1996-2000 & 2001-2010) |
|---|---|
| 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 switching into teen occupations. We count those directly entering teen occupations and those moving through and unemployment spells, *if* the most recent occupation before unemployment was a non-teen occupation. *Source*: Linked monthly Current Population Survey (CPS).

and all movements from a teen occupation into farming. We subtract the two and call this difference "net into" teen occupation from farming. We then calculate this net into teen occupation for each non-teen occupation in the 1991-2000 and 2001-2010 periods. We take the difference of these two net into teen occupation periods to obtain a *change* in flows into teen occupations. *Table 2* reports the occupations with the ten highest net into and change in net into teen occupation flows.

The lists of occupations from which workers move into teen occupations is largely comprised of middle skill occupations. The occupations are both manual and non-manual positions affected by skill-biased technical change, as in machine operators and administrative support. We also see positions that have clearly been affected by structural change like farming, or positions affected by offshoring such as sales workers. We use these occupations to inform our IV-regressions in the next section.

### 2.1.2 Regression Analysis

The descriptive statistics presented in *Section 2.1.1* suggest that crowding out of teenagers by adult workers is an important explanation of the decline in teen employment. To further investigate the degree to which adults competing with teenagers since 2000 has 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 ACS. Our main relationship of interest is given by the equation,

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

Where, $X_{c,t}$ is a vector of controls, $\phi_c$ are commuting zone fixed effects, and $\theta_t$ are time fixed effects. Given the fixed effects, we exploit commuting zone, time variation to identify the coefficients of interest. A more natural formulation is given by the first-differenced equation,

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

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 $\beta$ 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 $\beta$ 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. Since we observe that the increase of adults in teen occupations is (at least on average) driven by older and college educated adults, we exploit this demographic variation within commuting zones. Next, we build a Bartik-style instrument that relies on variation in the occupational distribution within commuting zones. As in Goldsmith-Pinkham et al. (2020), identification in both cases comes from the initial distribution of either demographics or occupations.

*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 workers born between $y_0$ and $y_T$ or the share of all workers born between $y_0$ and $y_T$ that have a college degree.

$$z_{c,t} = \sum_{a=y_0}^{y_T} s_{a,c,t} \tag{4}$$

Where $s_{a,c,t}$ is the share of cohort $a$ in location $c$ in initial period $t$. We discuss details of which cohorts are used below.

In order to minimize the potential endogeneity, we use lagged demographic shares. That is, instead of using shares of cohorts in 2000, we use their shares in 1990. This reduces any concerns of individuals moving into and out of commuting zones endogenously.

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

$$z_{c,t} = \sum_{o} s_{o,c,t} g_{o,t}. \tag{5}$$

Here, $s_{o,c,t}$ are the initial employment shares of each occupation $o$ in commuting zone $c$ in initial period $t$. We then weight, $g_{o,t}$, each of these shares by the national net inflows into teen employment from occupation $o$ in the period of interest. These weights are calculated using flows of workers as discussed in *Section 2.1.1*. In practice, we chose the top 20 previous

occupations of workers transitioning into teen occupations.[8]

#### 2.1.2.1 Instrument Exogeneity

As discussed in Goldsmith-Pinkham et al. (2020), the identifying assumption we make is that the initial shares $s_{o,c,t}$ and $s_{a,c,t}$ are uncorrelated with the *changes* in teen employment, except through their correlation with the changes of adults in teen occupations.[9] The underlying national shocks are, two post-2000 recessions, manufacturing decline and SBTC/automation. These shocks adversely affected workers in specific occupations.[10] Some of these workers, especially older workers and those with a college degree, look for employment in the less negatively affected teenage occupations. 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 to our instrument. The same holds for national changes in the demand for teen occupation products, such as structural change towards 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 that are adversely affected and therefore are 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 $X$. Finally, 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 lost income. We address this concern by re-estimating our model constructing our instrument only using

[8] We ensure that each occupation is not closely related to those defined to be a teen occupation.

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

[10] We show in *Appendix B.4* that many occupations identified in *Section 2.1.1* saw falling employment and wages after 2000.

adults without teenage children. Results are unchanged and reported in *Appendix B.6*.

There are further forces that might threaten identification. They are specific to each instrument and are discussed below. Generally, by including several independent instruments, we reduce the concerns of any of these individual factors to bias our results.

*Demographic Instrument* – Our hypothesis is, 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, as 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 preferences of teenagers for work. 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 grads before 1990 predict (expected) increasing demand for college grads after 2000. This would lead to a change in teenagers preference 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 life cycle (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 $\beta$ would be positively biased. Combined, a lower supply of teenage labor due to expected favorable conditions for college grads and larger demand for teen occupations'

products would bias $\beta$ in opposite directions. However, our results show very similar coefficients. Additionally these would both imply rising wages for workers in teen occupations. However, as we show in *Section 2.1.2.4*, wages for teens and adults in teen occupations are significantly reduced by increased adult shares.

*Previous Occupation Instrument* – For the second instrument, a similar logic holds. 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 preferences for work of teenagers. 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. So far as this demand change is a change for service goods in general, we again are controlling for the change in manufacturing share.

#### 2.1.2.2 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 then use 10 year differences, starting from the initial period 2000. Identification comes from 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-difference setting. Hence, we focus on a different time variation than Smith (2012) and Neumark and Shupe (2019). The former obtains identification through the pre-2000 period, while the latter exploit year by year changes without any relation to an initial period. We focus on variation stemming from the long run change.

Since our treatment happens in the year 2000, we regard the time before that as a type

of pre-period. In *Appendix B.4* we explore the correlation of our variables of interest in 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 the year 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.

Lastly, we showed in *Figure 3* that pre-2000, the share of adults working in teen occupations was continuously falling, with a trend reversal in 2000. In our baseline, we therefore normalize the change in adults working in teen occupations by its pre-2000 trend.

#### 2.1.2.3 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.[11] We report the estimates of the elasticity of teen employment to the adult share in teen occupations $\beta$ and the other key controls. The full regression table and first stage regression can be found in *Appendix B.4*, where we also display results of using several instruments together. This allows us to run overidentification tests which return large p-values, lending additional confidence to our instruments. The cohort instrument is constructed as the share of adults in a commuting zone in 1990 that was born between 1955 and 1969. Those are individuals who turn 40-65 in 2010.[12] For the education instrument, we use the same cohorts, but only college educated individuals. Finally, for the previous occupation instrument, we chose the top 20 occupations

[11] Our results are robust to average across years after 2010. See *Appendix B.4* for details

[12] 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.4* 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) |
|---|---|---|---|---|---|---|
| | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* |
| *AdultShare* | -3.98 | -3.48 | -2.54 | -3.08 | -5.11 | -3.78 |
| | (0.043) | (0.043) | (0.026) | (0.030) | (0.003) | (0.001) |
| $Z_{Cohort}$ | Yes | Yes | No | No | No | No |
| $Z_{Education}$ | No | No | Yes | Yes | No | No |
| $Z_{PreviousOcc}$ | No | No | No | No | Yes | Yes |
| F-stat | 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 |
| Observations | 741 | 741 | 741 | 741 | 741 | 741 |

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

with the largest change in net inflows into teen occupations between the 1990-2000 and 2000-2010 period.

We can see a significant negative causal relationship between the share of all adults that work in teen occupations and the share of teenagers that are employed. Columns (1), (3), (5) show the resulting elasticities when we do not normalize the change in adult share by it's pre-trend. Coefficients are all of similar magnitude. Comparing columns (1) and (3), shows that 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 2.2 percentage points, a back of the envelope calculation shows that adult crowding out explains up to 50 percent of the decline.

Looking at the elasticities in columns (2), (4) and (6) we see again very similar estimates. Naturally, these coefficients are smaller than their counterparts in (1), (3), (5) as the regressor is larger. With the same back of the envelope calculation, we can now explain more than 50

percent of the decline in teen employment.

Comparing our coefficients with the OLS estimates in *Table B.3*, we see that the 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. As seen from *Table 1*, 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 amount 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 towards a higher demand for service products, which includes teen labor products.

#### 2.1.2.4 Effect on Wages

In *Section 2.1.1* we argue that the fall in teenage employment and increase in adults in teenage 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

$$\Delta \text{TeenOccWages}_{c,t} = \beta \Delta \left( \frac{\text{Adults in Teen Jobs}}{\text{All Adults}} \right)_{c,t} + \gamma \Delta X_{c,t} + \Delta \theta_t + \epsilon_{c,t}. \tag{6}$$

Table 4: **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).

We estimate (6) 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.

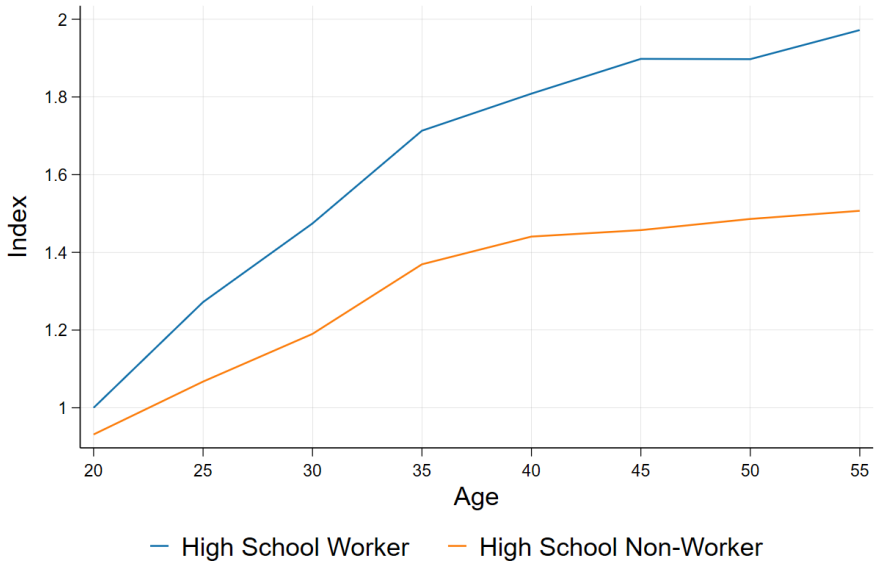
We find significant negative effects of an increased share of adults in teen occupations on wages within these occupations, for both teenagers and adults. This supports our findings that it is adults crowding out teenagers which leads to the fall in teen employment instead of adults taking up vacated 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 3). 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.

## 2.2 Returns to Teen Employment

We use the National Longitudinal Surveys of Youth (NLSY) to determine the returns or "value-added" of teen employment for earnings in adulthood. We put emphasis on the effects for adults who graduate high school but never attend college. See *Appendix B.5* for

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



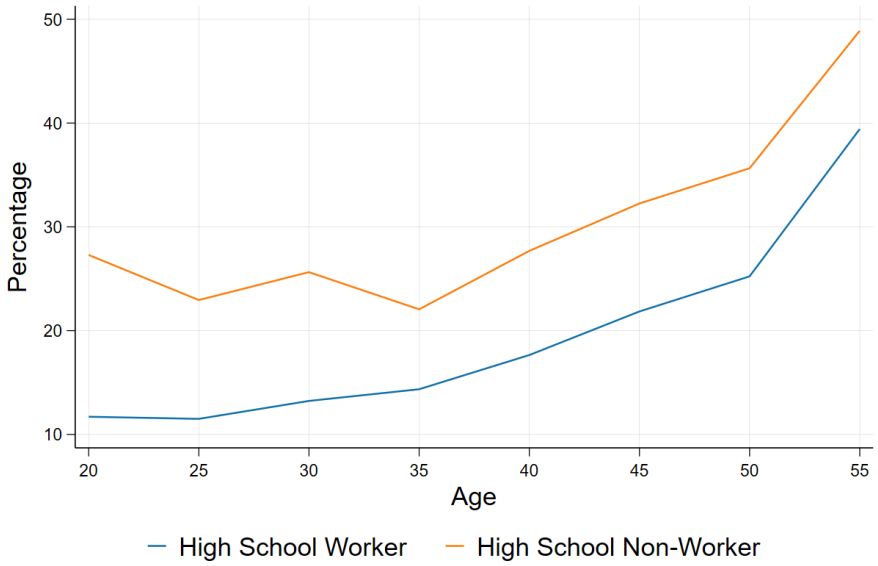

*Notes:* This figure plots real earnings from ages 20-55, for high school graduates who never attended college, split by those who worked while in high school and those who did not. Wages are indexed to wages of a 20 year old who worked while in high school. Real earnings are calculated using the 2012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

an analysis of the value-added for those who have a college degree.

### 2.2.1 Descriptive Statistics

The effects of working while in high school is 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 6* plots the raw difference over the lifecycle of working while attending high school. We demonstrate that working while attending high school *may* have important benefits both in earnings levels, but also growth. From *Figure 7* 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. *Section 2.2.2* investigates this more carefully in an IV-regression setting.

Figure 7: **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)

### 2.2.2 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, one has to 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 utilize 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 $\gamma_1$ from the regression,

$$W_i = \gamma_0 + \gamma_1 E_i^S + \gamma_2 X_i + \epsilon_i, \tag{7}$$

where $W_i$ is the natural logarithm of average lifetime wages for individual $i$, and $X_i$ is a set of individual and location controls. $\gamma_1$ 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 or motivation could directly 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 one to identify 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 past-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 their might be auto-correlation 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, race of individual teenagers, Armed Services Vocational Aptitude Battery (ASVAB or AFQT), and several controls for initial 1980 economic conditions in the geographic location.

We additionally require that, the employment rate of all teenagers is uncorrelated to the unobserved ability or preferences of an individual teenager. The key assumption is that the average local teenage ability and motivation does not vary between the different regions. If they did, and if higher ability teens work more, then higher local teenage employment would positively correlate with individual ability.

#### 2.2.2.1 Results

Columns (1)-(4) estimate our instrumental variables regression for individuals who graduate high school and do not graduate college. Appendix B.5 presents the first-stage results. The returns to teen employment is 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 earnings. As we add controls, the coefficient of interest ranges from 0.064 to 0.041. Our preferred specification is given by column (4) which then predicts that a one hour increase is average hours worked while in high school is associated with 6.6% higher average wages over the lifecycle. We will use this as a moment to identify the parameter governing returns to teen employment in our quantitative model.

Appendix B.5 presents additional results where the regression is broken up by age groupings to estimate the changing return over an agents lifecycle. We find that returns to teen employment are the largest during the middle of the lifecyle, particularly ages, 30-54. Although we can only observe individuals up to the age of 39, we also estimate out main regression using the NLSY97 and find a coefficient of similar magnitude. Finally, Appendix B.5 also reports the OLS regression, which precisely estimates a coefficient of 0.013 in our preferred specification. This indicates that the OLS estimate is negatively biased.

It is likely that the effects of working during high school vary for college and non-college workers. Therefore, we additionally estimate (7) separately by highest degree attainment. Column (5) shows returns for those who attend and graduate college. We find that high school work has no affect on later earnings for this group of individuals. This is not surprising, as higher skilled college educate jobs are likely to be poorly matched with the set of skills teens develop on the job while working in high school. Finally, column (6) estimates the return for all individuals.

Table 5: **High School Employment and Lifetime Earnings**

| | ln of average lifetime earnings | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Avg. hours worked HS | 0.064 | 0.057 | 0.051 | 0.041 | 0.007 | 0.036 |
| | (0.000) | (0.000) | (0.000) | (0.003) | (0.808) | (0.006) |
| Sex | | -0.122 | -0.130 | -0.145 | -0.236 | -0.146 |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| White | | -0.141 | -0.157 | -0.121 | -0.103 | -0.127 |
| | | (0.000) | (0.000) | (0.000) | (0.034) | (0.000) |
| Black | | -0.084 | -0.113 | -0.109 | -0.104 | -0.080 |
| | | (0.000) | (0.000) | (0.000) | (0.052) | (0.001) |
| AFQT score | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | | (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).

# 3 Model

Time is discrete and has an infinite horizon. One model period represents one biological year and is denoted by $j$. The economy is populated by a continuum of $J$ overlapping generations with a uniform demographic structure. Only steady states are considered and so time scripts 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. The model is developed in general equilibrium. *Figure 8* summarizes the phases of an agent's lifecycle.

The lifecycle of an agent begins at $j = 1$, (biological age 14) having just graduated middle school. The lifecycle before age 14 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 a schooling human capital $h_s$. Initial working human capital $h_e$ is homogeneous across agents and normalized to one.

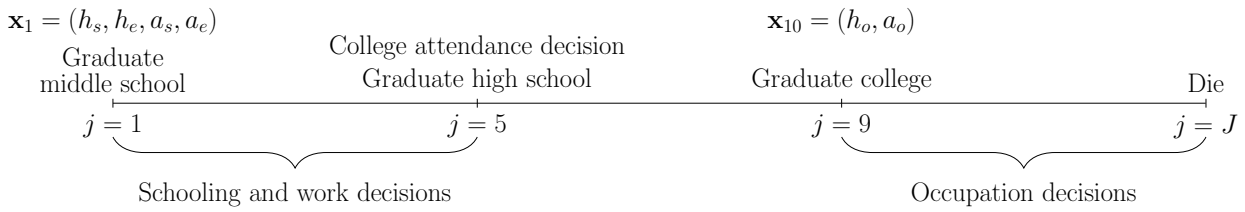
Over the next four periods $j = 1$ to $j = 4$ (biological age 14-18) the agent is enrolled in high school. Agents are endowed with one unit of time in each period. Individuals do not value leisure but divide their time between schooling and employment human capital accumulation. We assume that period utility is valued by the CRRA function $u(c) = \frac{c^{1-\chi}}{1-\chi}$, with $\chi$ as the coefficient of risk aversion.

At the beginning of period $j = 5$ (biological age 18) the agent graduates high school. 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 all employment human capital.

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 child human capital. Upon entering the workforce adults recieve an exogenous human capital profile $\mathcal{H}(h_o, a_o)$. Adults live until period $j = J$ at which time exogenous death/retirement is imposed.

At the beginning of each period, agents choose which occupation to work in. They work

Figure 8: **Lifecycle Timeline**




either an adult or teenage occupation. In the latter they compete with teenagers. Firms combine 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.

## 3.1 Agents

### 3.1.1 Human Capital and Ability

*Teens* – While enrolled in high school, agents accumulate two types of human capital. Schooling human capital $h_s$, accumulates when spending time in school and studying. Employment human capital $h_e$ accumulates when spending time supplying labor to the market. Both types of human capital $h_k$, accumulate according to,

$$h_k' = \epsilon' \Big( a_k (h_k n_k)^{\gamma_k} + h_k \Big), \quad \text{for} \quad k \in \{s, e\} \tag{8}$$

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

An agent must spend a minimum of $\bar{n}_s$ time accumulating schooling human capital. This represents both the time they are physically present in high school as well as some minimum time needed studying in order to graduate. Agents may spend at most $\bar{n}_e$ time employed while in high school. This represents child labor laws which limit the amount of time an

adolescent may work.

*Adults* – The distinction between schooling and employment human capital does not exist for adult workers. Hence, we must transform both types of child human capital and ability into those for adults. Upon entering the workforce and becoming an adult, child human capital is transformed into adult human capital according to the constant elasticity of substitution (CES) aggregator,

$$h_o = \epsilon\Big(\big(\alpha h_s^{\zeta} + (1-\alpha)h_e^{\zeta}\big)^{\frac{1}{\zeta}}\Big) \tag{9}$$

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

Adult ability is also a function of child abilities and is drawn from the normal distribution,

$$a_o \sim \mathcal{N}\big(\lambda a_s + (1-\lambda)a_e, \sigma_a^2\big) \tag{10}$$

Where $\lambda$ represents the relative weight placed on schooling versus employment ability and $\sigma_a^2$ is the variance of the ability draw. The initial adult human capital $h_o$ and ability $a_o$ then determine a lifecycle human capital profile given by $\mathcal{H}(h_o, a_o)$.

### 3.1.2 Recursive Decision Problems

*Problem for* $1 \leq j \leq 3$*:* Given a teen occupation wage $\omega_l$, agents choose time investments in schooling $n_s$ and time investment in employment $n_e$, in order to solve,

$$V(j, h_s, h_e, a_s, a_e) = \max_{n_s, n_e} \Big\{ u\big(\bar{c} + c\big) + \beta \mathbb{E}_{\epsilon_s, \epsilon_e} \big[ V(j', h_s', h_e', a_s, a_e) \big] \Big\}$$

$$\text{subject to,} \tag{11}$$

$$c = \omega_l(\psi + \phi h_e)$$

$$h_k' = \epsilon_k' \Big( a_k (h_k n_k)^{\gamma_k} + h_k \Big), \quad \text{for} \quad k \in \{s, e\}$$

$$n_s \in [\bar{n}_s, 1], \quad n_e \in [0, \bar{n}_e], \quad n_s + n_e = 1$$

where $c$ is consumption, $\bar{c}$ is some consumption provided by parents, and $\beta$ is the time discount factor. We discuss the interpretation of $\psi$ and $\phi$ in *Section 3.1.3* 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,

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

where $V^u$ and $V^{hs}$ denote the maximum possible continuation value of attending college and not attending college, respectively. Note, the agent chooses to attend college, or not, before the realization of adult ability, $a_o$ and human capital, $h_o$. We omit an explicit reformulation of equation (11) where the continuation value is given by equation (12) and laws of motion by equations (9) and (10).

While in college the agent spends their full time endowment accumulating schooling human capital ($n_s = 1$ in equation (8)) and consumes a fixed amount $\bar{c}_u$. Workers who chose

to go to college lose all their $h_e$ accumulated during high school.[13] The state variables while in college are thus given by $(h_s, a_s, a_e)$.

### 3.1.3 Occupational Choice

The only choice adults make is whether to work in teenage occupations ($l$) or adult occupations. We denote adult occupations of non-college grads by $m$ and those of college grads 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 that work in teen occupations (and teenagers) earn

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

The marginal product of a worker in an adult occupation corresponds to the adult's human capital. In teen occupations, we assume that workers can only use a fraction $\phi$ of their human capital, plus a fixed term $\psi$. 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 $\psi$. We assume that there are nevertheless productivity differences between workers, which capture both the ability of a worker (e.g. reliably show up to work) but also the more classical accumulation of skills that allow workers to complete the simple tasks more efficiently. Empirically, $\phi$ depends on the set of jobs that comprise teen occupations.

Mathematically, this formulation allows us to characterize occupational choice by a cut-off for adult human capital $h_o$. Workers below $h^*_{\{m,s\}}$ supply their labor in teen occupations and workers above in adult occupations. The cut-off value is given by,

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

[13] This implies that upon entering the labor force, college grads combine their accumulated $h_s$ with the initial level of $h_e$ according to (9). We interpret this as work experience during high school being essentially useless by the time college grads enter the labor force. This also abstracts from any work experience during college. Our empirical analysis in *Section 2.2.2* confirms this assumption where we estimate zero returns to teen employment for those that later graduate college.

## 3.2 Firms

Production is performed by a representative firm, which combines labor inputs from workers in teenage occupations and adults in non-college and college occupations according to the nested CES function,

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

Skill prices $\omega_{\{l,m,s\}}$ correspond to the first order conditions (FOC) of the firm problem. Here, $A_l, A_m, A_s$ are standard productivity parameters, while $\theta$ measures adult occupation productivity relative to teenage occupation productivity. We solve the model for two values of $\theta$, where we assume a negative, unanticipated shock to $\theta$ that implies a second steady state with more adults in teen occupations and less teenagers working. Labor is aggregated according to,

$$Y_l = \int_0^{h_m^*} (\psi + \phi h_o^m) dh_o^m + \int_0^{h_s^*} (\psi + \phi h_o^s) dh_o^s + \int (\psi + \phi h_e) n_h^K dh_e \tag{16}$$

$$Y_m = \int_{h_m^*}^{H_{max}} h_o^m dh_o^m \tag{17}$$

$$Y_s = \int_{h_s^*}^{H_{max}} h_o^s dh_o^s. \tag{18}$$

Together with the optimal labor supply of teenagers $n_h$, this closes the labor market.

## 3.3 Equilibrium

An equilibrium in this economy is a sequence of wages $(\omega_l, \omega_m, \omega_s)$, labor supply decisions of of teenagers $n_h$, occupational choices of adults $(h_m^*, h_m^*)$ and labor demands $(Y_l, Y_m, Y_s)$, such that,

1. Labor demand is consistent with the firms optimization problem.

2. Labor supply of teenagers and occupational choices of adults are consistent with the solution to (11).

3. The labor market clears.

## 3.4 Model Extensions

We show in *Section 5* that this benchmark model captures all salient features of teen labor supply dynamics described in *Section 2*. Nevertheless, our simple model omits several relevant and interesting frictions. This section briefly discusses a selection of these possible frictions.

### 3.4.1 Minimum Wage

In the efficient model laid out above, crowding out of teenagers works through downward pressure on the current and future wages of teens causing them to then optimally reduce 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, $w_l(\phi + \psi h) < w_{min}$. Teenagers with low human capital are then not allowed to work and $n_e = 0$. 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 amount of teens that are then crowded out by the minimum wage depends on the mass of teens that have human capital slightly above the cut-off value in the original steady state.

### 3.4.2 Unknown Abilities

The benchmark model assumes that agents have perfect information over their two types of ability; employment $a_e$ and schooling $a_s$. In reality, agents will update their beliefs over these different abilities as they spend time accumulating schooling or employment human capital (see for instance Guvenen et al. (2020)). In such a setting, crowding out of the labor force would cause some teens to be unable to learn their true employment ability. This *could*

cause a sub-optimal level of investment in schooling human capital, and perhaps as a result, "over-attendance" to college.

### 3.4.3 Financial Frictions

The benchmark model described above does not include a savings decision, or a monetary cost incurred when attending college. In practice, teens may seek employment while in high school in order to save for higher education. In this setting and with the presence of a borrowing constraint, crowding out of the labor force may cause some teens to be unable to attend post-secondary, when they otherwise would have found it optimal to do so.

# 4 Calibration

The main quantitative exercise involves choosing parameters for the model to match important cross-sectional and transitional moments of the U.S. data. The calibrated model is used to determine the distributional impacts of falling teen employment, decompose the underlying causes and conduct policy analysis.

## 4.1 External Parameters

In this section we describe how the exogenously set parameters are chosen. *Table 6* summarizes these parameters.

Agents spend four years in high school and then live as an adult for an additional forty years, to the age of 59. This corresponds to $J = 44$. The relative risk aversion is set to 1.0 which implies $u(c) = \ln(c)$. We choose a standard value of 0.95 for $\beta$; the time discounting.

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 to 0.5 (Browning, 1992, Apps and Rees, 2001; Browning and Ejrnæs, 2009). We

take the midpoint of 0.35 but show in *Appendix D.2* that our results are not sensitive to $\bar{c}$.

The variance of luck shocks $\sigma_\epsilon$ is set to a small value of 0.15 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)). See *Appendix D.3* for robustness checks showing results are not sensitive to the value of $\sigma_\epsilon$.

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 hours spent per day in school is 6.64. Correspondingly we set the minimum amount of time a student must spend in order to finish high school to be 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, since $\bar{n}_e < 1 - \bar{n}_s$ only $\bar{n}_e$ binds in the model.

In general, the two parameters governing the learning-by-doing style accumulation of adult human capital $\gamma_o$ and $\delta_o$ 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 from Blandin (2018) which presents an in-depth discussion of their estimation and robustness.

Finally, the elasticity of substitution between adult college educated and non-college

Table 6: **Externally Calibrated Parameters**

| Parameter | Description | Value | Source |
|---|---|---|---|
| *Preferences* | | | |
| $J$ | Model periods | 44 | Biological life 15-58 |
| $\beta$ | Discount factor | 0.95 | Standard |
| $\chi$ | Relative risk aversion | 1.0 | Ln utility |
| *Teens* | | | |
| $\bar{c}$ | Teen fixed consumption | 0.35 | Literature |
| $\sigma_\epsilon$ | 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* | | | |
| $\gamma_o$ | Adult human capital curvature | 0.20 | Literature |
| $\delta_o$ | Adult human capital depreciation | 0.05 | Literature |
| *Production* | | | |
| $\sigma$ | College/non-college elasticity | 0.31 | Literature |

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

educated labor is set to $0.31 = (1 - 1/1.44)$ in accordance with Katz and Murphy (1992) and Heckman et al. (1998).

## 4.2 Internal Parameters

The remaining 19 parameters are chosen to minimize the distance between 40 moments, simulated by the model and empirical counterparts. Empirical moments are estimated from the ACS and NLSY. Steady state moments calculated using the ACS are for the year 2000, with the exception of earnings profiles where we pool the 1980, 1990, and 2000 ACS to account for time-effects. Transitional moments using the ACS are calculated by comparing the years 2000 and 2010. This is inline with our empirical analysis presented in *Section 2*. 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. A summary of parameter values can be found in *Table 7*.

### 4.2.1 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 $\mu_{h_s}$. 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 $\sigma_{h_s}$. We then calculate schooling human capital profiles as,

$$ln(h_s^{data}) = \alpha_{h_s} + \beta_{h_s} \times age + \epsilon_{hs} \tag{19}$$

We plot the profiles separately for children who subsequently attend college and those who do not in *Figure 11*. The average growth rate of $h_s^{data}$ and the employment share of teenagers identifies $\mu_{a_e}$ and $\mu_{a_s}$. We normalize initial employment human capital to one for all agents. Similarly, we set $\mu_{h_s}$ to one.

### 4.2.2 Teens

The percentage of teens employed is estimated using the year 2000 ACS and discussed extensively in *Section 2* 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 being 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 2.2.2*. In the model we estimate the

return by running the OLS regression,

$$\ln(LFE_i) = \gamma_1^{model}(sn_e)_i + \gamma_2(a_e)_i + \gamma_3(a_s)_i + \gamma_4(h_{s,0})_i + \epsilon_i \tag{20}$$

where $LFE$ is the sum of lifetime earnings, $sn_e$ is the sum of time invested in employment human capital 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 $\gamma_1^{model}$ to our causal estimate of $\gamma_1$ 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, $\gamma_e$ and the elasticity of substitution between school and employment human capital, $\zeta$. We describe how $\zeta$ is determined by a separate moment below, leaving the returns to school employment to identify $\gamma_e$.

The curvature of schooling human capital, $\gamma_s$, 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 $\gamma_e$ on wages. The difference is that $h_s^{data}$ is only affected by $\gamma_s$. We can thus identify $\gamma_s$ 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 when graduating. In the data, we estimate a version of equation (7) with $h_s^{data}$ as the dependent variable, utilizing the same IV strategy (outlined above), i.e.

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

In the model we then estimate equation (20) with the dependent variable now $h_s^{data}$, i.e.

$$h_s = \delta_1^{model}(sn_e)_i + \delta_2(a_e)_i + \delta_3(a_s)_i + \delta_4(h_{s,0})_i + \epsilon_i$$

We finally match the coefficients $\delta_1$ and $\delta_1^{model}$ .[14] Data regression results are reported in *Appendix D.1*. More ours worked during high school has a negative and significant causal effect on schooling human capital acquired.

The relative weight on schooling human capital to employment human capital, $\alpha$ is most closely related to the intensive margin of teen employment, for both those attending college and not attending college. These moments are taken from the NLSY79.

Given $\alpha$, we can then directly infer $\zeta$ from the wages and $h_s^{data}$ of recent graduates that never worked. For those that never work, equation (9) reduces to $h_o = \epsilon\Big(\big(\alpha h_s^{\zeta} + (1-\alpha)\big)^{\frac{1}{\zeta}}\Big)$. Since $\epsilon$ is i.i.d., all variation in initial wages of workers entering the labor force then comes from $h_s$. A simple OLS in data and model determines $\zeta$.[15]

### 4.2.3 College

The curvature of schooling human capital production in college, $\gamma_c$, 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 ACS 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 associates degree and above, again calculated from the ACS.

### 4.2.4 Adults

The parameters $\lambda$ and $\sigma_{a_o}$ 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 earnings 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

[14] Note, as seen *Figure 11* schooling human capital growth is near linear. Our calibrated value of $\gamma_s = 0.95$ reflects this pattern.

[15] The exact specifications and regression results are in *Appendix D*.

constructing these earnings profiles. Using pooled 1980, 1990, and 2000, ACS samples, we run the regression,

$$\ln(E_{i,a,t}) = S_s + A_a + T_t + S_s A_a + S_s T_t + \epsilon_{i,a,t} \tag{21}$$

where, $E_{i,a,t}$ is wage earnings of individual $i$, at time $t$. $S_s$ is schooling effect, $A_a$ age effects, and $T_t$ time effects. The interaction terms are used to identify earnings profiles separately for those with and without a college education. The coefficients are then estimated for each education-age category to produce earnings profiles, and are plotted in *Figure 10*.

The parameters $\psi$ and $\phi$ define the human capital level of those who work in teen occupations. This in turn defines a cut off for those who work in teen vs. non-teen occupations, and hence governs the percentage of adults working teen occupations by age. *Figure 9* plots the percentage of adults employed in teen occupations by education status.

### 4.2.5 Production

The productivity parameters $A_l, A_m, A_s$, and $\theta$, govern income and employment shares in the initial steady state. We normalize $\theta$ to be a value of one. The remaining parameters to identify are $\nu$ and the shock to $\theta$. The shock to $\theta$ is the sole *exogenous* driver inducing a change in our economy. We calibrate the shock to $\theta$ 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, $\nu$, 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 else held fixed except for a negative shock to $\theta$, and (3) taking adult employment levels from (2) we simulate the model using all else fixed at (1), including $\theta$. This way, we can focus on the effects of adults taking up teen occupations without conflating it with other equilibrium effects of the productivity shock.

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 (6).

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

$$\frac{(\%\text{ teen not work})_3 - (\%\text{ teen not work})_1}{(\text{teen occ. rate})_2 - (\text{teen occ. rate})_1} \tag{22}$$

where subscripts refer to moments from economies (1)-(3). 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 $\nu$, as explained above.

The elasticity of teen labor supply to price changes is determined by a large set of parameters, which work through the aforementioned mechanisms. In 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 $\gamma_c$ is also important for pinning down this elasticity.

## 4.3 Model Fit

This section reports moments estimated in the data and model counterparts. The present version of the model has yet to be fully calibrated. However, the current model parameterization matches well the most important features of the data. Namely, positive returns to teen employment, adults increasing employment in teen occupations as a result of an aggregate shock, and teens starkly reducing employment as a result of inflowing adult workers.

The model exactly matches many moments including; % of teens working, college attendance rate, and % of those working in teen occupations. We are also able to calibrate

Table 7: **Internally Calibrated Parameters**

| **Parameter** | **Value** | **Description** |
|---|---|---|
| *Initial distributions* | | |
| $\sigma_{a_e}$ | 1.0 | Employment ability variance |
| $\sigma_{a_s}$ | 1.0 | Schooling ability variance |
| $\sigma_{h_s}$ | 0.725 | Initial schooling human capital variance |
| $\mu_{a_e}$ | 0.0 | Employment ability mean |
| $\mu_{a_s}$ | -1.0 | Schooling ability mean |
| *Teens* | | |
| $\gamma_e$ | 0.80 | Working human capital production |
| $\gamma_s$ | 0.95 | Schooling human capital production |
| $\alpha$ | 0.85 | CES human capital aggregator share |
| $\zeta$ | 0.75 | CES human capital aggregator elasticity |
| *College* | | |
| $\gamma_c$ | 0.50 | College human capital production |
| $\bar{c}_u$ | 1.15 | Fixed college consumption |
| *Adults* | | |
| $\lambda$ | 0.50 | Share of schooling ability |
| $\sigma_{a_o}$ | 0.05 | Variance of adult ability |
| $\psi$ | 3.0 | Fixed human capital, teen occupations |
| $\phi$ | 0.50 | Fraction human capital, teen occupations |
| *Production* | | |
| $\nu$ | 0.50 | Production CES elasticity |
| $A_l$ | 0.05 | Production CES productivity |
| $A_m$ | 0.50 | Production CES productivity |
| $A_s$ | 1.0 | Production CES productivity |
| $\theta$ shock | 0.17 | Percent shock to adult productivity |

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

the shock to $\theta$ so that the model accurately generates the influx of adult workers into teen occupations. The model is reasonably close on other moments, with the except of the wage premium.

Under the present calibration, the model struggles most to accurately generate wage premia. Under a similar class of models of the adult working lifecyle (e.g. Huggett et al. (2011)) a set of age-productivity profiles by education status are included to better fit the data. This inclusion would help us better match moments on earnings premia.

# 5 Results

While the current version of the model has yet to be fully calibrated, this section discusses qualitative 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 are referred 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 resolving the model with the sole difference being a negative shock to the productivity of adult labor, $\theta$. This is to capture 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 4.2* 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 solve for the counterfactual economy in order to isolate the effects of adults "crowding out" teen workers. For this reason we focus on results and mechanisms of the counterfactual economy. 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

Table 8: **Model Fit – ACS Moments**

| **Moment** | **Data** | **Model** |
|---|---|---|
| *Teens* | | |
| Decline regression coefficient | -3.78 | -2.17 |
| % teens working | 0.349 | 0.351 |
| Average hours worked for working | 20.1 | 32.0 |
| *Adults* | | |
| % working in teen occ. | 0.116 | 0.119 |
| % with college degree | 0.402 | 0.406 |
| % working in teen occ. – college | 0.049 | 0.099 |
| % working in teen occ. – non-college | 0.186 | 0.134 |
| $\Delta$ in adults working teen occ. | 0.022 | 0.021 |
| *Earnings* | | |
| College/non-college, all adult | 1.92 | 1.51 |
| College/non-college, non-teen occ. all adult | 1.85 | |
| College/non-college, 24-29 | 1.49 | |
| Non-teen occ./teen occ. | 1.79 | |
| Adult/teen, teen occ. | 3.78 | |
| Wage regression | -7.83 | -11.30 |

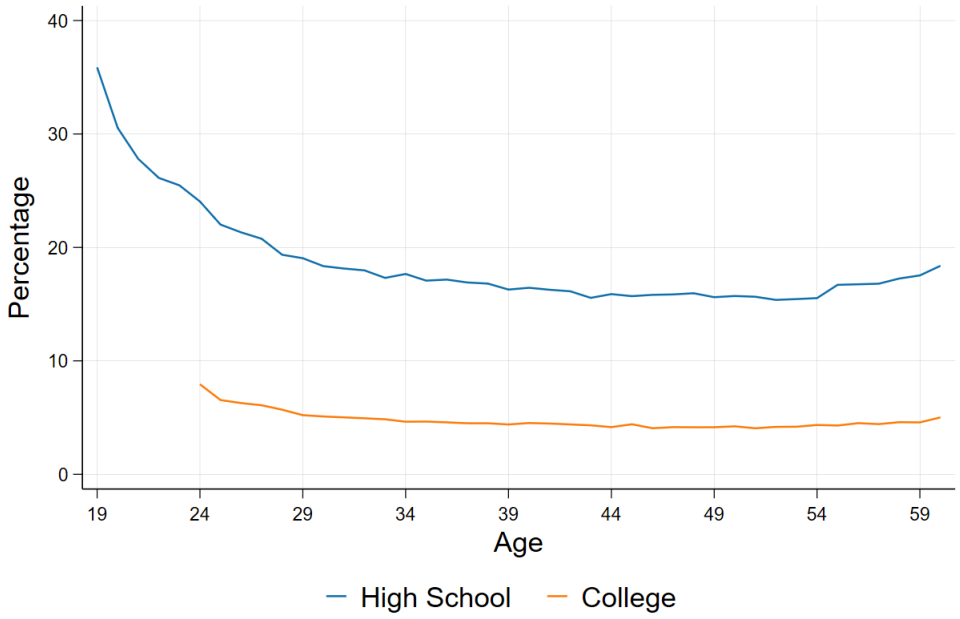
*Notes:* The columns compare the model to the data for selected targeted moments. All steady state moments in this table are taken from the 2000 year American Community Survey (ACS). Transitional moments are calculated using the 2000 and 2010 ACS.

Table 9: **Model Fit – NLSY Moments**

| **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 | 0.82 |
| SD($h_s^{data}(Grade8)$)/Mean($h_s^{data}(Grade8)$) | 0.80 | 0.75 |
| Average hours worked, non-college | 15.2 | 20.5 |

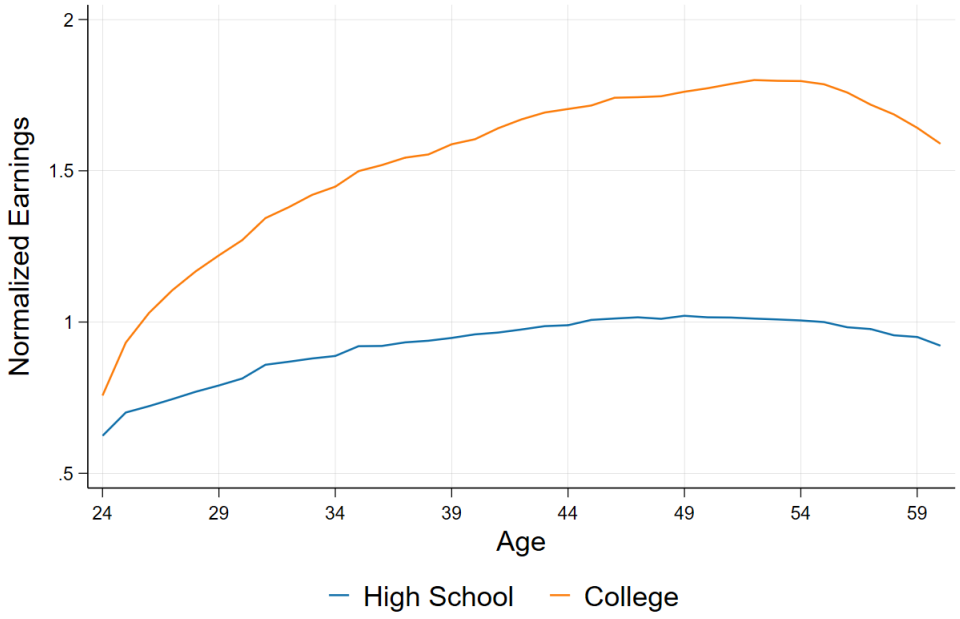
*Notes:* The columns compare the model to the data for selected targeted moments. *Source*: NLSY79 and NLSY97.

Figure 9: **Lifecycle Employment in Teen Occupations by Education**



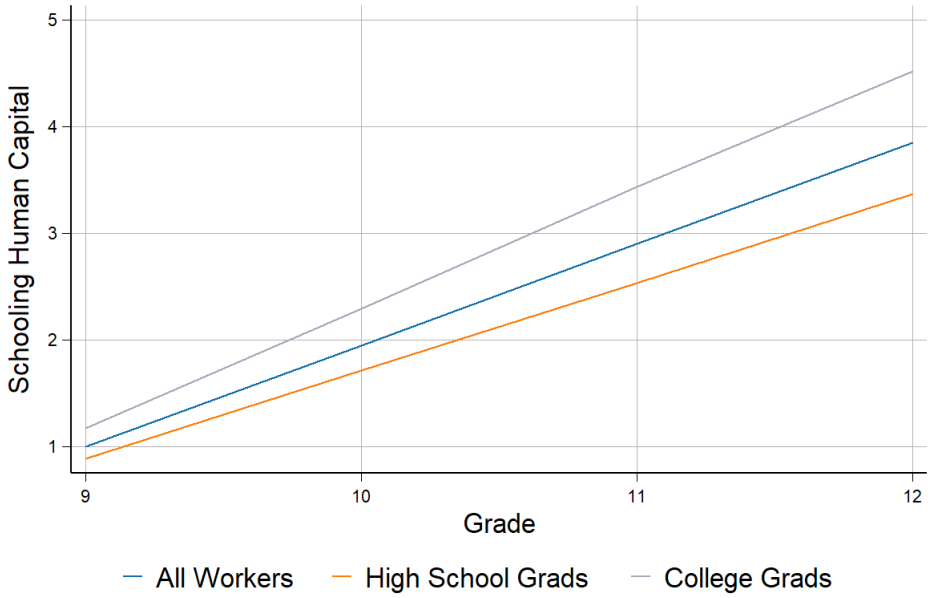

*Notes:* This figure plots the percentage of adults employed in a teen occupation, by adult age and education type. *Source*: 2000 American Community Survey (ACS).

Figure 10: **Lifecycle Earnings Profiles by Education**




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

Figure 11: **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.

steady state. All else (including $\theta$) is kept fixed at the initial steady state level. Again, see *Section 4.2* for more details.

## 5.1 Effects of Declining Teen Employment

This section discusses the new steady state and counterfactual economy in the baseline efficient model. We begin by discussing model mechanisms and then turn to a qualitative welfare discussion.

Under the counterfactual economy, teen occupation wages fall by roughly 14% while adult occupation (college and non-college) wages are largely unaffected (change by less than 0.5%). Overall, teen employment declines by approximately 8 percentage points, which would represent 40% of the total decline seen in the data.

Teen employment falls for two main reasons. First, the counterfactual economy induces a larger percentage of teens to attend college as the relative returns to college employment

are now higher. However, the decline is also partially driven by those who do not attend college as this type of agent also reduces employment while in high school. Partly, this is driven by uncertainty in the model, agents cannot perfectly predict if they will go to college. Additionally, lower wages imply less current consumption teens can afford from their hours worked, causing a reduction in work effort. For teens who continue to work, it is those with the highest working ability $a_e$, as we see average working ability rise. Finally, average working level $n_e$ of the working also rises in this counterfactual economy.

To conduct our welfare analysis we calculate the consumption equivalent variation for different groups of agents. We consider welfare changes for: (1) those who were teen workers in the first steady state and 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 worker*), and (4) those who are not teen workers in either steady state (*never workers*).

As is expected (*never workers*) experience essentially no welfare changes in the counterfactual economy. Those who are able to adjust and now become (*no longer workers*) see small welfare losses. Many of this type of workers will now attend college. For those who cannot adjust, (*still workers*), we observe the largest decrease in welfare.

In the new steady state, wages fall by 39, 46, and 53 percent for teen occupation, adult non-college, and adult college wages, respectively. Given larger wage changes in the new steady state, welfare changes are correspondingly much larger as well. However, now (*never workers*) see the largest welfare change, as these are agents who do not typically work in teen occupations and are most adversely affected by the negative productivity shock.

## 5.2 Policy Analysis

This section discusses a possible policy intervention for those teens who are adversely affected by crowding out of the labor market. We consider a policy exercise to mimic vocational

schooling, where we allow some fraction $\xi$ of time invested in forming schooling human capital, to act to increase employment human capital as well. 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 do not work will never choose to attend vocational training.

Compared to the benchmark model, the rise in adults working in teen occupations is identical, however, the fall in teen employment is now smaller. Welfare now also falls by less for those who are (*still workers*) and unable to adjust in the counterfactual economy. This policy also improves welfare for this type of agent in the new steady state. Welfare is mostly unaffected for other types of agents as prices are affected similarly and this type of agent simply does not choose to participate in vocational schooling.

## 5.3 Role of Minimum Wages

This section discusses the new steady state and counterfactual economy in the model extended to include minimum wages. 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. Parameter values and model fit for the re-calibrated model are in *Appendix D.4*. A small number of teenagers 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 that would optimally work. Looking at the post-fall steady state, teen employment falls to around 20%. The model can thus explain a large portion of the observed fall to around 15% in 2010.

Introducing the minimum wage has important welfare implications. The welfare losses of (*no longer workers*) increase substantially relative to (*still workers*). Now, many (*no longer workers*) cannot work anymore, although they would optimally choose to do so. It is

these workers that benefit most from policy interventions which offer alternative (vocational) means of accumulating employment human capital.

### 5.3.1 Decomposition

With inclusion of the minimum wage, we have three mechanisms through which adults crowd out teenagers. 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 for 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* 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 moving into different commuting zones for college and/or later employment. 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 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 $w_l$ (in the budget constraints of teenagers, equation (11)) to be at the 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 $w_l(\phi + \psi h) < w_{min}$ using $w_l$ from the initial steady state. Finally, the effect of future wages is turned off by setting all future wages in the adult problem to its initial steady state values.

*Results* – Given an incomplete calibration, results are still preliminary. However, various permutations of the decomposition exercise reveal that the current consumption channel is the least important. Only a fraction of teenagers choose to work for current consumption and thus almost none change their behavior because of it. We can not yet rank the importance of the other two mechanisms, but both seem to play an important role. 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 that are prevented from working lose important human capital accumulation opportunities.

# 6 Conclusion

Teen employment declined by an enormous amount over the last 30 years. Little is known about the causes and nothing is known about the consequences or the role of government policies. This paper sheds light on both points and provides policy recommendations in response using both reduced form and quantitative methods.

Empirically, we use an instrumental variables strategy to causally illustrate two key

points. First, the decline in teen employment is mainly caused by adults crowding out teen labor. This decline results from negative productivity shocks affecting adult occupations, including skill-biased technological change (SBTC), successive recessions, and structural change. Second, teen employment during high school has large and positive returns across the lifecyle for those who do not attend college. These two facts imply welfare losses for teens crowded out of the labor market, and motivates the mechanisms included in our quantitative framework. Additionally, these causal estimates are used to identify key parameters in our model.

Quantitatively, we develop a GE model of overlapping generations and occupation choice. Teens accumulate schooling and employment human capital, which combined determine which agents attend college and their later life earnings. Our model is able to capture the three key dynamics observed in the data: (1) positive returns to teen employment, (2) adults increasing teen employment as a result of an aggregate productivity shock, and (3) teens reducing employment as a result of adult crowding out.

Our model experiments find significant welfare losses to teen workers, with the largest for those who are no longer able to work. Our policy analysis simulates an optional vocational training program. This program is successful in minimizing welfare losses for the most adversely affected teenagers. Finally, we decompose the three channels through which the aggregate productivity shock acts to reduce teen employment. Changes in current earnings play a small role, whereas the roles of future earnings and the minimum wage are important and of similar magnitudes.

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# Online Appendix

## Appendix A Datasets and Sample Selection

This section discusses details of each dataset used, the variables used, and sample defined for analysis. Appendix B discusses details of concepts defined (i.e. adolescent employment or adolescent occupations) with each dataset.

### A.1 Current Population Survey

We use annual Current Population Survey (CPS) 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 analysis in 1986 as the variable for enrolled in high school is not observed before.

### A.2 American Community Survey

We used the American Community Survey (ACS) for all regression analysis establishing the crowding out of teen workers by adults in *Section 2.1*. We also confirmed 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.

### A.3 National Longitudinal Surveys of Youths

We use public access NLSY79 and NLSY97 which is then linked to restricted access geocoded NLSY variables at the county levels. We link counties to commuting zones using the cross-walks provided in Autor et al., 2013.

## A.4 American Time Use Survey

We use the ATUS to trend teen time usage. Our sample mirrors that of the CPS.

# Appendix B Robustness

## B.1 Teen Employment

Our baseline sample is defined over those aged 15 to 18 inclusive currently enrolled in high school. *Figures E.1-E.3* 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 E.4-E.8* 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 E.9*. *Figure E.10* shows that the 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 E.11* 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, are listed as; child, stepchild, sibling, grandchild, or foster child, who have never been married, and list positive hours worked in the previous week.

*Table E.1* reports the top 20 occupations used to define a teen occupation. The analysis in *Section 2.1* 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%

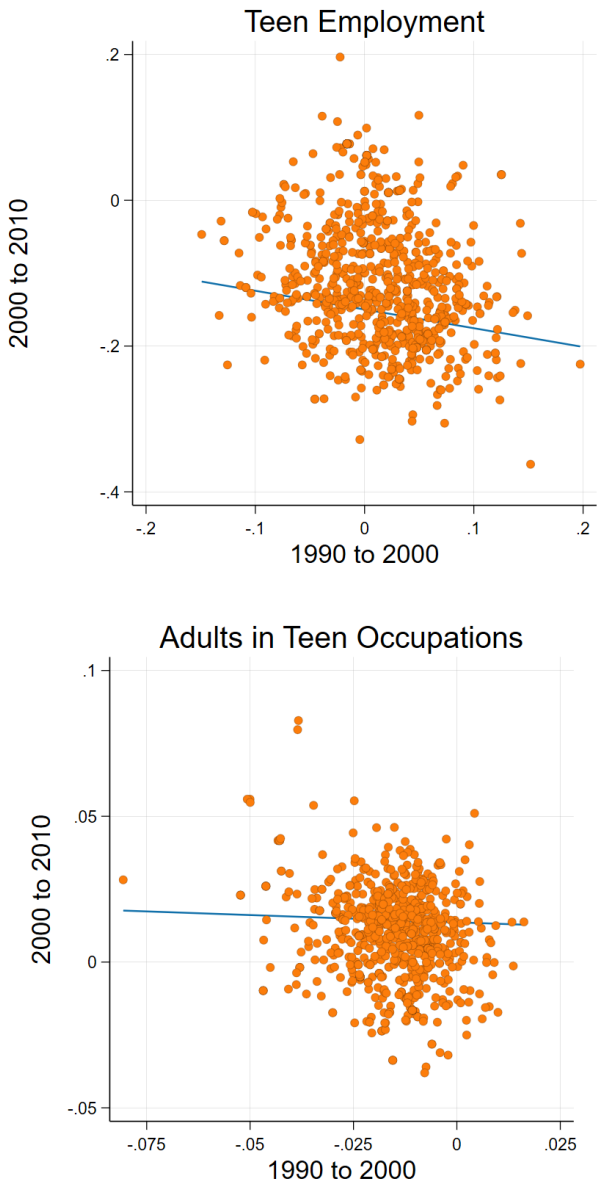
of total teen employment over this period. This of occupations list is stable across time with all occupations inside the top ten present over the entire time period. The largest changers for the 1986-1991 period are "Pumping Station Operators" and "Driver/Sales Workers and Truck Drivers" which are ranked $13^{\text{th}}$ and $15^{\text{th}}$ for this period, respectively. The largest changers for the 2016-2019 period are "Athletes, Coaches, Umpires, and Related Workers" and "Law enforcement workers, nec" which are ranked $17^{\text{th}}$ and $19^{\text{th}}$ for this period, respectively. None of these occupations are present on the averaged list.

## B.3 Teen Employment Transitions

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 fourth month waves. We aggregate 4-digit NAICS occupations from which an adult originates into 81 classifications. We follow the natrual aggregation given by the IPUMS CPS categories.

## B.4 Employment Decline Regression Analysis

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




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

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 show 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 |
|---|---|---|---|---|---|---|---|---|
| | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* |
| *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 |

Table B.4: P-values show in brackets. Wages in 10.000 *Source*: American Community Survey (ACS).

Table B.5: **Overidentification Tests**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* |
| *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 show in brackets. *Source*: American Community Survey (ACS).

Table B.6: **Employment Decline Regressions, Omitting Parents**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* | *TeenEmp.* |
| *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 show in brackets. This table reports robustness excluding parents. To do so, we must use initial shares in 2000 *not* 1990. 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.7: **Different Time Changes**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $TeenEmp.$ | $TeenEmp.$ | $TeenEmp.$ | $TeenEmp.$ |
| | 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 show 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.5 Value Added Regression Analysis

Table B.8: **First-Stage for Value Added 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 all workers. Column (6) is for college graduates. *Source*: NLSY79

Table B.9: **First-Stage for Value Added 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.10: **Second-Stage for Value Added Regressions by Age Group**

| | ln of average earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Avg. hours worked HS | -0.000 | 0.009 | 0.029 | 0.030 | 0.061 | 0.055 | 0.031 | 0.011 |
| | (0.979) | (0.454) | (0.040) | (0.003) | (0.000) | (0.001) | (0.102) | (0.658) |
| Median real 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.11: **First-Stage for Value Added 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.12: **Second-Stage for Value Added Regressions with NLSY97**

| | ln of average earnings | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Avg. hours worked HS | 0.036 | 0.042 | 0.016 | 0.024 |
| | (0.144) | (0.192) | (0.470) | (0.303) |
| Median real 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.13: **Ordinary Least Squares for Value Added Regressions**

| | ln avg. lifetime earnings | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Avg. hours worked HS | 0.023 | 0.015 | 0.015 | 0.013 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Sex | | -0.174 | -0.175 | -0.180 |
| | | (0.000) | (0.000) | (0.000) |
| White | | -0.110 | -0.131 | -0.105 |
| | | (0.000) | (0.000) | (0.000) |
| Black | | -0.100 | -0.127 | -0.124 |
| | | (0.000) | (0.000) | (0.000) |
| AFQT score | | 0.000 | 0.000 | 0.000 |
| | | (0.000) | (0.000) | (0.000) |
| Avg. life unemp. rate | | | -0.010 | -0.008 |
| | | | (0.000) | (0.059) |
| Median real 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 Computation

The dynamic programming problem is solved by backwards 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 $\mathbb{E}_{a_o,\epsilon_s,\epsilon_o}\big[V^{u}\big(j=5,h_s,h_e,a_s,a_e\big)\big]$.

For all periods a uniform rectangular grid is set over continuous variables $(h_e,h_s)$. The initial distribution over states $(a_e,a_s,h_s)$ and the distributions for market luck shocks $\epsilon$ are discretized using the equal-mass approach of Kennan (2006). When solving for optimal policies we interpolate using cubic splines over next periods value functions. We solve for policy functions using a modified Nelder-Mead to allow for rectangular box constraints.

To simulate moments from the model we take some arbitrary vector of parameters $\Theta$ and solve the model to obtain all decision rules. We then simulated $N=1,000,000$ agents. We first simulate cross-sectional moments and then resolve and simulate model to calculate transitional moments.

# Appendix D Calibration

## D.1 Returns to Schooling Human Capital

To calibrate $\zeta$ in the model. We use the fact that equation (9) reduces to $h_o = \epsilon\Big(\big(\alpha h_s^{\zeta} + (1-\alpha)\big)^{\frac{1}{\zeta}}\Big)$ for teenagers that never work. We thus regress wages of recent high school grades that do attend college on their accumulated $h_s^{data}$.[16] 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.

## D.2 Teen Fixed Consumption

To be shown when final calibration is completed.

## D.3 Market Luck Shocks

To be shown when final calibration is completed.

## D.4 Minimum Wage Model Calibration

[16] As described in main *Section 4*, $h_s^{data}$ is the cumulative GPA weighted sum of credits for each student.

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) | (0.025) |
| 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 | 5.12 |
| 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) | (0.140) |
| 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 | 5.12 |
| Observations | 3,096 | 3,096 | 3,096 |

*Notes*: P-values shown in brackets. *Source*: NLSY97

Table D.3: **Minimum Wage Model: Internally Calibrated Parameters**

| **Parameter** | **Value** | **Description** |
|---|---|---|
| *Initial distributions* | | |
| $\sigma_{a_e}$ | 1.0 | Employment ability variance |
| $\sigma_{a_s}$ | 1.0 | Schooling ability variance |
| $\sigma_{h_s}$ | 1.0 | Initial schooling human capital variance |
| $\mu_{a_e}$ | -0.32 | Employment ability mean |
| $\mu_{a_s}$ | -1.0 | Schooling ability mean |
| *Teens* | | |
| $\gamma_e$ | 0.8 | Working human capital production |
| $\gamma_s$ | 0.9 | Schooling human capital production |
| $\alpha$ | 0.85 | CES human capital aggregator share |
| $\zeta$ | 0.75 | CES human capital aggregator elasticity |
| *College* | | |
| $\gamma_c$ | 0.5 | College human capital production |
| $\bar{c}_u$ | 2.0 | Fixed college consumption |
| *Adults* | | |
| $\lambda$ | 0.5 | Share of schooling ability |
| $\sigma_{a_o}$ | 0.05 | Variance of adult ability |
| $\psi$ | 5.0 | Fixed human capital, teen occupations |
| $\phi$ | 0.5 | Fraction human capital, teen occupations |
| *Production* | | |
| $\nu$ | 0.5 | Production CES elasticity |
| $A_l$ | 0.05 | Production CES productivity |
| $A_m$ | 0.5 | Production CES productivity |
| $A_s$ | 1.0 | Production CES productivity |
| $\theta$ 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.

Table D.4: **Minimum Wage Model Fit – ACS Moments**

| **Moment** | **Data** | **Model** |
|---|---|---|
| *Teens* | | |
| Decline regression coefficient | -3.78 | -3.19 |
| % teens working | 0.349 | 0.388 |
| Average hours worked for working | 20.1 | 14.1 |
| *Adults* | | |
| % working in teen occ. | 0.116 | 0.153 |
| % with college degree | 0.402 | 0.406 |
| % working in teen occ. – college | 0.049 | 0.100 |
| % working in teen occ. – non-college | 0.186 | 0.189 |
| $\Delta$ in adults working teen occ. | 0.022 | 0.021 |
| *Earnings* | | |
| College/non-college, all adult | 1.92 | 1.60 |
| College/non-college, non-teen occ. all adult | 1.85 | |
| College/non-college, 24-29 | 1.49 | |
| Non-teen occ./teen occ. | 1.79 | |
| Adult/teen, teen occ. | 3.78 | |
| 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.

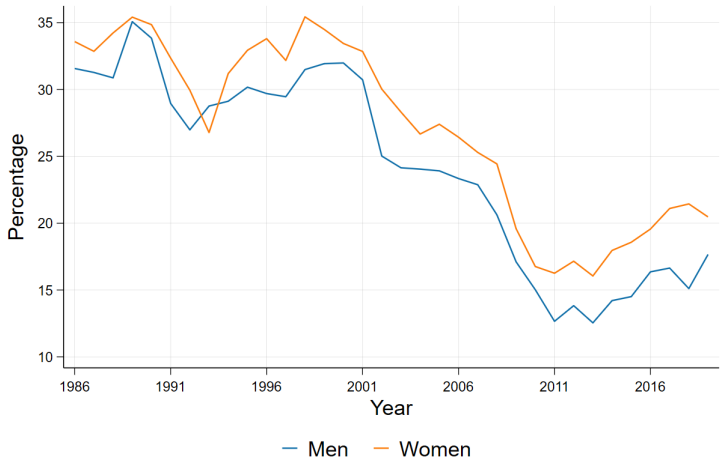
Table D.5: **Minimum Wage Model Fit – NLSY Moments**

| **Moment** | **Data** | **Model** |
|---|---|---|
| *Teens* | | |
| Returns to employment on wages | 0.041 | |
| Returns to schooling on grades | -0.047 | |
| % Growth of $h_s^{data}$, grade 9-12 | 338 | 321 |
| Returns to $h_s^{data}$ | 0.24 | |
| SD($h_s^{data}(Grade8)$)/Mean($h_s^{data}(Grade8)$) | 0.80 | 0.85 |
| Average hours worked, non-college | 15.2 | 0.23 |

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

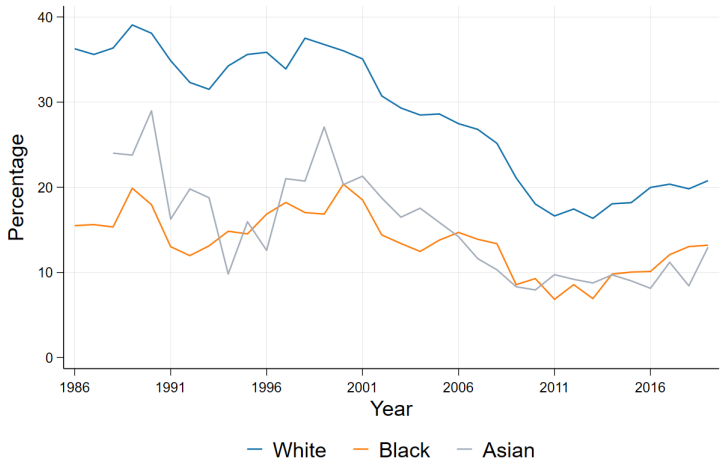
# Appendix E Additional Figures and Tables

Figure E.1: **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).

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



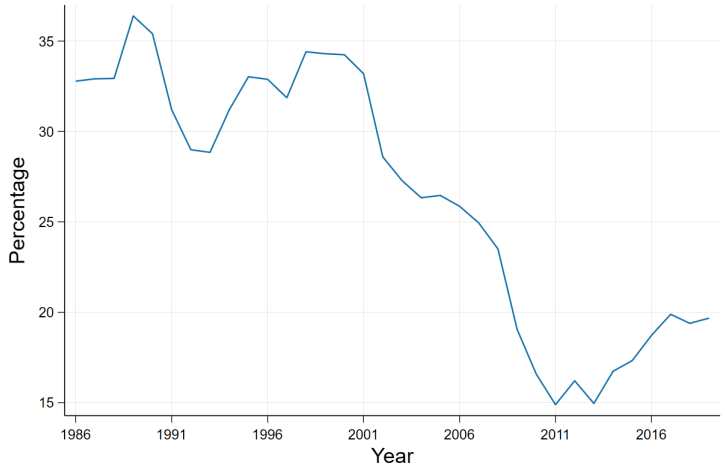

*Notes:* This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined to be those with positive hours worked over the preceding week. *Source*: Current Population Survey (CPS).

Figure E.3: **Teen Employment Decline by Parental Income**



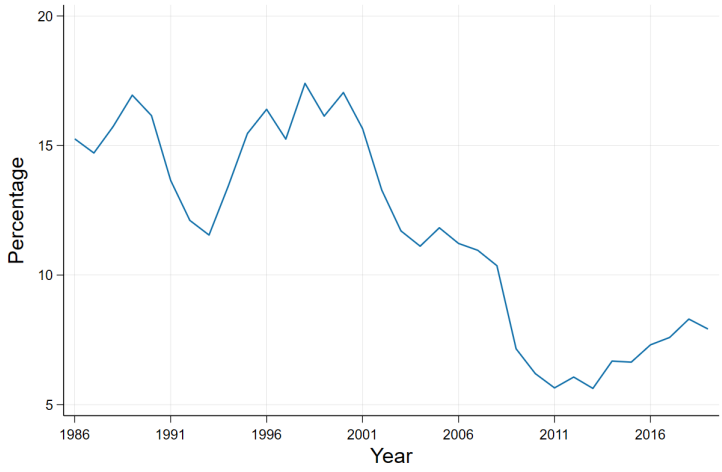

*Notes:* This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined to be those with positive hours worked over the preceding week.*Source*: Current Population Survey (CPS).

Figure E.4: **Teen Employment Decline – Employment Indicator**



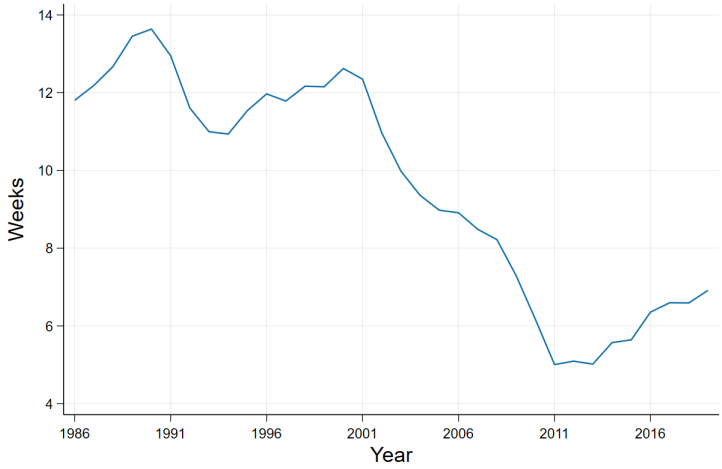

*Notes:* This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined using the indicator variable for employment status. *Source*: Current Population Survey (CPS).

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



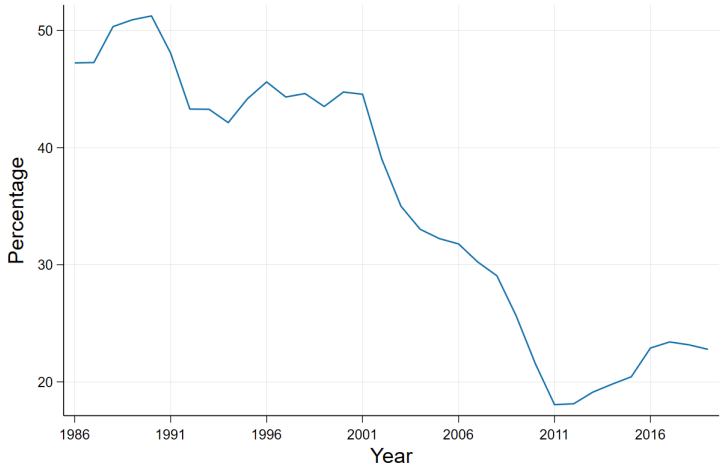

*Notes:* This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined as those working greater than 15 hours per week . *Source*: Current Population Survey (CPS).

Figure E.6: **Teen Employment Decline – Average Weeks Worked**



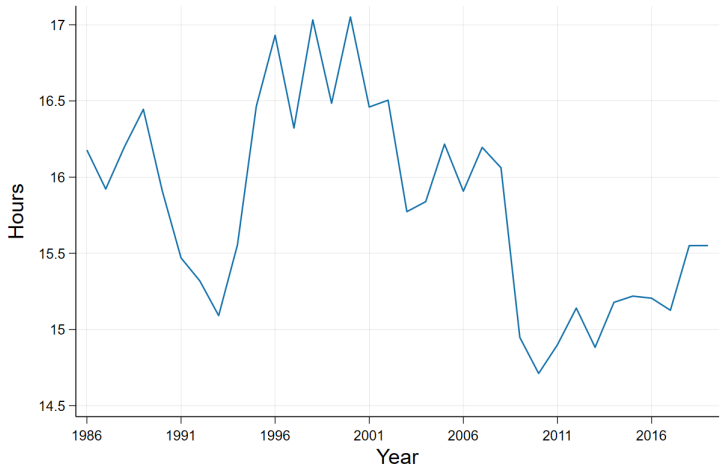

*Notes:* This figure plots the average weeks worked for 15-18 year olds currently enrolled in high school. *Source*: Current Population Survey (CPS).

Figure E.7: **Teen Employment Decline – Usual Hours**



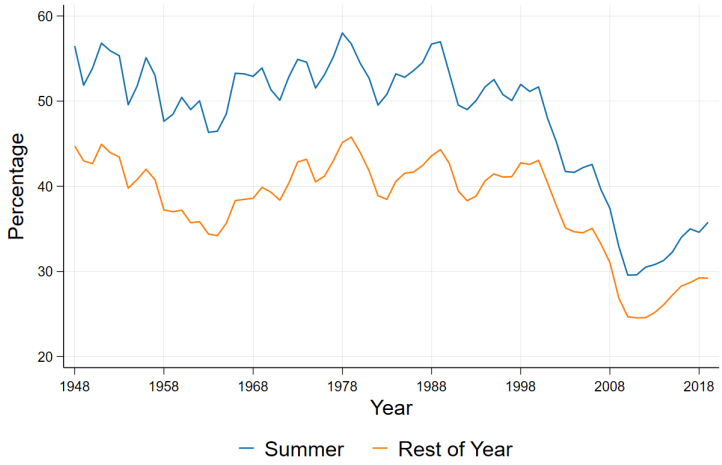

*Notes:* This figure plots the employment rate for 15-18 year olds currently enrolled in high school. Employment is defined as positive usual hours worked per week.*Source*: Current Population Survey (CPS).

Figure E.8: **Teen Employment Decline – Average Hours of Workers**



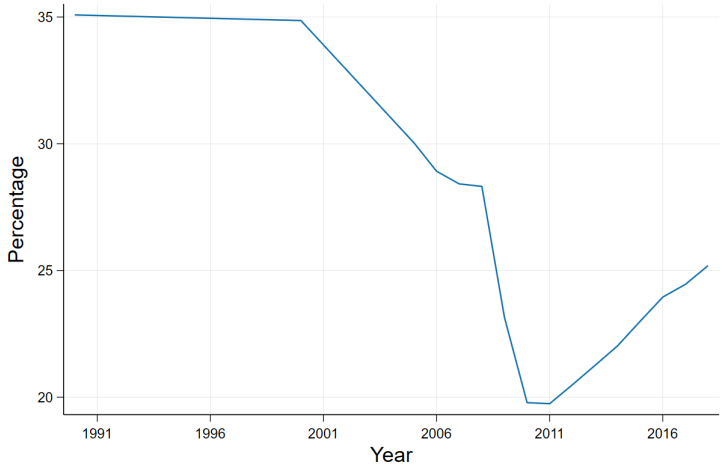

*Notes:* This figure plots the average hours worked for employed 15-18 year olds currently enrolled in high school. *Source*: Current Population Survey (CPS).

Figure E.9: **Teen Employment Decline – Summer vs. Rest of Year**



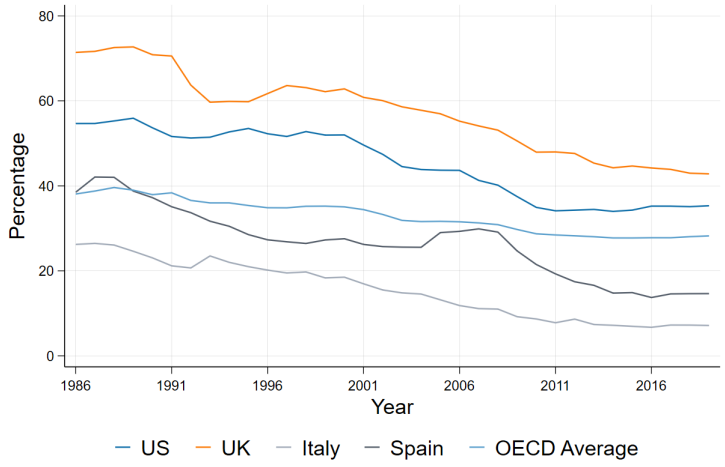

*Notes:* This figure plots the employment to population ratio for 16-19 year olds. *Source*: Bureau of Labor Statistics (BLS).

Figure E.10: **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 E.11: **Teen Employment Decline – Across Countries**



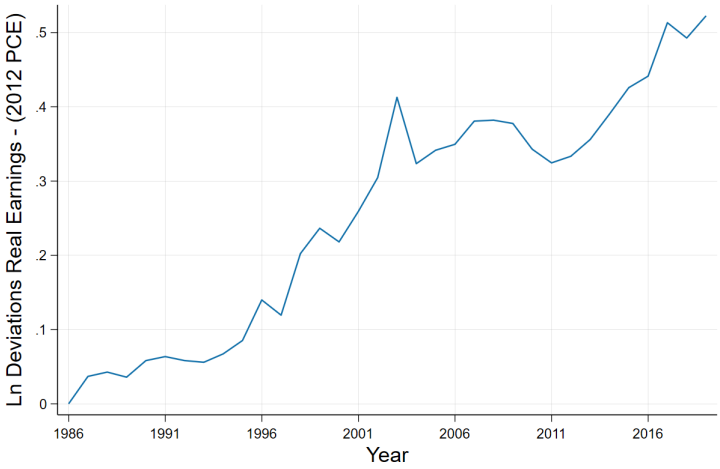

*Notes:* This figure plots the employment to population ratio for 16-19 year olds. *Source*: Economic Co-operation and Development (OECD) tables.

Table E.1: **Teen Occupations**

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

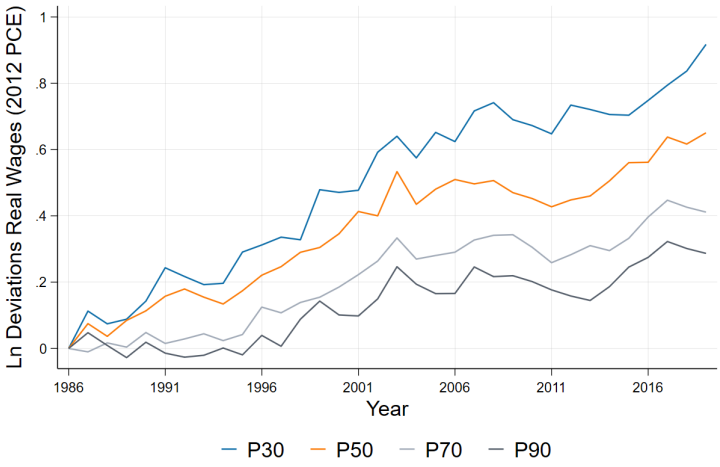
*Notes:* This table reports the top 20 teen occupations that are aggregated to define a teen occupation. *Source*: Current Population Survey (CPS).

Figure E.12: **Mean Earnings in Teen Occupations**



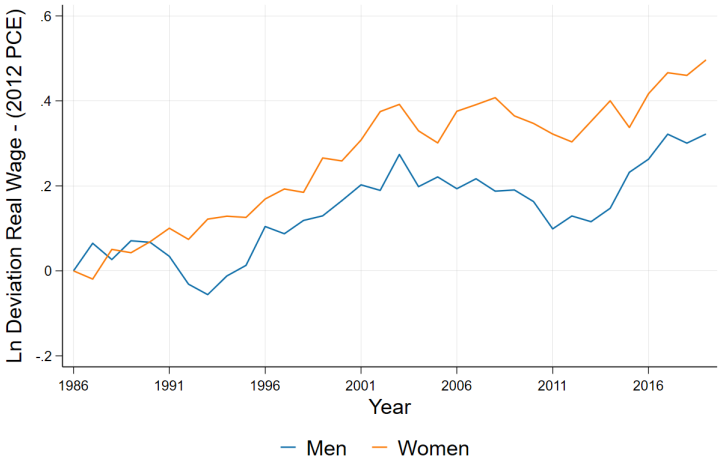

*Notes:* This figure plots mean earnings in teen occupations for ages 15 and older. Zero earnings reported are dropped and 98th percentile and above earnings are Winsorized. Real earnings are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: Current Population Survey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

Figure E.13: **Percentiles of Earnings in Teen Occupations**



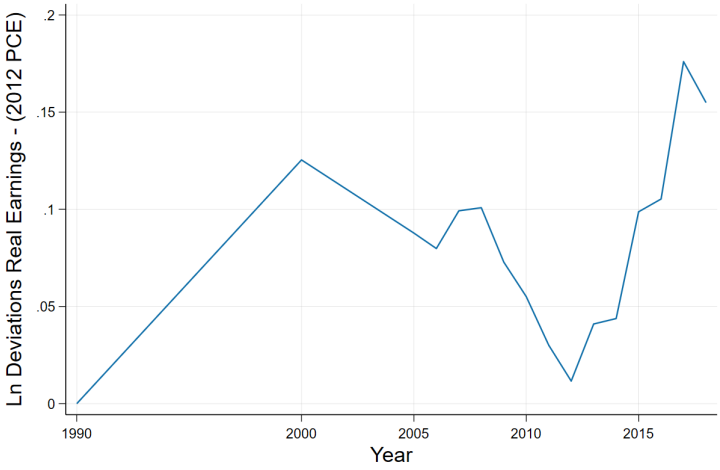

*Notes:* This figure plots certain percentile earnings in teen occupations for ages 15 and older. Zero earnings reported are dropped and 98th percentile and above earnings are Winsorized. Real earnings are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: Current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

Figure E.14: **Median Earnings in Teen Occupations by Gender**



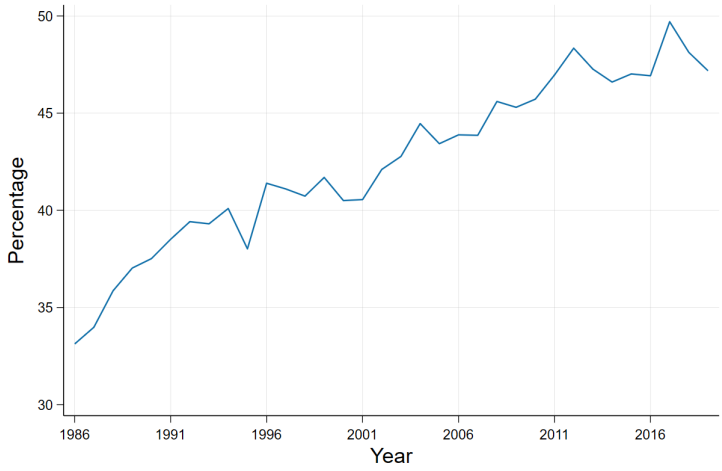

*Notes:*This figure plots median earnings in teen occupations for ages 19 and older, not enrolled in an academic institution. Zero earnings reported are dropped and 98th percentile and above earnings are Winsorized. Real earnings are calculated using the 2012 person consumption expenditures (PCE) price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

Figure E.15: **Median Earnings in Teen Occupations – ACS**



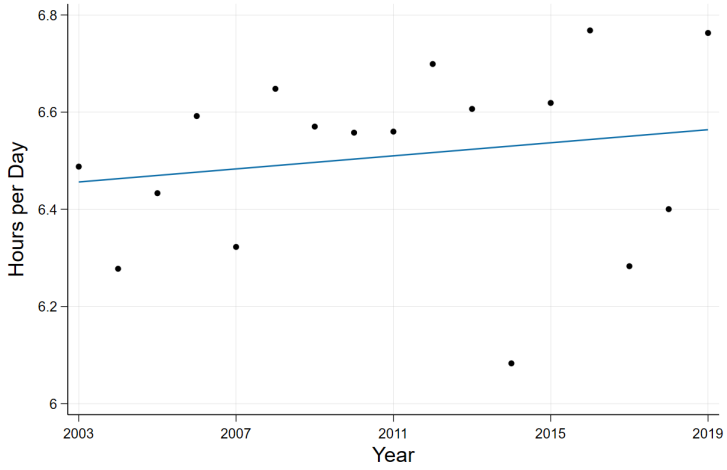

*Notes:* This figure plots median earnings in teen occupations for ages 15 and older. Zero earnings reported are dropped and 98th percentile and above earnings are Winsorized. Real earnings are calculated using the 2012 person consumption expenditures (PCE) price index. *Source*: American Community Survey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

Figure E.16: **College Enrollment**



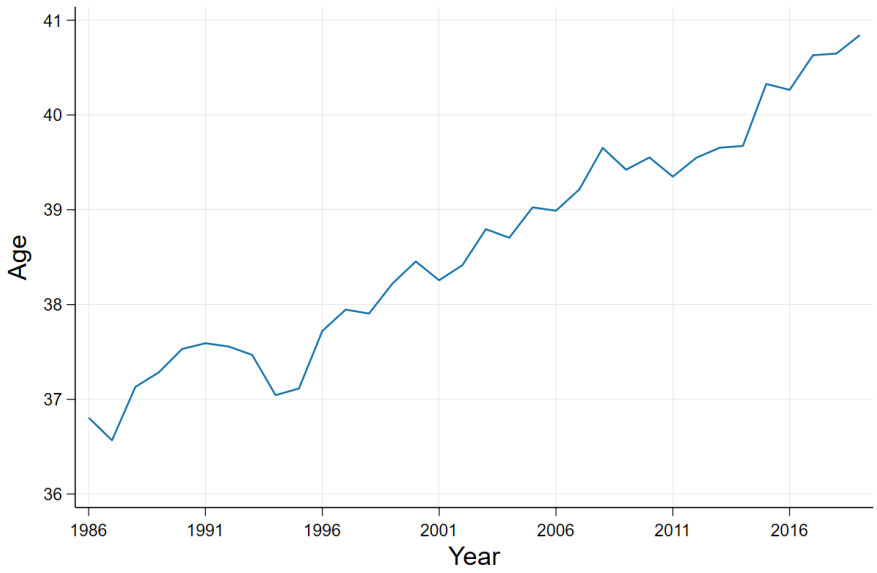

*Notes:* This figure plots the percentage of those aged 19-22 currently enrolled part-time or full-time in college. *Source*: Current Population Survey (CPS).

Figure E.17: **Schooling Time Use**



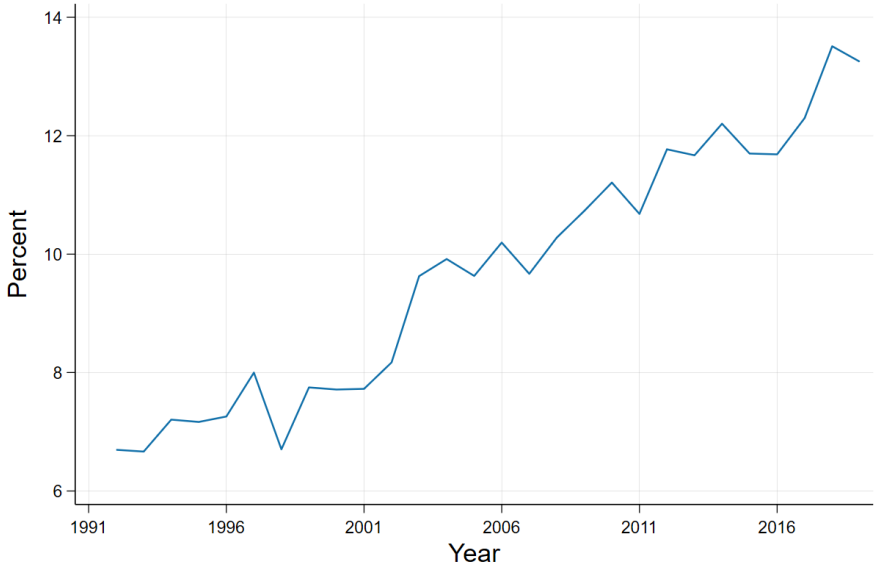

*Notes:* This figure plots average daily time spent on schooling activities. *Source*: American Time Use Survey (ATUS).

Figure E.18: **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 E.19: **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 and have at least a Bachelor's degree. *Source*: Current Population Survey (CPS).