The Minimum Wage and Teen Educational Attainment

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Abstract

Teen employment effects are central to the minimum wage debate, but important indirect effects on education receive relatively little attention. I investigate the effect of changes in the minimum wage on high school dropout decisions. Consistently across two sources of variation and three individual-level datasets, I find that increases in the minimum wage substantially reduce the dropout likelihood of low-socioeconomic status (SES) teens but have no effect on other teens.

Keywords: *Minimum Wage, Teen Labor Market, Educational Attainment, High School Dropout*

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1 Introduction

The economic literature on the consequences of the minimum wage is both vast and contentious. Researchers concentrate mainly on the possible disemployment effects of the minimum wage, frequently focusing on teens, the age group most subject to the minimum wage.[1] Much less attention has been paid to the policy's impact on teen educational investments, despite the growing literature finding substantial effects of labor demand shocks on educational attainment (Charles, Hurst, and Notowidigdo 2018; Atkins 2016; Cascio and Narayan 2017) and the primary importance generally accorded to teen educational attainment over teen employment by policymakers. I contribute to this literature by using multiple data sources and sources of variation in concert to establish the causal effect of minimum wage changes on the educational choices of high-risk teens.

While the effect of the minimum wage on educational investment is indirect, it is an intuitive byproduct of a simple model of human capital investment where teens decide whether to drop out of high school by weighing their opportunity cost and psychic cost of schooling against the expected future return to earning a high school diploma. To the extent that changes in the minimum wage alter the teen labor market (Neumark and Wascher 2008), these changes will also alter the opportunity cost of schooling and therefore their dropout decision. Furthermore, to the extent that returns to a high school diploma increase more steeply with ability for higher socio-economic status (SES) teens (e.g. due to better school quality, job networks, or likelihood of proceeding

[1] One quarter of 16-19 year old wage earners earn the minimum wage (and many more are just above it), while only a tenth of 20-24 year old and a twentieth of 25-34 year old wage earners earn the minimum wage (calculations from March CPS).

to higher education) or the distribution of ability differs by socio-economic status (e.g. due to differences in parental investments or accumulated past exposure to school quality), then we would expect the impacts of a minimum wage change on high school dropout decisions to differ dramatically by SES.[2]

I investigate the impact of changes in the minimum wage on high school dropout decisions using two distinct sources of variation and three individual-level datasets. I use two decades of the Current Population Survey (CPS), one decade of the American Community Survey (ACS), and the 1996, 2001, 2004, and 2008 4-year panels of the Survey of Income and Program Participation (SIPP). To identify the effect of a minimum wage change, I leverage both variation in minimum wage rates within states over time and variation in minimum wage rates between neighboring localities on either side of a state border at a given point in time. Each of these sources of data and variation have their own advantages and disadvantages in measuring the educational effect of minimum wage changes. I use them in concert to address a variety of internal validity threats that would not be possible to address with only one source of data and variation.

Consistently across data sources, sources of variation, and empirical specifications, I find that an increase in the minimum wage lowers the likelihood that low-SES teens will drop out of high school but has no effect on the likelihood of drop out for other teens. The effect on low-SES teens, who have a higher *ex ante* dropout rate, is substantial. I find that a ten percent increase in the minimum wage, equivalent to an increase of 73 cents per hour at the

[2]Figures A1 and A2 show descriptive evidence that both of these conditions are likely to be met in practice. Figure A1 shows that the relationship between cognitive test scores and income in adulthood differs by SES for high school graduates in the National Longitudinal Survey of Youth 1997. Figure A2 uses the same sample to show that the distribution of cognitive test scores differs substantially by SES.

current federal minimum, lowers the likelihood of dropping out by 0.5 to 1.0 percentage points, or between four and ten percent of the average dropout rate for the low-SES group.

Taken together, my results suggest that the focus of prior research on the teen employment effects of the minimum wage may have missed part of the larger picture of this policy's impact on teens. While increasing the minimum wage may reduce contemporaneous teen employment outcomes, it may also increase the future productivity and labor market prospects for teens from low-SES families, making the long-run effects on this group far less clear.

2 Educational Attainment, Labor Market Shocks, and the Minimum Wage

In traditional models of endogenous schooling (e.g. Becker 1962; Card 2001), individuals choose their optimal educational attainment by comparing the future lifetime benefits of additional education (i.e. the present discounted value of increased future income) with the more immediate costs of that education (i.e. tuition, psychic, and opportunity costs). A growing number of recent studies have tested the implications of this model by investigating the impact on educational attainment of labor market shocks that changed either the benefits or costs of education. They find that increased labor demand for high school dropouts due to fracking (Cascio and Narayan 2015) and Mexican export manufacturing growth (Atkins 2016) led to increases high school dropout rates, while increased labor demand for non-college educated workers due to housing booms led to reductions in college enrollment (Charles, Hurst, and Notowidigdo 2018). In each of these cases, the demand shift could po-

tentially have increased the cost of education, while simultaneously decreasing the benefit, but the authors find that the effects on educational attainment were driven by changes in the opportunity cost of education. I contribute to this literature by investigating the impact of a policy shock to the teen labor market from the minimum wage.

The impact of the minimum wage on educational attainment will depend on the effect of the minimum wage on the teen labor market. Neoclassical economic theory generates a relatively simple prediction for the effect of the minimum wage on the work hours of teens: Firms will respond to an increase in the minimum wage by shifting their inputs away from these workers and toward other (substitutable) production inputs, such as higher-skilled workers or capital. This yields an unambiguous prediction that demand for low-skilled labor will decrease.[3,4,5] The empirical literature examining the effects of the minimum wage on the teen labor market tend to find at least small disemployment effects. The large literature in this area can be divided broadly into two camps with differing methodologies. The first, led by Neumark and Wascher in several works (Neumark 1992, 2006; Neumark and Wascher 1995, 2008; Neu-

[3]Under the simple neoclassical model, if high-SES teens are seen as better skilled than low-SES teens, then we would expect to see a larger decrease in demand for low-SES teens and the effect on high-SES teens would be ambiguous.

[4]The predictions of the simple neoclassical model do not necessarily hold for models incorporating search. For example, Lang and Kahn (1998) find an increase in employment from a minimum wage in a bilateral search model with heterogeneous workers, while Finn (2006) finds that employment may increase or decrease in a search-match model with endogenous contract rates. As in the simple neoclassical model, Lang and Kahn (1998) find the minimum wage results in worse outcomes for less productive workers relative to more productive ones.

[5]Incorporating the labor market participation decision into a model of job search, as in the model of Pissarides (1978), could yield the opposite conclusion under certain conditions. If high-SES teens have shorter work horizons in the low wage labor market than low-SES teens (e.g. they are more likely to leave their job and go to college), then an increase in the minimum wage that reduces the probability of a job offer, but increases the wage conditional on an offer, could differentially reduce high-SES relative to low-SES teen labor force participation (since high-SES teens would have a shorter time period to benefit from a successful search).

mark, Salas, and Wascher 2013), use the generalized difference-in-differences approach and find substantial disemployment effects (elasticities between -0.1 and -0.3).[6] The second, pioneered by Card and Krueger (1992) and exemplified by Allegretto et al. (2013), criticize the traditional approach for failing to account for spatial heterogeneity in labor market shocks and advocate the use of local area controls. Primarily, they use cross border designs which compare neighboring localities that cross a state border. These studies tend to find small or null disemployment effects.[7]

Recent studies in the U.S. and other developed countries have come to conflicting conclusions regarding the effects of the minimum wage on teen educational outcomes. A number of studies have found negative enrollment or attainment effects (Neumark and Wascher 1995, 2003; Turner and Demiralp 2001; Chaplin et al. 2003; Neumark and Nizalova 2007) while others have found mixed or null enrollment effects (Warren and Hamrock 2010; Campioleti et al. 2005; Pacheco and Cruickshank 2007) or positive enrollment effects (Matilla 1978, 1982). I use multiple individual-level data sources in concert, which improve on prior data used in U.S. studies, particularly those finding negative effects on teen educational outcomes.

First, I use data spanning up to 20 years of minimum wage changes (compared to two years in Turner and Demiralp 2001) and including more recent changes than elsewhere in the literature. Second, in my analysis using the SIPP, I observe nearly all teens and can therefore rule out that my results are

[6] Meer and West (2015) argue that minimum wage changes have dynamic rather than discrete impacts on employment and therefore these fixed effects specifications, particularly those using state-specific time trends, will underestimate the true magnitude of disemployment effects.

[7] Jardim, et al. (2017) use detailed administrative data to show that defining the labor market by wage-level rather than by demographics (i.e. teens) or industry (i.e. restaurants) yields larger elasticity estimates (in the context of Seattle's recent minimum wage increase).

driven by sample selection, a concern for Neumark and Wascher (1995, 2003) which use a 65% matched sample of teens observed in consecutive years of the May CPS.[8] Third, I observe individual-level contemporaneous measures of drop out and enrollment rather than aggregate state cohort-level educational outcomes as in Neumark and Nizalova (2007) and Chaplin et al. (2003).

These aggregate measures do not distinguish between changes in educational outcomes and changes in cell composition. Neumark and Nizolava use state of residence (at age 25-29) by year by age cell averages from the Current Population Survey for 1979-2001 to estimate the effect of minimum wage exposure at earlier ages on educational attainment by age 25-29, finding a large negative relationship that they interpret as "suggestive evidence"(p. 436). However, they find that the negative effect of minimum wage exposure at age 20-24 on high school degree attainment (by age 25-29) is actually larger in magnitude than the effect of exposure at age 16-19. Since age 20-24 is after the high school degree would be obtained in most cases, this result seems likely to be driven by differential migration rather than changes in degree attainment (e.g. if older high school dropouts are more likely to come to a state with a higher minimum wage). In fact, using Neumark and Nizolova's specification with individual-level American Community Survey data, I find that earlier minimum wage exposure increases the likelihood that a 25-29 year old was born in the state where they reside, and this is especially strong for high school dropouts (Table A11).

Chaplin et al. use state-grade-year enrollment levels from the Common

[8]I focus narrowly on high school dropout and enrollment outcomes (age 16-18), unlike Neumark and Wascher (1995, 2003) and Turner and Demiralp (2001), which look at joint enrollment-employment outcomes (age 16-19). Limiting my sample to 16-18 year olds narrows my focus to decisions regarding completing high school, whereas including 19 year olds, as in Neumark and Wascher (1995, 2003), would mean also capturing decisions of whether to go to college.

Core of Data to find that increases in the minimum wage reduce teen school enrollment, specifically at the 9th to 10th grade transition. However, as Warren and Hamrock (2010) point out, this measurement approach does not account for grade retention and changes in incoming cohorts over time. They adopt a similar approach, but construct a high school completion rate using estimated first-time ninth grade enrollment three years earlier as the denominator, and find imprecise null results.

In addition to the data-related contributions listed above, I make two other primary contributions to the literature. First, to my knowledge, I am the first to use local cross-border variation in minimum wage in a given year in the investigation of educational effects of the minimum wage. Second, I investigate the effect of the minimum wage on high school dropout behavior separately by SES. This is a critical distinction, not made elsewhere in the literature, which enables a focus on the teens who are at the highest risk of dropping out.

3 High School Droupout Decision

As a simple conceptual framework to motivate my empirical analysis, I adapt the model of college-going used by Kerwin, Hurst, and Notowidigdo (2018) to the high school dropout decision context. In this framework, teens will drop out of high school if the benefit of a high school diploma, the future income premium, does not exceed the opportunity and psychic costs of obtaining the diploma (tuition is assumed to be zero). They make this decision in period $t = 0$ by either choosing to attend school or join the labor market and then receive a stream of future income based on their decision (periods $t \in [1, T]$).

Teens differ in academic ability θ_i which is distributed smoothly over the interval [0,1]. Income increases linearly with academic ability for those who obtain a HS Diploma, but for those who don't obtain a high school diploma, income in each period is a function of the minimum wage, $Y_t(w)$.[9] The benefit of graduating from high school, $B(\theta_i, w)$ is the difference between the present value of these future income streams.[10]

The cost of obtaining a high school diploma, $C(\theta_i, w)$, is determined by two factors. First, the opportunity cost of the time required to remain in school and graduate rather than entering the labor market in period $t = 0$ and earning $Y_0(w)$. Second, the psychic cost of graduating from high school, which is decreasing linearly in academic ability.[11]

In this framework, teen i will choose to drop out of high school if their academic ability, θ_i, is below a threshold value $\bar{\theta}$ defined by $B(\bar{\theta}, w) = C(\bar{\theta}, w)$. Figure 1 depicts this threshold value. The predicted effect of an increase in the minimum wage on the rate of high school dropouts will depend on the directions and magnitudes of the change's impact on the lifetime income of high school dropouts (i.e. the change in diploma benefit) and the opportunity cost of attending high school. The empirical literature finding disemployment effects on teens (Neumark and Wascher 2008) suggests a likely reduction in the opportunity cost of attending high school. Figure 2 shows the possible

[9]Figure A4 shows the distribution of wages relative to the effective minimum wage for 25-35 year-olds with and without a HS Diploma. It shows that wages of adults without a HS diploma are lower and more likely to be impacted by the minimum wage than those with a HS diploma.

[10]I parameterize this benefit as $B(\theta_i, w) = \sum_{t=1}^{T}(1 + \alpha\theta_i)\beta^t Z_t - \beta^t Y_t(w)$, where $Y_t(w)$ is the income in period t for high school dropouts,Z_t is the baseline (i.e. zero academic ability) income in period t for a teen who obtains a HS diploma, α is a constant denoting the relationship between academic ability and income for high school graduates, and β^t is the discount rate.

[11]I parameterize this cost as $C(\theta_i, w) = \kappa - \rho\theta_i + Y_0(w)$, where κ and ρ are constants defining the relationship between academic ability and the psychic cost of obtaining a high school diploma.

predictions under this scenario.[12] Panel A shows the predicted reduction in high school dropouts in the case where the minimum wage change reduces the lifetime income of high school dropouts. Panel B shows the predicted reduction in high school dropouts in the case where the minimum wage change increases the lifetime income of high school dropouts, but by less than the reduction in the opportunity cost of attending high school. Panel C shows the predicted increase in high school dropouts in the case where the minimum wage change increases the lifetime income of high school dropouts by more than the reduction in the opportunity cost of attending high school. While Figure A4 suggests that adult high school dropouts are more likely to be affected by the minimum wage than high school graduates, the empirical literature finding negative effects on employment (Sabia, Burkhauser, and Hansen 2012) and job growth (Meer and West 2016) for adult high school dropouts suggests that a large increase in lifetime income for this group, and therefore an increase in high school dropouts (as in Panel C), is unlikely.

3.1 Differences by Socio-economic Status

The large difference in high school dropout rates by socio-economic status (SES) has been well-documented. I account for these differences in family background in two ways. First, I allow the effect of academic ability on the future income of high school graduates to be larger for high-SES teens than low-SES teens.[13] Figure A1 provides descriptive evidence consistent with this assumption. It shows that adult income increases more steeply with cognitive test scores for high-SES than low-SES individuals in the National Longitudinal

[12] Analytically, the direction of the effect of a minimum wage increase on the high school dropout rate can be characterized as follows, $\frac{d\bar{\theta}}{dw} < 0$ if $\frac{dY_0(w)}{dw} < \sum_{t=1}^{T} \beta^t \frac{dY_t(w)}{dw}$.

[13] I implement this by allowing α in $B(\theta_i, w)$ to differ by SES where $\alpha^H > \alpha^L$.

Survey of Youth 1997 (NLSY97). Similarly, Bell et al. (2019) finds that high math scores lead to large increases in later patent rates for high-SES, but not low-SES, children. Second, I allow the relationship between academic ability and the psychic costs of obtaining a high school diploma to differ by SES in order to reflect differences in peer, parental, school, and neighborhood factors that may make graduating more difficult for low-SES teens. Specifically, I assume that the psychic cost for a low-SES teen with zero academic ability is higher and decreases more slowly with ability than for a similar high-SES teen.[14] Figure A3 provides descriptive evidence consistent with this assumption. It shows that low-SES teens in the NLSY97 are less likely than high-SES teens with the same cognitive test score to earn a HS diploma. For below average test scores, the likelihood of a HS diploma increases more slowly with cognitive test scores for low-SES than high-SES teens.

Under these assumptions, the threshold academic ability for dropping out of high school is higher for low-SES teens than high-SES teens, $\bar{\theta}^H < \bar{\theta}^L$, implying a higher dropout rate for low-SES teens (if the ability distribution of low-SES teens is the same or lower than high-SES teens). Furthermore, the magnitude of the effect of a change in minimum wage on $\bar{\theta}$ will be larger for low-SES teens than high-SES teens, $|\frac{d\bar{\theta}^H}{dw}| < |\frac{d\bar{\theta}^L}{dw}|$. Figure 3 demonstrates this graphically for the scenario where a minimum wage increase causes (identical) small reductions in the benefit and larger reductions in the cost of obtaining a high school diploma for high and low-SES teens. A larger minimum wage effect on $\bar{\theta}$ for low-SES teens implies a larger effect on the high school dropout rate of low-SES teens if both groups have the same ability distribution. In

[14] I implement this by allowing κ and ρ in the psychic cost component of $C(\theta_i, w)$, $\kappa - \rho\theta_i$ to differ by SES where $\kappa^H < \kappa^L$ and $\rho^H > \rho^L$.

fact, this differential effect will be even larger if the distribution of low-SES teen ability is more concentrated near the threshold than high-SES teen ability (e.g. due to quality differences in past schooling).[15]

4 Data

I match data on state-level minimum wage rates and local labor market characteristics to three individual-level datasets with information on teens' labor market, educational outcomes, and parental education: the Current Population Survey Out-going Rotation Group (CPS), the 2000 Census and American Community Survey (ACS), and the Survey of Income and Program Participation (SIPP). Each of these datasets has advantages and disadvantages in measuring the impact of minimum wage changes on teen educational outcomes. Taken as a group, these datasets allow me to avoid the major drawbacks of the data used in prior research (e.g. imprecise measures and potentially substantial endogenous sample selection), while also allowing me to differentiate effects on high and low-SES teens.

I use the CPS to construct a nationally-representative monthly cross-section of 16-18 year olds for 1992-2012 (CPS).[16] Each month's sample is relatively small and only contains coarse geographic information (i.e. state of residence) for all individuals.[17] The 2000 Census and 2005-2011 ACS provide a larger sample (1-in-20 and 1-in-100, respectively) and residence information

[15]Figure A2 shows that this is likely to be the case, as the distribution of cognitive test scores are lower for low-SES than high-SES teens in the NLSY97.

[16]Prior to 1992, the IPUMS-CPS does not differentiate between having attended 12 years of school and obtaining a high school diploma or equivalent.

[17]The IPUMS-CPS contains county of residence and metropolitan area of residence for some individuals in large counties or metropolitan areas, but the sample size is not large enough for meaningful analysis at this geographic level.

at the Public-Use Microdata Area (PUMA) level for all individuals, while the 2001-2004 ACS provides a sample of less than 1-in-230 and only state of residence information.[18] I use the 2000 Census and ACS datasets to construct four distinct samples with increasing geographic specificity: (1) An annual cross-section for 2000-2011 that identifies residence at the state-level (ACS), (2) An annual cross-section for 2005-2011 that identifies residence at the PUMA-level (ACS-P), (3) An annual cross-section for 2005-2011 that identifies residence at the county-level for residents of large counties (ACS-C), (4) An annual cross-section for 2005-2011 with a probabilistic match between the Public Use Microdata Areas (PUMAs) in the ACS-P sample and their corresponding commuting zones (ACS-CZ).[19]

Observing a teen's parents/guardians is a requirement for determining her socio-economic status. In the CPS and ACS, parents/guardians will only be observed if they reside in the same household as the teen. While this is true for more than 86% of 16-18 year olds in the CPS and ACS samples, there is a possibility that this selectively observed sample could bias estimates of the minimum wage's impact on drop out. Unlike these cross-sectional datasets, the SIPP reliably tracks the same individuals for 3-4 years (regardless of changes in residence), and therefore observes parental/guardian education for more than 98% of 16-18 year olds.[20] I combine the 1996, 2001, 2004, and 2008 panels of the SIPP to construct an individual-level panel where educational outcomes are observed three times per year and labor market outcomes are observed

[18] PUMA codes are only comparable across the 2000 Census and 2005-2011 ACS. PUMA boundaries were were changed in 2012.

[19] I obtain the geographic crosswalk file matching PUMAs to 1990 Commuting Zones from Autor and Dorn (2013).

[20] In Table A2, results are also shown for a subsample of the SIPP including only 16-18 year olds who appear in the first wave of a given panel. Parent/guardian education is observed for more than 99% of this subsample.

monthly.

In my primary analysis, I define a teen's socio-economic status using the educational attainment of her parents. Specifically, I define a teen as "high SES" if all of her observed parents (or guardians) have graduated from high school. I define a teen as "low SES" if any of her observed parents (or guardians) has not graduated from high school. In all data samples, roughly 80% of 16-18 year olds are classified as high SES (see Table 2).[21] In all samples, I create a simple dropout indicator as follows: teen i has dropped out if she is not currently enrolled in school and she has not obtained a high school diploma (or greater level of education).[22,23] This is a stock variable indicating those who are currently dropouts (regardless of how recently they dropped out), rather than a flow variable, which would indicate those who had newly transitioned from enrolled to dropout. Table 2 shows the average dropout rates by SES (9-12% for low-SES and 3-4% for high-SES) for select data samples under these definitions. Figure 4 shows the modest downward trends in these dropout rates over time, particularly among low-SES teens.[24]

I obtain state-by-month information on state minimum wage rates for

[21] I provide robustness checks with alternative definitions of high SES teens as those whose parents attended "some college" or whose household income (excluding their own income) is above the p^{th} percentile of the yearly distribution, for $p \in 20, 30, 40, 50$. My primary formulation has two advantages over these potential alternatives. First, family income is relatively volatile from year-to-year and may be affected by the minimum wage. Second, using parental high school education to define low SES effectively identifies teens who are at highest risk of dropping out.

[22] For comparability between datasets and over time within datasets, I count GED recipients as equivalent to HS diploma holders in the primary analysis. I also include students enrolled part-time as currently enrolled in my primary analysis.

[23] For the SIPP, I only count a teen as a dropout if she satisfies this definition for two waves in a row.

[24] It is possible that some portion of this trend is driven by increased GED recipients, but my main data sources do not treat GED recipients separately from high school graduates for sufficient time periods to analyze. Therefore, to ensure that this or some other aspect of my dependent variable construction is not driving my results, I repeat all analyses using a simple enrollment indicator as the dependent variable. Additionally, results using only the October CPS, which enables GEDs to be counted as dropouts, do not differ substantively from the main CPS results.

1992-2012 from the Tax Policy Center at the Urban Institute and Brookings Institution and merge it with the individual-level information on teens in each data sample.[25,26] Figures 5 and 6 show the substantial variation over the last two decades in effective state minimum wages, constructed as the maximum of federal and state minimum wage laws. Figure 5 depicts the variation in the minimum wages over time.[27] The federal minimum is depicted as the black line, while states with minimums above the federal minimum are in gray (the size of the bubble denotes the number of states in a given $0.25 bin). Figure 6 maps the difference between state and federal minimum wages geographically and over time, in percentage terms.

5 Empirical Strategy

I utilize two different sources of variation and multiple data sources to identify the effect of minimum wage increases on teen high school dropout decisions (overall and by SES). First, I estimate a generalized difference-in-differences (state and year fixed effects) and a cumulative event study similar to Dube et al. 2010, which leverage the variation within-states, over time in the minimum wage. Second, I use a cross-border design which leverages variation in the minimum wage at a given point in time between nearby PUMAs in the same commuting zone on either side of a state border.

[25]This data is compiled by the Tax Policy Center from January issues of the Bureau of Labor Statistics' Monthly Labor Review, the 1968-1999 Book of the States published by the Council of State Governments (for 1990-1999), and U.S. Department of Labor data (for 2000-2012).

[26]I also obtain yearly state and county unemployment rates from the Bureau of Labor Statistics' Local Area Unemployment Statistics.

[27]During the sample time period, three localities (with less than 0.5% of the U.S. population) have minimum wages that differ from the state minimum. Given how little of the population is affected, the resulting measurement error is likely to be very small.

5.1 Generalized Difference-in-Differences

I begin by adopting an approach that has been used frequently in the minimum wage literature to investigate employment effects and applying it to all three datasets (CPS, ACS, and SIPP). This approach includes state fixed effects to remove time-invariant differences between states that may be related to both differences in teen outcomes and minimum wage levels, such as the industrial structure of the state economy, the generosity of social welfare programs, and the quality of the state educational system. In my preferred specifications, state-specific polynomial time trends are included to account for these differences evolving smoothly over time. Year fixed effects are included to remove differences between years, common to all states, that may be related to both outcomes and minimum wage levels, such as shocks to the national economy and the political climate at the federal level. The effect of the minimum wage is identified by variation over time in a state's effective minimum wage (the maximum of the state and federal minimum wages). This baseline specification is as follows:

$$y_{isgt} = \beta_0 + \beta_1 ln(mw_{st}) + \gamma X_{isgt} + \nu_t + \theta_g + \sigma_s(t) + \epsilon_{isgt}, \tag{1}$$

where y_{isgt} is the outcome of interest. For the main results, the outcome of interest is an indicator for whether individual i in state s and geography g at time t is identified as a high school dropout.[28] $ln(mw_{st})$ is the log of the minimum wage in state s at time t. X_{isgt} are demographic characteristics of individual i (i.e. indicators for age, sex, race, and whether she is above the

[28] Depending on the sample, geography g may be measured at the state-, county-, or PUMA-level. t is measured in years for ACS samples, in months for the CPS sample, and in trimesters for the SIPP primary sample.

state's compulsory schooling age) and characteristics of the labor market in state s at time t (i.e. state unemployment rate). ν_t and θ_g are year and geography fixed effects.[29] $\sigma_s(t)$, included in some specifications, is a state-specific polynomial time trend to account for differential trends across states. The primary coefficients of interest are β_1, which captures the impact of changes in the minimum wage on the likelihood that low-SES teens will drop out of high school, and $\beta_1 + \beta_3$, which captures the same effect for high-SES teens. I estimate this equation using OLS with standard errors clustered at the g-level.

Estimates using the finer geographic granularity for g available in the ACS-P (PUMA-level) and ACS-C (county-level) samples leverage the same within-state minimum wage variation over time for identification, but remove time-invariant differences at the PUMA or county-level, rather than the state-level. While unobserved (time-invariant) spatial heterogeneity at this more local level is unlikely to create endogeneity problems since minimum wage policy during this period is generally determined at the state-level, removing it should improve estimates by reducing noise from persistent differences across localities in industrial structure and school quality. Estimates using the SIPP sample provide a check of whether the results using the CPS and ACS samples are driven by sample selection (since SES is observed for more than 98% of the SIPP sample).

Table 3 (columns 1-5) presents OLS estimates for β_1 in Equation 1 using my preferred specification for each of the samples discussed above (CPS, ACS, ACS-P, ACS-C, and SIPP).[30] These overall high school dropout results are

[29]Since the SIPP sample is an aggregation of four panels, I include panel-by-state fixed effects rather than only state fixed effects. This accounts for any systematic differences between panels for a given state, such as the samples selected.

[30]For the CPS sample I select a cubic trend (following Neumark et al., 2013) and for the samples with shorter timeframes (i.e. SIPP, ACS, ACS-P, and ACS-C) I select a linear trend. While the

small and not statistically significant.

These null results are not surprising in the context of the conceptual framework discussed in Section 3. Under those assumptions, the sensitivity of high school dropout decisions to the minimum wage will be much greater for low-SES teens than high-SES teens. I therefore adjust my baseline specification in Equation 2 to include an interaction between log minimum wage and an individual's socio-economic status, allowing me to examine the differential effects of minimum wage by family background.

$$y_{isgt} = \beta_0 + \beta_1 ln(mw_{st}) + \beta_2 HSES_{isgt} + \beta_3 ln(mw_{st}) \times HSES_{isgt} + \gamma X_{isgt} + \nu_t + \theta_g + \sigma_s(t) + \epsilon_{isgt}, \quad (2)$$

where $HSES_{isgt}$ is an indicator equal to one if individual i is high SES, that is, if all of his observed parents/guardians have at least a high school diploma.

Table 4 (columns 1-5) shows the OLS estimates for β_1 (effect of minimum wage change on low-SES teens) and β_3 (differential effect of minimum wage change on high-SES teens compared to low-SES teens) in Equation 2 using my preferred specification for each of the sample.[31] Across these samples, I find that raising the minimum wage significantly reduces the likelihood of dropping out among low-SES teens (β_1), but has a much smaller or null impact on the likelihood of dropping out among high-SES teens ($\beta_1 + \beta_3$). A 10% increase in the minimum wage produces a 0.5-1.0 percentage point decrease in the dropout likelihood of low-SES teens (approximately 4-10% of this group's dropout rate) and a near zero impact on high-SES teens. The low-SES estimates are signif-

SIPP sample timeframe is four-fifths of CPS, the selected SIPP specification also includes state by panel fixed effects, leaving much less variation remaining to accommodate a higher polynomial state-specific time trend.

[31] In all tables, standard errors clustered at the state-level are presented in parentheses.

icant at the 1 percent level for CPS and ACS samples, and at the 8 percent level for the SIPP sample. Notably, the SIPP coefficient estimates are similar to the CPS and ACS estimates (though smaller in magnitude than the ACS estimates), suggesting that any bias in the ACS and CPS due to the selection of a sample with observed parental education (parental education is observed for nearly all teens in the SIPP) is not driving the results.

5.2 Dynamic Responses

Estimates of Equation 2 may simply be capturing elements of states' labor or educational environments that pre-date minimum wage changes and are not accounted for by state-specific polynomial time trends. Endogenous policy change would be one example of this possibility, where state politicians adjust the minimum wage in response to changes in the state that are correlated with state dropout rates. I address this concern by adopting the strategy of Dube et al. (2010) to estimate dynamic high school dropout responses to increases in the minimum wage. Because there are multiple overlapping minimum wage change "events", this approach necessarily differs from a standard event study. It estimates the cumulative response to minimum wage changes rather than response in individual time periods. The specification is as follows,

$$y_{ist} = \beta_0 + \sum_{\tau \in [-2,3]} \Big(\alpha_\tau \Delta ln(mw_{s,t-\tau}) \Big) + \alpha_4 ln(mw_{s,t-4}) + \gamma X_{ist} + \nu_t + \theta_s + \sigma_s(t) + \epsilon_{ist}, \tag{3}$$

where $\Delta ln(mw_{s,t-\tau})$ is the year-to-year difference in the log minimum

wage τ years prior to year t ($\tau < 0$ refers to changes after year t).[32] As all but the last lag $(t-4)$ are specified as differences, the estimates of α_τ can be interpreted as the cumulative response to minimum wage increases in year $t-\tau$. If my effect estimates from Equation 2 are capturing pre-existing conditions rather than effects of minimum wage changes, then estimates of α_τ or $\alpha_\tau + \delta_\tau$ (or both) would be significant for $\tau < 0$.

Figure 7 depicts estimates of α_τ using the preferred specification for the ACS sample.[33] As in Table 3 the estimates of α_τ show null effects.

I repeat this dynamic response specification including an SES interaction to allow for differential effects of the minimum wage by SES.

$$\begin{aligned} y_{ist} = \beta_0 + \sum_{\tau \in [-2,3]} \Big(\alpha_\tau \Delta ln(mw_{s,t-\tau}) + \delta_\tau \Delta ln(mw_{s,t-\tau} \times HSES_{ist}) \Big) \\ + \alpha_4 ln(mw_{s,t-4}) + \delta_4 ln(mw_{s,t-4} \times HSES_{ist}) \\ + \eta HSES_{ist} + \gamma X_{ist} + \nu_t + \theta_s + \sigma_s(t) + \epsilon_{ist}, \end{aligned} \tag{4}$$

Figure 8 depicts estimates of α_τ (low-SES) and $\alpha_\tau + \delta_\tau$ (high-SES) using the ACS sample. Consistent with the minimum wage change the reduction in low-SES HS dropouts, these estimates show flat pre-trends and then a large reduction in dropout in $\tau = 0$ for low-SES teens, but not for high-SES teens.

5.3 Cross-Border Design

The existence of time-varying heterogeneity in local labor markets could raise concerns regarding the internal validity of the generalized difference-in-differences

[32] Following Dube et al. (2010), I include four years of lags and two years of leads.
[33] The controls and samples are those from column 3 in Table 4.

approach. For example, Allegretto et al. (2013) show that states experiencing greater increases in minimum wages differ systematically from other states in terms of the severity of economic downturns, the reduction of routine task intensive jobs, and the growth in upper-half wage inequality. To the extent that these types of differential trends across states are not sufficiently smooth to be captured by state-specific polynomial time trends, they will bias the estimates of Equation 2.

I address this possibility by employing an approach used by Allegretto et al. (2013) to look at the employment effects of the minimum wage. This framework leverages variation in minimum wage within a commuting zone, that spans a state border, in a given year.[34] I apply this approach to the ACS-CZ sample, which has a sample size large enough to allow for analysis at geographic levels finer than state of residence. The ACS-CZ sample includes all teens in the ACS.

The specification is largely the same as Equation 2 except that it includes commuting zone (z) by year fixed effects, ρ_{zt}, and geography (PUMA) fixed effects, θ_g.

$$y_{iszgt} = \beta_0 + \beta_1 ln(mw_{st}) + \beta_2 HSES_{iszgt} + \beta_3 ln(mw_{st}) \times HSES_{iszgt} + \gamma X_{iszgt} + \rho_{zt} + \theta_g + \epsilon_{isgt}. \quad (5)$$

This approach accounts for time-varying local labor market heterogeneity as well as time-invariant differences between PUMAs, but also reduces external validity. The estimates are identified by comparing teens in the same commuting zone on either side of a state border, where the difference in minimum

[34] I obtain commuting zones from Autor and Dorn (2013).

wages on either side of the border changes during 2005-2011. If teens in these border-spanning commuting zones are more or less responsive to minimum wage changes than typical American teens, the estimates of β_1 and β_3 will not represent the average effect nationwide of a minimum wage increase. Figure 9 shows the commuting zones that have minimum wage variation within commuting zone-years during the period 2005-2011.[35]

5.4 Internal Validity

The consistency of the results in Table 4 across data samples and empirical approaches along with the cumulative event study help to alleviate three major internal validity concerns. First, the SIPP coefficient estimates are similar to the CPS and ACS estimates (though smaller in magnitude than the ACS estimates), suggesting that any bias in the ACS and CPS due to the selection of a sample with observed parental education (parental education is observed for nearly all teens in the SIPP) is not driving the results. Second, the similarity of the cross-border estimates (column 6) and generalized difference-in-difference estimates (columns 1-5) suggest that time-varying spatial heterogeneity is not driving the latter estimates.[36] Third, the flat pre-period in the cumulative event study, followed by the notable decrease in low-SES dropouts coinciding with the minimum wage change, provides support for the parallel trends assumption of the generalized difference-in-differences strategy. This pattern

[35]Figure A5 gives an example of the identifying variation in one such commuting zone, Jacksonville, FL, which includes 7 counties: 5 in Florida and 2 in Georgia. For half of the years from 2005-2011, residents on the Florida side of the border faced a higher minimum wage than residents on the Georgia side.

[36]The robustness across empirical approaches in the educational effects of the minimum wage, but not the employment effects (as seen in the contentious literature), suggests that state minimum wage policy decisions may be endogenous with respect to employment outcomes but not with respect to educational outcomes. This could occur if state minimum wage policy changes are made in response to the overall unemployment rate.

does not support a hypothesis that endogenous policy change is producing my results.

5.5 Additional Robustness Checks

The results in Table 4 are robust to alternative definitions of SES. Table 5 shows the results for the same specifications as Table 4, but varies the definitions of high SES. Column 2 defines a teen as high SES if all of her observed parents have gone to college, coded as "some college" in the various datasets. Columns 3-6 define high SES by whether household income (excluding the teen) is above various percentile thresholds of the household income distribution for teens in that year. The results are consistent with the estimates in Table 4, but predictably, as the defined threshold between high and low SES moves up the socioeconomic distribution (i.e. from high school diploma to some college or from 20th to 50th income percentile), the magnitudes of the estimates for low-SES teens decrease. This is consistent with a concentration of the dropout effects among the lowest-SES teens.[37]

Additional appendix tables show the robustness of the estimates in Table 4 to alternative specifications and/or time periods.[38] Table A1 finds similar results to column 1 of Table 4 using the CPS sample and an alternative March CPS sample with various state-specific trends.[39] Table A2 shows similar results

[37]The low SES dropout rate decreases as the threshold between high and low SES increases, but not sufficiently for the magnitude of the effect estimates to be constant in percentage terms (Table A13). Table A6 replicates Table 5 using an enrollment indicator as the dependent variable. The results are largely similar though less precise in some cases.

[38]Tables A7, A10, and A9 repeat these robustness checks using an enrollment indicator for the dependent variable.

[39]Table A8 shows the same dropout results as Table A1 (and enrollment results as Table A7) for a time period that excludes the Great Recession (1992-2007). The enrollment results are consistent with Table A7, though less precise. The dropout results are imprecise but consistent with Table A1 for the March sample but the magnitudes of the coefficient estimates drop substantially for the main CPS sample (Out-going Rotation Group).

to column 2 of Table 4 using the SIPP sample and a "first wave only" sample with various state-specific time trends and state or state by panel fixed effects. These are consistent with the primary estimates, except for the state fixed effect and state-specific quadratic time trend specification (Column 6 and 12), which yields an insignificant estimate of β_1.[40] Table A3 shows similar results to column 3-6 of Table 4 using the ACS, ACS-P, ACS-C, and ACS-CZ samples for various state-specific time trends. The results are significant and similar in magnitude across all specifications.[41]

6 Conclusion

The long-run cost of a teen's decision to drop out of high school is public as well as private. A high school dropout yields less tax revenue, uses more social safety net benefits, and is more likely to be arrested or incarcerated. According to one estimate, the lifetime cost to the government of a high school dropout is $200,000 higher than a high school graduate (Levin et al. 2007). Externalities of this magnitude suggest that effects on high school graduation, even if indirect, may have dramatic consequences for the social welfare effects of labor market policies such as the minimum wage.

Using three individual-level datasets and two distinct sources of variation, I find that an increase in the minimum wage substantially lowers the likelihood of dropping out for low-SES teens, but has no observed effect on other teens. My estimates suggest that an increase in the federal minimum wage from $7.25

[40] Enrollment estimates of β_1 in Table A9 are similar in magnitude to the dropout estimates in Table A2 but are not significantly different from zero in most specifications (β_3 estimates remain significant).

[41] Table A10 shows simlar results to Table A3 using an enrollment indicator for the dependent variable.

to $9, a level supported by the majority of Republicans and Democrats (Kull et al. 2017), would lead to a 1-2 percentage point decrease in the likelihood that a low-SES teen will drop out of high school, roughly 10-24% of the rate for this group.[42,43] Taken together, my results suggest that the current minimum wage literature's focus on teen employment neglects important aspects of the policy's broader effects on the later-life outcomes of teens and the associated spillover effects on society at large.

[42]This would be an upper bound for the impact of a federal minimum wage increase to $9, since fewer than half of states in the U.S. have an effective minimum wage of $7.25.

[43]As with any empirical estimates, the extent to which these estimates can be linearly extrapolated to predict future policy effects will likely deteriorate for treatments far larger than those used to generate the estimates (e.g. a federal minimum wage increase from $7.25 to $15).

References

Allegretto, Sylvia A, Arindrajit Dube, and Michael Reich. 2011. "Do minimum wages really reduce teen employment? Accounting for heterogeneity and selectivity in state panel data." *Industrial Relations: A Journal of Economy and Society*, 50(2): 205–240.

Allegretto, Sylvia, Arindrajit Dube, and Michael Reich. 2009. "Spatial Heterogeneity and Minimum Wages: Employment Estimates for Teens Using Cross-State Commuting Zones." *Institute for Research on Labor and Employment*.

Allegretto, Sylvia, Arindrajit Dube, Michael Reich, and Ben Zipperer. 2013. "Credible Research Designs for Minimum Wage Studies." Working Paper 148-13. Institute for Research on Labor and Employment, UC Berkeley.

Angrist, Joshua D, and Jörn-Steffen Pischke. 2008. *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Atkin, David. 2016. "Endogenous Skill Acquisition and Export Manufacturing in Mexico." *American Economic Review*, 106(8): 2046–85.

Autor, David, and David Dorn. 2013. "The growth of low-skill service jobs and the polarization of the US labor market." *The American Economic Review*, 103(5): 1553–1597.

Becker, Gary S. 1962. "Investment in Human Capital: A Theoretical Analysis." *Journal of Political Economy*, 70(5, Part 2): 9–49.

Belfield, Clive R, and Henry M Levin. 2007. *The price we pay: Economic and social consequences of inadequate education.* Brookings Institution Press.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen. 2019. "Who becomes an inventor in America? The importance of exposure to innovation." *The Quarterly Journal of Economics*, 134(2): 647–713.

Campolieti, Michele, Tony Fang, and Morley Gunderson. 2005. "How minimum wages affect schooling-employment outcomes in Canada, 1993–1999." *Journal of Labor Research*, 26(3): 533.

Card, David. 2001. "Estimating the return to schooling: Progress on some persistent econometric problems." *Econometrica*, 69(5): 1127–1160.

Card, David, and Alan B Krueger. 1993. "Minimum wages and employment: A case study of the fast food industry in New Jersey and Pennsylvania." National Bureau of Economic Research.

Card, David, and Alan B Krueger. 1995. "Time-series minimum-wage studies: a meta-analysis." *The American Economic Review*, 85(2): 238–243.

Card, David, and Alan B Krueger. 2000. "Minimum wages and employment: a case study of the fast-food industry in New Jersey and Pennsylvania: reply." *The American Economic Review*, 90(5): 1397–1420.

Cascio, Elizabeth U, and Ayushi Narayan. 2015. "Who needs a fracking education? The educational response to low-skill biased technological change." National Bureau of Economic Research.

Chaplin, Duncan D, Mark D Turner, and Andreas D Pape. 2003. "Minimum wages and school enrollment of teenagers: a look at the 1990's." *Economics of Education Review*, 22(1): 11–21.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo. 2018. "Housing Booms and Busts, Labor Market Opportunities, and College Attendance." *American Economic Review*, 108(10): 2947–94.

Dube, Arindrajit, Suresh Naidu, and Michael Reich. 2007. "The economic effects of a citywide minimum wage." *ILR Review*, 60(4): 522–543.

Dube, Arindrajit, T William Lester, and Michael Reich. 2010. "Minimum wage effects across state borders: Estimates using contiguous counties." *The review of economics and statistics*, 92(4): 945–964.

Dube, Arindrajit, T William Lester, and Michael Reich. 2016. "Minimum wage shocks, employment flows, and labor market frictions." *Journal of Labor Economics*, 34(3): 663–704.

Heckman, James J, and Paul A LaFontaine. 2010. "The American high school graduation rate: Trends and levels." *The review of economics and statistics*, 92(2): 244–262.

Jardim, Ekaterina, Mark C Long, Robert Plotnick, Emma van Inwegen, Jacob Vigdor, and Hilary Wething. 2017. "Minimum Wage Increases, Wages, and Low-Wage Employment: Evidence from Seattle." National Bureau of Economic Research.

King, Miriam, Steven Ruggles, J Trent Alexander, Sarah Flood, Katie Genadek, Matthew B Schroeder, Brandon Trampe, and Re-

becca Vick. 2010. "Integrated public use microdata series, current population survey: Version 3.0.[machine-readable database]." *Minneapolis: University of Minnesota*, 20.

Kull, Steven, Clay Ramsay, Evan Lewis, and Antje Williams. 2017. "Americans on Federal Poverty Programs." Program for Public Consultation, School of Public Policy, University of Maryland.

Levin, Henry M, Clive Belfield, Peter A Muennig, and Cecilia Rouse. 2007. "The costs and benefits of an excellent education for all of America's children."

Lochner, Lance. 2011. "Non-production benefits of education: Crime, health, and good citizenship." National Bureau of Economic Research.

Lochner, Lance, and Alexander Monge-Naranjo. 2012. "Credit constraints in education." *Annu. Rev. Econ.*, 4(1): 225–256.

Mattila, J Peter. 1978. "Youth labor markets, enrollments, and minimum wages." 134–40.

Mattila, J Peter. 1982. "Determinants of male school enrollments: A time-series analysis." *The Review of Economics and Statistics*, 242–251.

Meer, Jonathan, and Jeremy West. 2015. "Effects of the minimum wage on employment dynamics." *Journal of Human Resources*.

Neumark, David, and William L Wascher. 2008. *Minimum wages*. MIT Press.

Neumark, David, and William Wascher. 1992. "Employment effects of minimum and subminimum wages: panel data on state minimum wage laws." *ILR Review*, 46(1): 55–81.

Neumark, David, and William Wascher. 1995*a*. "Minimum wage effects on employment and school enrollment." *Journal of Business & Economic Statistics*, 13(2): 199–206.

Neumark, David, and William Wascher. 1995*b*. "Minimum-wage effects on school and work transitions of teenagers." *The American Economic Review*, 85(2): 244–249.

Neumark, David, and William Wascher. 2000. "Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania: Comment." *The American Economic Review*, 90(5): 1362–1396.

Neumark, David, and William Wascher. 2003. "Minimum wages and skill acquisition: Another look at schooling effects." *Economics of Education Review*, 22(1): 1–10.

Neumark, David, JM Ian Salas, and William Wascher. 2014. "Revisiting the Minimum Wage—Employment Debate: Throwing Out the Baby with the Bathwater?" *ILR Review*, 67(3_suppl): 608–648.

Pacheco, Gail A, and Amy A Cruickshank. 2007. "Minimum wage effects on educational enrollments in New Zealand." *Economics of Education Review*, 26(5): 574–587.

Rothstein, Donna S. 2007. "High school employment and youths' academic achievement." *Journal of Human Resources*, 42(1): 194–213.

Ruhm, Christopher J. 1997. "Is high school employment consumption or investment?" *Journal of labor economics*, 15(4): 735–776.

Sabia, Joseph J, Richard V Burkhauser, and Benjamin Hansen. 2012. "Are the effects of minimum wage increases always small? New evidence from a case study of New York state." *ILR Review*, 65(2): 350–376.

Turner, Mark D. 1994. "The effects of part-time work on high school students' academic achievement."

Turner, Mark D, Berna Demiralp, et al. 2001. "Do higher minimum wages harm minority and inner-city teens?" *Review of Black Political Economy*, 28(4): 95–118.

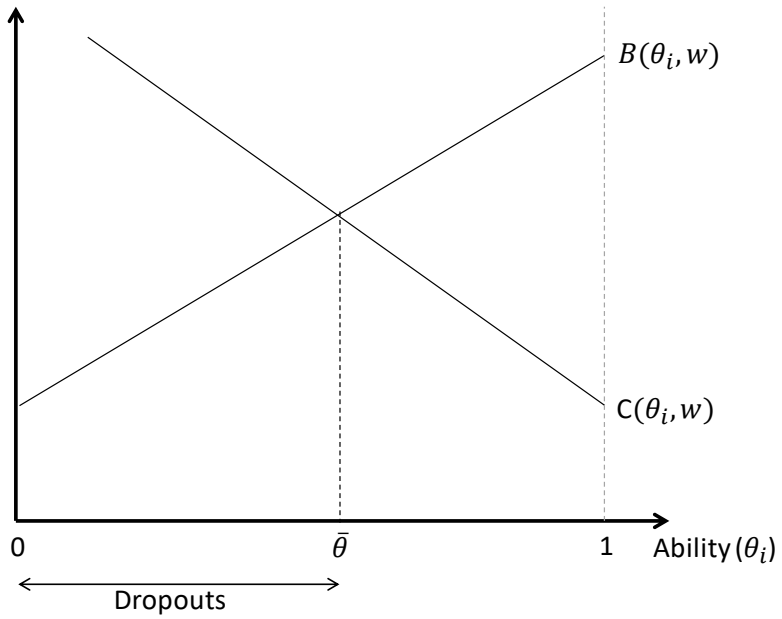
Warren, John Robert. 2005. "State-level high school completion rates: Concepts, measures, and trends." *education policy analysis archives*, 13(51): n51.

Warren, John Robert, and Caitlin Hamrock. 2010. "The effect of minimum wage rates on high school completion." *Social forces*, 88(3): 1379–1392.

Warren, John Robert, Krista N Jenkins, and Rachael B Kulick. 2006. "High school exit examinations and state-level completion and GED rates, 1975 through 2002." *Educational Evaluation and Policy Analysis*, 28(2): 131–152.

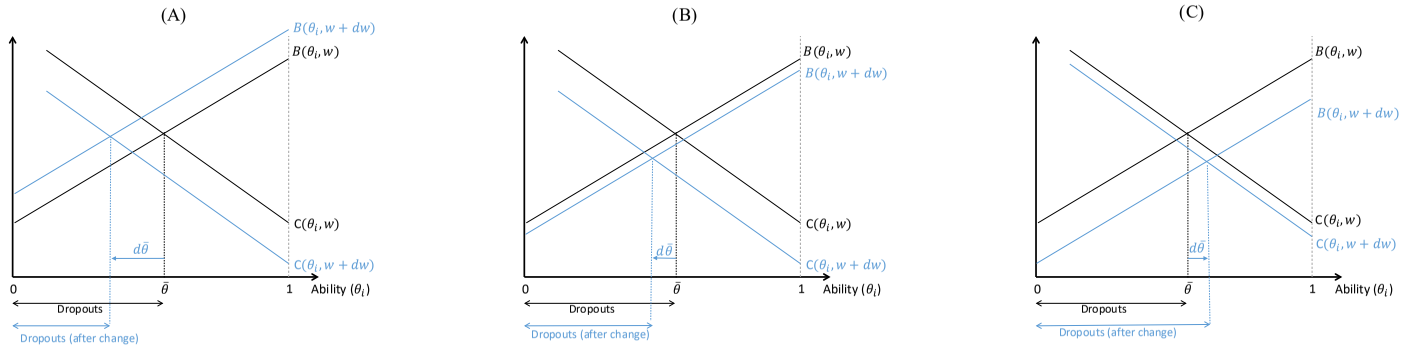
Wascher, William, and David Neumark. 2006. *Minimum Wages and Employment: A Review of Evidence from the New Minimum Wage Research.* National Bureau of Economic Research.

Figure 1: HS Dropout Decision



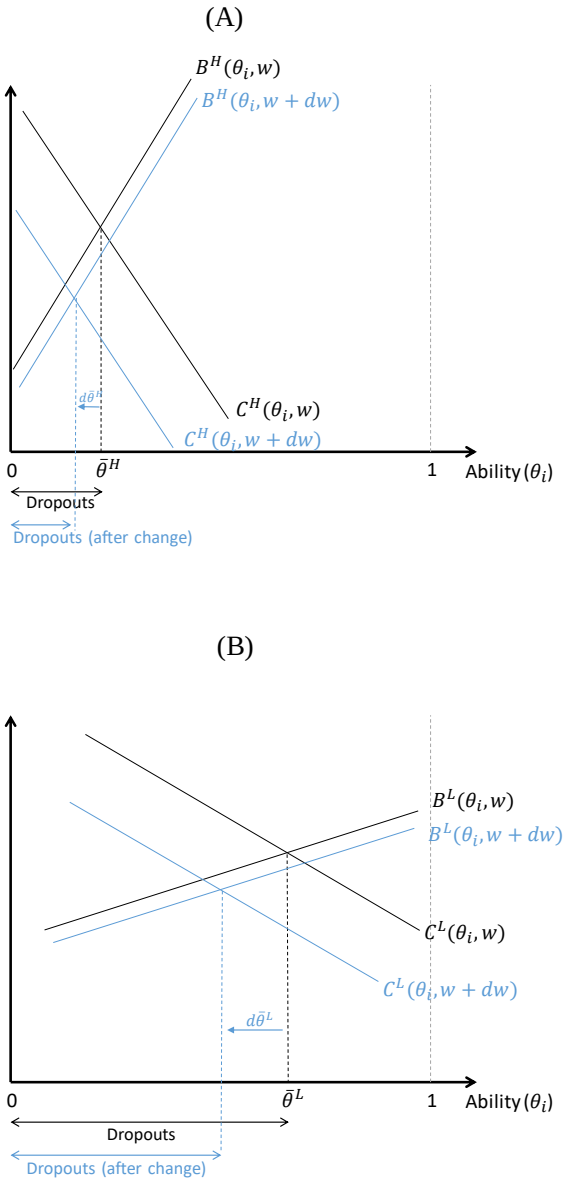
Note: Figure shows the segment of the ability distribution that will choose to drop out of high school in the given the simple conceptual framework discussed in Section 3. $B(\theta_i, w)$ is benefit of graduating from high school, parameterized as $B(\theta_i, w) = \sum_{t=1}^{T}(1 + \alpha\theta_i)\beta^t Z_t - \beta^t Y_t(w)$, where $Y_t(w)$ is the income in period t for high school dropouts as a function of the minimum wage w, Z_t is the baseline (i.e. zero academic ability) income in period t for a teen who obtains a HS diploma, α is a constant denoting the relationship between academic ability and income for high school graduates, and β^t is the discount rate. $C(\theta_i, w)$ is the cost of obtaining a high school diploma, parameterized as $C(\theta_i, w) = \kappa - \rho\theta_i + Y_0(w)$, where θ_i is academic ability, and κ and ρ are constants defining the relationship between academic ability and the psychic cost of obtaining a high school diploma.

Figure 2: Possible Effect of Minimum Wage Change on HS Dropout



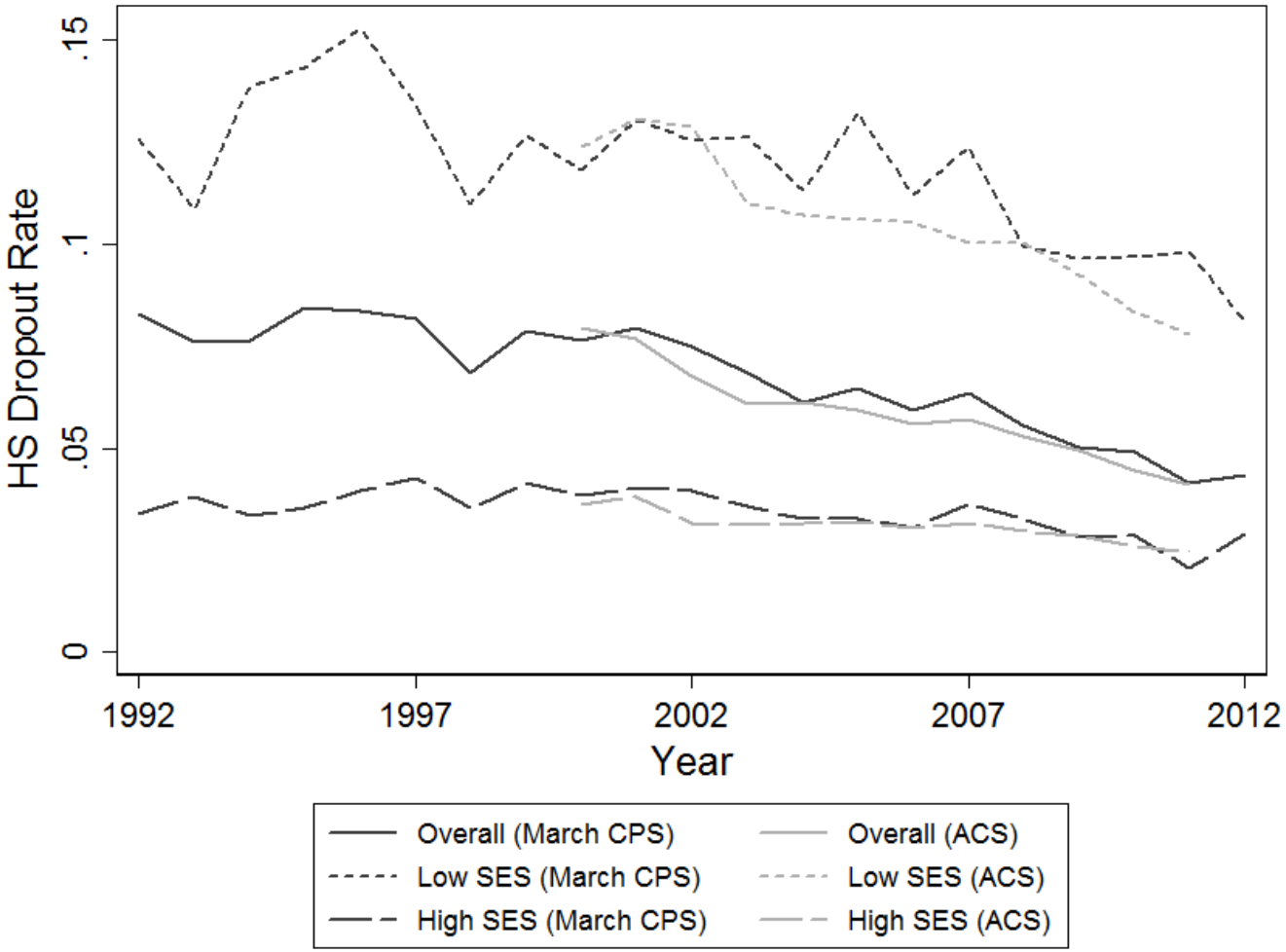
Note: Figure shows the possible change in HS dropout resulting from a minimum wage increase that changes the discounted future income of high school dropouts (the diploma benefit) and reduces the opportunity cost of high school (a reduction in the diploma cost). Panel A shows the possibility where the change in diploma benefit is positive. Panel A shows the possibility where the change in cost exceeds the reduction in benefit, while Panel B shows the possibility where the reduction in benefit exceeds the reduction in cost. $B(\theta_i, w)$ is benefit of graduating from high school, while $C(\theta_i, w)$ is the cost of obtaining a high school diploma. See text for details.

Figure 3: Possible Differential Effect of Minimum Wage Change by SES



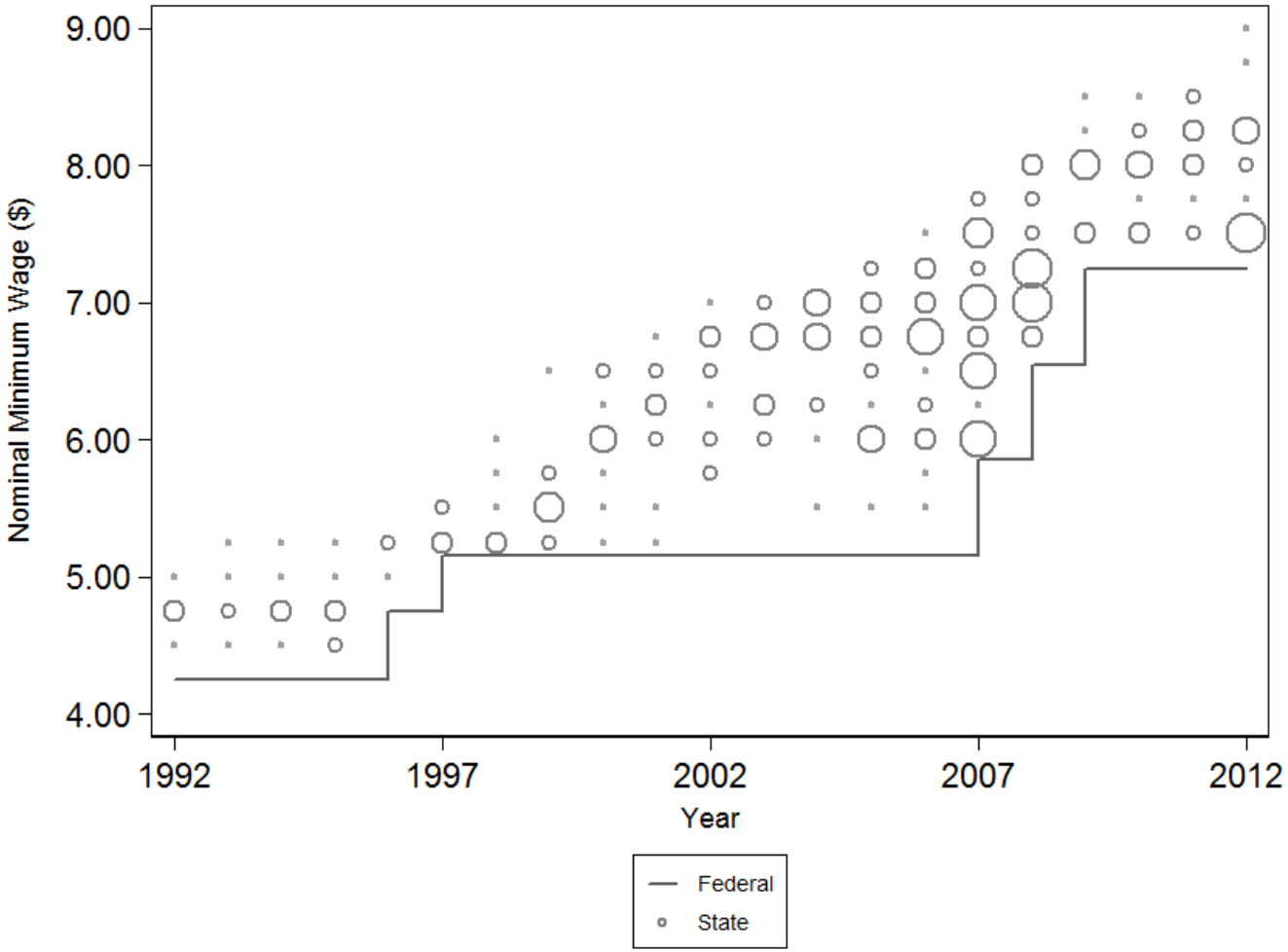
Note: Figure shows how the increase in HS dropout seen in Figure 2A could differ in magnitude between high-SES (Panel A) and low-SES (Panel B) teens as a result of a change in the minimum wage. $B(\theta_i, w)$ is benefit of graduating from high school, while $C(\theta_i, w)$ is the cost of obtaining a high school diploma. See text for details.

Figure 4: HS Dropout Rate by SES (CPS and ACS)



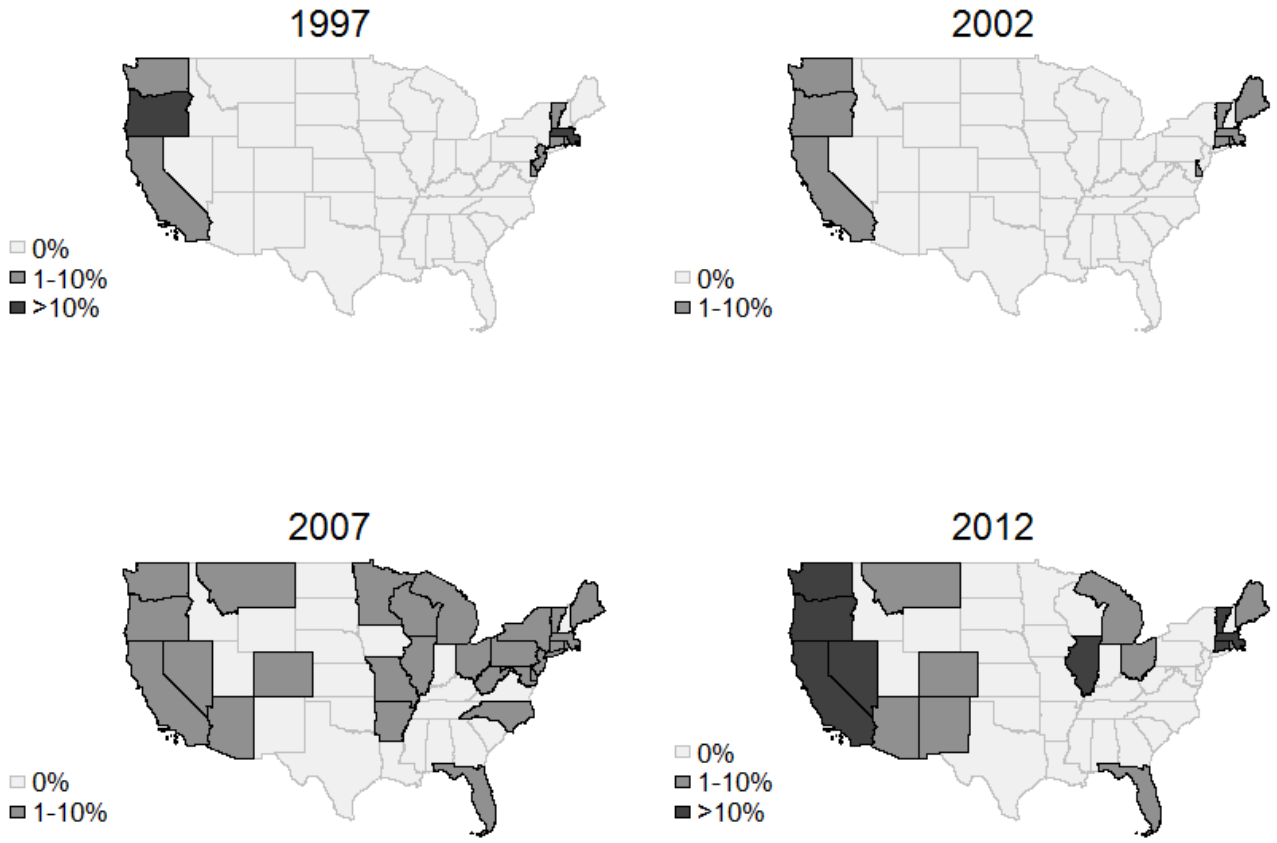
Note: Figure shows the high school dropout rate for teens aged 16-18 by year and by socio-economic status (SES) using the March Current Population Survey and the 2000 Census and the American Community Survey. A teen is considered a high school dropout if he/she is not currently enrolled and does not have a H.S. diploma or GED. High SES defined as having all parent/guardians with a high school diploma (or equivalent).

Figure 5: State and Federal Minimum Wages (1992-2012)



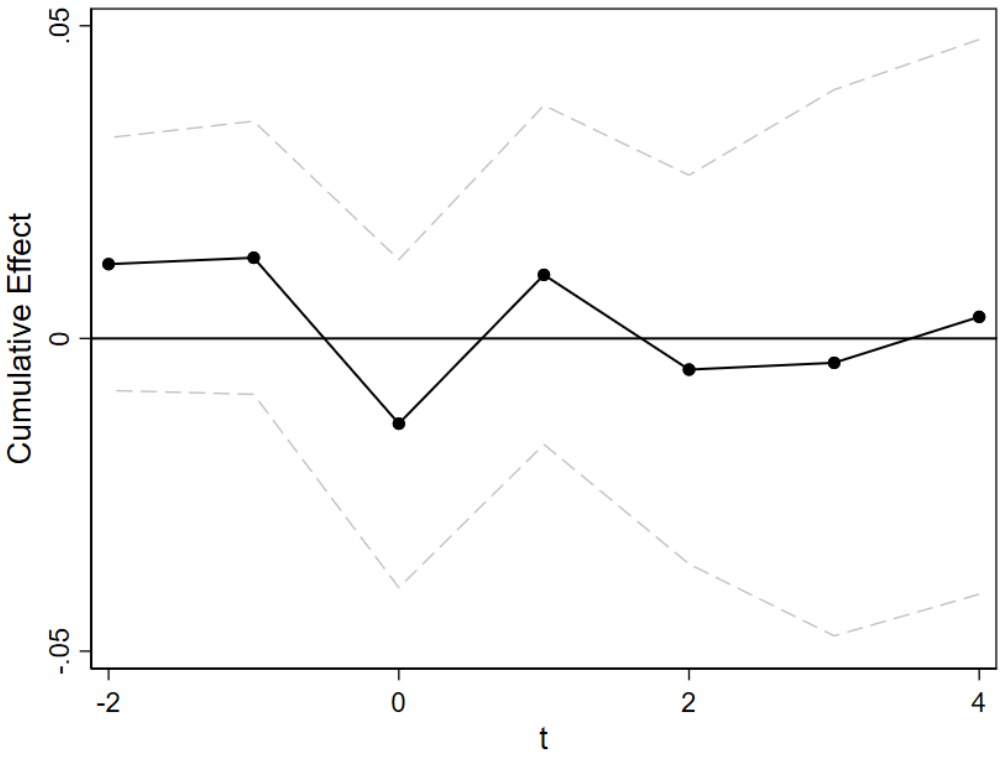
Note: State minimum wages that exceed the federal minimum wage are grouped into $0.25 bins. Bubble size denotes the number of states in the given minimum wage bin (dot denotes one state). State minimum wage data was obtained from the Tax Policy Center at the Urban Institute and Brookings Institution.

Figure 6: Geographic Minimum Wage Variation Over Time



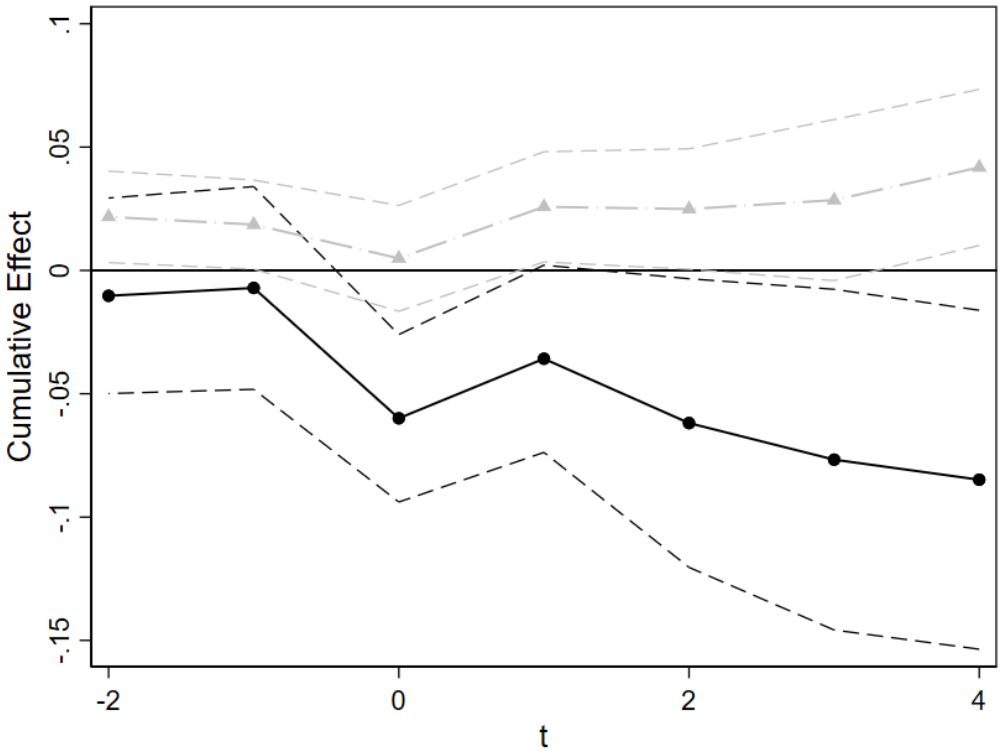
Note: States are shaded according to the percent by which their minimum wage exceeds the federal minimum wage in each year. State minimum wage data was obtained from the Tax Policy Center at the Urban Institute and Brookings Institution.

Figure 7: Cumulative Event Study



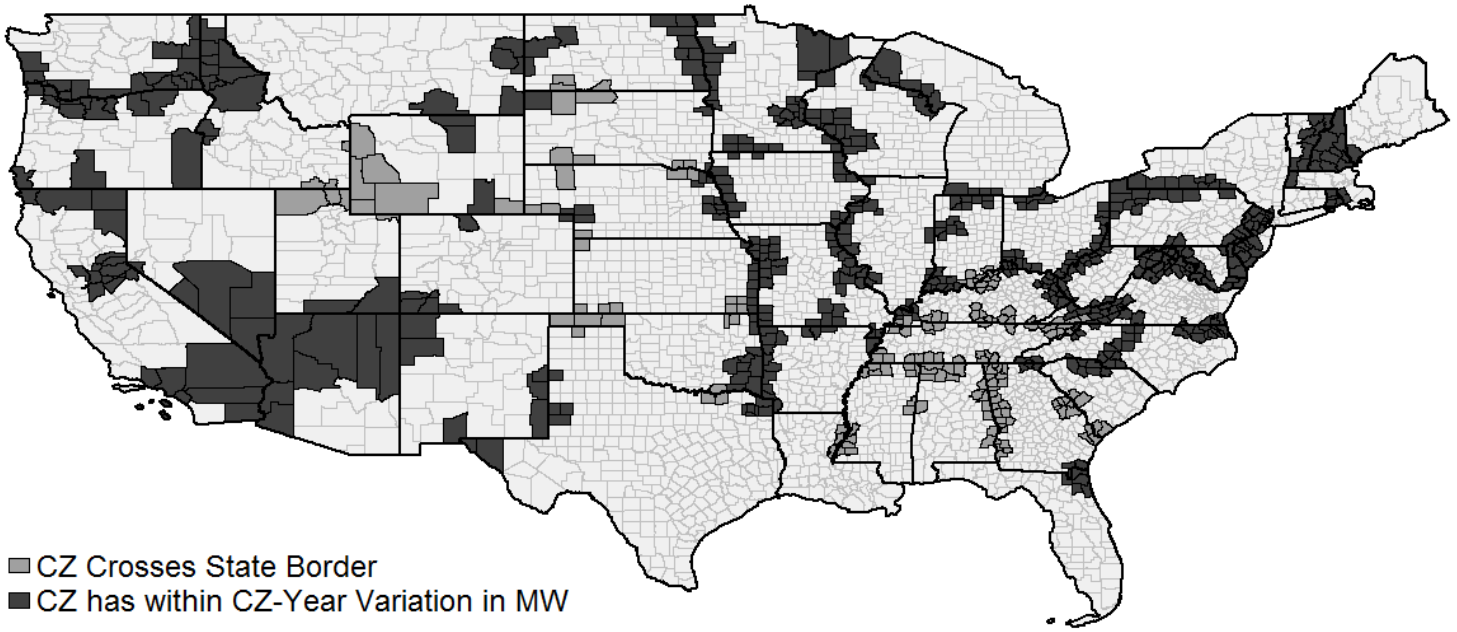
Note: Each dot shows the estimate of an α_τ from Equation 3 using the ACS sample. Zero represents the year of the minimum wage change. Dotted lines show 95% confidence intervals for each coefficient estimate. See text for details.

Figure 8: Cumulative Event Study, by SES



Note: Each black dot shows the estimate of an α_τ (low SES) and each grey dot shows an estimate of $\alpha_\tau + \delta_\tau$ (high SES) from Equation 4 using the ACS sample. Zero represents the year of the minimum wage change. Dotted lines show 95% confidence intervals for each coefficient estimate. See text for details.

Figure 9: Within Commuting Zone (CZ) by Year Minimum Wage Variation (2005-2011)



Note: All commuting zones stradling state borders are shaded. Commuting zones where there is CZ-Year variation in the minimum wage during the 2005-2011 time period are shaded dark gray. Commuting zone data was obtained from Autor and Dorn (2013). State minimum wage data was obtained from the Tax Policy Center at the Urban Institute and Brookings Institution.

Table 1: Overview of Select Data Samples

Sample Name	Years	Frequency	Geography Used	Source/Construction
CPS	1992-2012	Monthly Cross-Section	State	IPUMS - Outgoing Rotation Groups (excluding summer months)
SIPP	1996-2012	Individual Panel (3 Observations per Annum)	State	SIPP 1996, 2001, 2004, and 2008 panels appended
ACS	2000-2011	Annual Cross-Section	State	IPUMS - Census 2000 & ACS 2001-2011
ACS-P	2005-2011	Annual Cross-Section	State, PUMA	IPUMS - ACS 2005-2011
ACS-C	2005-2011	Annual Cross-Section	State, County	IPUMS - ACS 2005-2011 (county of residence observed)
ACS-CZ	2005-2011	Annual Cross-Section	State, PUMA, Commuting Zone	Probabilistic match of IPUMS - ACS 2005-2011 PUMAs to CZs (observations weighted by proportion of PUMA in each CZ)

Note: Table defines various samples (see text for details). Each sample is restricted to individuals aged 16-18 for whom parent or guardian education is observed.

Table 2: Summary Statistics

	CPS (1)	SIPP (2)	ACS (3)	ACS-P (4)	ACS-C (5)	ACS-CZ (6)
Fraction Missing SES	0.08	0.02	0.14	0.14	0.14	0.14
Fraction High-SES (of Observed)	0.79	0.82	0.80	0.81	0.79	0.81
Low-SES Dropout Rate	0.12	0.13	0.11	0.10	0.08	0.10
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
High-SES Dropout Rate	0.03	0.04	0.03	0.03	0.03	0.03
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	*313,571*	*161,135*	*1,690,820*	*892,351*	*499,467*	*1,323,146*
Individuals	*313,571*	*41,694*	*1,690,820*	*892,351*	*499,467*	*892,362*
PUMA/Counties	.	.	.	*2,066*	*373*	*2,066*
Commuting Zones	.	.	.	.	.	*741*

Note: Each column presents select summary statistics for a different data sample. All samples are restricted to individuals aged 16-18. High SES indicator is equal to one if all of a teen's parent/guardians have a high school diploma (or equivalent), it is missing if parent/guardian education is not observed. Dropout indicator is equal to one if the teen is not currently enrolled and has no H.S. diploma or GED. Standard errors for dropout rates are in parentheses.

Table 3: Effect of Minimum Wage on Teen Dropout

	CPS	SIPP	ACS	ACS-P	ACS-C	ACS-CZ
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(State Min Wage)	0.004	0.006	-0.016	-0.011	-0.008	0.018
	(0.012)	(0.023)	(0.009)	(0.008)	(0.011)	(0.024)
Obs	266,489	161,134	1,690,849	892,740	499,467	1,713,160
R-Sqr	0.02	0.02	0.02	0.03	0.02	0.04
Mean Dropout Rate	0.07	0.06	0.06	0.05	0.05	0.06
Specification:						
Fixed Effects	*State*	*State X Panel*	*State*	*PUMA*	*County*	*PUMA*
	Year	*Year*	*Year*	*Year*	*Year*	*CZ X Year*
	Month	*Month*				
State-Specific Time Trend	*Cubic*	*Linear*	*Linear*	*Linear*	*Linear*	
Years	*1992-2012*	*1996-2012*	*2000-2011*	*2005-2011*	*2005-2011*	*2005-2011*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is HS dropout (equal to 1 if not currently enrolled and have no H.S. diploma or GED). All regressions include indicators for age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate (and county unemployment rate in column 5). See text for descriptions of CPS, SIPP, ACS, ACS-P, ACS-C, and ACS-CZ data samples. Standard errors clustered at the state level for column 1 and 3, at the individual-level for column 2, at the PUMA-level for columns 4, at the county-level for column 5, and at the commuting zone by year level for column 6 are in parentheses.

Table 4: Effect of Minimum Wage on Teen Dropout by SES

	CPS	SIPP	ACS	ACS-P	ACS-C	ACS-CZ
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(State Min Wage)	-0.052	-0.053	-0.096	-0.084	-0.078	-0.076
	(0.016)	(0.030)	(0.023)	(0.011)	(0.015)	(0.024)
Ln(State Min Wage) x High SES	0.069	0.072	0.101	0.083	0.091	0.088
	(0.009)	(0.021)	(0.024)	(0.008)	(0.013)	(0.010)
Obs	244,710	158,525	1,455,883	764,535	430,298	1,365,826
R-Sqr	0.04	0.05	0.04	0.04	0.03	0.05
Mean Dropout Rate:						
Low SES	0.12	0.13	0.11	0.09	0.08	0.12
High SES	0.03	0.04	0.03	0.03	0.03	0.03
Specification:						
Fixed Effects	*State*	*State X Panel*	*State*	*PUMA*	*County*	*PUMA*
	Year	*Year*	*Year*	*Year*	*Year*	*CZ X Year*
	Month	*Month*				
State-Specific Time Trend	*Cubic*	*Linear*	*Linear*	*Linear*	*Linear*	
Years	*1992-2012*	*1996-2012*	*2000-2011*	*2005-2011*	*2005-2011*	*2005-2011*

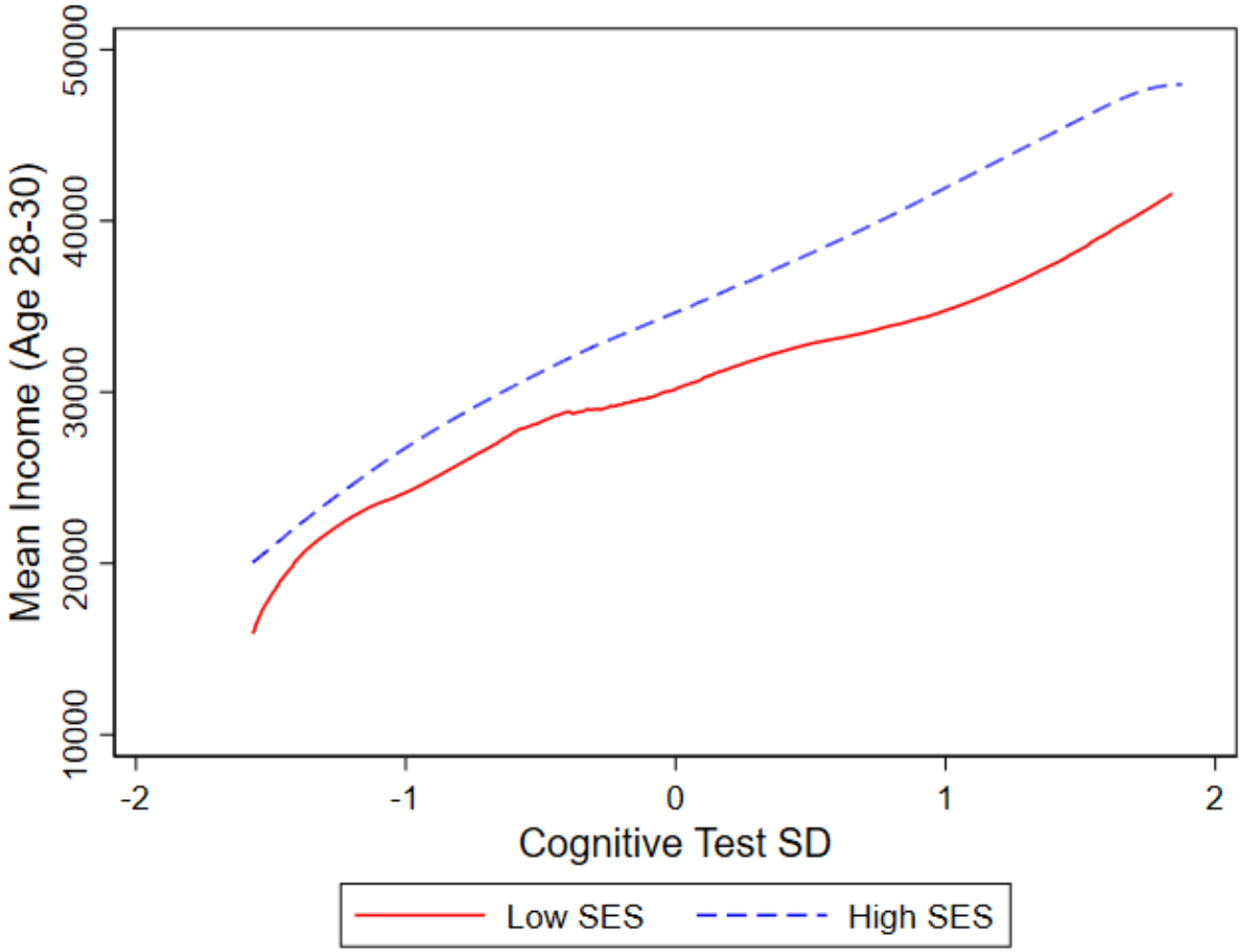
Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is HS dropout (equal to 1 if not currently enrolled and have no H.S. diploma or GED). All regressions include indicators for age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate (and county unemployment rate in column 5). High SES indicator is equal to one if all of a teen's parent/guardians have high school diploma (or equivalent). See text for descriptions of CPS, SIPP, ACS, ACS-P, ACS-C, and ACS-CZ data samples. Standard errors clustered at the state level for column 1 and 3, at the individual-level for column 2, at the PUMA-level for columns 4, at the county-level for column 5, and at the commuting zone by year level for column 6 are in parentheses.

Table 5: Effect of Minimum Wage on Teen Dropout with Various SES Definitions

	All Parent's Education		Houeshold Income Percentile			
	HS Diploma	Some College	20+	30+	40+	50+
	(1)	(2)	(3)	(4)	(5)	(6)
CPS (1992-2012)						
State, Month, and Year FE, State Cubic Trend						
Ln(State Min Wage)	-0.052	-0.014	-0.088	-0.074	-0.055	-0.041
	(0.016)	(0.013)	(0.020)	(0.019)	(0.019)	(0.019)
Ln(State Min Wage) x High SES	0.069	0.040	0.123	0.112	0.100	0.089
	(0.009)	(0.004)	(0.010)	(0.010)	(0.011)	(0.011)
Obs	244,710	244,710	180,881	180,881	180,881	180,881
SIPP (1996-2012)						
State-Panel, Month, and Year FE, State Linear Trend						
Ln(State Min Wage)	-0.048	-0.025	-0.052	-0.050	-0.033	-0.030
	(0.029)	(0.022)	(0.025)	(0.024)	(0.023)	(0.022)
Ln(State Min Wage) x High SES	0.067	0.051	0.070	0.078	0.058	0.059
	(0.021)	(0.010)	(0.015)	(0.012)	(0.011)	(0.010)
Obs	634,159	634,159	633,911	633,911	633,911	633,911
ACS (2000-2011)						
State and Year FE, State Linear Trend						
Ln(State Min Wage)	-0.096	-0.033	-0.069	-0.056	-0.047	-0.042
	(0.023)	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
Ln(State Min Wage) x High SES	0.101	0.041	0.069	0.061	0.055	0.054
	(0.024)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Obs	1,455,883	1,455,883	1,578,768	1,578,768	1,578,768	1,578,768
ACS-P (2005-2011)						
PUMA and Year FE, State Linear Trend						
Ln(State Min Wage)	-0.084	-0.031	-0.052	-0.043	-0.038	-0.033
	(0.011)	(0.008)	(0.011)	(0.009)	(0.009)	(0.009)
Ln(State Min Wage) x High SES	0.083	0.034	0.053	0.049	0.047	0.046
	(0.008)	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)
Obs	764,535	764,535	826,679	826,679	826,679	826,679
ACS-CZ (2005-2011)						
PUMA and CZ X Year FE						
Ln(State Min Wage)	-0.076	-0.022	-0.021	-0.015	-0.008	-0.002
	(0.024)	(0.022)	(0.027)	(0.027)	(0.027)	(0.027)
Ln(State Min Wage) x High SES	0.088	0.034	0.059	0.056	0.049	0.048
	(0.010)	(0.005)	(0.007)	(0.006)	(0.005)	(0.005)
Obs	1,365,826	1,365,826	1,512,356	1,512,356	1,512,356	1,512,356

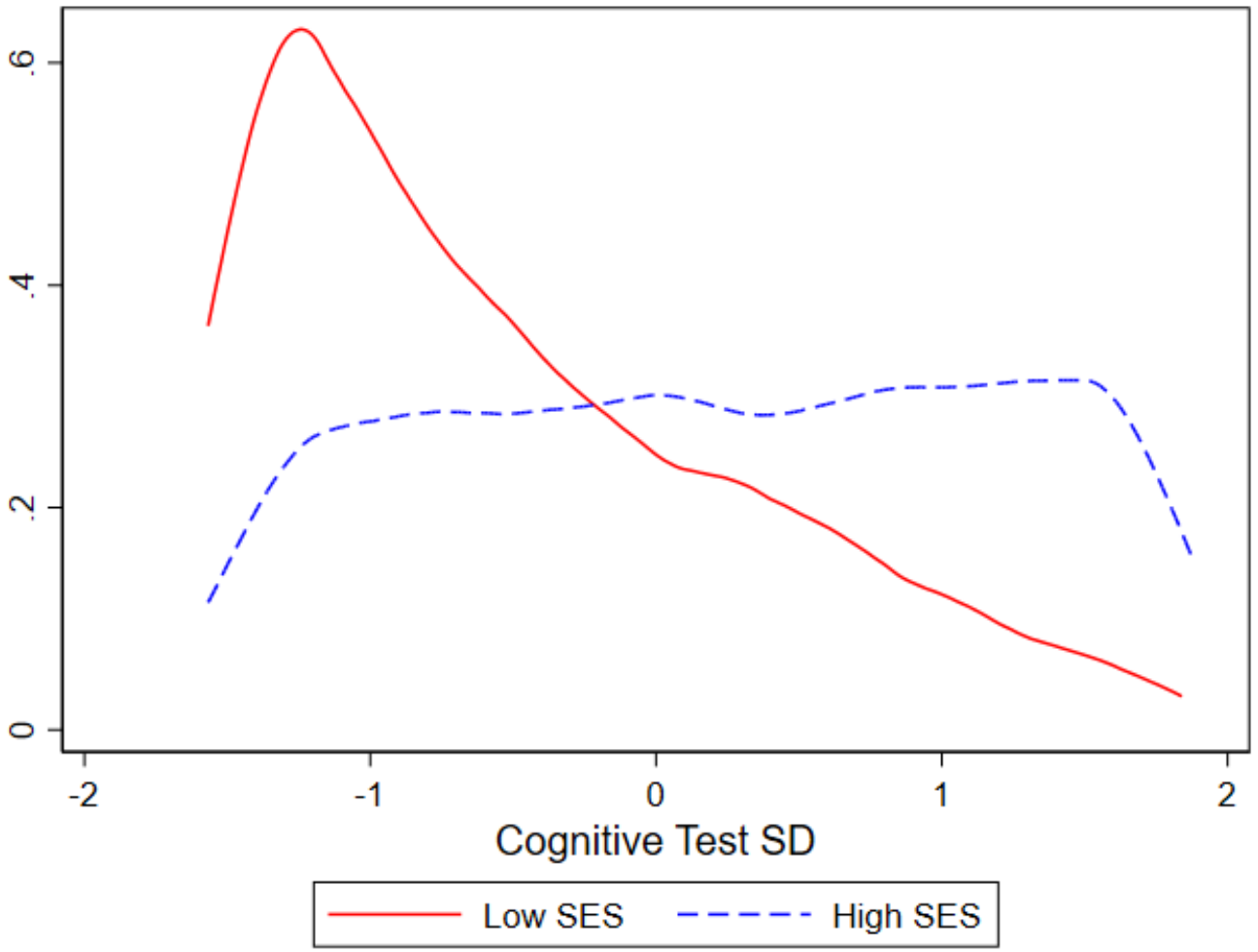
Note: Each panel-column combination shows coefficients from separate least squares regression using relevant population weights. Each column presents a different definition of SES, while each panel represents a different data sample and preferred specification. Column 1 replicates estimates from Table 4. See text for descriptions of CPS, SIPP, ACS, ACS-P, ACS-C, and ACS-CZ data samples. Columns 3-6 for the CPS panel use the Annual Social and Economic Supplement of the CPS rather than the Outgoing Rotation Group. The dependent variable for all regressions is HS dropout (equal to 1 if not currently enrolled and have no H.S. diploma or GED). See Table A13 for the means for each dependent variable by SES. All regressions include indicators for age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate (and county unemployment rate in column 5). From top panel to bottom panel (respectively), standard errors clustered at the state-level, individual-level, state-level, PUMA-level, and commuting zone by year-level are in parentheses.

Figure A1: Relationship between Adult Income and Cognitive Test Scores of HS Graduates by SES



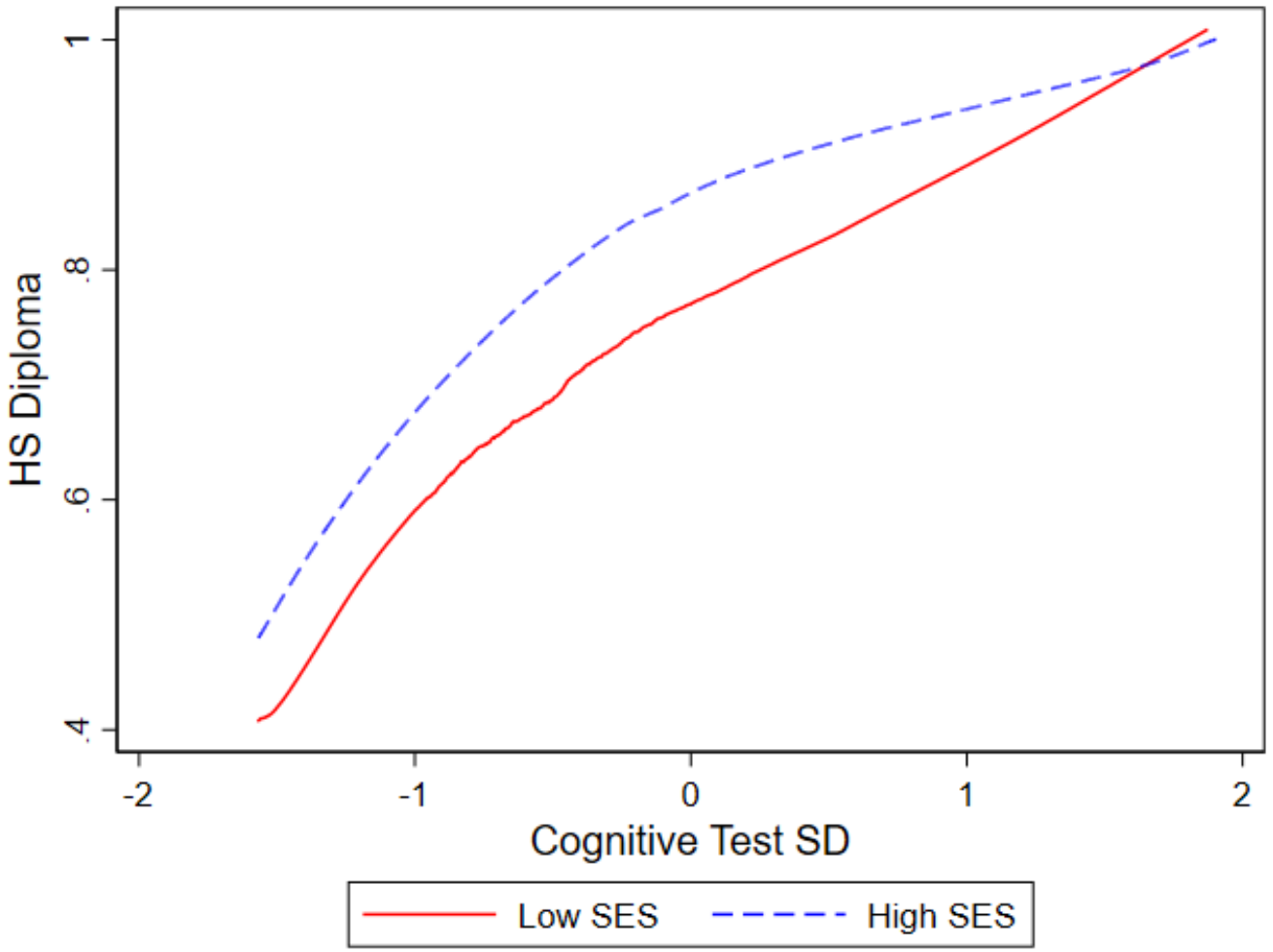
Note: Figure shows a locally weighted regression of mean income at age 28-30 on AFQT score (standardized by cohort) by SES for HS graduates in the National Longitudinal Survey of Youth 1997.

Figure A2: Distribution of Cognitive Test Scores by SES



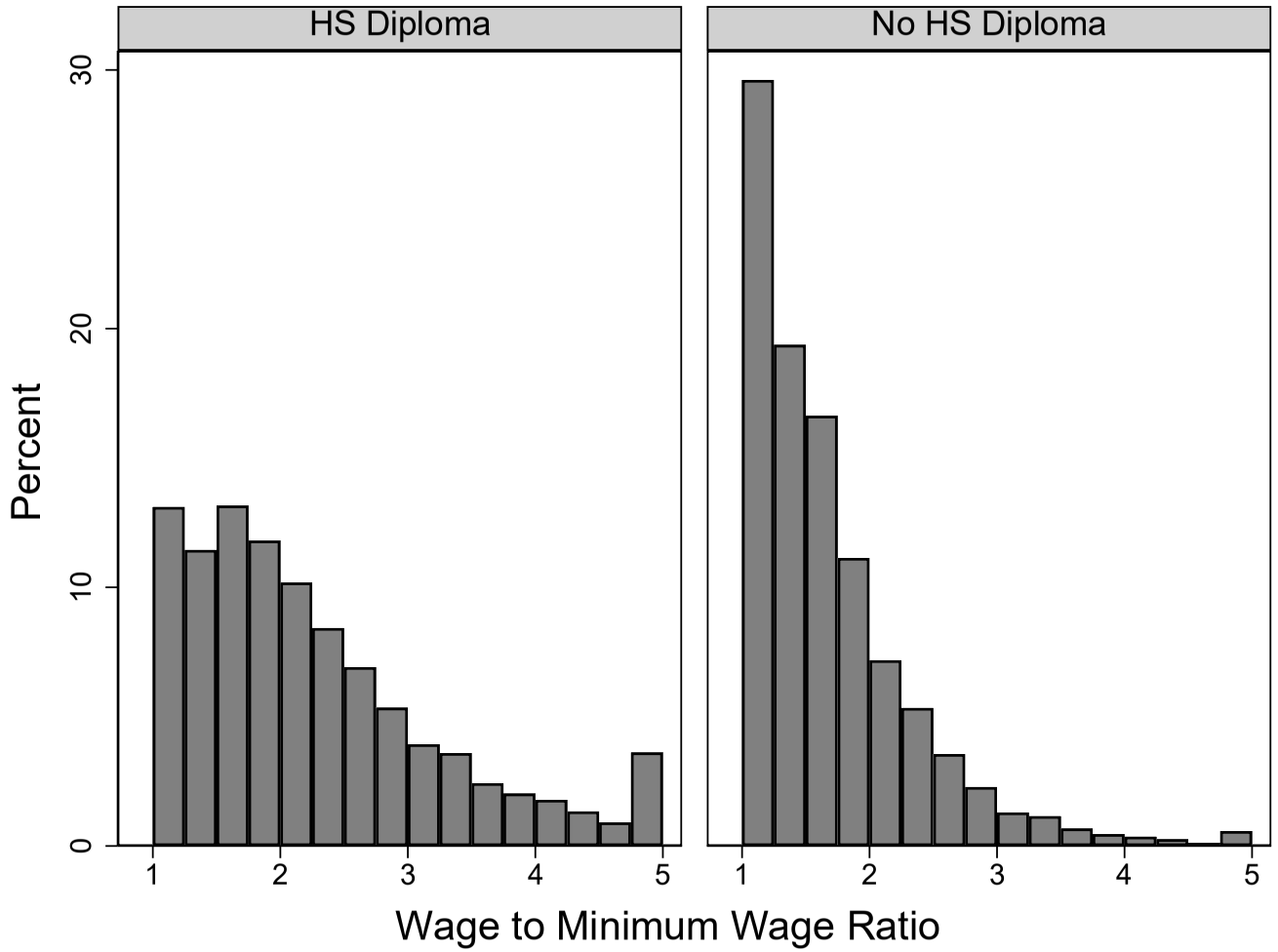
Note: Figure shows the density of AFQT score (standardized by cohort) by SES for the sample of taking National Longitudinal Survey of Youth 1997.

Figure A3: Relationship between HS Graduation and Cognitive Test Scores by SES



Note: Figure shows a locally weighted regression of HS graduation on AFQT score (standardized by cohort) by SES for the National Longitudinal Survey of Youth 1997.

Figure A4: Ratio of Wage to Minimum Wage by HS Diploma (Age 25-35)



Note: Figure shows the distribution of the ratio of hourly wage to effective state minimum wage for adult workers by HS Diploma status. Sample includes employed individuals aged 25-35 in the Current Population Survey Outgoing Rotation Group (1992-2012). Missing hourly wages are imputed for those with weekly earnings but missing hourly wages. Ratios below 1 or above 5 are assigned 1 or 5, respectively.

Figure A5: Example of Within CZ-Year Variation - Jacksonville, FL

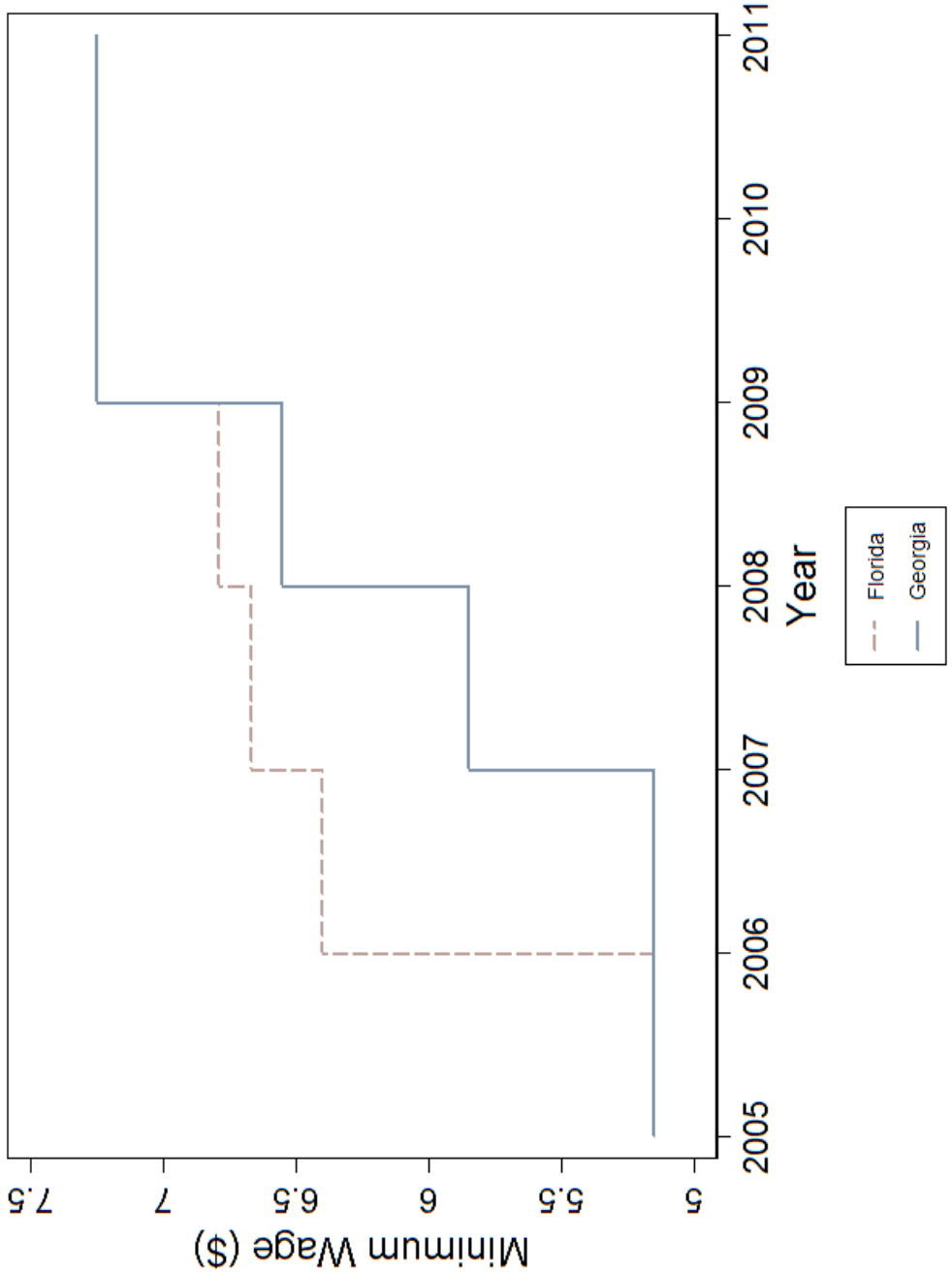
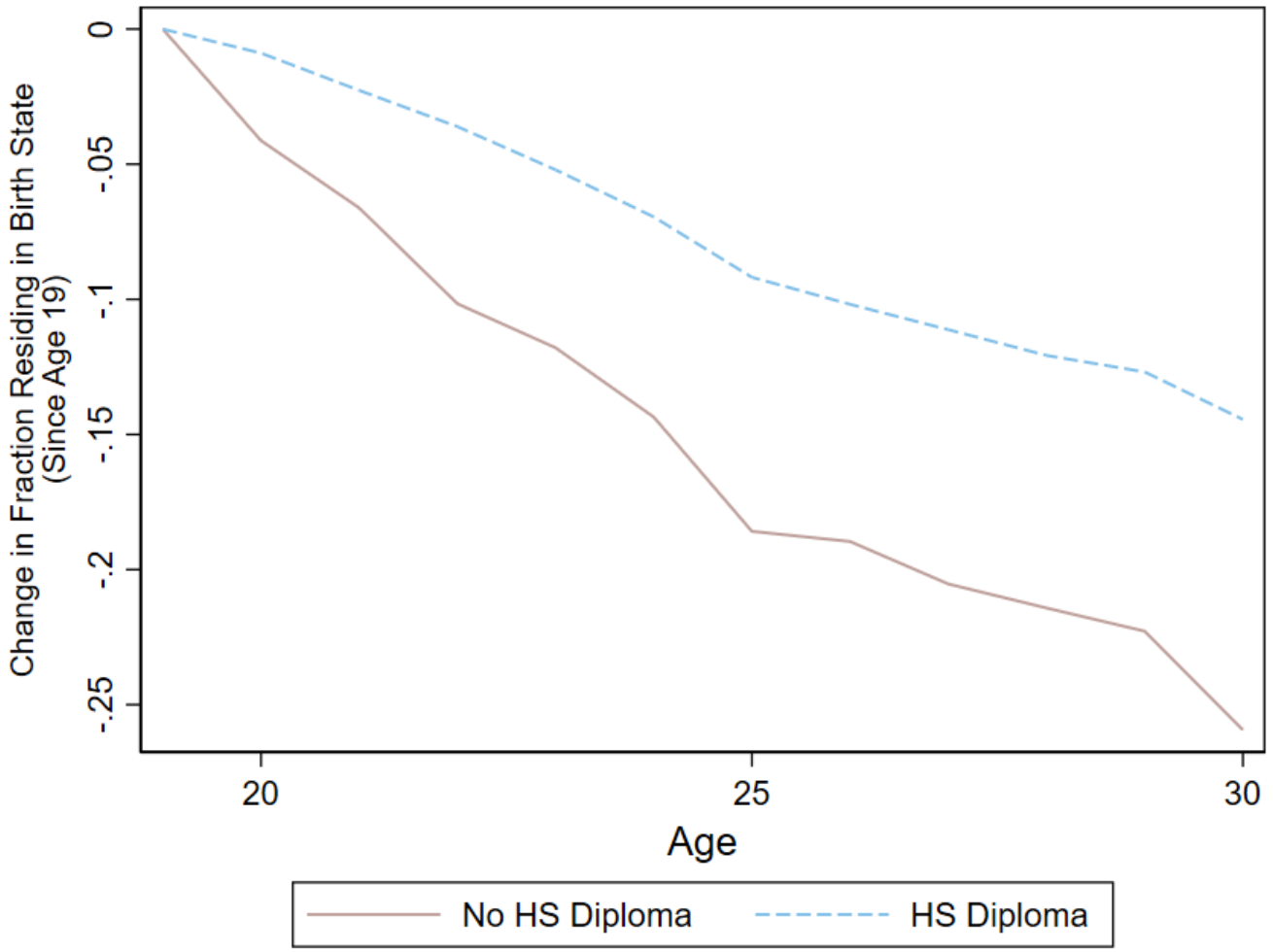


Figure A6: Change in Fraction Residing in State of Birth by Age (Compared to Age 19)



Note: Figure shows the difference between the fraction of adults that reside in their state of birth at a given age and the fraction at age 19, by HS Diploma status. Sample includes 19-30 year olds in the ACS (2000-2011).

Table A1: Effect of Minimum Wage on Dropout (CPS Alternate Samples/Trends)

	CPS Sample (ORG)				Alternative CPS Sample (March)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(State Min Wage)	-0.059	-0.055	-0.051	-0.052	-0.070	-0.064	-0.067	-0.054
	(0.012)	(0.014)	(0.016)	(0.016)	(0.020)	(0.022)	(0.021)	(0.023)
Ln(State Min Wage) x High SES	0.069	0.069	0.069	0.069	0.065	0.065	0.065	0.065
	(0.009)	(0.009)	(0.009)	(0.009)	(0.014)	(0.015)	(0.015)	(0.015)
Obs	244,710	244,710	244,710	244,710	166,045	166,045	166,045	166,045
R-Sqr	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Mean Dropout Rate:								
Low SES	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
High SES	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State-Specific Trend		*Linear*	*Quad*	*Cubic*		*Linear*	*Quad*	*Cubic*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is HS dropout (equal to 1 if not currently enrolled and have no H.S. diploma or GED). All regressions include indicators for calendar month, age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate. High SES indicator is equal to one if all of a teen's parent/guardians have a high school diploma (or equivalent). Columns 1-4 use the primary CPS sample of outgoing rotation groups (ORG) while columns 5-8 use the Annual Social and Economic Supplement. In the CPS, students on summer vacation are counted as not enrolled (in the last week), therefore I exclude summer months (June, July, and August) from the ORG sample. See text for description of CPS sample. Standard errors clustered at the state-level are in parentheses.

Table A2: Effect of Minimum Wage on Teen Dropout (SIPP Alternate Trends)

	All 16-18 Year Olds						16-18 Year Olds Observed in First Wave					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(State Min Wage)	-0.053	-0.063	-0.062	-0.057	-0.058	-0.039	-0.049	-0.059	-0.058	-0.054	-0.055	-0.044
	(0.030)	(0.030)	(0.030)	(0.028)	(0.028)	(0.030)	(0.031)	(0.031)	(0.031)	(0.028)	(0.029)	(0.031)
Ln(State Min Wage) x High SES	0.072	0.071	0.071	0.077	0.074	0.073	0.072	0.072	0.072	0.077	0.075	0.073
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Obs	158,525	158,525	158,525	158,525	158,525	158,525	145,002	145,002	145,002	145,002	145,002	145,002
R-Sqr	0.05	0.05	0.05	0.04	0.04	0.05	0.05	0.05	0.05	0.04	0.05	0.05
Mean Dropout Rate:												
Low SES	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
High SES	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03
State X Panel FE	*X*	*X*	*X*				*X*	*X*	*X*			
State FE				*X*	*X*	*X*				*X*	*X*	*X*
State-Specific Trend		*Linear*	*Quad*		*Linear*	*Quad*		*Linear*	*Quad*		*Linear*	*Quad*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is HS dropout (equal to 1 if not currently enrolled and have no H.S. diploma or GED). All regressions include indicators for trimester, age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate. High SES indicator is equal to one if all of teenager's parent/guardians have a high school diploma (or equivalent). See text for description of SIPP data sample. Standard errors clustered at the individual-level are in parentheses.

Table A3: Effect of Minimum Wage on Teen Dropout (ACS Alternate Trends)

	2000-2011				2005-2011					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(State Min Wage)	-0.094	-0.096	-0.085	-0.080	-0.080	-0.084	-0.081	-0.078	-0.076	-0.080
	(0.023)	(0.023)	(0.022)	(0.022)	(0.010)	(0.011)	(0.014)	(0.015)	(0.024)	(0.027)
Ln(State Min Wage) x High SES	0.102	0.101	0.096	0.096	0.083	0.083	0.090	0.091	0.088	0.088
	(0.024)	(0.024)	(0.008)	(0.008)	(0.008)	(0.008)	(0.013)	(0.013)	(0.010)	(0.010)
Obs	1,455,883	1,455,883	2,347,074	2,347,074	764,535	764,535	430,298	430,298	1,365,826	1,365,826
R-Sqr	0.04	0.04	0.06	0.06	0.04	0.04	0.03	0.03	0.05	0.05
Mean Dropout Rate:										
Low SES	0.11	0.11	0.12	0.12	0.09	0.09	0.08	0.08	0.12	0.12
High SES	0.03	0.03	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03
Fixed Effects	*State Year*	*State Year*	*PUMA CZ X Year*	*PUMA CZ X Year*	*PUMA Year*	*PUMA Year*	*County Year*	*County Year*	*PUMA CZ X Year*	*PUMA CZ X Year*
State-Specific Trend		*Linear*		*Linear*		*Linear*		*Linear*		*Linear*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is HS dropout (equal to 1 if not currently enrolled and have no H.S. diploma or GED). All regressions include indicators for calendar month, age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate. High SES indicator is equal to one if all of a teen's parent/guardians have a high school diploma (or equivalent). 2001-2004 are not available for ACS-CZ sample. See text for descriptions of ACS, ACS-P, ACS-C, and ACS-CZ data samples. See text for descriptions of ACS, ACS-P, ACS-C data samples. Standard errors clustered at the state level for columns 1-2, at the commuting zone-year-level for columns 3-4 and 9-10, at the PUMA-level for columns 5-6, and at the county-level for columns 7-8, are in parentheses.

Table A4: Effect of Minimum Wage on Teen Enrollment

	CPS	SIPP	ACS	ACS-P	ACS-C	ACS-CZ
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(State Min Wage)	-0.002	-0.010	0.015	0.005	0.019	-0.015
	(0.021)	(0.030)	(0.014)	(0.010)	(0.014)	(0.030)
Obs	266,489	161,134	1,690,849	892,740	499,467	1,713,160
R-Sqr	0.09	0.08	0.07	0.08	0.07	0.15
Mean Enrollment Rate	0.88	0.89	0.89	0.90	0.90	0.84
Specification:						
Fixed Effects	*State*	*State X Panel*	*State*	*PUMA*	*County*	*PUMA*
	Year	*Year*	*Year*	*Year*	*Year*	*CZ X Year*
	Month	*Month*				
State-Specific Time Trend	*Cubic*	*Linear*	*Linear*	*Linear*	*Linear*	
Years	*1992-2012*	*1996-2012*	*2000-2011*	*2005-2011*	*2005-2011*	*2005-2011*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is an enrollment indicator. All regressions include indicators for age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate (and county unemployment rate in column 5). See text for descriptions of CPS, SIPP, ACS, ACS-P, ACS-C, and ACS-CZ data samples. Standard errors clustered at the state level for column 1 and 3, at the individual-level for column 2, at the PUMA-level for columns 4, at the county-level for column 5, and at the commuting zone by year level for column 6 are in parentheses.

Table A5: Effect of Minimum Wage on Teen Enrollment by SES

	CPS	SIPP	ACS	ACS-P	ACS-C	ACS-CZ
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(State Min Wage)	0.049	0.039	0.080	0.083	0.082	0.083
	(0.024)	(0.036)	(0.022)	(0.013)	(0.017)	(0.029)
Ln(State Min Wage) x High SES	-0.060	-0.069	-0.088	-0.086	-0.088	-0.094
	(0.012)	(0.023)	(0.022)	(0.009)	(0.013)	(0.011)
Obs	244,710	158,525	1,455,883	764,535	430,298	1,365,826
R-Sqr	0.09	0.09	0.08	0.09	0.08	0.17
Mean Enrollment Rate:						
Low SES	0.83	0.81	0.84	0.85	0.86	0.78
High SES	0.92	0.91	0.93	0.93	0.93	0.89
Specification:						
Fixed Effects	*State Year Month*	*State X Panel Year Month*	*State Year*	*PUMA Year*	*County Year*	*PUMA CZ X Year*
State-Specific Time Trend	*Cubic*	*Linear*	*Linear*	*Linear*	*Linear*	
Years	*1992-2012*	*1996-2012*	*2000-2011*	*2005-2011*	*2005-2011*	*2005-2011*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is an enrollment indicator. All regressions include indicators for age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate (and county unemployment rate in column 5). High SES indicator is equal to one if all of a teen's parent/guardians have high school diploma (or equivalent). See text for descriptions of CPS, SIPP, ACS, ACS-P, ACS-C, and ACS-CZ data samples. Standard errors clustered at the state level for column 1 and 3, at the individual-level for column 2, at the PUMA-level for columns 4, at the county-level for column 5, and at the commuting zone by year level for column 6 are in parentheses.

Table A6: Effect of Minimum Wage on Teen Enrollment for Various SES Definitions

	All Parent's Education		Houeshold Income Percentile			
	HS Diploma	Some College	20+	30+	40+	50+
	(1)	(2)	(3)	(4)	(5)	(6)
CPS (1992-2012)						
State, Month, and Year FE, State Cubic Trend						
Ln(State Min Wage)	0.049	0.017	0.128	0.114	0.091	0.078
	(0.024)	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)
Ln(State Min Wage) x High SES	-0.060	-0.034	-0.132	-0.119	-0.101	-0.095
	(0.012)	(0.006)	(0.017)	(0.015)	(0.016)	(0.015)
Obs	244,710	244,710	180,830	180,830	180,830	180,830
SIPP (1996-2012)						
State-Panel, Month, and Year FE, State Linear Trend						
Ln(State Min Wage)	0.053	0.040	0.052	0.058	0.043	0.036
	(0.034)	(0.029)	(0.031)	(0.030)	(0.029)	(0.028)
Ln(State Min Wage) x High SES	-0.060	-0.058	-0.053	-0.071	-0.051	-0.043
	(0.023)	(0.013)	(0.017)	(0.014)	(0.013)	(0.012)
Obs	634,159	634,159	633,911	633,911	633,911	633,911
ACS (2000-2011)						
State and Year FE, State Linear Trend						
Ln(State Min Wage)	0.080	0.020	0.071	0.053	0.045	0.038
	(0.022)	(0.011)	(0.017)	(0.016)	(0.015)	(0.014)
Ln(State Min Wage) x High SES	-0.088	-0.025	-0.077	-0.063	-0.058	-0.055
	(0.022)	(0.007)	(0.012)	(0.010)	(0.011)	(0.009)
Obs	1,455,883	1,455,883	1,578,768	1,578,768	1,578,768	1,578,768
ACS-P (2005-2011)						
PUMA and Year FE, State Linear Trend						
Ln(State Min Wage)	0.083	0.029	0.061	0.044	0.038	0.032
	(0.013)	(0.010)	(0.013)	(0.012)	(0.011)	(0.011)
Ln(State Min Wage) x High SES	-0.086	-0.037	-0.074	-0.061	-0.059	-0.056
	(0.009)	(0.006)	(0.009)	(0.007)	(0.007)	(0.006)
Obs	764,535	764,535	826,679	826,679	826,679	826,679
ACS-CZ (2005-2011)						
PUMA and CZ X Year FE						
Ln(State Min Wage)	0.083	0.030	0.050	0.038	0.031	0.023
	(0.029)	(0.027)	(0.033)	(0.033)	(0.033)	(0.033)
Ln(State Min Wage) x High SES	-0.094	-0.042	-0.082	-0.072	-0.068	-0.067
	(0.011)	(0.007)	(0.010)	(0.009)	(0.008)	(0.007)
Obs	1,365,826	1,365,826	1,512,356	1,512,356	1,512,356	1,512,356

Note: Each panel-column combination shows coefficients from separate least squares regression using relevant population weights. Each column presents a different definition of SES, while each panel represents a different data sample and preferred specification. Column 1 replicates estimates from Table 4. See text for descriptions of CPS, SIPP, ACS, ACS-P, ACS-C, and ACS-CZ data samples. Columns 3-6 for the CPS panel use the Annual Social and Economic Supplement of the CPS rather than the Outgoing Rotation Group. The dependent variable for all regressions is an enrollment indicator. All regressions include indicators for age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate (and county unemployment rate in column 5). High SES indicator is equal to one if all of a teen's parent/guardians have high school diploma (or equivalent). From top panel to bottom panel (respectively), standard errors clustered at the state-level, individual-level, state-level, PUMA-level, and commuting zone by year-level are in parentheses.

Table A7: Effect of Minimum Wage on Teen Enrollment (CPS Robustness Checks)

	CPS Sample (ORG)				Alternative CPS Sample (March)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(State Min Wage)	0.064	0.051	0.038	0.049	0.104	0.104	0.089	0.079
	(0.020)	(0.022)	(0.023)	(0.024)	(0.026)	(0.027)	(0.022)	(0.027)
Ln(State Min Wage) x High SES	-0.061	-0.061	-0.061	-0.060	-0.066	-0.066	-0.066	-0.066
	(0.013)	(0.012)	(0.012)	(0.012)	(0.016)	(0.016)	(0.016)	(0.016)
Obs	244,710	244,710	244,710	244,710	166,001	166,001	166,001	166,001
R-Sqr	0.09	0.09	0.09	0.09	0.07	0.07	0.07	0.07
Mean Enrollment Rate:								
Low SES	0.83	0.83	0.83	0.83	0.84	0.84	0.84	0.84
High SES	0.92	0.92	0.92	0.92	0.93	0.93	0.93	0.93
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State-Specific Trend		*Linear*	*Quad*	*Cubic*		*Linear*	*Quad*	*Cubic*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is an enrollment indicator. All regressions include indicators for calendar month, age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate. High SES indicator is equal to one if all of a teen's parent/guardians have high school diploma (or equivalent). Columns 1-4 use the primary CPS sample of outgoing rotation groups (ORG) while columns 5-8 use the Annual Social and Economic Supplement. In the CPS, students on summer vacation are counted as not enrolled (in the last week), therefore I exclude summer months (June, July, and August) from the ORG sample. See text for more details on CPS sample. Standard errors clustered at the state-level are in parentheses.

Table A8: Effect of Minimum Wage on Teen Dropout (Alternate CPS Time Period: 1992-2007)

	CPS Sample (ORG)				Alternative CPS Sample (March)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Dropout								
Ln(State Min Wage)	-0.027	-0.019	-0.013	-0.010	-0.060	-0.065	-0.031	-0.046
	(0.020)	(0.028)	(0.027)	(0.026)	(0.027)	(0.030)	(0.033)	(0.037)
Ln(State Min Wage) x High SES	0.045	0.046	0.046	0.045	0.061	0.060	0.059	0.059
	(0.018)	(0.019)	(0.019)	(0.019)	(0.024)	(0.024)	(0.025)	(0.025)
Obs	186,330	186,330	186,330	186,330	118,002	118,002	118,002	118,002
Dependent Variable: Enrollment								
Ln(State Min Wage)	0.047	0.029	0.026	0.042	0.096	0.101	0.055	0.095
	(0.023)	(0.030)	(0.026)	(0.031)	(0.032)	(0.033)	(0.034)	(0.040)
Ln(State Min Wage) x High SES	-0.056	-0.056	-0.056	-0.056	-0.072	-0.071	-0.069	-0.070
	(0.017)	(0.017)	(0.016)	(0.016)	(0.021)	(0.021)	(0.021)	(0.021)
Obs	186,330	186,330	186,330	186,330	117,971	117,971	117,971	117,971
State FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
Year FE	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
State-Specific Trend		*Linear*	*Quad*	*Cubic*		*Linear*	*Quad*	*Cubic*

Note: Each column by panel shows a pair of coefficient estimates from a separate least squares regression using relevant population weights. Dependent variable for is HS dropout (equal to 1 if not currently enrolled and have no H.S. diploma or GED) and an enrollment indicator for the bottom panel. All regressions include indicators for calendar month, age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate. High SES indicator is equal to one if all of teenager's parent/guardians have high school diploma (or equivalent). See text for description of CPS data sample. Standard errors clustered at the state-level are in parentheses.

Table A9: Effect of Minimum Wage on Teen Enrollment (SIPP Robustness Checks)

	All 16-18 Year Olds						16-18 Year Olds Observed in First Wave					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(State Min Wage)	0.039	0.050	0.035	0.051	0.054	0.028	0.034	0.045	0.030	0.048	0.051	0.030
	(0.036)	(0.036)	(0.037)	(0.031)	(0.032)	(0.036)	(0.037)	(0.037)	(0.038)	(0.032)	(0.033)	(0.037)
Ln(State Min Wage) x High SES	-0.069	-0.069	-0.068	-0.075	-0.072	-0.069	-0.069	-0.069	-0.068	-0.073	-0.071	-0.069
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Obs	158,525	158,525	158,525	158,525	158,525	158,525	145,002	145,002	145,002	145,002	145,002	145,002
R-Sqr	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Mean Enrollment Rate:												
Low SES	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81
High SES	0.91	0.91	0.91	0.91	0.91	0.91	0.92	0.92	0.92	0.92	0.92	0.92
State X Panel FE	*X*	*X*	*X*				*X*	*X*	*X*			
State FE				*X*	*X*	*X*				*X*	*X*	*X*
State-Specific Trend		*Linear*	*Quad*		*Linear*	*Quad*		*Linear*	*Quad*		*Linear*	*Quad*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is an enrollment indicator. All regressions include indicators for trimester, age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate. High SES indicator is equal to one if all of teenager's parent/guardians have high school diploma (or equivalent). See text for description of SIPP sample. Standard errors clustered at the individual-level are in parentheses.

Table A10: Effect of Minimum Wage on Teen Enrollment (ACS Robustness Checks)

	2000-2011				2005-2011					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln(State Min Wage)	0.078	0.080	0.066	0.062	0.084	0.083	0.088	0.082	0.083	0.077
	(0.021)	(0.022)	(0.027)	(0.026)	(0.011)	(0.013)	(0.016)	(0.017)	(0.029)	(0.029)
Ln(State Min Wage) x High SES	-0.088	-0.088	-0.082	-0.082	-0.086	-0.086	-0.086	-0.088	-0.094	-0.094
	(0.022)	(0.022)	(0.010)	(0.010)	(0.009)	(0.009)	(0.013)	(0.013)	(0.011)	(0.011)
Obs	1,455,883	1,455,883	2,347,074	2,347,074	764,535	764,535	430,298	430,298	1,365,826	1,365,826
R-Sqr	0.08	0.08	0.17	0.17	0.09	0.09	0.08	0.08	0.17	0.17
Mean Enrollment Rate:										
Low SES	0.84	0.84	0.77	0.77	0.85	0.85	0.86	0.86	0.78	0.78
High SES	0.93	0.93	0.88	0.88	0.93	0.93	0.93	0.93	0.89	0.89
Fixed Effects	*State Year*	*State Year*	*PUMA CZ X Year*	*PUMA CZ X Year*	*PUMA Year*	*PUMA Year*	*County Year*	*County Year*	*PUMA CZ X Year*	*PUMA CZ X Year*
State-Specific Trend		*Linear*		*Linear*		*Linear*		*Linear*		*Linear*

Note: Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is an enrollment indicator. All regressions include indicators for calendar month, age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate. High SES indicator is equal to one if all of a teen's parent/guardians have a high school diploma (or equivalent). See text for descriptions of ACS, ACS-P, ACS-C data samples. Standard errors clustered at the state level for columns 1-2, at the commuting zone-year-level for columns 3-4 and 9-10, at the PUMA-level for columns 5-6, and at the county-level for columns 7-8, are in parentheses.

Table A11: Past Min Wage Exposure and Residing in State of Birth (Age 25-29)

	All	HS Grads	Non-HS Grads
	(1)	(2)	(3)
Ln(Mean Min Wage Age 16-19)	0.177	0.151	0.210
	(0.071)	(0.056)	(0.084)
Ln(Mean Min Wage Age 20-24)	0.186	0.141	0.291
	(0.099)	(0.086)	(0.069)
Ln(Mean Min Wage Age 25-29)	0.007	-0.015	0.090
	(0.036)	(0.037)	(0.064)
Rate of Residing in Birth State	0.54	0.56	0.43
Observations	2,355,610	2,032,563	323,047

Note: Each column shows coefficient estimates from a separate least squares regression using population weights. The dependent variable for all regressions is an indicator equal to one if an individual is residing in their state of birth. The specification for each regression follows Neumark and Nizolava (2007), with state and year fixed effects, but uses individual-level data from the ACS sample.

Table A12: Effect of Minimum Wage on Teen Dropout
(Excluding States with Compulsory Schooling Age Changes)

	CPS	SIPP	ACS	ACS-P	ACS-C	ACS-CZ
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(State Min Wage)	-0.040	-0.031	-0.092	-0.083	-0.071	-0.113
	(0.023)	(0.041)	(0.027)	(0.012)	(0.015)	(0.029)
Ln(State Min Wage) x High SES	0.073	0.073	0.095	0.082	0.090	0.083
	(0.012)	(0.027)	(0.027)	(0.009)	(0.013)	(0.011)
Obs	145,602	94,034	1,049,264	618,327	370,273	1,086,274
R-Sqr	0.04	0.05	0.03	0.04	0.03	0.05
Mean Dropout Rate:						
Low SES	0.12	0.13	0.10	0.09	0.08	0.11
High SES	0.03	0.03	0.03	0.03	0.03	0.03
Specification:						
Fixed Effects	*State*	*State X Panel*	*State*	*PUMA*	*County*	*PUMA*
	Year	*Year*	*Year*	*Year*	*Year*	*CZ X Year*
	Month	*Month*				
State-Specific Time Trend	*Cubic*	*Linear*	*Linear*	*Linear*	*Linear*	
Years	*1992-2012*	*1996-2012*	*2000-2011*	*2005-2011*	*2005-2011*	*2005-2011*

Note: This table replicates Table 4, but excludes any states with compulsory schooling age changes during the given sample period. Each column shows coefficient estimates from a separate least squares regression using relevant population weights. The dependent variable for all regressions is HS dropout (equal to 1 if not currently enrolled and have no H.S. diploma or GED). All regressions include indicators for age, race, sex, and whether the individual is above the state compulsory schooling age, as well as state unemployment rate (and county unemployment rate in column 5). High SES indicator is equal to one if all of a teen's parent/guardians have high school diploma (or equivalent). See text for descriptions of CPS, SIPP, ACS, ACS-P, ACS-C, and ACS-CZ data samples. Standard errors clustered at the state level for column 1 and 3, at the individual-level for column 2, at the PUMA-level for columns 4, at the county-level for column 5, and at the commuting zone by year level for column 6 are in parentheses.

Table A13: Dropout Rates by SES for Various SES Measures

	All Parent's Education		Houeshold Income Percentile			
	HS Diploma	Some College	20+	30+	40+	50+
	(1)	(2)	(3)	(4)	(5)	(6)
CPS (1992-2012)						
State, Month, and Year FE, State Cubic Trend						
Low-SES	0.12	0.07	0.14	0.12	0.11	0.10
High-SES	0.03	0.02	0.05	0.04	0.04	0.03
SIPP (1996-2012)						
State-Panel, Month, and Year FE, State Linear Trend						
Low-SES	0.13	0.08	0.09	0.09	0.08	0.08
High-SES	0.04	0.03	0.04	0.04	0.04	0.03
ACS (2000-2011)						
State and Year FE, State Linear Trend						
Low-SES	0.11	0.07	0.11	0.10	0.09	0.08
High-SES	0.03	0.02	0.04	0.03	0.03	0.03
ACS-P (2005-2011)						
PUMA and Year FE, State Linear Trend						
Low-SES	0.09	0.06	0.10	0.09	0.08	0.07
High-SES	0.03	0.02	0.04	0.03	0.03	0.02
ACS-CZ (2005-2011)						
PUMA and CZ X Year FE						
Low-SES	0.12	0.07	0.12	0.11	0.10	0.09
High-SES	0.03	0.02	0.04	0.04	0.03	0.03

Note: Each panel-column combination shows low-SES and High-SES dropout rates for different definitions of SES and data samples. See text for descriptions of CPS, SIPP, ACS, ACS-P, ACS-C, and ACS-CZ data samples. Columns 3-6 for the CPS panel use the Annual Social and Economic Supplement of the CPS rather than the Outgoing Rotation Group.