

CRIME SCARS: RECESSIONS AND THE MAKING OF CAREER CRIMINALS

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Abstract—Recessions lead to short-term job loss, lower happiness, and decreasing income levels. There is growing evidence that workers who first join the labor market during economic downturns suffer from poor job matches that can have sustained detrimental effects on wages and career progressions. This paper uses U.S. and U.K. data to document a more disturbing long-run effect of recessions: young people who leave school during recessions are significantly more likely to lead a life of crime than those entering a buoyant labor market. Thus, crime scars resulting from higher entry-level unemployment rates prove to be long lasting and substantial.

1. Introduction

DO the labor market conditions the young encounter when first leaving school play a role in initiating and forming criminal careers? Think of two otherwise identical school leavers who left high school in 2010—one in North Dakota, the other in Michigan. Both have completed education and try to get a job. But the North Dakota school leaver faced a state unemployment rate of only 3.8% while it was 12.7% in Michigan. At the margin, the Michigan youngster is more likely to proceed down the wrong path—no luck getting a job, no welfare to fall back on, hanging out with similarly unfortunate juveniles, trouble with the police, some petty larceny, and so on—than the North Dakota youngster. Indeed this is just the standard Becker (1968) model in action. As youths leave school, they face a trade-off between legal and illegal activities. At higher unemployment rates, the expected returns to legal activity (i.e., work) are lower. All else equal, this encourages some youths to commit crime who would otherwise have avoided such a result in a more buoyant labor market.

But what might happen as these same youngsters age? Two obvious mechanisms link their experience straight out of high school with later ones. First, earlier experiences of crime can increase their stock of criminal knowledge and potentially reduce the costs of subsequent crime participation. Second, a previous criminal record (and less on-the-job human capital accumulation) may reduce the expected wage in the legal labor market. Both can be expected to increase the likelihood that the individual eventually ends up becoming a career criminal.

A substantial body of criminological evidence points to the importance of the experience of youths for understanding crime patterns. Almost two hundred years ago, Adolphe

Quetelet (1831) showed that crime in early nineteenth-century France peaked when individuals were in their late teens. Subsequent research has confirmed the strong age-crime pattern, with crime peaking in the late teens and declining with age quite rapidly.¹ Unsurprisingly in our data, the same patterns emerge.² The peak is at age 17 or 18 and then declines reasonably smoothly. However, it is still the case that the offender rate at age 29 is a lot higher than at age 39—showing criminality to be not just a feature of teenage years.

Evidence also points to strong links between criminality in teenage years and subsequent criminal behavior.³ In our data, for example, 72% of men aged over 25 in the United Kingdom who were convicted of a crime in 2002 had a criminal record that went back to their teenage years. Thus, factors that increase criminal behavior for juveniles have scope to raise the lifetime criminal participation rate. The focus of this paper is whether the state of the labor market at entry is such a factor.

In pursuing this research question, our analysis contributes to two distinct strands of literature. First, there has been an extensive, though partly unresolved, debate over the link between recessions and crime, studying whether crime rates, and in particular property crime rates, are countercyclical. The place where one can identify effects of unemployment on crime is for young adults.⁴ Thus, Gould, Weinberg, and Mustard (2002) examine the impact of contemporaneous unemployment and wages on the criminal behavior of less educated young males. Exploiting a panel of U.S. counties, they find significant effects for both wages and unemployment on property and violent crime. Fougère, Kramerz, and Pouget (2009) find strong effects from youth unemployment (but not overall unemployment) on crime in France, while Grönqvist (2013) uses Swedish register data

¹ See Hirschi and Gottfredson (1983) for the development of the formulation that crime-age profiles are invariant over time and space, and the subsequent body of research trying to refute this claim that followed (e.g., Greenberg, 1985; Hansen, 2003; and the metastudy of Pratt & Cullen, 2000).

² Figure A1 in the online appendix plots the average male offender rate by age for the United States and United Kingdom from 2000 to 2010. Full details on the data used in the chart are provided in section IV and the online data appendix. The chart shows the average offender rate (arrested in the United States and convicted in the United Kingdom), defined as the number of offenders in each age group divided by population in each age group. The data are averaged over the period 2000 to 2010.

³ See the many papers cited in the review of Nagin and Paternoster (2000), which frames the positive link at the individual level between past and future criminality in terms of individual heterogeneity and state dependence.

⁴ Indeed, Freeman's (1999) survey notes the relationship across the whole population to be "fragile, at best." More recent reviews confirm this, and therefore more focus can be placed on youth crime and unemployment to see labor market effects on crime (e.g., see Mustard, 2010, and Buonanno et al., 2011).

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to uncover a strong and precisely estimated link between youth unemployment and crime for both property and violent crimes.

Second, there is a growing literature on the effects of entering the labor market during recessions on outcomes later in life. That literature so far has focused on whether such workers experience sustained long-run negative consequences. Early contributions by Ellwood (1982) and Gardecki and Neumark (1998) found somewhat contrasting evidence on whether initial labor market experience affected subsequent outcomes, with Ellwood finding significant effects on wages but not on future spells of unemployment, while Gardecki and Neumark found little evidence of a sustained negative effect. More recently, Hershbein (2012) finds that a recession reduces starting wages of high school graduates by about 6% but that this penalty fades away within six years. Oreopoulos, von Wachter, and Heisz (2012) exploit a large Canadian longitudinal data set to show that the cost of a recession for new graduates is substantial and long lasting. A typical recession—a 5 percentage point rise in the unemployment rate—is associated with an initial loss of earnings of about 9% that halves within five years, and finally fades to 0 by ten years. The economic mechanism operates via initial placements with lower-paying employers and succeeding recoveries through gradual job mobility to better firms. Graduates in the lower quintile of the ability distribution suffer permanently lower wages, while the more able graduates quickly bounce back. Similar results are reported by Kahn (2010), who uses longitudinal data on U.S. college graduates, though some of her results suggest that the wage penalty is longer lasting. By contrast, Benedetto, Gathright, and Stinson (2010) find no evidence of a persistent impact of graduation-year unemployment on earnings using U.S. social security earnings data.⁵

Taking a somewhat different approach, Oyer (2006, 2008) has examined the career paths of particular occupations, economists and investment bankers, to assess the importance of initial conditions. He shows that stock market conditions at the time of graduation have a strong effect on whether M.B.A. students go directly to Wall Street or instead pursue alternatives such as jobs in consulting firms. Further, he shows that starting a career in investment banking directly after graduation causes a person to be more likely to stay in the job and earn significantly more. These effects are substantial in size, amounting to several million dollars in terms of present value.

Outside of the labor market literature, labor market entry conditions have been shown to have impacts on other outcomes. MacLean (2013), for example, finds that men who graduate from high school during a recession show worse health outcomes at age 40 than those graduating in a better

labor market. This is true for both self-reported health measures and objective measures of physical and mental health. Giuliano and Spilimbergo (2014) show that those who enter the labor market in recession are more likely to believe that success in life depends more on luck than effort and support more government redistribution. Again, these effects are seen to be long lasting. The protective effect of education for cohorts who graduate in recessions is studied by Cutler, Huang, and Lleras-Muney (2014) in their analysis of Eurobarometer data. They report evidence of lower wages and life satisfaction, together with higher obesity and a greater propensity to smoke and drink later in life, for individuals who graduate in recession years, with higher education levels significantly moderating these negative outcomes.

Our results uncover a more disturbing long-run effect of recessions. Based on a variety of individual and cohort-level data for men aged up to 39 from the United States and the United Kingdom, we report evidence of a systematic empirical link between crime and entry-level unemployment that very clearly shows that young people who leave school in the midst of recessions are significantly more likely to lead a life of crime than those entering a buoyant labor market. Thus, as other economic and social outcomes are significantly affected by the state of the business cycle at the time when individuals potentially enter the labor market, so is criminal activity. We conclude that recessions play a role in the making of career criminals, as crime scars from higher-entry-level unemployment rates are both long lasting and substantial.

The rest of the paper is structured as follows. In section II, we discuss possible links between initial conditions at labor market entry and the future path of criminal behavior, as well as the underlying dynamics to motivate our empirical research. In section III, we discuss the empirical strategy. We present the cohort panel results and individual-level evidence in sections IV and V, respectively. Section VI concludes.

II. Theoretical Background

In the standard Becker (1968) economics of crime model, individuals act as rational decision makers and choose between legal and illegal activity. Their choice is based on the expected returns to both options. In this simple yet powerful framework, returns to legal activity are solely determined by the market earnings from employment, whereas returns to illegal activity take into account the potential crime payoff, the probability of getting caught, and the expected sanction if caught. If the expected return to illegal activity outweighs the expected return to legal activity, the individual chooses to commit crime. In the Becker model, higher unemployment reduces the returns to legal activity. Thus, individuals facing unemployment or higher risk of unemployment may become more likely to commit crime than they would have been otherwise. That effect is expected to be higher for young people, who typi-

⁵ See also the international comparison of unemployment entry effects on labor market outcomes in the United States and Japan by Genda, Kondo, and Ohta (2010).

cally are less attached to the legal labor market than older individuals further on in their careers.

The model has proved valuable in highlighting the economic incentives associated with criminal activity and its basic predictions on incentive and deterrence effects on crime have received substantial empirical support (see the reviews of Draca & Machin, 2015; Freeman, 1999; and Chalfin & McCrary, 2017). Its weakness and limitation for our purposes is that it is explicitly static. Individuals make a one-off decision to commit crime or work in the legal sector. There is no process through which decisions made in the current period have implications for both future decisions and the choices available to the individual in later periods.

Mocan, Billups, and Overland (2005) develop a dynamic model that links recessions, human capital, and crime.⁶ Individuals are lifetime utility maximizers with income coming from the legal and the criminal sectors. Individuals have endowments of legal and criminal human capital, which depreciate over time. Both types of human capital rise with experience in the sector and are increased by investment in the respective sectors. The individual's income is a function of human capital and rates of return in both sectors. In each period, individuals solve a dynamic stochastic optimization problem. They decide how much time to allocate to legal and criminal work and then decide on the optimal level of consumption.

Crime is risky since a criminal faces a certain probability of being caught and sent to prison (or being punished otherwise). The probability of prison depends on the skill of the criminal as measured by criminal human capital and the amount of time spent in the criminal sector. While legal human capital may decline in prison in addition to depreciation effects (e.g., due to reputation effects), criminal human capital may increase if criminals in prison learn from each other.

In this model, recessions have an impact on crime through the respective dynamic evolutions of legal and criminal human capital. In that sense, the long-term impact of recessions on crime differs with the length and the depth of a recession. In a recession, the returns to legal human capital fall. Following the arguments from the standard Becker (1968) model, involvement in criminal activity rises depending on the relative and absolute returns to crime. If involvement in criminal activity increases, the criminal human capital stock is expected to grow while the legal human capital stock depreciates. Once the recession ends, returns to legal human capital increase again, and the relative returns to criminal activity decrease. In a short recession, the stock of legal human capital typically remains significantly higher than the stock of criminal human capital, and the individual exits the criminal sector. Basically, in such a short recession, the individual is encouraged to get

involved in criminal activity but is not exposed to these conditions for a long enough period to develop sufficient criminal capital in order to yield higher returns in the crime market than in the legal market once the recession ends.

If an individual is exposed to an unexpectedly long recession, the decision between legal and illegal activity changes in the same way as in a short recession. However, the individual's criminal human capital stock grows over a longer time period, whereas the legal human capital stock is expected to decline even more than in a shorter recession. These two effects may result in higher returns to criminal activity than to legal activity even after the recession ends. We expect more permanent effects of a recession on criminal behavior in that case. In addition, with higher involvement in criminal activity, the chances of being caught and imprisoned will rise. As explained above, if imprisoned, an individual's criminal human capital stock may rise further in absolute terms, and certainly it rises further relative to legal human capital. In that situation, hysteresis can occur and trigger criminal careers.

These mechanisms are likely to be stronger for those individuals with initially low levels of legal human capital. New entrants to the labor market have developed less legal human capital and are less attached to the legal labor market. In our empirical analysis, we study cohorts entering the labor market in different economic conditions and estimate the effect of entering the labor market in a recession on subsequent crime outcomes.

There has been extensive focus on the concept of a criminal career and how it develops with age in the criminology literature (see Piquero, Farrington, & Blumstein, 2003). A criminal career is often characterized by various stages: onset, persistence, escalation/specialization and desistance. Sampson and Laub (1993, 2005) characterize crime as a product of persistent individual differences and local life events. They find that incarceration in later life is strongly related to the difficulty in securing stable work as individuals entered young adulthood.

Our research question of whether labor market entry conditions matter for crime fits naturally into this framework. Unemployment at labor market entry (a local life event) can contribute to the onset of criminal behavior or can encourage the persistence of those youths who have already begun a criminal career, or both. The long-run effect of unemployment at labor market entry then depends on the persistence and desistance effects. There has been less research on the duration of criminal careers. One study (Piquero et al., 2003) finds that for offenders with two or more offenses, the average duration of criminal careers was 10.4 years.

In the discussion thus far we have implicitly assumed that unemployment at labor market entry causes the criminal career to begin at that point (or to intensify for those youths already active in crime). A complementary alternative would be that entry unemployment could have delayed effects on criminal behavior. Zara and Farrington (2010) study a group of late-onset offenders (those who commit

⁶ Other dynamic crime participation models include Flinn (1986) and Lochner (2004).

their first crime aged 21 or over). They find a significant effect of high unemployment at ages 16 to 18 as a predictor of subsequent offending (relative to a nonoffending control group). To address this in our empirical analysis, we consider an approach that is flexible enough to permit differential timing of the effects of labor market entry unemployment effects on crime.

III. Empirical Strategy

Our empirical analysis exploits both panel data on year-of-birth cohorts over space and time and individual data for the United States and the United Kingdom. The data are discussed in more detail in the following sections, as well as in the online data appendix.

For the panel data, we observe age/birth cohorts as they enter the labor market and follow them through their (potential) working lives up to age 39. Our unit of analysis is defined at the year-of-birth cohort (c), region (r), and calendar year (t) level where region refers to states in the United States and to standard regions in the United Kingdom. We can estimate the long-run effect of initial labor market conditions by exploiting the regional variation in entry unemployment rates across cohorts using the following equation:

$$\log(C)_{crt} = \alpha_c + \alpha_r + \alpha_t + \alpha_a + \beta U_{cr,0} + \gamma X_{crt} + \varepsilon_{crt}. \tag{1}$$

In equation (1), the dependent variable is the log crime rate for the cohort, region, and time cell, and we include fixed effects α_c , α_r , α_t , and α_a for cohort, region, time, and age. X is a set of control variables (defined below), and ε is an error term. Labor market entry occurs at date 0, so $U_{cr,0}$ denotes the cohort-region specific unemployment rate at that date.

The first pertinent feature of equation (1) is that (in common with a number of other applications when cohort data of different ages are followed over time) it is well known that one cannot separately identify age, cohort, and time effects. We follow the standard approach of including a full set of age, cohort, and time fixed effects and arbitrarily dropping one additional cohort effect.⁷ Second, in order to adjust for cohort compositional differences, we include the X set of covariates at the level of our unit of analysis. In particular, we adjust for the average share of immigrants, male graduates, black males, married males, and females per cohort in the region over the sample period.⁸

The baseline model in equation (1) is restrictive in that it assumes that subsequent unemployment rates that the cohort experiences have no effect on their criminal behav-

ior. In effect, the model allows us to estimate the average effect of entering the labor market in a recession on crime over the life cycle, given the usual pattern of regional unemployment that cohorts experience after entry. For the focus of this paper, we are arguably more interested in the effect of entry unemployment net of subsequent labor market conditions. To isolate this effect, we can include regional unemployment rates that the cohort experiences in the years after labor market entry. We measure these as $U_{cr,i}$, where $i > 0$ is the number of years since entry. This gives us a second, more general model to estimate:

$$\log(C)_{crt} = \alpha_c + \alpha_r + \alpha_t + \alpha_a + \beta U_{cr,0} + \sum_{i=1}^I \delta_i U_{cr,i} + \gamma X_{crt} + \varepsilon_{crt}, \tag{2}$$

where i can theoretically take any value up to the latest year observed since labor market entry (e.g., when $t = 0$ corresponds to age 16, it could run from 1 to 23 years subsequent to entry up to our maximum age of 39). A fully saturated unemployment rate model would allow the unemployment rate the cohort experienced in every year of his or her labor market experience to affect this person's crime rate. However, we restrict the coefficients on the i -dated unemployment rates to affect the cohort crime rate only when the cohort reaches that point in the life cycle. For example, the coefficient on regional unemployment five years after the cohort enters the labor market is restricted to be 0 until the cohort reaches five years of experience. This ensures that future unemployment rates cannot affect current crime, which is intuitively sensible.

Next, we introduce dynamics by further generalizing equations (1) and (2) to permit the main coefficient of interest on the initial unemployment rate, β , to vary with labor market experience/years since assumed labor market entry.⁹ This enables us to see to what extent the average effect of entry unemployment on a cohort occurs because of early scarring effects that erode as time since labor market entry increases or because of more persistent effects:

$$\log(C)_{crt} = \alpha_c + \alpha_r + \alpha_t + \alpha_a + \sum_{e=1}^E \beta_e [\mathbf{I}(\text{Exp} = e) \times U_{cr,0}] + \gamma X_{crt} + \varepsilon_{crt}. \tag{3}$$

This specification allows β to vary with potential labor market experience (Exp, for experience groups $e = 1, \dots, E$) to measure the extent to which any effect of initial unemployment on criminal behavior persists with length of time since labor market entry.

⁷ We could alternatively have required the cohort-effects to sum to 0 (Deaton, 1997), and our results prove to be robust to this alternative.

⁸ The specific control variables included are to account for demographic correlates of crime and for changing patterns of immigration (for examples of papers studying directly the connections between crime and immigration, see Bell, Fasani, & Machin, 2013; Bianchi, Buonanno, & Pinotti, 2012; and Mastrobuoni & Pinotti, 2015).

⁹ Potential experience here is years since labor market entry (i.e., age – [age at year $t = 0$], with $t = 0$ being the assumed labor market entry age as defined below) so the notation of the age/experience fixed effect in the estimating equations can be interchangeably used as either α_a or α_e .

Our final and most general estimating equation allows for the unemployment experienced after labor market entry to have permanent or transitory effects:

$$\begin{aligned} \log(C)_{crt} = & \alpha_c + \alpha_r + \alpha_t + \alpha_a \\ & + \sum_{e=1}^E \beta_e [I(\text{Exp} = e) \times U_{cr,0}] \\ & + \sum_{i=1}^I \sum_{e=1}^E \delta_{ie} [I(\text{Exp} = e) \times U_{cr,i}] \\ & + \gamma X_{crt} + \varepsilon_{crt}. \end{aligned} \quad (4)$$

In equation (4), both the β 's and the δ 's are allowed to depend on the length of time that passes since the entry and subsequent unemployment rate were experienced by the cohort. Again, the effects of subsequent unemployment are restricted to be 0 until the cohort reaches the relevant age.

It is important to be clear that identification comes from within-cohort variation in entry unemployment rates across states or regions. We view this as the most convincing approach that can be taken with the available data, and this therefore forms the basis of most of our results. However, it could be argued that removing the aggregate national unemployment rate at entry (which follows from including cohort fixed effects) removes much of the variation over time. To address this, we also report specifications using the national unemployment rate at labor market entry, including a quadratic cohort trend to account for changing cohort quality.

For the microlevel data, we observe cross-sections of individuals and can identify those who are incarcerated (in the U.S. data) and those who report having ever been arrested (in the U.K. data). For each individual, we can match the unemployment rate at the time of labor market entry by area of residence and estimate probability models to explore the effect on criminal outcomes in later life.

IV. Cohort Panel Evidence

A. Details of U.S. Panel Data

For the U.S. panel analysis, our measure of criminality is arrests. Use of arrests data is driven by two considerations. First, consistent annual incarceration data at the state and cohort level simply do not exist in the United States (see Pfaff, 2011). Second, it is of interest to measure criminality in a broad way to check that the results are robust. We therefore use arrest data from the FBI Uniform Crime Reports (UCR). The UCR reports the number of arrests by year, state, age, gender, and crime type. Our sample runs from 1980 to 2010.

We obtain the number of arrests for property and violent crimes by, respectively, aggregating arrests over crime types. Our measure for property crime includes arrests for burglary, larceny, vehicle theft, and arson, and our measure for violent crime includes arrests for murder, rape, robbery,

and assault. We produce arrest rates by dividing the number of arrests by the annual population in the observational unit, and scale by 1,000. Population data are retrieved from the U.S. Census population estimates.

The sample covers men aged between 16 and 39, the group of individuals with the highest crime propensity. The original data are grouped by age. Up to the age of 24, the data are reported by single age year, while for ages 25 and above, the data are grouped in five-year age bands (25–29, 30–34, 35–39). As our empirical strategy exploits year-of-birth cohorts, we assume that year-of-birth cohorts within these older age groups of 25–29, 30–34, and 35–39 are homogeneous in terms of arrest rates. We then construct the number of arrests for single-year-of-birth cohorts within these age groups by dividing the number of arrests by five. Our sample comprises year-of-birth cohorts that run from 1941 to 1994.¹⁰ Assuming that individuals enter the labor market at age 16, labor market entry would therefore occur from 1957 to 2010. We have data on state annual insured unemployment rates from 1957 until 2010.¹¹

Since data for some states are systematically missing, we exclude these states from our analysis.¹² States with missing data for a limited number of years only are included for the nonmissing years, leading to an unbalanced panel.¹³ There is, however, no evidence to suggest that the states that do not report data differ significantly in terms of entry unemployment rates. We also exclude state-year observations that cover arrests for less than 95% of the state population in that year.

Two conceptual issues arise with these data. First, since we link the current arrest rate for a particular cohort in a given state to the entry unemployment rate of that cohort in the same state, we assume cohorts do not substantially move across states over time. So, for example, we assume that the criminal behavior of the 30-year-old cohort in California in the year 2000 is affected by the unemployment rate in California in the year 1986, when that cohort entered the labor market. The empirical validity of this relies on no interstate mobility since school-leaving age. If there is mobility but it is random since school exit, the estimates will merely be noisy. But if mobility is driven by self-selection, the coefficient of interest may be biased. Following Dahl (2002), we present robustness tests based on mobility corrections from the U.S. Census.

¹⁰ Our first year of data on arrests is 1980 and the oldest age we consider is 39, so this cohort was born in 1941. Similarly, our data end in 2010, and the youngest age is 16 (i.e., the 1994 birth-cohort).

¹¹ The downside of using those data is that they do not allow us to distinguish between total and youth unemployment rates at labor market entry or provide measures of the duration of unemployment.

¹² As described in the online data appendix in more detail, excluded states are Indiana, Louisiana, Mississippi, Montana, Nebraska, New Hampshire, New Mexico, New York, Ohio, South Dakota, and Washington. As an example, New York is excluded since New York City (specifically the NYPD) systematically does not report arrests, and thus arrest data at state level would be heavily undercounted.

¹³ For example, Florida reports arrests until 1995 but not afterward. Thus, we include Florida in our sample until 1995.

TABLE 1.—U.S. COHORT PANEL ESTIMATES, BASIC SPECIFICATIONS

Crime Type	(1) All	(2) All	(3) Property	(4) Property	(5) Violent	(6) Violent
Panel A						
National entry unemployment rate at age 16–18	1.550*** (0.506)		1.419* (0.732)		1.871*** (0.519)	
State entry unemployment rate at age 16–18		2.039*** (0.443)		2.115*** (0.598)		2.156*** (0.524)
Panel B						
Mobility-adjusted state entry unemployment rate at age 16–18		2.470*** (0.609)		2.016** (0.771)		3.288*** (0.776)
State, year, and age fixed effects	X	X	X	X	X	X
Quadratic cohort trend	X		X		X	
Cohort fixed effects		X		X		X
Compositional adjustment	X	X	X	X	X	X
Sample size	19,429	19,429	19,429	19,429	19,429	19,429

Dependent variable is the log male arrest rate from the UCR. Sample runs from 1980 to 2010. Individual year-of-birth cohorts run from 1941 to 1994. We assume that cohorts enter the labor market between the ages of 16 and 18. All insured unemployment rates are measured as the average unemployment rate at the three potential years of labor market entry. All regressions include year, age, and state fixed effects. We include control variables for cohort compositional adjustments (average share of immigrants, male graduates, black men, married men, and women per cohort in that state 1980 to 2010). Columns 1, 3, and 5 include the cohort-level national unemployment rate at labor market entry and include a cohort quadratic trend. Columns 2, 4, and 6 include cohort-level state unemployment rates and include cohort fixed effects. Standard errors in parentheses are clustered at the state-cohort level and regressions are weighted by the male cell population. Significant at *10%, **5%, and ***1%.

Second, in our empirical work for the United States, we use the average unemployment rate that the cohort experienced at ages 16 to 18 as our measure of entry unemployment. This is motivated by the observation that the majority of arrested criminals have low educational attainment and generally leave school at or around the compulsory school-leaving age. In the U.S. Census data that we use in our microdata analysis, 86% of those incarcerated over the 1980–2010 sample had high school or less (twelve or fewer years of education) as their highest level of education. Since school-leaving ages differ slightly across time and states and unemployment within a cohort or state observation is autocorrelated, we use the age 16 to 18 average unemployment rate to characterize the state of the labor market that the cohort first experiences. An alternative would be to use the age 16 (or indeed age 17 or 18) unemployment rate only. We will show that our results are robust to these alternative approaches to defining entry unemployment.

B. Details of U.K. Panel Data

Crime data for the U.K. panel come from the Offenders Index Database (OID) and the Police National Computer (PNC). The measure of crime is convictions. This has the advantage of capturing actual offenders (subject, of course, to wrongful conviction) rather than the proportion of a particular cohort that come into contact with the police. The OID/PNC provides data on gender, date of birth, region of conviction, and offense category. This data sample again runs from 1980 to 2010. Our variable construction matches that of the U.S. panel. However, in contrast to the United States, there is a standard national school-leaving age in the United Kingdom. For those leaving school by 1972, the compulsory school-leaving age was 15, and from 1973 onward, it was 16. We use this compulsory age to date labor market entry for each cohort rather than taking the age 16 to 18 average. However, results are reported that again

show that our conclusions are robust to this alternative measure of labor market entry.

C. U.S. Results

We begin our analysis of the panel data by presenting evidence on the average effect of initial labor market conditions on criminal activity. In terms of the equations, this corresponds to equation (1), which restricts the coefficient β to be the same across experience groups. Panel a of table 1 shows the results for the United States. The dependent variable is the log of the crime rate. Columns 1, 3, and 5 consider the national unemployment rate at labor market entry, while columns 2, 4, and 6 use the state unemployment rate at labor market entry (our preferred specification). All regressions include year, state and age fixed effects, and cohort composition variables. The national results control for a quadratic cohort trend, while the state results include a full set of cohort fixed effects. The regressions are weighted by cell population, and robust standard errors are clustered at the state-cohort level.

Columns 1 and 2 of table 1 show a strong, positive estimated coefficient on the entry unemployment rate, whether we use the national or state-level variation in entry unemployment. For the state-level entry unemployment rate specification in column 2, the average arrest rate for a cohort entering the labor market in a recession is estimated to be around 10.2% higher than for a similar cohort entering into a normal labor market (using a 5 percentage point increase in unemployment as a measure of recession relative to normal).¹⁴ The estimate is statistically significant at the 1% level.

¹⁴ We have used a 5 percentage point increase to measure a recession. This is in line with the scale of the unemployment rate increase in the Great Recession in the United States and also with the recessions seen in the United Kingdom over the whole period we analyze. However, this may be a little high for the United States for pre-2000 recessions, where perhaps a 3 percentage point increase is a more appropriate magnitude of increase. Of course, the impact on the arrest rate would need to be scaled down by three-fifths for this recession size, so in the example here, it would drop to 6.1%.

This amounts to a substantial estimate of labor market entry effects on crime, but in some respects, the average effect of recessions may not be the most relevant parameter of interest. Within a cohort, there will be a substantial share for which the marginal effect is 0 since their optimal decision will be unaffected—that is, they are at an interior solution that results in no illegal behavior and the recession does not move them across the threshold. Thus, the average effect that we estimate is a combination of a zero effect for potentially a large share of the cohort and a substantial effect for those close to the legal/illegal threshold in the absence of a recession. Indeed, the results from the analysis of the individual-level Census data presented in section V suggest that this is the case, as the estimated entry-level unemployment effects are seen to be much larger for the less educated. The remaining columns show results for property crime and violent crime using both national and state unemployment variation. The results suggest very similar and statistically significant effects in all cases. In all subsequent results, we report only those that use state-level unemployment rates because we view this as providing the most convincing identification.¹⁵

One may have potential concerns about interstate mobility in the U.S. data. More precisely, the presence of mobility raises the question of what the correct (best measured) entry unemployment rate is for cohort c at time t in state s . So far, we have used the unemployment rate in state s at the time that cohort c left high school. This ignores any mobility, and if potential criminals move across state boundaries, this could be of concern. Some of those in cohort c at time t in state s will have completed high school in state k and entered the labor market there. For this part of the cohort, the correct entry unemployment rate is, of course, the unemployment rate in state k at the time cohort c left high school. Dahl (2002) makes the same point regarding estimates of state-specific earnings returns to education, which he shows differ substantially across states. His solution is to use reported migration flows across states to correct the estimated returns. We can follow broadly the same procedure here for the United States, though such data are not available for the United Kingdom. We use the 5% U.S. Census for 1980, 1990, and 2000 and the 2010 ACS to calculate for each cohort c in state s the distribution of states of birth. Assuming that state of birth and state at 16 are highly correlated, we generate a mobility-adjusted entry unemployment rate for cohort c in state s as

$$U_{cs} = \sum_{k=1}^K p_{csk} U_{ck}, \quad (5)$$

¹⁵ We have also broken down property and violent crime into more disaggregated measures of crime types (breaking violent crime separately into murder, rape, assault and robbery, and property crime separately into burglary, larceny theft, vehicle theft, and arson) and find there to be significant positive estimates of entry-level unemployment rates for all crimes with the exception of murder. These results are in table A1 of the online appendix.

where p is the proportion of cohort c in state s born in state k .

Panel B of table 1 reports estimates using this mobility-adjusted entry unemployment rate. The results are robust to the new specification, in that a positive and substantial entry-level unemployment rate effect on crime remains. The effect tends to be slightly larger in magnitude (at 2.470 compared to 2.039 in column 2), but very much validates the earlier results. Hence, this robustness check offers a useful corroboration of our main results; if anything, we appear to marginally underestimate the effect of initial unemployment at labor market entry on crime when we do not adjust for interregional mobility (although all the differences between mobility-adjusted and nonadjusted estimates are not distinguishable from one another in terms of statistical significance).

For the 1980–2000 time period, we also explored what happened to the entry-level unemployment rate on inclusion of the state-level “crack index” constructed by Fryer et al. (2013). The main results fully survived its inclusion, and the crack index itself displayed a positive and significant relation with the arrest rate.¹⁶ Thus, the results remain robust to controlling for the crack prevalence index that has been shown to be a driver of U.S. crime rates in the period that we study.

D. U.K. Results

The initial U.K. results are shown in table 2. The only specification difference compared to the U.S. results is that we allow cohort composition effects to have different coefficients in London compared to the rest of the United Kingdom. The differences in these estimated coefficients are statistically significant, suggesting that over time, cohort composition and their effects on crime have differed substantially between London and the rest of the United Kingdom.¹⁷

We again find a statistically significant effect of entry unemployment on overall crime. Taking the estimated coefficient in column 2, a recession that raises the (regional) unemployment rate by 5 percentage points would raise the

¹⁶ In fact, when the impact of the crack index was broken down into the subperiods that Fryer et al. (2013) use—1980–1884, 1985–1989, 1990–1994, and 1995–2000—we obtain similar estimates with the most important positive crime association being from 1985 to 1989. But the estimated coefficient on the entry-level unemployment rate was barely affected. For the 1980–2000 time period, the estimated coefficient (standard error) on specifications comparable to column 2 of table 1 were 1.156 (0.393) for the entry-level unemployment rate and 1.480 (0.557) for the mobility-adjusted rate. On inclusion of the time-varying crack index, these, respectively, became 1.155 (0.383) and 1.549 (0.548).

¹⁷ An alternative would be to estimate the models using the regional dimension outside London only. Results available on request show that this generates the same qualitative results as reported in the main text, though the precision tends to be somewhat higher. We prefer to include London and control directly for differences in the effect of cohort composition. Note that we do not allow for separate cohort effects for London, since this would remove any variation in entry unemployment for London.

TABLE 2.—U.K. COHORT PANEL ESTIMATES, BASIC SPECIFICATIONS

Crime Type	(1) All	(2) All	(3) Property	(4) Property	(5) Violent	(6) Violent
Panel A						
National entry unemployment rate at age 16	2.664*** (0.189)		3.443*** (0.249)		0.803*** (0.191)	
Region entry unemployment rate at age 16		0.811*** (0.277)		0.712** (0.350)		1.531*** (0.365)
Panel B						
Region entry short-term unemployment rate at age 16		-1.188* (0.620)		-1.008 (0.767)		-1.074 (0.933)
Region entry long-term unemployment rate at age 16		1.687*** (0.372)		1.466*** (0.474)		2.673*** (0.464)
Region, year, and age fixed effects	X	X	X	X	X	X
Quadratic cohort effect	X		X		X	
Cohort fixed effects		X		X		X
Compositional adjustment	X	X	X	X	X	X
Sample size	7,440	7,440	7,440	7,440	7,440	7,440

The dependent variable is the log male conviction rate from the OJD/PNC. The sample runs from 1980 to 2010. Individual year-of-birth cohorts run from 1941 to 1994. We assume that cohorts enter the labor market at age 15 or 16. All unemployment rates are measured in year of labor market entry. We include control variables for cohort compositional adjustments (average share of immigrants, male graduates, nonwhite men, and married men in each cohort or region, 1980–2010), allowing for differential effects of composition in London. All regressions include year, age, and region fixed effects. Columns 1, 3, and 5 include the cohort-level national unemployment rate at labor market entry and include a cohort quadratic trend. Columns 2, 4, and 6 include cohort-level region unemployment rates and include cohort fixed effects. Standard errors in parentheses are clustered at the region-cohort level, and regressions are weighted by the male cell population. Significant at *10%, **5%, and ***1%.

lifetime conviction rate by 4%. We are somewhat skeptical about magnitudes when using national entry unemployment as the source of identification. The difficulty arises because we have to assume a specific functional form for the cohort effect, whereas when regional entry unemployment is used, we can nonparametrically control for the cohort effect since identification comes from within-cohort variation across regions. To see the sensitivity of the results to this, note that the coefficient on national entry unemployment in column 1 of table 2 is 2.664 (0.189) when we allow a quadratic cohort trend. If instead we allow a quartic cohort trend, this coefficient drops to 1.007 (0.189). We prefer to focus on the results that exploit within-cohort variation.

Panel B of table 2 focuses on whether all recessions are alike. A feature of the labor market common to European countries over the past forty years, but almost completely absent for the United States (until the Great Recession), has been the incidence of long-term unemployment. We might expect, and the model of Mocan et al. (2005) predicts, that recessions characterized by rising rates of long-term unemployment would be much worse for potential scarring. Of course, initially a rising duration for the stock of currently unemployed is positive for new entrants since the stock of unemployed provides less competition for available vacancies, but we might expect this effect to be fleeting before the negative effects of unemployment duration on new entrants take their toll. To examine this, we divide the entry unemployment rate in the United Kingdom into the short-term and long-term unemployment rate. Short-term unemployment covers all those with a current unemployment spell of less than twelve months. For our entire sample, the average unemployment rate of 7.4% is made up of a short-term rate of 4.6% and a long-term rate of 2.8%. The results reported in panel B show strongly that deep and long recessions characterized by high long-term unemployment are particularly problematic.

E. Dynamic Effects

The specification used in tables 1 and 2 implies that subsequent unemployment rates do not matter or are at least orthogonal to the entry unemployment rate. There is no reason for this to be the case, and so we follow the earnings study of Oreopoulos et al. (2012) in allowing for subsequent unemployment rates to affect our outcome of interest, crime, in addition to the entry rate. We do so by including the average unemployment rates for ages 19 to 21, 22 to 24, and 25 to 27. In essence, this means that for a particular cohort, we allow for their crime path to be explained by both the unemployment they experience when entering the labor market and the unemployment rates they experience over the next ten years.¹⁸

Tables A2 and A3 in the online appendix present the results of this exercise. It is perhaps most useful to focus on column 3, where we allow for two changes, breaking the age 16–18 unemployment rate into its component parts and allowing for subsequent unemployment rates. On the first of these, when we allow for separate estimated effects for any individual year of unemployment, the estimates are imprecise. However, the *p*-value from a hypothesis test of the joint significance of the three individual year effects is significant at the 1% level. The reason is that there is a high degree of autocorrelation in the within-cohort unemployment rate.¹⁹ We therefore prefer to use either the age 16 effect alone (recognizing that it is picking up effects for age 17 and 18 as well) or the three-year average. As columns 1 and 2 show, it matters little which we choose. The second

¹⁸ We have also experimented with including unemployment rates prior to school-leaving age. Their additional inclusion leaves the positive and significant estimated impact of entry unemployment intact.

¹⁹ Online appendix figures A2 and A3 show this strong persistence in the autocorrelations of unemployment rates within a cohort/state group for the United States and United Kingdom, respectively.

TABLE 3.—U.S. COHORT PANEL ESTIMATES, EFFECTS BY LABOR MARKET EXPERIENCE GROUPS

Crime Type	(1) All	(2) All	(3) Property	(4) Violent
State entry unemployment rate at age 16–18×Exp(0–5)	3.609*** (0.626)	3.290*** (0.702)	1.481** (0.717)	5.151*** (1.124)
State entry unemployment rate at age 16–18×Exp(6–11)	1.926*** (0.535)	1.705*** (0.617)	0.965 (0.737)	2.615*** (0.821)
State entry unemployment rate at age 16–18×Exp(12–17)	1.475*** (0.556)	1.558** (0.643)	2.151** (0.911)	0.883 (0.752)
State entry unemployment rate at age 16–18×Exp(18–21)	1.515*** (0.566)	2.421*** (0.707)	3.345*** (0.959)	2.032** (0.859)
State, year, cohort, and age fixed effects	X	X	X	X
Compositional adjustment	X	X	X	X
Allowing for subsequent U rates		X	X	X
Sample size	19,429	19,429	19,429	19,429

Exp: experience. As for columns 2, 4, and 6 specifications of panel a, table 1. Significant at *10%, **5%, and ***1%.

TABLE 4.—U.K. COHORT PANEL ESTIMATES, EFFECTS BY LABOR MARKET EXPERIENCE GROUPS

	(1) All	(2) All	(3) Property	(4) Violent
Region entry unemployment rate at age 16×Exp(0–5)	0.861*** (0.305)	0.967*** (0.316)	0.972*** (0.362)	1.034* (0.532)
Region entry unemployment rate at age 16×Exp(6–11)	0.913*** (0.284)	0.970*** (0.298)	1.050*** (0.365)	0.996** (0.444)
Region entry unemployment rate at age 16×Exp(12–17)	0.832** (0.343)	0.809** (0.358)	0.733 (0.448)	1.369*** (0.435)
Region entry unemployment rate at age 16×Exp(18–23)	0.582 (0.369)	0.529 (0.405)	0.124 (0.502)	2.701*** (0.504)
Region, year, cohort, and age fixed effects	X	X	X	X
Compositional adjustment	X	X	X	X
Subsequent unemployment interactions		X	X	X
Sample size	7,440	7,440	7,440	7,440

Exp: experience. As for columns 2, 4, and 6 specifications of panel a, table 2. Significant at *10%, **5%, and ***1%.

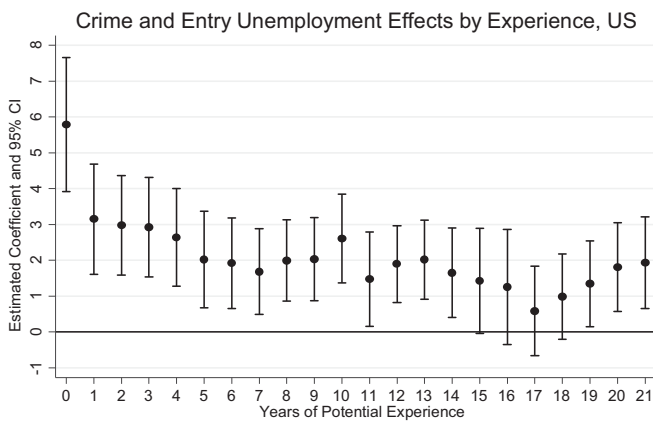
key result of column 3 is that none of the subsequent three-year average unemployment rates that the cohort experiences has an individually significant effect on arrests. This helps us to better understand a puzzle in the literature that we referred to in section I: the overall link between crime and unemployment appears quite weak in many studies. Our results show that the key effect from unemployment on a cohort's crime trajectory is the early experience of unemployment rather than the average unemployment experienced over the life cycle.

Tables 1 and 2 demonstrated a statistically significant and economically substantial effect of initial unemployment conditions on the arrest rates of cohorts over their entire lifetime. But we are also interested in the persistence of this. Is the entry unemployment effect primarily driven by a very large impact on crime in the early years after labor market entry that subsides as the young age and go on to establish a stable legal career? Or is the effect persistent, with some of those affected by harsh labor market conditions at labor market entry pushed into a criminal career that becomes self-perpetuating for the reasons discussed in section II? To study this, we allow the coefficient on initial unemployment to vary by years since labor market entry as outlined in equation (3) of section III.

We group experience into four categories (0–5, 6–11, 12–17, and 18–21 years) and use an identical regression specification as in table 1. Experience is set to 0 for ages 16 to 18. The results are shown in tables 3 and 4 for the United States and United Kingdom, respectively, with columns 1 and 2 showing results for all crimes and columns 3 and 4 for property and violent crime, respectively. Column 1 is estimated without controlling for subsequent unemployment, whereas columns 2 to 4 allow for these effects interacted with experience dummies—equation (4). There are strong, positive effects of entry unemployment on arrests in the early years in the labor market that fall as experience increases. However, even a decade after leaving school, there remain significant positive effects from entry unemployment on crime rates. Juveniles who leave school in a recession have higher crime rates during their first few years in the labor market *and* higher crime rates over a decade later than juveniles who leave school in a buoyant economy.

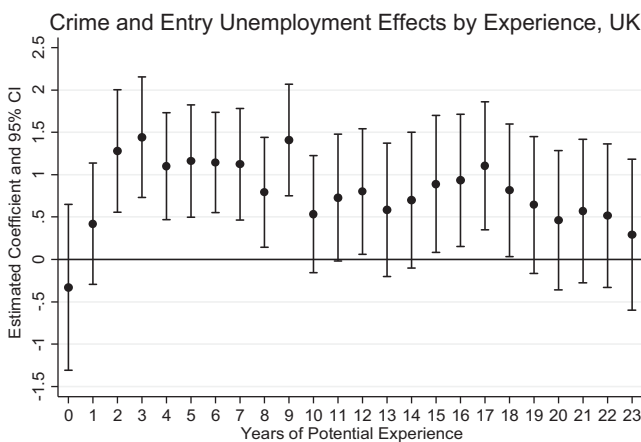
An alternative specification to examine the persistence of entry unemployment allows the interaction term with experience to vary with individual years of experience (rather than group experience as in tables 3 and 4). Figures 1 and 2 plot the estimated coefficients (together with the

FIGURE 1.—ENTRY UNEMPLOYMENT EFFECTS BY EXPERIENCE, UNITED STATES



Derived from specification comparable to that in column 1 of table 3, with separate estimates for each year of experience.

FIGURE 2.—ENTRY UNEMPLOYMENT EFFECTS BY EXPERIENCE, UNITED KINGDOM



Derived from specification comparable to that in column 1 of table 4, with separate estimates for each year of experience.

95% confidence intervals) for every year of labor market experience for the United States and United Kingdom, respectively.²⁰ Again, the drop in the effect after the first few years of labor market entry is clear, but the individual-year estimates suggest a consistent longer-lasting scarring effect for both countries.

V. Individual-Level Evidence

A. Details of U.S. Microdata

The microlevel data on U.S. incarceration of individuals come from the U.S. decennial Census and American Community Survey (ACS) data. We study all males aged 18 to 39 from the 5% samples of the 1980, 1990, and 2000 Census and the 2008–2012 ACS from IPUMS-USA (Integrated Public Use Microdata Series). We identify the institutiona-

²⁰ Figures A4 and A5 in the online appendix show the respective results when one allows unemployment rates later in life to enter the regression. The figures show patterns that are substantively the same.

lized population using the Group Quarters variable contained in these data sources. However, only in the 1980 sample is that variable available at a detailed enough level to uniquely identify those in correctional facilities. In subsequent censuses (and in the ACS), the institutionalized population includes the following additional categories: correctional facilities, nursing homes and mental hospitals, and juvenile institutions. Fortunately for our purposes, among the younger ages we focus on, the share of the total institutionalized population accounted for by those in correctional facilities is very high in our sample (see online appendix table A4 and its surrounding discussion in the online data appendix on the validity of this). The additional covariates from the Census data include race, marital status, veteran status, and education.

B. Details of U.K. Microdata

Our microlevel data for the United Kingdom come from the British Crime Survey (BCS), a large (45,000 individuals) annual cross-section survey used to construct measures of crime victimization. Each year, a subsample of respondents is asked whether they have ever been arrested by the police. There is no information on the type of crime for which they were arrested or on the eventual outcome. However, because we used conviction data in the U.K. panel analysis, it is useful to have an alternative counterpoint measure of criminal behavior (as in Lochner & Moretti, 2004) to evaluate robustness. We have a broad array of personal characteristics, including education, ethnicity, marital status, housing status, and employment and income.

C. U.S. Results

Panel A of table 5 reports marginal effects from a probit regression on the Census incarceration data. We use state at birth to identify the state in which the individual went to school (Dahl, 2002) and so restrict the data to those born in the United States. Column 1 reports the results for the full sample of males aged 18 to 39, and the subsequent three columns focus on samples defined by educational attainment. All regressions include a full set of year, state of residence, state of birth, and cohort effects, a quartic in age, and controls for race, education, marital status, and veteran status.

The estimated coefficient on entry unemployment in column 1 is 0.038. The mean of the dependent variable is 0.030 (i.e., 3% of males aged 18 to 39 are incarcerated). Thus, entering the labor market in a time of recession (defined as the unemployment rate being 5 percentage points higher than normal) results in a 6.3% increase in the probability of being incarcerated at the time of subsequent Census survey dates. However, we can see from the subsequent columns that this effect is almost entirely due to the high school dropouts. A recession increases this group's probability of incarceration by 6.6% from an already high mean of 8.9%. These are sizable effects, taking into account

TABLE 5.—U.S. INDIVIDUAL LEVEL ESTIMATES, CENSUS/ACS INCARCERATION REGRESSIONS, 1980–2010

Sample:	(1) All Males	(2) High School Dropouts	(3) High Scholl Graduates	(4) Four-Year College
A. Aged 18 and over				
State entry unemployment rate at age 16–18	0.038** (0.018)	0.117* (0.063)	0.023 (0.030)	–0.002 (0.008)
B. Aged 18 and over, 1980 Redefined				
State entry unemployment rate at age 16–18	0.035* (0.018)	0.130** (0.062)	0.016 (0.030)	–0.007 (0.008)
Year, state, and cohort effects	X	X	X	X
State/race effects	X	X	X	X
State of birth effects	X	X	X	X
Age quartic	X	X	X	X
Sample size	5,759,537	798,546	2,552,973	1,164,030

The table reports estimated marginal effects from a probit where the dependent variable is a dummy equal to 1 if the individual is institutionalized and 0 otherwise. The sample covers males aged 18 to 39 who are not in school and were born in the United States. Entry unemployment is the unemployment rate at age 16 in the state of birth. Data are from the 1980, 1990, and 2000 5% IPUMS U.S. Census and the 2008–2012 IPUMS ACS. Regressions also include marital status, race, education, and veteran status indicators. Standard errors in parentheses are clustered at the state/cohort level, and regressions are weighted with the Census person weight. Significant at *10%, **5%, and ***1%.

TABLE 6.—U.K. SELF-REPORT ARREST REGRESSIONS, 2001/2 TO 2010/11

	(1) Ever Arrested	(2) Ever Arrested, Age 16 Qualification	(3) Ever Arrested, Age 18 or Older Qualification
Region entry unemployment rate at age 16	0.259** (0.125)	0.543*** (0.166)	0.055 (0.207)
Year dummies	X	X	X
Personal controls	X	X	X
Mean of dependent variable	0.216	0.288	0.153
Sample size	22,281	7,849	9,006

The table reports estimated marginal effects from a probit where the dependent variable is a dummy equal to 1 if the individual reports having ever been arrested and 0 otherwise. Personal controls include age (10 categories), ethnic group (5 categories), education (9 categories where appropriate), student status, marital status (4 categories), income (18 categories), economic status (15 categories), number of children (10 categories), housing tenure (8 categories), years at address (9 categories), years in area (9 categories), and government office region (10 categories). The sample covers ages 16 to 65 of pooled British Crime Surveys, 2001–2002 to 2010–2011. Regressions use individual sample weights. Standard errors in parentheses are clustered at the government office region level. Significant at *10%, **5%, and ***1%.

that this is averaged over more than twenty years of the individual's postschool experience.

Finally, columns 3 and 4 show only weak effects for those who successfully graduate from high school and no effect at all for those with four years of college—who should, of course, not be affected by the unemployment rate at the compulsory school-leaving age.²¹ The results in panel B show that redefining the 1980 measure of incarceration by explicitly excluding those not in correctional facilities (see the online data appendix for discussion) does not alter the conclusions. This suggests that policy focused explicitly on the least educated during periods of high unemployment would likely reduce crime substantially more within that group than the average estimate from the previously reported panel regressions would imply.

D. U.K. Results

For the United Kingdom, we look at individual-level data on self-reported arrests. The data provide information on the age at which the respondent left full-time education and

so allow us to precisely date the year of labor market entry. The data also provide an extensive set of personal characteristics, which we would expect to be correlated with criminal activity. There are two key disadvantages in using these microdata. First, there is the usual concern associated with the self-reporting of arrests. In the context of this study, however, this would bias our estimates only if the self-reporting probability varied within a cohort depending on the initial entry unemployment rate. It seems hard to us to make such a case. Second, we have no information of when the arrest occurred; the question is simply whether the individual has ever been arrested. That means that these data allow us to estimate the average impact of initial entry unemployment on the probability of being arrested in adulthood but do not allow us to investigate the time pattern of the persistence of such effects.

We estimate probit models with the dependent variable taking the value 1 if the respondent reports having ever been arrested by the police. We include survey year dummies and an extensive set of personal controls. Table 6 reports the results. Column 1 shows an estimated significant positive coefficient on the entry unemployment rate: a recession (again defined as a 5 percentage points higher than normal unemployment rate) is associated with a 5.7% increase in the probability of ever being arrested.

In the second column, we restrict attention to those whose highest educational qualification was achieved at age 16 and therefore definitely left education at age 16. Here,

²¹ To further examine the sensitivity of our results to mobility, we restricted the Census sample in table 5 to include only those observations where the state of residence was the same as the state of birth. Reestimating table 5 with this restricted sample produces estimated coefficients (and associated standard errors) of 0.047 (0.024) and 0.161 (0.074) for the first two columns. The coefficients in the final two columns remain small in magnitude and statistically insignificant.

we can more closely link the exit from education and the initial unemployment rate, which results in a sample that is likely to contain a larger fraction of individuals at risk of criminal behavior. As expected, we find a substantially larger and more significant impact of entry unemployment for this group: a recession raises the probability of ever being arrested by 8%.

In the final column, we conduct a placebo-type experiment. We examine the arrest record of individuals who report educational qualifications that require school attendance at least to age 18. This group should not have been directly affected by the unemployment rate when they were 16. Sure enough, we no longer find a positive effect for these individuals. Indeed the estimated coefficient on the entry unemployment rate is indistinguishable from 0, though the standard error is large.

Overall, then, the individual-level analysis of the relationship between crime and entry-level unemployment produces results that are very similar to the cohort panel analysis of section IV. This is true for both countries, despite some differences in the nature of the data that are available. The individual data permit us to study variations across individuals with different levels of education in more detail than the more macro cohort analysis, which does not permit such differentiation. It is highly reassuring that the overall pattern of results are very consistent across the two.

VI. Conclusion

We have presented the first evidence that recessions can lead to substantial and persistently higher rates of criminal behavior among those likely to be most affected by such conditions: those newly entering the labor market. In contrast to much of the evidence on the long-run effect of initial unemployment on wages and career trajectories, we find that the effect on criminal behavior remains substantial, though attenuated, a number of years after labor market entry. These sizable and persistent entry-level unemployment effects show that recessions can produce career criminals. One might argue that our results are also consistent with a one-time criminal event for individuals in a particular cohort that happens at different times since leaving school and that the probability of such a subsequent event could be higher if entry-level unemployment were higher. Such a view would, however, be in conflict with two key empirical findings in the criminology literature, both consistent with our interpretation of the results: late-onset offending is extremely rare, and prolific offenders account for a disproportionate share of total crime.

This evidence of a crime-scarring effect from unemployment at the time of labor market entry emerges from empirical analysis of a range of different U.S. and U.K. data sources at the level of the individual and from longitudinal analysis of age and birth cohorts over time. While the reported effects are likely to be one factor among several that can plausibly explain the sizable swings in youth crim-

inality that have occurred in both countries in the past few decades, the evidence of crime scars does demonstrate a rather more disturbing long-run effect of recessions. In doing so, it also adds to the research picture that the state of the business cycle when people leave school and enter the labor market can have profound and sizable impacts on economic and social outcomes across their life.

REFERENCES

- Becker, Gary S., "Crime and Punishment: An Economic Approach," *Journal of Political Economy* 76 (1968), 169–217.
- Bell, Brian, Francesco Fasani, and Stephen Machin, "Crime and Immigration: Evidence from Large Immigrant Waves," *this REVIEW* 95 (2013), 1278–1290.
- Benedetto, Gary, Graton Gathright, and Martha Stinson, "The Earnings Impact of Graduating from College during a Recession," U.S. Census Bureau mimeograph (2010).
- Bianchi, Milo, Paolo Buonanno, and Paolo Pinotti, "Do Immigrants Cause Crime?" *Journal of the European Economic Association* 10 (2012), 1318–1347.
- Buonanno, Paolo, Francesco Drago, Roberto Galbiati, and Giulio Zanella, "Crime in Europe and the United States: Dissecting the 'Reversal of Misfortunes,'" *Economic Policy* 26 (2011), 347–385.
- Chalfin, Aaron, and Justin McCrary, "Criminal Deterrence: A Review of the Literature," *Journal of Economic Literature* 55 (2017), 5–48.
- Cutler, David M., Wei Huang, and Adriana Lleras-Muney, "When Does Education Matter? The Protective Effect of Education for Cohorts Graduating in Bad Times," *Social Science and Medicine* 127 (2015), 63–73.
- Dahl, Gordon, "Mobility and the Return to Education: Testing a Roy Model with Multiple Markets," *Econometrica* 70 (2002), 2367–2420.
- Deaton, Angus, *The Analysis of Household Surveys: A Microeconomic Approach to Development Policy* (Baltimore: Johns Hopkins University Press, 1997).
- Draca, Mirko, and Stephen Machin, "Crime and Economics Incentives," *Annual Review of Economics* 7 (2015), 389–408.
- Ellwood, David T., "Teenage Unemployment: Permanent Scars or Temporary Blemishes," in Richard Freeman and David A. Wise, eds., *The Youth Labor Market Problem: Its Nature, Causes, and Consequences* (Chicago: University of Chicago Press for NBER, 1982).
- Flinn, Christopher, "Dynamic Models of Criminal Careers," in Alfred Blumstein, Jacqueline Cohen, Jeffrey A. Roth, and Christy A. Visher, eds., *Criminal Careers and "Career Criminals"* (Washington DC: National Academy Press, 1986).
- Fougère, Denis, Francis Kramarz, and Julien Pouget "Youth Unemployment and Crime," *Journal of the European Economic Association* 7 (2009), 909–938.
- Freeman, Richard, "The Economics of Crime," in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 3c (Amsterdam: North-Holland Press, 1999).
- Fryer, Roland G., Paul S. Heaton, Steven D. Levitt, and Keven M. Murphy "Measuring Crack Cocaine and Its Impact," *Economic Inquiry* 51 (2013), 1651–1681.
- Gardecki, Rosella, and David Neumark, "Order from Chaos? The Effects of Early Labor Market Experiences on Adult Labor Market Outcomes," *Industrial and Labor Relations Review* 51 (1998), 299–322.
- Genda, Yuji, Ayako Kondo, and Souichi Ohta, "Long-Term Effects of a Recession at Labor Market Entry in Japan and the United States," *Journal of Human Resources* 45 (2010), 157–196.
- Giuliano, Paola, and Antonio Spilimbergo, "Growing Up in a Recession," *Review of Economic Studies* 81 (2014), 787–817.
- Gould, Eric, Bruce Weinberg, and David Mustard, "Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997," *this REVIEW* 84 (2002), 45–61.
- Greenberg, David F., "Age, Crime and Social Explanation," *American Journal of Sociology* 91 (1985), 1–21.
- Grönqvist, Hans, "Youth Unemployment and Crime: Lessons from Longitudinal Population Records," Stockholm University mimeograph (2013).

- Hansen, Kirstine, "Education and the Crime-Age Profile," *British Journal of Criminology* 43 (2003), 141–168.
- Hershbein, Brad J., "Graduating High School in a Recession: Work, Education and Home Production," *B. E. Journal of Economic Analysis and Policy* 12 (2012), 1–32.
- Hirschi, Travis, and Michael Gottfredson, "Age and the Explanation of Crime," *American Journal of Sociology* 89 (1983), 552–584.
- Kahn, Lisa, "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," *Labor Economics* 17 (2010), 303–316.
- Lochner, Lance, "Education, Work and Crime: A Human Capital Approach," *International Economic Review* 45 (2004), 811–843.
- Lochner, Lance, and Enrico Moretti, "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests and Self-Reports," *American Economic Review* 94 (2004), 155–189.
- MacLean, Johanna, "The Health Effects of Leaving School in a Bad Economy," *Journal of Health Economics* 32 (2013), 951–964.
- Mastrobuoni, Giovanni, and Paolo Pinotti, "Legal Status and the Criminal Activity of Immigrants," *American Economic Journal: Applied Economics* 7 (2015), 175–206.
- Mocan, Naci, Stephen C. Billups, and Jody Overland, "A Dynamic Model of Differential Human Capital and Crime," *Economica* 72 (2005), 655–681.
- Mustard, David, "How Do Labor Markets Affect Crime? New Evidence on an Old Puzzle," in Bruce L. Benson and Paul R. Zimmerman, eds., *Handbook on the Economics of Crime* (Northampton, MA: Elgar, 2010).
- Nagin, Daniel, and Raymond Paternoster, "Population Heterogeneity and State Dependence: State of the Evidence and Directions for Future Research," *Journal of Quantitative Criminology* 16 (2000), 117–144.
- Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, "The Short- and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics* 4 (2012), 1–29.
- Oyer, Paul, "Initial Labor Market Conditions and Long-Term Outcomes for Economists," *Journal of Economic Perspectives* 20 (2006), 143–160.
- "The Making of an Investment Banker: Macroeconomic Shocks, Career Choice and Lifetime Income," *Journal of Finance* 63 (2008), 2601–2628.
- Pfaff, John, "The Myths and Realities of Correctional Severity: Evidence from the National Corrections Reporting Program," *American Law and Economics Review* 13 (2011), 491–531.
- Piquero, Alex, David Farrington, and Alfred Blumstein, "The Criminal Career Paradigm," *Crime and Justice* 30 (2003), 359–506.
- Pratt, Travis, and Francis Cullen, "The Empirical Status of Gottfredson and Hirschi's General Theory of Crime: A Meta-Analysis," *Criminology* 38 (2000), 931–964.
- Quetelet, Adolphe, *Research on the Propensity for Crime at Different Ages*, translated and introduced by Sawyer F. Sylvester (Cincinnati: Anderson, 1831 [1984]).
- Sampson, Robert, and John Laub, *Crime in the Making: Pathways and Turning Points through Life* (Cambridge, MA: Harvard University Press, 1993).
- "A Life-Course View of the Development of Crime," *Annals of the American Academy of Political and Social Science* 602 (2005), 12–45, 73–79.
- Zara, Georgia, and David P. Farrington, "A Longitudinal Analysis of Early Risk Factors for Adult-Onset Offending: What Predicts a Delayed Criminal Career?" *Criminal Behaviour and Mental Health* 20 (2010), 257–273.