# Youth Employment Opportunities and Crime

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**Abstract**

Criminal involvement has been shown to peak at a young age. While Becker's theory of the rational criminal is often referenced as a justification for increasing punishments and policing, his model also suggests that improving labor market options reduces criminality. For this reason, I estimate the impact of youth labor market opportunities on arrest rates. I instrument for shocks in local employment demand with national industry trends using a shift share approach. My estimates suggest that a 1 percent increase in labor market opportunities leads to a 1.08 percent decrease in arrests for 14-18-year-olds.

# 1 Introduction

The age profile of criminal activity peaks in late teenage years, then falls (Hirschi and Gottfredson 1983; Steffensmeier and Ulmer 2008). Decreasing juvenile criminal participation is therefore an important public policy objective. While criminal sentences are more severe for young adults than juveniles, criminal participation has been shown to drop only slightly across this age threshold due to harsher punishments (Lee and McCrary 2005; McCrary and Lee 2009). Juvenile incarceration has been shown to reduce the likelihood of high school completion and increase the likelihood of adult incarceration (Aizer and Doyle 2015). This evidence suggests that the "stick" may not be the most effective tool for reducing crime, and may actually increase future crime. Becker's (1968) model suggests the "carrot" may also reduce incentives to engage in criminal behaviors by increasing the payoff to non-crime activities. This makes the steady decline in youth employment over the last few decades particularly concerning (Mixon Jr. and Stephenson 2016). The employment-population ratio for 16-19-year-olds is at an all-time low and is expected to be even lower by 2024 (Morisi 2017). Employment may be becoming more difficult for youth to attain (Goodman 2008). According to Becker's model, Decreased opportunities in the labor market could increase the incentive to participate in the criminal market. This paper tests this potential mechanism for youth. Specifically, I look at the effects of changes in labor market opportunities on juvenile and young adult arrests.

Theoretically, whether youth employment results in more or less crime is unclear. First, I discuss the possible mechanisms through which employment could reduce crime, then I offer some ways in which employment could cause crime. Time spent working could simply incapacitate individuals from committing crime. Additionally, if youth are concerned about losing their job if caught committing crime, there might be a deterrence effect of employment on crime. On the other hand, employment could stimulate crime if the workplace represents the first time individuals come in contact with a cash register or if new employees learn illegal activities from existing employees or customers. The average juvenile does not have a job, which means working youth receive greater income than do their non-working peers. Additional income could be a catalyst for juvenile delinquency. Particularly, this income could be used to purchase alcohol, which has a well-established positive relationship with crime (Carpenter 2005; Carpenter 2007; Carpenter and Dobkin 2015).

## 2 Background

Since Becker's (1968) introduction of the theory of the rational criminal, economists have been testing the model's predictions empirically. The empirical literature that has developed can broadly be split into two categories, one of which tests the responsiveness of crime to changes in punishments or policing (the stick) (Levitt 1995; Chiras and Crea 2004; Evans and Owens 2007; Corman and Mocan 2005; Kessler and Levitt 1999), and the other of which tests the responsiveness of crime to local labor market conditions (the carrot). Research analyzing the response of crime to labor market opportunities utilizes two distinct methods of measuring the opportunity cost of crime. One method looks at the responsiveness of crime to unemployment; the other looks at the responsiveness of crime to changes in wages. Wages are thought to be the legal opportunity cost of committing crime, while unemployment is a proxy for the opportunity cost of crime. Unemployment generates incentives to participate in criminal activity through the consumption smoothing motive. Additionally, being unemployed could trigger frustration and anger, which subsequently leads to violent behavior (Agnew 1992).

In the empirical research examining the relationship between unemployment and crime, most studies find small positive effects for property crime and no effect for violent crime (Raphael and Rudolf 2001; Fougere et al. 2009; Lin 2008; Gronqvist 2013). These empirical estimates are small and sensitive to the population and time period being studied, despite the clear theoretical predictions (Chalfin and McCrary 2017).

In the body of research analyzing the effects of wages on crime, the effects are much larger and robust (Grogger 1998; Doyle et al. 1999; Machin and Meghir 2004). Within the wage literature, some studies consider only changes in the minimum wage and its effect on crime (Corman and Mocan 2005; Hansen and Machin 2002; Fernandez and Pepper 2014). Most of these studies find a strong negative relationship between minimum wages and crime. Gould et al. (2002) span the two literatures by looking at wages and unemployment contemporaneously. They find higher wages and lower unemployment reduce property crime for male youths.

Employment measures like wages and unemployment are equilibrium observations, which means they occur at the intersection of labor supply and labor demand. Using these observed labor equilibria as an explanation for changes in crime confounds whether changes in crime that are attributed to changes in employment conditions are driven by shocks to labor supply or labor demand; a crucial question from a policy perspective. To disentangle the effect of shifts in demand, one can use use demand shifting events that affect only the demand side of the economy or an instrumental variable that is highly correlated with the employment measure but is only driven by shifts from the demand side of the economy. I create an instrument for shocks in labor demand, following the shift share method first used by Bartik (1991) and later by Katz and Murphy (1992) and Blanchard et al. (1992). I construct estimated quarterly employment demand at the state level. I use predicted changes in employment demand to explain changes in crime. The panel analysis is similar to approaches used in research on employment conditions and crime. These studies often consider the level of unemployment, which is the number of people who are looking for a job but remain jobless. I exploit predicted changes in employment demand, which measures predicted changes in labor market opportunities, to isolate a causal impact on arrests.

Existing research considering youth employment opportunities and crime utilizes concentrated populations, for example Heller (2014) finds that teen employment does reduce crime in a randomized control trial among disadvantaged youth in Chicago. Gelber et al. (2014) find aligned results looking at summer employment lotteries in New York City. The job corps has also been show to be an effective way to decrease crime, though at a negative net benefit due to the cost of the program (Schochet et al. 2008). This paper analyzes systematic changes in employment opportunities for the entire U.S. population of employed youth over a 14-year time period.

# 3 Data

I use the Federal Bureau of Investigation's Uniform Criminal Reporting (UCR) monthly files, which report the number of men and women arrested by age, type of offense[1], and agency at the monthly level from 2000-2012[2]. Arrest data has both its benefits and drawbacks. Arrests may not be the best measure of criminal activity, because not all crime that occurs results in an arrest. Arrests are also highly dependent on the level of policing. However, Cook et al. (2014) suggest they provide a reasonably accurate measure of criminal activity. An advantage to using arrests instead of reports is that arrests, unlike reports, generate individual-specific information like sex, age, and race.

The UCR arrest files are voluntarily reported at the agency level. While these agencies voluntarily report crime data through the UCR program or directly to the FBI, between 88 and 96 percent of the U.S. population is covered by agencies that do report to the UCR (Maltz 1999). Proper use of these data requires thorough cleaning. To ensure the arrest observations are as clean as possible, I plot agencies' shares of state arrests over time. This allows me to see how much each agency contributes to total state arrests for each time period. I drop agencies that have erratic reporting patterns, agencies that report only in month 12 of a year, and agencies that drop out of voluntary reporting during the sample.[3] Arrest counts

[1]There are 29 offense categories and14 sub offense categories; this results in 43 offense classifications.

[2]These data are available for download from the NACJD.

[3]I drop the following agencies from their respective states: Hoover and Mobile from Alabama; Arvada, Grand Junction and Greeley from Colorado; Boston from Massachusetts; Apple Valley, Eagan, Minneapolis, and St Paul from Minnesota; Nassau, and New York from New York; Columbus, Lima and Toledo from Ohio; and Seattle from Washington. Additionally, I drop Rhode Island before 2005, and Wisconsin before 2003. Washington DC and Illinois are dropped completely. These agencies are all dropped due to inconsistent reporting.

are aggregated to the quarterly level to match the employment data.

Quarterly Workforce Indicator (QWI) data are used for quarterly employment totals by state, industry[4], and age group. Stable counts of employment, which are measured as jobs that are held for the duration of the quarter, are my key employment variable. The QWI job counts are aggregated from employment data reported by firms to each state's Unemployment Insurance wage reporting system[5]. The Longitudinal Employer Household Dynamics (LEHD) program creates a longitudinal employment and earnings database with demographic characteristics by matching records from state unemployment insurance programs to Census Bureau data. These data are aggregated to the quarterly level to create the QWI (Abowd et al. 2009).

Population data come from The National Cancer Institute's Surveillance, Epidemiology, and End Results Program (SEER). I obtain population estimates by state, age, sex, and year for the duration of my panel. The SEER data are a modification of the intercensal and vintage 2015 annual estimates produced by the US Census Bureau's Population Estimates Program. I aggregate these data to the state level and group them by sex and age so they can be merged with the UCR and QWI data.

The number of sworn officers employed in each state-year is obtained from the UCR Law Enforcement Officer Killed in Action (LEOKA) files. Police employees are used as a proxy for the amount of policing in a particular state. My final sample consists of quarterly observations of arrests and employment for 46 states from 1998 to 2012 with two age-bins (14-18 and 19-21), and sex identifiers.

Figure 1 shows national employment levels and the corresponding growth rate for each

[4]The 20 industry categories include: (1) Agriculture, Forestry, Fishing and Hunting; (2) Mining, Quarrying, and Oil and Gas Extraction; (3) Utilities; (4) Construction; (5) Manufacturing; (6) Wholesale Trad; (7) Retail Trade; (8) Transportation and Warehousing; (9) Information; (10) Finance and Insurance; (11) Real Estate and Rental and Leasing; (12) Professional, Scientific, and Technical Services; (13) Management of Companies and Enterprises; (14) Administrative and Support and Waste Management and Remediation Services; (15) Educational Services; (16) Health Care and Social Assistance; (17) Arts, Entertainment, and Recreation; (18) Accommodation and Food Services; (19) Other Services (except Public Administration); (20) Public Administration.

[5]Consequently, these data do not include informal employment opportunities, which may be of importance for youth and young adults.

age group and sex at the quarterly level for the duration of my sample. Figure 2 shows national arrest levels and the corresponding growth rate for each age group and sex at the quarterly level for the duration of my sample. Both arrests and employment are highly seasonal. Females are employed at slightly higher rates than males, but males dominate arrest counts for all age groups. Generally, employment growth is strong in the late '90s, flattens out from 2000 to late 2008, then decreases in 2008. These trends are not surprising as these data capture the transition from the dot-com boom to the great recession. Arrests follow a similar pattern, albeit with smaller magnitudes of growth and decline.

# 4 Methodology and Estimation

I create an estimate of predicted employment growth to determine how changes in the number of arrests can be explained by predicted changes in the employment level. Predicted employment growth is calculated by predicting the level of employment in the next time period, then calculating the growth rate from the actual level of employment in previous time periods. The next period's employment for each state $\hat{L}_{st}$ is calculated as follows:

$$\hat{L}_{st} = \sum_i \left[ \left( \frac{\text{US Emp in Industry } i \text{ at time } t}{\text{US Emp in Industry } i \text{ at time } t-1} \right) \times (\text{State } s \text{ Emp in Industry } i \text{ at } t-1) \right]$$

Where $s$ indexes states and $t$ indexes time by quarter. The predicted employment level for the next quarter relies on national industry-specific growth rates and state-industry composition. Predicted employment growth is then

$$\hat{g}_{st} = \frac{\hat{L}_{st} - L_{s,t-1}}{L_{s,t-1}},$$

which can be written as

$$\hat{g}_{st} = \frac{\sum_i \left[ \overbrace{\left( \frac{L_{it} - L_{i,t-1}}{L_{i,t-1}} \right)}^{G_{it}} L_{si,t-1} \right]}{L_{s,t-1}} = \frac{\sum_i G_{it} L_{si,t-1}}{L_{s,t-1}}. \tag{1}$$

This allows us to see how the national industry-specific growth $G_{it}$ interacts with the state-level industry composition to create predicted employment growth. Each state's specific industry sector is predicted to grow at the national rate. Blanchard et al. (1992) note that this predicted employment growth is a valid instrument if industry national growth rates are uncorrelated with state-level labor-supply shocks. This is true if there is no industry for which employment is concentrated in any state and there is sufficient variation in state-level industry composition. Figure 3 shows average industry shares for all 46 states for each age-sex group in my sample. Each bar represents a state's average industry composition over the 14-year period. Each column has 46 horizontal bars; each bar represents the share of total state employment in that particular industry. Each color represents a state; the shares across all industries for each state add to one. The retail sector and food-service sector dominate most states for youth and vary more than 20% in share of employment across states. Additionally, the maximum sector share is less than 50% for any particular state.

Figure 4 plots actual growth against instrumented growth for each state-quarter in the sample for each age-sex group, weighted by population. Actual growth plotted on the vertical axis is an equilibrium outcome, the change in employment due to changes in supply and demand. Estimated growth on the horizontal axis is growth due only to estimated changes on the demand side of the labor market. The slope coefficient from the regression of estimated growth on actual growth is reported near the bottom of each plot in figure 4.

Generally, the clusters of large estimated growth in the right of the plots is made up of observations from 1998-2000, when both employment and arrests were increasing. Years before 2001 are excluded in figure 5, and the slope coefficient from the regression of actual growth on estimated growth is around one for all age groups and sexes. From 2001 onward, estimated growth is an excellent predictor of actual growth. This is less true from 1998-2000, which may be due to the instrument's variance in high-growth periods. Figure 6 plots actual growth and estimated growth for every state over time side-by-side for each sex-age group. Figure 6 illustrates how each state's instrumented growth is similar to the national growth trend but different due to state-specific industry composition.

Table 1 reports regression results from estimated growth regressed on actual growth across various fixed-effect specifications. Columns 2-5 incrementally add time and location fixed effects. The exogeneity of the instrument requires industry national growth rates to be uncorrelated with state-level labor-supply shocks. This may not be the case if a particular state is driving the national shock. To address this concern, I calculate the instrument for each state, while leaving out its own contribution to national employment growth. The formula to calculate the leave-own-out predicted employment growth $\hat{loog}_{st}$ is below in equation (2), where $g_{sit}$ is state-specific industry employment growth. Column 6 reports the same specification as column 5 using the leave-own-out predicted employment growth specification for predicted employment growth.

$$\hat{loog}_{st} = \frac{\sum_i \left[G_{it} - g_{sit}\right] L_{si,t-1}}{L_{s,t-1}} \tag{2}$$

The construction of a valid instrument for predicting employment growth allows me to employ a simple empirical strategy. I use ordinary least squares linear regression to analyze the effect of the instrument directly on my dependent variable. I am estimating the reduced-form effect of estimated employment growth on arrests, instead of a typical two-stage instrumental variables approach.

My estimating equation is a linear regression with time and location fixed effects as follows:

$$\%\Delta arrests_{sayq} = \alpha + \beta \hat{g}_{sayq} + \delta Police_{sy} + \phi_y + \omega_q + \gamma_s + \epsilon_{sayq},$$

where $\%\Delta arrests$ is calculated as $\frac{Arrests_t - Arrests_{t-1}}{Arrests_{t-1}}$ for each state and age-sex group from quarter to quarter. Indices $sayq$ index state, age-sex[6], year, and quarter for each observation. Estimated growth $\hat{g}_{sayq}$ is constructed from employment data according to equation (1). $Police_{sy}$ is the count of payroll officers in a given state-year. Year fixed effects $\phi_y$ are included to capture broader economic trends that may be simultaneously affecting employment levels and arrests across all states. Seasonal variation is controlled for with quarter fixed effects $\omega_q$. Systematic differences in states that are constant across time are controlled for with state fixed effects $\gamma_s$. Finally, $\epsilon_{sayq}$ is the error term.

Identifying variation comes from changes in arrest levels within a state, quarter, and year for a particular sex-age group. Estimated standard errors are clustered at the state level. Regressions are weighted by the age-sex population in a given state-year. The coefficient of interest is $\beta$, which is interpreted as the percentage change in arrests due a one percent increase in estimated employment growth. My identifying assumption is that the predicted measure of employment growth is conditionally uncorrelated with the unobservable component of change in arrests.

# 5 Results

Table 2 reports regression results across various specifications. Column 1 reports estimates for estimated growth regressed on change in arrests. Column 2 adds state, year, and quarter fixed effects. Column 4 adds state-by-year fixed effects. Columns 3 and 5 are similar specifications to 2 and 4, but are estimated using leave-own-out growth as in equation (2). Robustness across these columns rules out the concern that states are driving their own employment shocks via the national growth rate. Table 3 reports the same specification as column 2, including average arrest levels and average employment levels. These averages are combined with the elasticities to calculate the estimated effect size. Effect size is interpreted as the change in arrests caused by 100 new jobs for the age-sex group for a given

[6]Age-sex categories include male, female, and all sexes for ages 14-18, 19-21, and 14-21.

state-quarter.

I find increased employment opportunities lead to decreased arrests. 14-18 year old males are most responsive to increases in job opportunities. Young adults are much less responsive. For male youth the coefficient of -1.055 is interpreted as the percentage change in arrests at the state level for a given quarter due to a one percent increase in employment opportunities. This translates to 46 fewer youth arrests due to 100 new employment opportunities for 14-18 year old males in a particular state-quarter. Young adults see 0.298 percent fewer arrests due to a one percent increase in employment opportunities. Females are slightly less responsive, but have a much smaller effect size. This is consistent with the fact that females engage in much less criminal activity than males. These estimates are generated using arrest data, which is a lower bound estimate of criminal activity since all crime is not reported as an arrest. The reduction in criminal activity not resulting in arrest could be much larger.

These results are similar in direction but larger in magnitude than those of Heller and Gelber, who look at participation in different summer employment opportunities. Heller finds a 43-percent reduction in violent crime arrests per youth for disadvantaged youth who were randomly offered summer employment opportunities through Chicago public schools. Gelber finds participation in New York City's Summer Youth Employment Program reduced the probability of incarceration by 0.10 percentage points. Both of these studies examine only disadvantaged populations and summer employment. Of the disadvantaged youth, 96 percent are black in Heller's study, and 48 percent are black in Gelber's. Neither study uses a nationally representative sample.

I analyze the differential effect by race for juveniles in table 4. I use arrest counts by race as the dependent variable across 4 categories: White, Black, Asian, and Native American. I report estimates only for males and females combined, since arrests by race are not recorded by sex. The elasticities vary only slightly across white and black. The difference in effect size, however, is quite large. The effect size of 5.4 fewer arrests for blacks due to 100 new employment opportunities at the state level is comparable to Heller's findings, which translate to 4 fewer arrests if 100 disadvantaged youth (96 percent of which are black) are given summer employment opportunities. While blacks are responding proportionally similarly to whites, whites make up a much larger fraction of the population; thus, including whites explains the difference in magnitudes seen between my results and those of previous studies. Asians and Native Americans have more than twice the response of whites and black, but due to their relatively low level of criminal activity, their effect sizes are small relative to other races. An important note is that I am allowing only the dependent variable to differ by race; I do not have employment data by race. These results, therefore, do not capture the fact that job opportunities are likely not equally distributed across races. In fact, my results are consistent with differential job opportunities across races. One possible explanation that whites see a larger reduction in crime due to predicted job opportunities is that whites are filling proportionally more of the potential job opportunities, which means that more whites are removed from the criminal labor market.

To further investigate the mechanisms driving the results in tables 2 and 3, I categorize arrests by offense type. Arrests are recorded in 29 offense groups and 14 subgroups, which makes 43 categories and subcategories. I group these categories into non-mutually exclusive groups by offense type in table 4[7]. Group 1 is violent crimes; group 2 is financially motivated crimes; group 3 is mischief type crimes; group 4 is personal offenses; group 5 is drug related crimes; and group 6 is substance abuse crimes. The incentives to commit offenses in different groups vary substantially. Violent crimes are personal offenses often triggered by anger and other emotional responses. Financially motivated crimes are categorized as crime that could be an arguable substitute for income. Mischief crimes are crimes that youth "up to no good" may commit. These crimes seem to be driven by boredom, so the incapacitation of employment is expected to play a role in decreasing these crimes. Personal offenses are sex crimes or family crimes. Drug-related crimes are any arrests dealing with drug sale or drug possession. Finally, substance-abuse crimes are alcohol-related crimes or drug-possession

[7]The total number offenses listed in table 4 is less than 43 because some sub-categories are omitted to prevent double-counting. For instance, drug sale and drug possession aggregate to equal drug offenses.

crimes.

The regression results for each of these groups by age-sex group are presented in table 6. I adjust significance levels for multiple hypothesis testing using the Benjamini-Hochberg step-up method (Benjamini and Hochberg 1995). Table 6 identifies which grouping of crimes are driving the aggregate results in tables 2 and 3. All types of crimes for all sex-age groups still seem to be decreasing in predicted employment opportunities. For male youth, all groups except drug-related crimes are estimated to decrease as employment opportunities are expected to increase. Female youth are much less responsive, as only three groups have coefficients significantly different from zero. The negative coefficient of financially motivated crimes is suggestive that they are inferior goods, decreasing as income increases.

Consistent with the aggregate regressions, young adults are less responsive than youth. For financially motivated crimes, young adult males are about a third as responsive as youth to predicted increases in employment opportunities. The result that youths respond more to predicted changes in employment opportunities for financially motived crimes is suggestive that financially motivated crimes are more of a substitute for youth than for young adults. Youth are constrained in the types of jobs they are eligible to work at due to many over-18 policies. This can been seen in figure 1 subfigures (a) and (b). Youths tend to be employed only in retail, and food. The relatively lower availability of employment opportunities could be an explanation for why youths seem to be substituting toward financially rewarding crimes. Another possible explanation for young adult arrests being less responsive to increases employment opportunities is that since the young adults are much less likely to be dependents and much more likely to be employed, the observed arrests are happening to employed individuals. Youth, on the other hand, are typically dependents and much less likely to be employed, so increases in employment opportunities have a larger incapacitating effect than for young adults. This is an intuitive finding if incapacitation is concave in employment. Since youth have a much lower level of employment than young adults, the marginal effect is much larger.

I split arrests by offense type to analyze which individual offenses respond to changes in employment opportunities. I adjust significance levels for multiple hypothesis testing using the Benjamini-Hochberg step-up method. Regressions by offense are included in tables 7, 8, and 9. Table 7 is youth offenses, table 8 is young adult offenses, and table 9 is both age groups. For youth, most offenses have a negative coefficient. This table illustrates which individual offenses are driving the aggregate results seen in tables 2 and 3. For youth males, robbery, aggravated assault, burglary, larceny, motor theft, fraud, stolen property, vandalism, weapon, drug, drug possession, non-narcotic drug sale, liquor laws, and suspicion, are all decreasing as predicted employment opportunities increase. Young adult males see a reduction only in robbery arrests as employment opportunities increase. This result suggests that robbery is a substitute for income. For both age groups, robbery, burglary, and larceny, other assault, vandalism, weapon, drug sale, disorderly , and other offenses all decrease with employment opportunities. Many of these significant results are driven by the youth results. A few offenses, like disorderly conduct, are not significant for either age group but significant for the combined age group. Overall, income substitutes seem to be moving the most for young adult males, a result that is consistent with Gould et al. (2002) and Mocan and Rees (2005).

None of the offenses are changing at a rate significantly different from zero for females. This is likely due to the fact that females are committing significantly fewer crimes than males, so slicing the data by offense strips away any identifying power.

# 6 Conclusion

Effectively decreasing the incidence of juvenile crime is a central interest of public policy. While a large body of research shows that increasing the certainty of apprehension reduces crime, doing so comes at a cost. A rational model of crime posits alternative sources of income can also be an effective way to reduce crime. I test this relationship for youths by predicting employment growth and analyzing how youth arrests respond to predicted changes in employment levels.

This paper makes two major contributions to the economic literature on employment conditions and crime. The first contribution is that it provides external validity to the RCT findings of Heller (2014) and Gelber et al. (2014), which document the reduction of criminal activity due to the random assignment of youth employment opportunities in large cities. This paper looks at systematic predictions for job growth across 46 states, encompassing a much larger population over a much larger time period. The second is the distinction between labor market conditions, which are equilibrium outcomes, and labor market opportunities, which isolate predicted demand side shocks in the labor market.

To examine the effect of labor market opportunities on crime, I use a shift-share analysis to create predicted employment growth only due to demand side shocks. I then use changes in expected employment growth to explain changes in arrest rates. I find youth arrests decrease 1.08% due to a 1% increase in employment opportunities. This translates into 30 fewer youth arrests due to 100 new youth job opportunities in a given state for a given quarter. Arrests are a lower-bound estimate of criminal activity, so actual youth crime could be decreasing even more. For young adults, this response is considerably smaller. A 1% increase in employment opportunities leads to a 0.29% decrease in arrests, which translates to 6 fewer arrests for every 100 new job opportunities in a given state for a given quarter.

Violent, financially motivated, mischief, personal offenses, and substance-abuse-related arrests all decrease for male youths as employment opportunities increase. Young adult male arrests respond about a third as much as youth arrests for financially motivated crimes, which is an intuitive result if incapacitation is concave in employment. Since young adults are employed at much higher levels than youth, the marginal effect of increased employment is much larger for youth.

Slicing arrests by offense type, robbery, aggravated assault, burglary, larceny, motor theft, fraud, stolen property, vandalism, weapon, drug, drug possession, non-narcotic drug sale, liquor laws, and suspicion all decrease as a result of increased employment opportunities for youth males. A possible limitation of these findings is that they rely on voluntarily reported arrests. Only a fraction of criminal activity results in an arrest since many crimes go undetected or unreported, so these results likely understate the effect of employment opportunities on crime. Secondly, many youth employment opportunities, such as babysitting or yard work for a neighbor, will not be recorded in my data, since I see only employment for the duration of a quarter recorded by firms for unemployment insurance obligations. Nonetheless, these results are informative about youth and young adult responses to increased employment opportunities in the formal sector.

A natural extension of the work is to shift time periods for youths to capture summertime employment separately from school-year employment. Also, obtaining employment data by race would allow for an analysis of the opportunity of employment across races. Finally, in coming work, I plan to apply a similar shift-share analysis at the state level and use counties as the local geographies responding to changes statewide trends.

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Figure 1: Employment Trends

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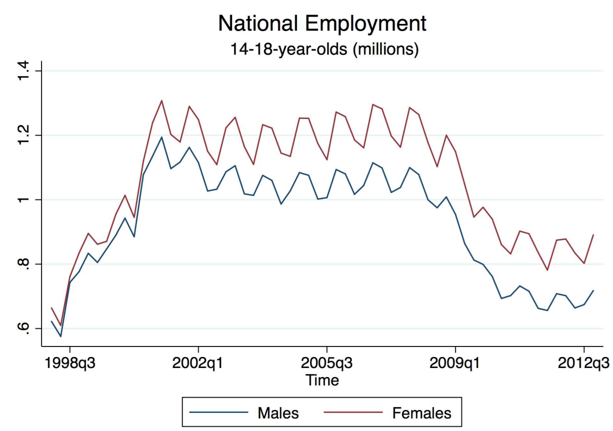


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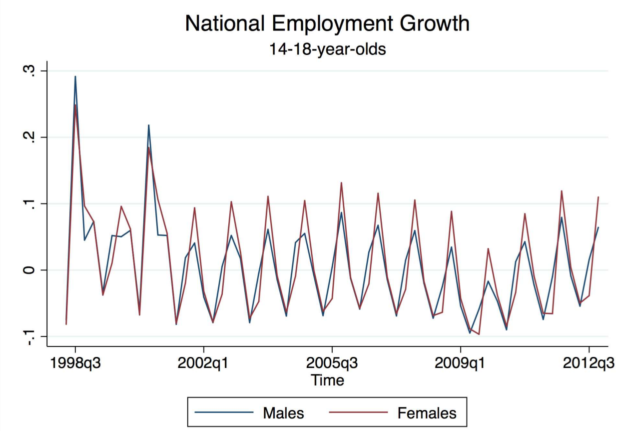


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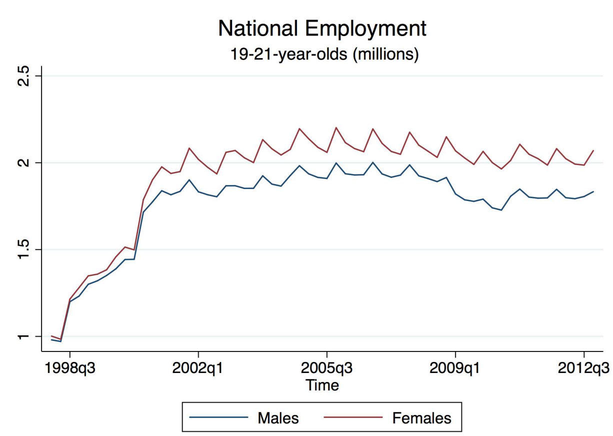


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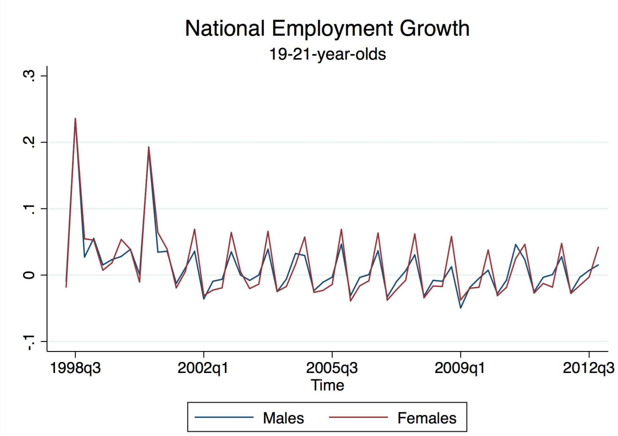


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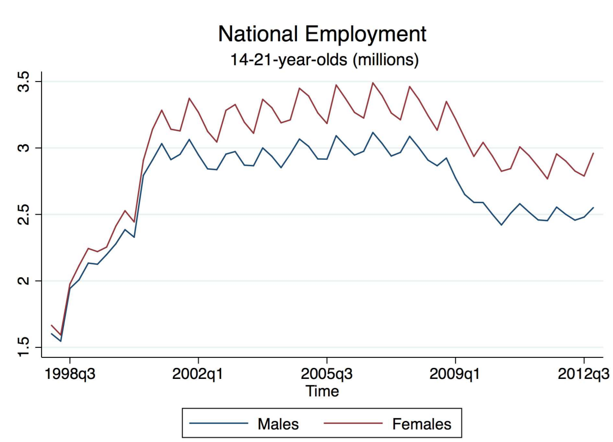


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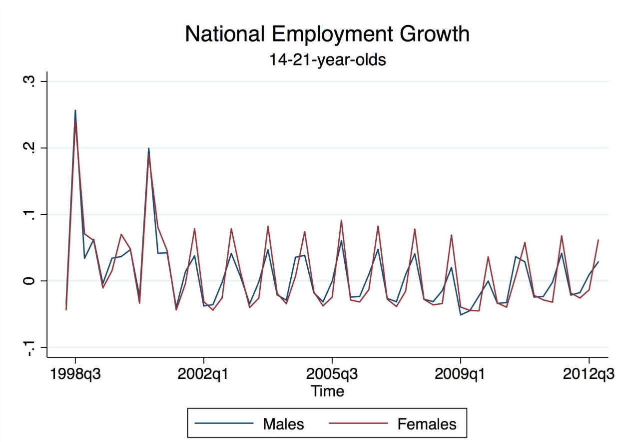
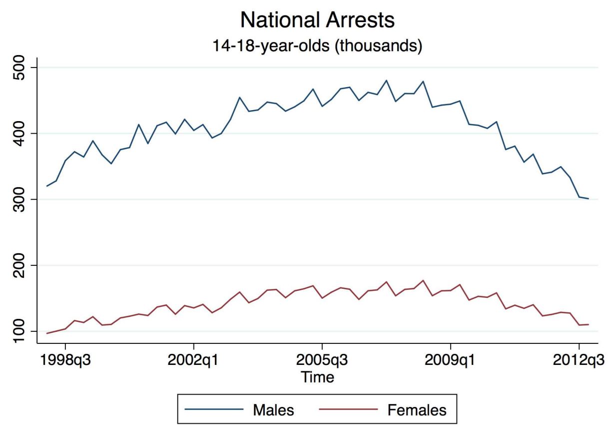


Figure 2: Arrest Trends

(a)

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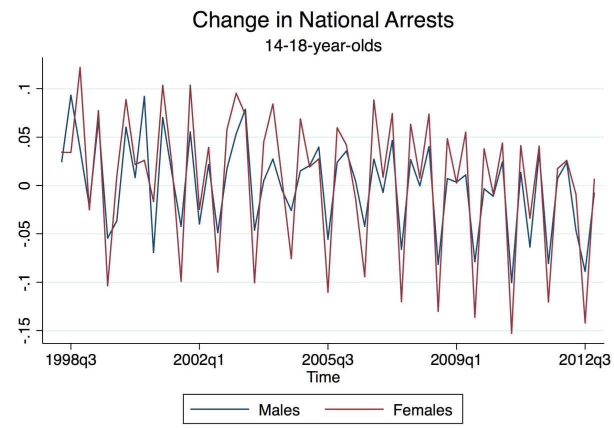


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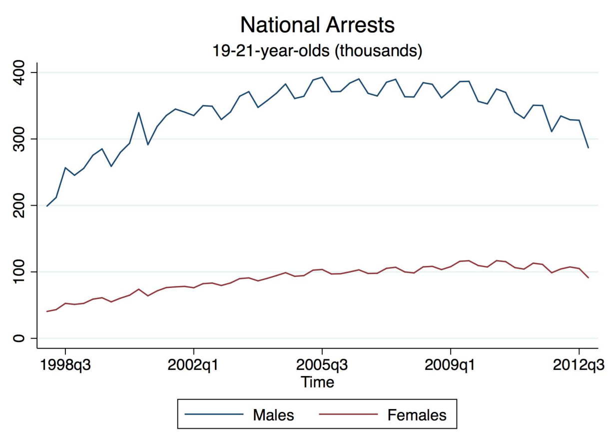


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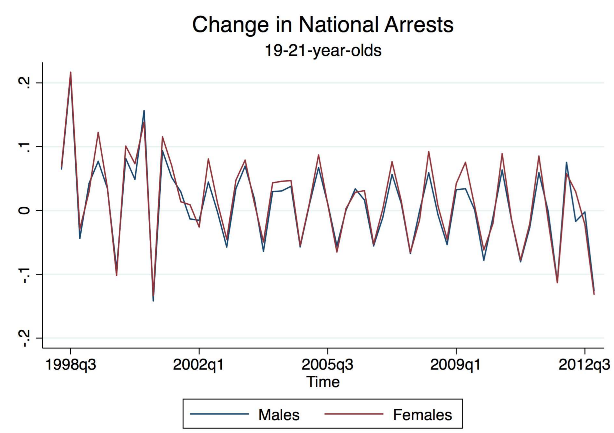


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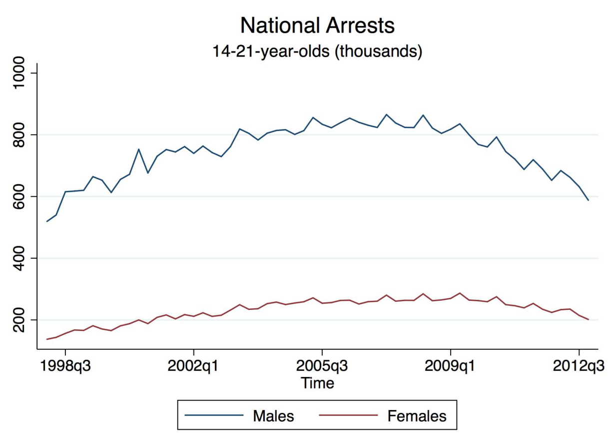


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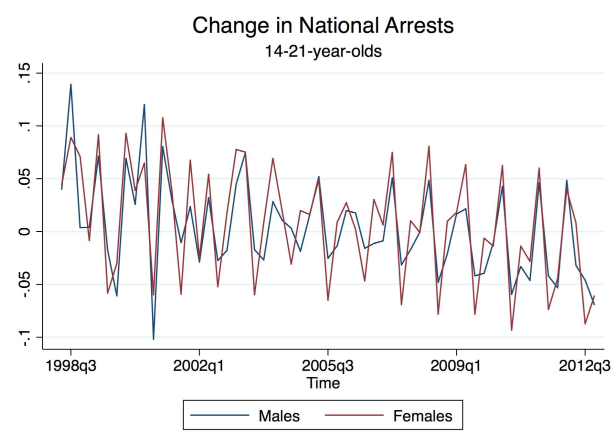
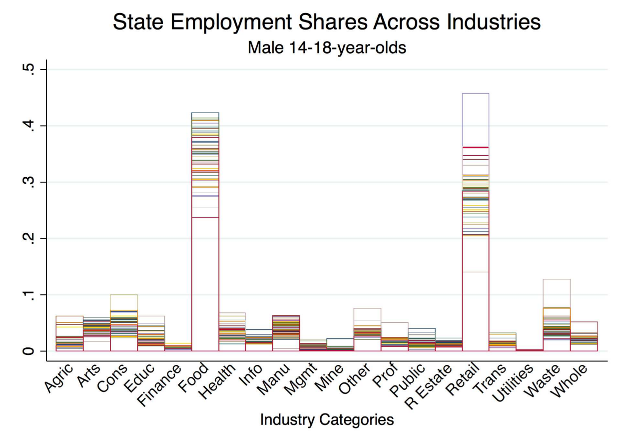


Figure 3

(a)

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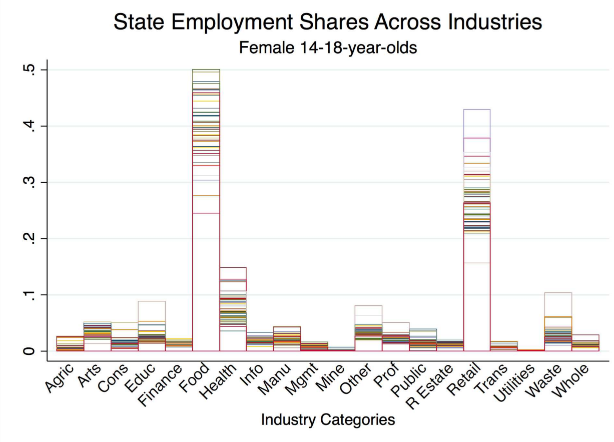


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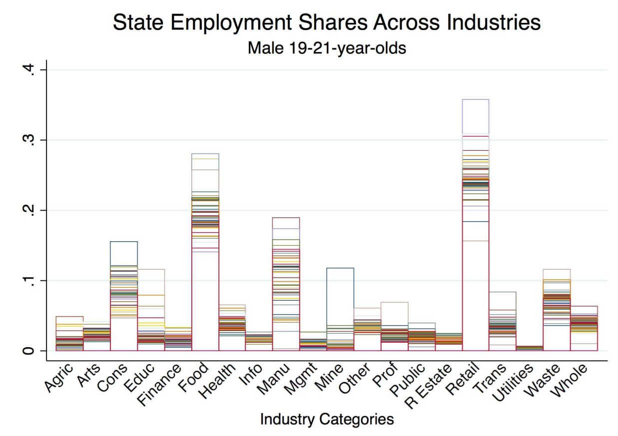


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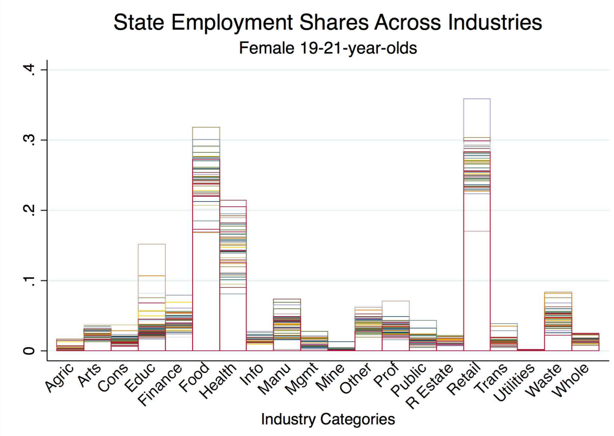


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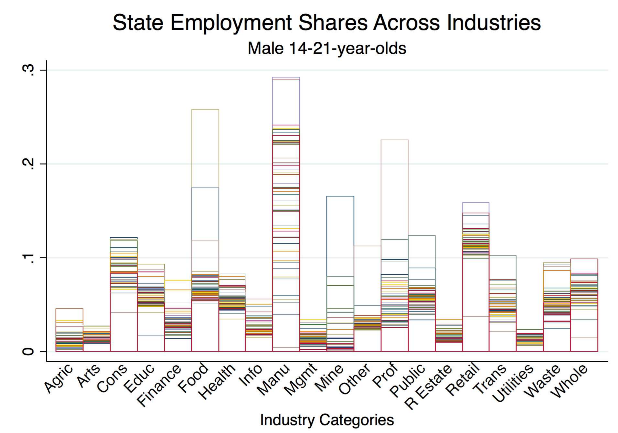


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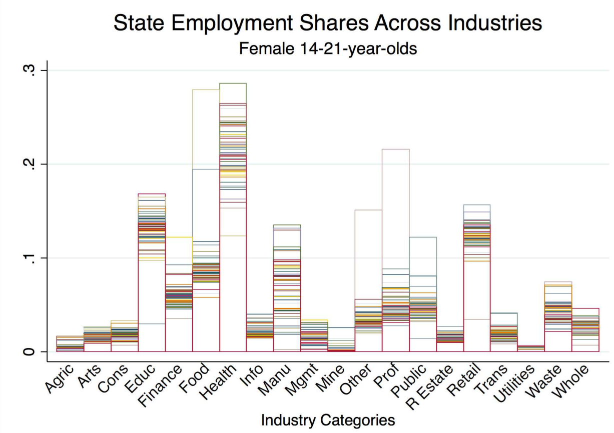
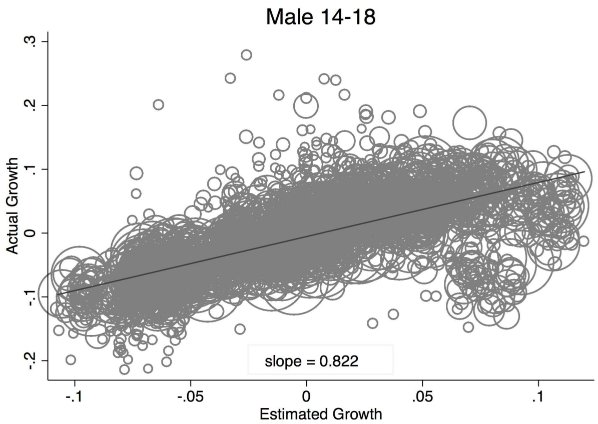



Note: This figure illustrates the variation of industry composition across states. Each bar represents a state's industry-share of total employment. Each column has 46 bars, one representing each state in the sample.

Figure 4

(a)

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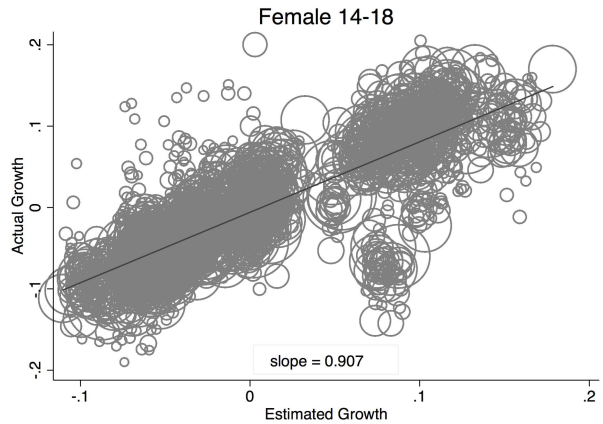


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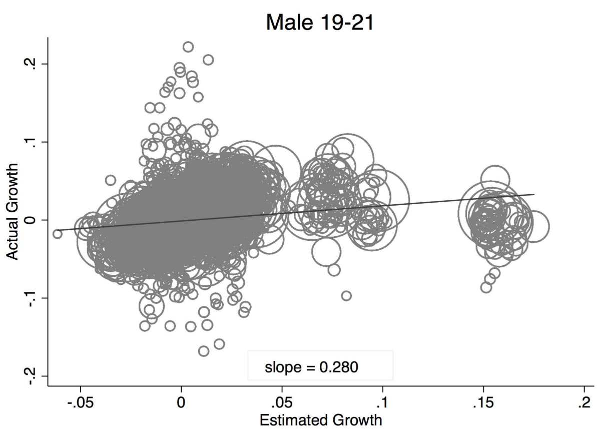


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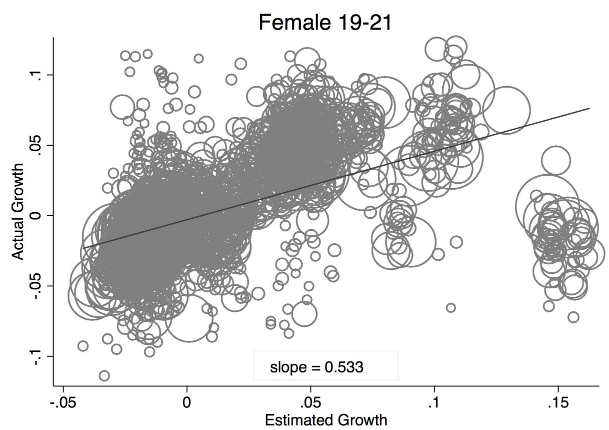


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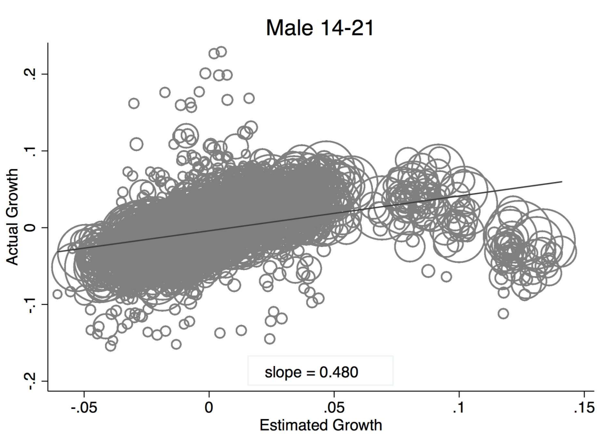


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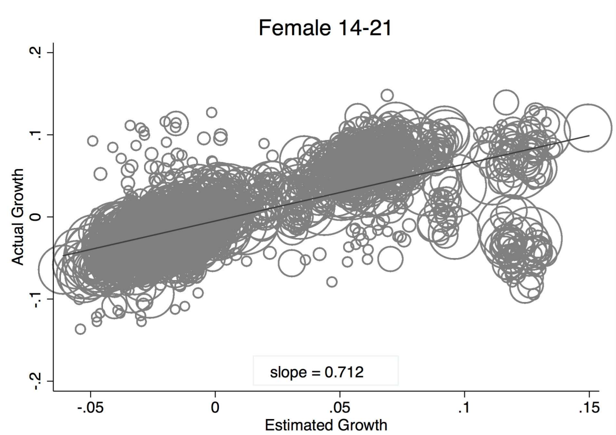
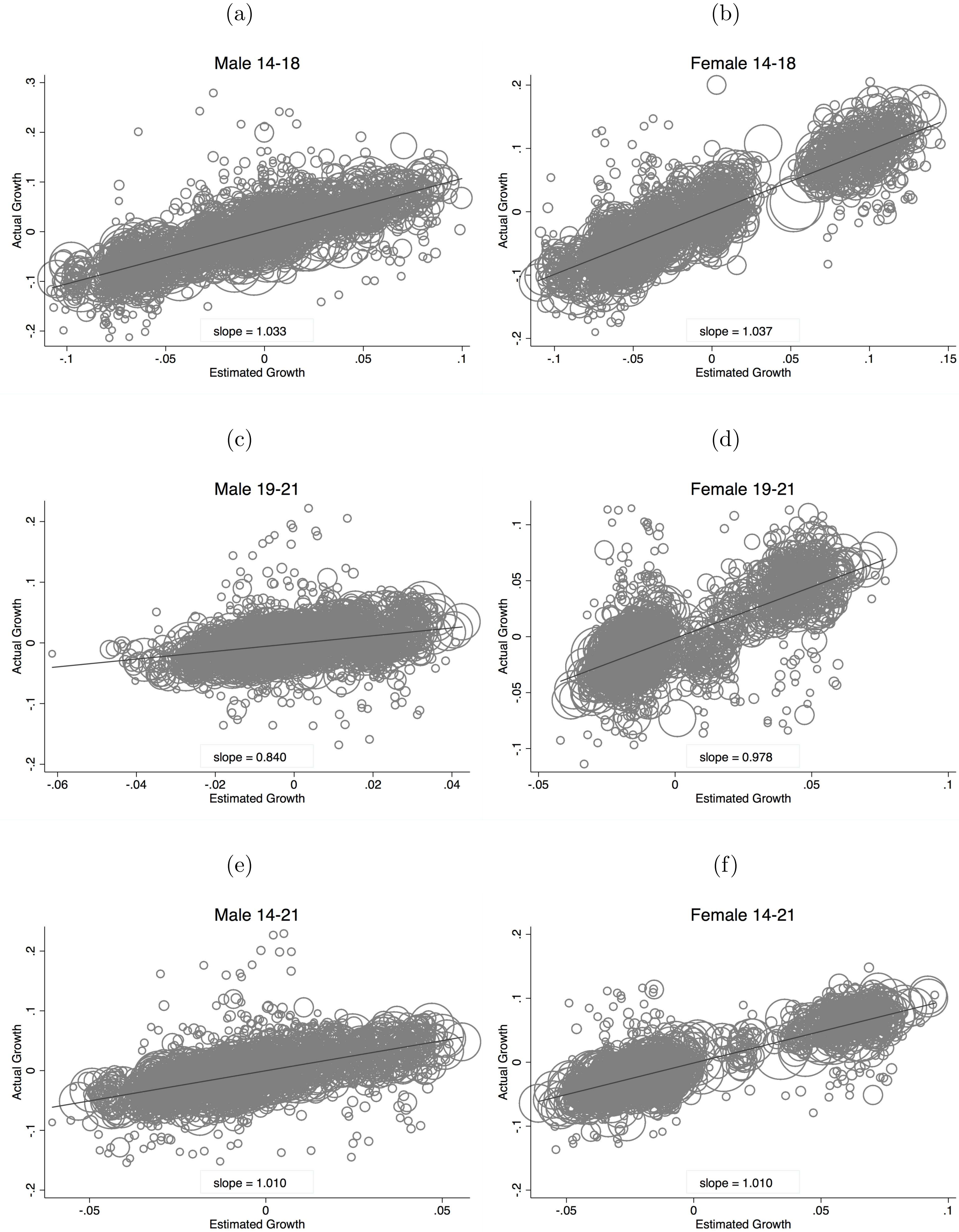



Note: This figure plots estimated employment growth due to demand shocks against actual state employment growth from 1998-2012. Each observation is a state-quarter. Observations weighted by population.

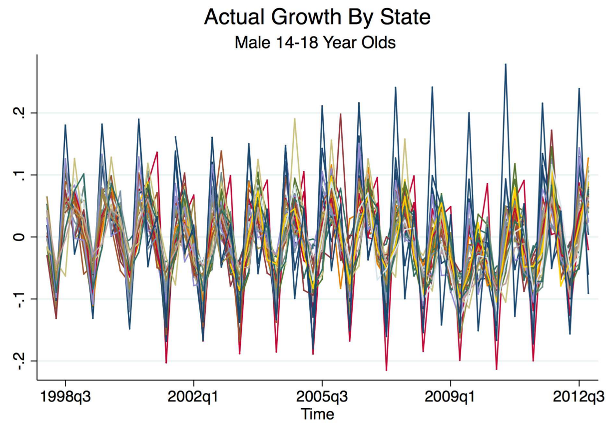
Figure 5




Note: This figure plots estimated employment growth due to demand shocks against actual state employment growth from 2001-2012. Each observation is a state-quarter. Observations weighted by population.

Figure 6

(a)

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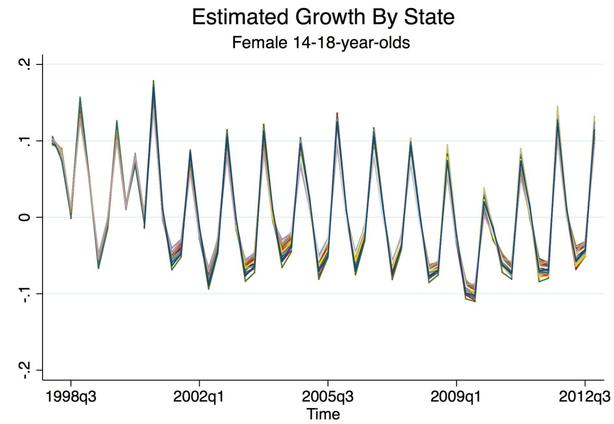


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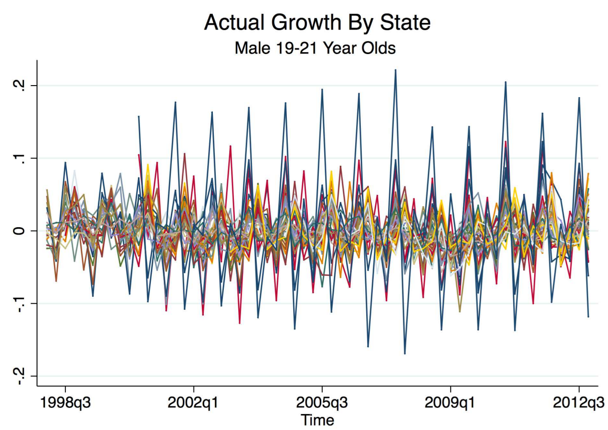


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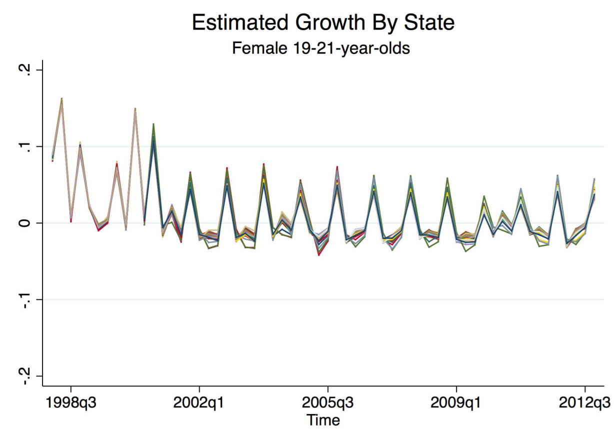


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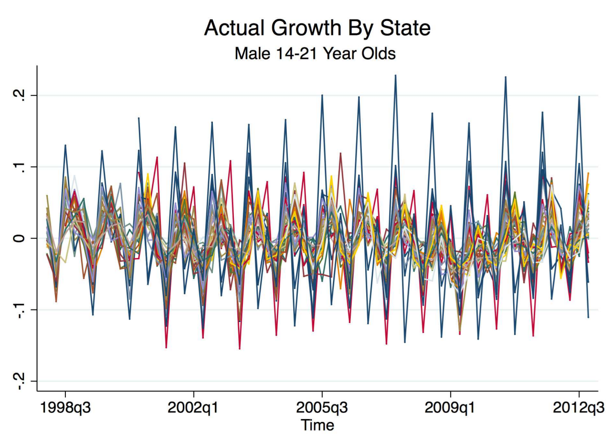


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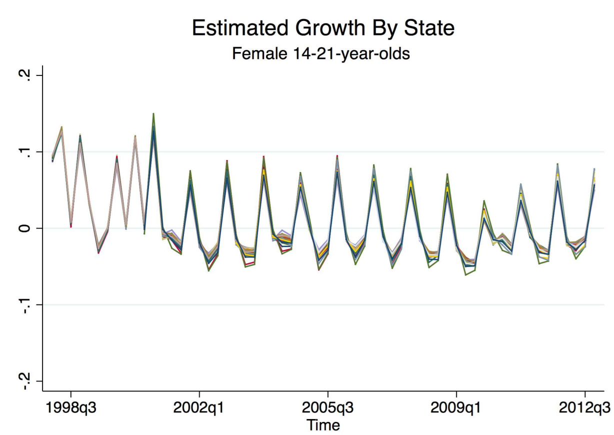


Note: This figure plots actual employment growth on the right and estimated employment growth on the left. Estimated growth is driven by national industry specific growth but varies across state due state specific industry composition.

Table 1: Actual Employment Growth Predicted by Estimated Employment Growth

| | | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|---|
| 14-18 | Male | 0.826*** | 0.346*** | 0.227*** | 0.353*** | 0.242*** |
| | | (0.015) | (0.033) | (0.032) | (0.036) | (0.035) |
| | Female | 0.910*** | 0.427*** | 0.289*** | 0.438*** | 0.308*** |
| | | (0.011) | (0.034) | (0.033) | (0.037) | (0.036) |
| | All Sexes | 0.875*** | 0.383*** | 0.261*** | 0.392*** | 0.278*** |
| | | (0.013) | (0.033) | (0.031) | (0.036) | (0.034) |
| 19-21 | Male | 0.278*** | 0.137*** | 0.086*** | 0.142*** | 0.090*** |
| | | (0.016) | (0.023) | (0.021) | (0.026) | (0.024) |
| | Female | 0.534*** | 0.122*** | 0.076*** | 0.130*** | 0.083*** |
| | | (0.013) | (0.02) | (0.019) | (0.022) | (0.021) |
| | All Sexes | 0.403*** | 0.116*** | 0.073*** | 0.123*** | 0.078*** |
| | | (0.014) | (0.02) | (0.019) | (0.023) | (0.021) |
| 14-21 | Male | 0.482*** | 0.152*** | 0.095*** | 0.158*** | 0.102*** |
| | | (0.017) | (0.025) | (0.024) | (0.028) | (0.026) |
| | Female | 0.714*** | 0.147*** | 0.082*** | 0.157*** | 0.092*** |
| | | (0.012) | (0.024) | (0.022) | (0.026) | (0.025) |
| | All Sexes | 0.612*** | 0.139*** | 0.082*** | 0.148*** | 0.091*** |
| | | (0.014) | (0.024) | (0.022) | (0.026) | (0.024) |
| State FE | | n | y | y | y | y |
| Year FE | | n | y | y | y | y |
| Quarter FE | | n | y | y | y | y |
| State×year FE | | n | n | n | y | y |
| Leave-out-own Growth | | n | n | y | n | y |

This table reports estimates for the percentage change in total arrests due to a one percent increase in youth employment opportunities.
Significance is indicated by ***p<0.01, **p<0.05, *p<0.1. Standard Errors are reported in Parenthesis.
Errors are clustered at the state level. Regressions are weighted by annual state population for a particular age-sex group.
Columns (3) and (5) calculate predicted growth using national growth that was calculated for each leaving out own state contribution to national growth.

Table 2: Effects of Employment Opportunities on Crime

Specification Analysis

$$\%\Delta arrests_{sayq} = \alpha + \beta\hat{g}_{sayq} + \delta Police_{sy} + \phi_y + \omega_q + \gamma_s + \epsilon_{sayq}$$

| Age | Sex | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|---|
| 14-18 | Male | -0.348* | -1.056*** | -0.992*** | -1.063*** | -0.980*** |
| | | (0.206) | (0.337) | (0.31) | (0.393) | (0.348) |
| | Female | 0.323 | -0.985*** | -0.921** | -0.980** | -0.890** |
| | | (0.202) | (0.382) | (0.358) | (0.439) | (0.389) |
| | All Sexes | -0.064 | -1.081*** | -1.005*** | -1.085*** | -0.988*** |
| | | (0.221) | (0.36) | (0.332) | (0.416) | (0.367) |
| 19-21 | Male | -0.724*** | -0.296** | -0.286** | -0.312* | -0.282* |
| | | (0.196) | (0.135) | (0.13) | (0.173) | (0.147) |
| | Female | -1.103*** | -0.260 | -0.238 | -0.276 | -0.233 |
| | | (0.176) | (0.175) | (0.168) | (0.217) | (0.192) |
| | All Sexes | -1.030*** | -0.270* | -0.253* | -0.285 | -0.249 |
| | | (0.2) | (0.149) | (0.145) | (0.189) | (0.164) |
| 14-21 | Male | -0.716*** | -0.684*** | -0.624*** | -0.697** | -0.615** |
| | | (0.245) | (0.232) | (0.214) | (0.282) | (0.242) |
| | Female | -0.187 | -0.573** | -0.509* | -0.581* | -0.491* |
| | | (0.219) | (0.288) | (0.27) | (0.343) | (0.298) |
| | All Sexes | -0.564** | -0.663*** | -0.593** | -0.674** | -0.580** |
| | | (0.242) | (0.255) | (0.237) | (0.306) | (0.265) |
| State FE | | n | y | y | y | y |
| Year FE | | n | y | y | y | y |
| Quarter FE | | n | y | y | y | y |
| State×year FE | | n | n | n | y | y |
| Leave-out-own Growth | | n | n | y | n | y |

This table reports estimates for the percentage change in total arrests due to a one percent increase in youth employment opportunities. Significance is indicated by ***p<0.01, **p<0.05, *p<0.1. Standard Errors are reported in Parenthesis.
Errors are clustered at the state level. Regressions are weighted by annual state population for a particular age-sex group.
Columns (3) and (5) calculate predicted growth using national growth that was calculated for each leaving out own state contribution to national growth.

Table 3: Effect Size of 100 New Employment Opportunities on Arrests

| Age | Sex | $\beta$ | $R^2$ | $\overline{\text{Crime}}$ | $\overline{\text{Emp}}$ | Effect Size |
|---|---|---|---|---|---|---|
| 14-18 | Male | -1.055*** (0.336) | 0.089 | 9924 | 22646 | -46.4 |
| | Female | -0.985*** (0.382) | 0.163 | 3442 | 25857 | -13.1 |
| | All Sexes | -1.081*** (0.36) | 0.107 | 13366 | 48503 | -29.8 |
| 19-21 | Male | -0.298** (0.136) | 0.201 | 8254 | 42817 | -5.7 |
| | Female | -0.261 (0.139) | 0.192 | 2181 | 46755 | -1.2 |
| | All Sexes | -0.270* (0.15) | 0.204 | 10435 | 89572 | -3.1 |
| 14-21 | Male | -0.685*** (0.233) | 0.106 | 18178 | 65463 | -19 |
| | Female | -0.574** (0.289) | 0.121 | 10435 | 72612 | -4.4 |
| | All Sexes | -0.664*** (0.256) | 0.107 | 23801 | 138075 | -11.4 |

This table reports estimates for the percentage change in total arrests due to a one percent increase in youth employment opportunities.
Significance is indicated by ***p<0.01, **p<0.05, *p<0.1. Standard Errors are reported in Parenthesis.
Errors are clustered at the state level. Regressions are weighted by annual state population for a particular age-sex group.
Effect size is the change in arrests due to 100 new job opportunities at the state-quarter level.

Table 4: Juvenile Crime by Race

14-18 All Sexes

| Race | $\beta$ | $\overline{\text{Emp}}$ | $\overline{\text{Crime}}$ | Effect Size |
|---|---|---|---|---|
| White | -1.283*** | 45,627 | 6531 | -19.2 |
| | (0.404) | | | |
| Black | -0.926* | 48,523 | 2852 | -5.4 |
| | (0.419) | | | |
| Asian | -2.142*** | 51,166 | 160 | -0.7 |
| | (0.419) | | | |
| Native American | -2.433* | 48,503 | 131 | -0.7 |
| | (1.258) | | | |
| All | -1.081 | 48,503 | 13366 | -29.8 |
| | (0.36) | | | |

This table reports estimates for the percentage change in arrests (by race) due to a one percent increase in youth employment opportunities.
Only arrests are categorized by race, employment opportunities is not.
Significance is indicated by ***p<0.01, **p<0.05, *p<0.1. Standard Errors are reported in Parenthesis.
Errors are clustered at the state level. Regressions are weighted by annual state population for a particular age-sex group.
Effect size is the change in arrests due to 100 new job opportunities at the state-quarter level.

Table 5: Grouping of Offenses

| Violent Crimes | Financially Motivated | Mischief | Personal Offenses |
|---|---|---|---|
| Murder | Larceny | Vandalism | Sex Offense |
| Manslaughter | Motor Theft | Arson | Family Offense |
| Rape | Forgery | Disorderly | |
| Aggrivated Assault | Fraud | Vagrancy | **Drug-related** |
| Weapon | Embezzlement | Suspicion | |
| Other Assault | Stolen Property | Curfew | Drug |
| | Prostitution | Runaway | |
| | Gambling | | **Substance Abuse** |
| | Robbery | | |
| | Burglary | | DUI |
| | Drug Sale | | Liquor Laws |
| | | | Drunkenness |
| | | | Drug Possession |

These groupings are not mutually exclusive. Drug includes several categories for sale and possession. Drug sale is included in financially motivated offenses while drug possession is included in substance abuse. Both categories are included in drug-related offenses.

Table 6: Effects of Employment Opportunities on Crime

By Groups of Offenses

| Group: | 14-18 | | | 19-21 | | | 14-21 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Male | Female | All Sexes | Male | Female | All Sexes | Male | Female | All Sexes |
| Violent Crimes | -0.693** | -0.659 | -0.667* | -0.422* | -0.744 | -0.494* | -0.662** | -0.825 | -0.705** |
| Financially Motivated | -1.257*** | -0.595* | -1.073*** | -0.405* | -0.271 | -0.343* | -0.847*** | -0.341 | -0.743*** |
| Mischief | -1.241*** | -1.404* | -1.304** | -0.466 | -0.129 | -0.494 | -0.907** | -0.922 | -0.903* |
| Drug-related | -0.073 | 0.199 | -0.150 | -0.249 | -1.499 | -0.402 | -0.247 | -0.496 | -0.325 |
| Personal Offense | -1.069** | -0.931 | -1.172** | -0.258 | -0.351 | -0.374 | -0.702** | -0.691 | -0.696* |
| Substance Abuse | -0.902*** | -1.08** | -1.018*** | -0.084 | -0.343 | -0.367 | -0.408** | -0.418 | -0.381* |

This table reports estimates for the percentage change in arrests (by grouping) due to a one-percent increase in youth employment opportunities.
Significance is indicated by ***p<0.01, **p<0.05, *p<0.1.
Errors are clustered at the state level. Regressions are weighted by annual state population for a particular age-sex group.
Significance levels are adjusted for multiple hypothesis testing using the Benjamini-Hochberg step-up method.

Table 7: The Effect of Employment Opportunities on Arrests by Offense

Ages 14-18

| Offense | Male | Female | All Sexes |
|---|---|---|---|
| Murder | -2.508 | -5.867 | -2.249 |
| Manslaughter | -1.127 | 5.071 | 0.257 |
| Rape | -0.343 | -4.281 | -0.491 |
| Robbery | -1.164** | 1.046 | -0.855* |
| Aggrivated Assault | -0.732** | -0.670 | -0.696* |
| Burglary | -1.461*** | -0.782 | -1.424*** |
| Larceny | -1.409*** | -0.734 | -1.156** |
| Motor Theft | -1.075** | -0.528 | -1.022* |
| Other Assault | -0.593 | -0.628 | -0.604 |
| Arson | -0.868 | -4.305 | -0.995 |
| Forgery | -0.907 | -0.461 | -0.665 |
| Fraud | -1.744** | 0.208 | -1.050* |
| Embezzlement | -1.021 | -0.605 | -0.763 |
| Stolen Property | -1.830** | -2.439 | -1.892** |
| Vandalism | -1.856*** | -1.821 | -1.813*** |
| Weapon | -1.130** | -0.505 | -1.131** |
| Prostitution | -1.470 | -0.242 | -1.581 |
| Sex Offense | -0.364 | -0.934 | -0.235 |
| Drug | -1.074** | -0.958 | -1.173* |
| Drug Sale | -0.811 | -0.662 | -0.916 |
| Drug Possession | -0.958** | -0.767 | -1.081* |
| Opium Sale | -0.187 | 0.413 | 0.314 |
| Marijuana Sale | -1.614 | -0.752 | -1.738 |
| Synthetic Narcotic Sale | -0.887 | -13.701 | -6.134 |
| Non Narcotic Sale | -0.230** | 1.488 | -0.370** |
| Opium Possession | -0.906 | -1.610 | -0.774 |
| Marijuana Possession | -1.096 | -1.495 | -1.311 |
| Synthetic Narcotic Possession | -2.402 | -0.242 | -2.347 |
| Non-narcotic Possession | -0.801 | 0.572 | -0.632 |
| Gambling | -7.222 | -1.357 | -7.615 |
| Family Offense | -0.607 | 2.548 | 4.009 |
| DUI | -0.264 | -0.096 | -0.168 |
| Liquor Laws | -0.445** | -0.928 | -0.694* |
| Drunkenness | -1.914 | -1.097 | -2.953 |
| Disorderly | -1.957** | -2.539 | -2.217** |
| Vagrancy | -3.781 | -6.550 | -2.238 |
| Other Offenses | -1.283 | -1.711 | -1.440 |
| Suspicion | -12.001* | -5.072 | -15.499* |
| Curfew | -2.212 | -0.945 | -1.876 |
| Runaways | -0.794 | -0.465 | -0.647 |

This table reports estimates for the percentage change in arrests (by offense category) due to a one-percent increase in youth employment opportunities.
Significance is indicated by ***p<0.01, **p<0.05, *p<0.1.
Errors are clustered at the state level. Regressions are weighted by annual state population for a particular age-sex group.
Significance levels are adjusted for multiple hypothesis testing using the Benjamini-Hochberg step-up method.

Table 8: The Effect of Employment Opportunities on Arrests by Offense

| Ages 19-21 | | | |
|---|---|---|---|
| Offense | Male | Female | All Sexes |
| Murder | -1.759 | -6.855 | -0.448 |
| Manslaughter | -0.838 | -1.969 | -0.761 |
| Rape | -0.203 | -0.248 | -0.354 |
| Robbery | -1.321* | -1.721 | -1.371 |
| Aggrivated Assault | -0.584 | -0.913 | -0.693 |
| Burglary | -0.254 | -0.934 | -0.305 |
| Larceny | -0.36 | -0.373 | -0.422 |
| Motor Theft | -0.62 | 0.808 | -0.603 |
| Other Assault | -0.391 | -0.605 | -0.456 |
| Arson | 1.108 | -0.95 | 0.036 |
| Forgery | -0.724 | 0.575 | -0.277 |
| Fraud | -0.371 | -0.189 | -0.257 |
| Embezzlement | -0.419 | -0.791 | -0.325 |
| Stolen Property | -0.725 | 1.201 | -0.664 |
| Vandalism | -0.59 | -0.494 | -0.59 |
| Weapon | -0.659 | -2.519 | -0.675 |
| Prostitution | -2.076 | -1.363 | -1.008 |
| Sex Offense | 0.281 | -2.097 | 0.192 |
| Drug | -0.258 | -0.351 | -0.195 |
| Drug Sale | -0.505 | 0.166 | -0.442 |
| Drug Possession | -0.212 | -0.278 | -0.146 |
| Opium Sale | -0.097 | -0.902 | -0.141 |
| Marijuana Sale | -0.971 | 0.72 | -0.783 |
| Synthetic Narcotic Sale | -2.113 | 2.038 | -1.55 |
| Non-narcotoc Sale | -1.478 | -0.802 | -1.463 |
| Opium Possession | -0.511 | -0.32 | -0.426 |
| Marijuana Possession | -0.061 | -0.135 | -0.033 |
| Synthic Narcotic Possession | -2.073 | -2.099 | -1.802 |
| Non-narcotic Possession | -0.463 | 0.453 | -0.373 |
| Gambling | -5.618 | 1.575 | -4.538 |
| Family Offense | 2.07 | -0.2 | -0.68 |
| DUI | 0.171 | -0.034 | 0.223 |
| Liquor Laws | -0.132 | -0.54 | -0.228 |
| Drunkenness | -0.545 | -0.917 | -0.563 |
| Disorderly | -0.837 | 0.213 | -0.624 |
| Vagrancy | -1.661 | 5.535 | -0.401 |
| Other Offenses | -0.481 | -0.207 | -0.383 |
| Suspicion | 0.769 | -4.638 | -1.641 |

This table reports estimates for the percentage change in arrests (by offense category) due to a one-percent increase in youth employment opportunities.
Significance is indicated by ***p<0.01, **p<0.05, *p<0.1.
Errors are clustered at the state level. Regressions are weighted by annual state population for a particular age-sex group.
Significance levels are adjusted for multiple hypothesis testing using the Benjamini-Hochberg step-up method.

Table 9: The Effect of Employment Opportunities on Arrests by Offense

Ages 14-21

| Offense | Male | Female | All Sexes |
|---|---|---|---|
| Murder | -1.816 | -4.585 | -1.202 |
| Manslaughter | 3.317 | -5.082 | 4.309 |
| Rape | -0.406 | -4.276 | -0.51 |
| Robbery | -1.407*** | -0.43 | -1.304*** |
| Aggrivated Assault | -0.53* | -0.814 | -0.6* |
| Burglary | -0.857*** | -1.101 | -0.904*** |
| Larceny | -0.94*** | -0.388 | -0.785** |
| Motor Theft | -0.553 | 0.052 | -0.538 |
| Other Assault | -0.654* | -0.779 | -0.703 |
| Arson | -0.517 | -2.157 | -0.651 |
| Forgery | -0.577 | 0.236 | -0.269 |
| Fraud | -0.588 | 0.028 | -0.319 |
| Embezzlement | -0.364 | -0.928 | -0.569 |
| Stolen Property | -1.18 | -0.96 | -1.184 |
| Vandalism | -1.155** | -1.381 | -1.129* |
| Weapon | -1.053*** | -1.156 | -1.106** |
| Prostitution | -3.154 | -0.956 | -1.098 |
| Sex Offense | -0.371 | -2.081 | -0.378 |
| Drug | -0.702 | -0.686 | -0.696 |
| Drug Sale | -0.722* | -1.169 | -0.697 |
| Drug Poss | -0.527 | -0.542 | -0.559 |
| Opium Sale | 0.045 | -0.331 | 0.267 |
| Marijuana Sale | -1.577 | 0.007 | -1.673 |
| Synthitic Narc Sale | -2.244 | -6.216 | -2.513 |
| Non-narcotic Sale | -0.82 | -4.486 | -1.092 |
| Opium Possession | -0.713 | -0.623 | -0.633 |
| Marijuana Possession | -0.529 | -0.802 | -0.634 |
| Synthetic Narcotic Possession | -1.257 | -2.7 | -1.708 |
| Non-narcotic Possession | -0.765 | 0.303 | -0.64 |
| Gambling | -6.007 | 1.468 | -4.262 |
| Family Offense | -0.709 | 2.606 | 0.603 |
| DUI | 0.048 | 0.038 | 0.146 |
| Liquor Laws | -0.314 | -0.445 | -0.384 |
| Drunkenness | 0.105 | 0.134 | 0.862 |
| Disorderly | -1.633* | -2.024 | -1.785* |
| Vagrancy | -3.371 | -0.543 | -1.772 |
| Other Offenses | -0.903* | -0.931 | -0.904 |
| Suspicion | -6.363 | -3.296 | -6.225 |

This table reports estimates for the percentage change in arrests (by offense category) due to a one-percent increase in youth employment opportunities.
Significance is indicated by ***p<0.01, **p<0.05, *p<0.1.
Errors are clustered at the state level. Regressions are weighted by annual state population for a particular age-sex group.
Significance levels are adjusted for multiple hypothesis testing using the Benjamini-Hochberg step-up method.