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EMPLOYMENT, DYNAMIC DETERRENCE AND CRIME

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ABSTRACT

Using monthly panel data we solve and estimate, using maximum likelihood techniques, an explicitly dynamic model of criminal behavior where current criminal activity adversely affects future employment outcomes. This acts as "dynamic deterrence" to crime: the threat of future adverse effects on employment payoffs when caught committing crimes reduces the incentive to commit them. We show that this dynamic deterrence effect is strong in the data. Hence, policies which weaken dynamic deterrence will be less effective in fighting crime. This suggests that prevention is more powerful than redemption since the latter weakens dynamic deterrence as anticipated future redemption allows criminals to look forward to negating the consequences of their crimes. Static models of criminal behavior neglect this and hence sole reliance on them can result in misleading policy analysis.

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1 Introduction

From any perspective, the *U.S.* is a land of contradictions. It is the land of plenty, yet it is also the land of poverty and crime. From 1960 to 1991, the crime rate in the *U.S.* has approximately tripled. The clearance rate, the ratio of arrests to known crimes, has fallen from around 31% to 21%, the median time served has fallen, as has the probability of imprisonment.[1] Yet as Freeman (1996) points out there has been mass incarceration, so much so that "All told, 7 percent as many men were under the 'supervision of the criminal justice system' (incarcerated, paroled or probated) as were in the work force." He points out that in 1993, the number incarcerated alone was about the same proportion of the labor force as the long term unemployed who are on the dole in many European countries. The incarcerated are disproportionately young black men, with low educational status. The numbers are frightening. For example, 34% of black high school dropouts between the age of 25 and 34 were incarcerated in 1993.[2] The costs of dealing with such levels of crime are enormous. Freeman (1996) points out that California spent 9.9% of its state budget in 1995 on prison while it spent 9.5% on higher education. In comparison, in 1980 these numbers were 2% and 12.6% respectively. He estimates that about 2% of *GDP* is spent on controlling crime by private

[1] See Ehrlich (1996) Table 1 for details.

[2] There is recent evidence that the crime wave is receding. The 1999 figures from the FBI show the uniform crime index as being the lowest since 1973 and having fallen by 8% from1998 and 27% from 1990. Preliminary data for 2000 shows a fall of only .3% suggesting that this improvement may be levelling off. Whether this is a short run aberration or a longer term trend is hard to know at this time.

individuals and public agencies while the cost incurred by society of criminal behavior could be another 2%.

Thus, public policy in this area is of great importance. Criminal behavior involves choices which impact on the future, and on the payoffs from choices made in the future. Hence, explicitly dynamic models of individual behavior need to be constructed and estimated. Individuals form expectations on future benefits and costs of crime and take them into account when making choices. Dynamic deterrence works through the threat of future adverse effect on payoffs when caught committing crimes. Thus, if one wishes to uncover overall deterrence effects of policy, it is hard to do so without using a dynamic model. For example, consider the effect of rehabilitation in prison. While this would reduce crime upon release by raising the payoff of not committing crimes, it would tend to increase crimes early on because of a reduction in dynamic deterrence. However, much of the work by economists has been static and/or reduced form in nature, see for example, the seminal theoretical work by Becker (1968), and recent empirical work by Tauchen et. al. (1994), and Grogger (1995). While such work is undoubtedly useful, it may give different policy insights than a dynamic model would, as discussed above, as well as being less amenable to counter factual policy experiments than would a more structural approach.

There is evidence that dynamic aspects are important in understanding criminal behavior. For example, since juvenile records are sealed at age 18 and juvenile courts sanctions are much milder than those in adult courts, there is reason to expect crime to be higher below age 18. Levitt (1997) shows that states where juvenile punishments are relatively mild compared to adult ones see a sharper drop off in the age arrest profile after 18 than states where juvenile punishments are relatively harsh. This is consistent with anticipatory behavior on the part of individuals. There is also evidence that fines are relatively ineffective deterrents compared to punishments that are more publicly visible, such as social service. If the latter have longer term effects, such as eroding social status, they may act as a strong dynamic deterrent.

The only paper we are aware of that begins to take a dynamic structural approach is that of Williams and Sickles (1997). However, their focus is on how differences across individuals in the extent of initial social capital translate into different behavior and hence different paths of social capital and career choices. This explains how criminals and non criminals can face similar wages yet make different choices. They estimate a model of continuous choice of hours of criminal activities using the Euler equation GMM approach. They focus on hours worked versus spent on criminal activity and omit any individuals below the age 18 from their data. In contrast, we use a maximum likelihood approach and emphasize the choice of whether to commit a crime or not and the consequences on future employment outcomes. We also include both criminal choice during high school and beyond into our estimation.[3]

Since we allow criminal behavior to affect employment outcomes, we can model the vicious cycle whereby crime and unemployment serve to reinforce each other. There have been studies, such as Grogger (1995) and Kling (1998), which estimate the effect of past arrests on current employment and wages. They conclude that after taking account of the unobserved heterogeneity via fixed effect or instruments, the wage and employment effect of past arrests are small and temporary. However, in their work, it may be the fixed effects which capture the vicious cycle of crime and unemployment. This may well also be why wage and employment effects of past arrests are small and temporary in such estimations. Despite this, the cumulative effects of crime and unemployment could be large in a dynamic model. Recently, Grogger (1998) estimates a static model of wage and employment as well as criminal behavior. He concludes that wages significantly affect criminal behavior. However, such an approach cannot capture any expectational effects. For example, in the static model, an increase in unemployment results in an increase in crime. In contrast, in the dynamic model, a permanent anticipated increase in unemployment reduces crime. Why? Current criminal activity adversely affects future employment outcomes. This acts as dynamic

[3] The Euler equation GMM estimation technique used by Sickes and Williams (1997) works well with continuous data, and not so well with the discrete crime data they use, because they have to infer the number of hours allocated for criminal activities on the basis of arrests. In addition, they do not focus on dynamic deterrence or counterfactual experiments.

deterrence to crime. A permanent reduction in unemployment reduces the deterrence effect of greater future unemployment as a consequence of being caught and hence raises criminal activity.

Lochner (1999) uses a 2 period model to look at some simple dynamic relations between education, work and crime. The correlations suggested by this model are examined using data from the 1980 crime survey and the other panel data of the NLSY. In his paper, he emphasizes the role of human capital accumulation on criminal behavior. But he only uses a one year crime survey, and thus cannot adequately deal with the issue of unobserved heterogeneity. There have also been simulation studies of criminal behavior based on calibrated dynamic models of representative agents. Among them are Flinn (1986), Leung (1994), Bearse (1997) and Imrohoroglu et. al. (2000). However, there has been little effort devoted to actually fit a dynamic model to the data.

We model the choice of whether to commit a crime or not as a function of wages and employment today as well as future wages and employment, which are affected by the outcome today. Our contribution is to explicitly consider the effect of increased criminal records on future wages and employment opportunities. This serves as a dynamic deterrence against crime.[4] That is, we explicitly solve the dynamic choice problem faced by agents. We also allow for unobserved heterogeneity insomuch as there are 4 types of individuals.

[4]Previous work has focused on more standard deterrence variables such as police expenditures and sentencing, among others.

Which type an agent is likely to fall into is determined by the data. In other words, type probability assignment is estimated to maximize the likelihood function. We find that although current wages and employment opportunities have a relatively weak effect on current crime, there is a strong dynamic deterrence effect. Our approach also allows us to conduct counter factual experiments. The paper proceeds as follows. The data are described in Section 2. The model specification is discussed in Section 3, and estimation results are in Section 4. Section 5 presents some simulation exercises including policy experiments. Section 6 contains some concluding remarks. The details of the model and its solution algorithms are presented in the Appendix.

2 Data

We estimate our model using data from the 1958 Philadelphia Birth Cohort Study developed by Figlio et. al. (1994). However, instead of converting the data into an annual panel, as is usually done, we construct a monthly panel of arrests and employment activities. In this way we obtain a more detailed panel history of the employment transition of each individual and his criminal activities. We think this difference is important. If we used annual data, almost everybody works positive hours. But with monthly data, we observe the long unemployment spells and job transitions which young workers frequently experience. The data provides detailed juvenile as well as adult arrest records, basic demographic information, and employment and schooling records,[5] among others. The demographic information includes variables such as sex, race, date of birth, church membership, and the socioeconomic status of the individual. Juvenile arrests records from age 14 are compiled from rap sheet and police investigation reports provided by the Juvenile Aid Division of the Philadelphia Police Department. Adult arrest records up to age 26 come from the Municipal and Common Pleas Courts of Philadelphia. Data on education, employment, health, and some self reported variables on criminal activities, etc. were collected in a 1988 follow-up survey interview.

The unique characteristic of this data set is that it contains information on the individual's criminal activities and background variables, as well as variables such as schooling and employment. The data is drawn from the general youth population of Philadelphia. This is in contrast to many data sets on crime, which only focus on delinquents. In Figure 1, we plot the average age arrest profiles of the male and female sample. We can see that the age arrest profile of females is much lower than that of males. In our estimation exercise we chose only the male sample because males are significantly more criminally active. For this reason, public interest, as well as past empirical studies, focus their attention on the criminal behavior of young males.

Figures 1 to 5 depict how arrests, unemployment, wages and incarceration are related to age. From Figure 1, we see that the arrest rate of males peaks

[5] We drop all agents going to college from the sample. 76 individuals out of 440 sample, i.e. less than 20 percent of the sample went to college. We also ignore the choices of individuals who went to trade schools and other similar institutions, since attendance was sporadic.

at 18.[6] In Figure 5, we see that the age incarceration profile increases sharply until age 17. Thereafter it remains roughly constant until 26. Hence, the age incarceration profile cannot by itself explain the age pattern of arrests of young individuals. Some sample statistics are shown in Table 1. In Figure 4, we plot the age arrest profiles for individuals with different past criminal records. Note that these profiles shift up with past arrests. This is consistent with the fact that repeat offenders account for large proportion of arrests. In Figure 3, we plot the mean and median age wage profiles. The mean wage profile is far above the median. This is typical of wage data, since wages are known to have many outliers. Since maximum likelihood estimation tries to fit the distribution it is robust against the outliers, and as we will see later, the model fits the data well in terms of the median.

3 Model Specification

In each period an individual chooses whether or not to commit a crime. His objective is to maximize the expected present value of lifetime utility. In the terminal period, T, at age 33,[7] he receives a payoff of $V_T(n_{cT})$ which depends on his past arrests n_{cT}. The criminal history in the terminal period is summarized by the index n_{cT}. The final period value function is assumed

[6] It is interesting that in the original work of Quetelet more than 15 years ago, the age crime profile peaked at age 24 or therabouts. This is reported in Leung (1991).

[7] We chose this somewhat early age, because we only have the data of young individuals until the age 26. Since the parameters estimated are based on data from age 14 to 26, it makes little sense to solve the model too far out.

to take a simple polynomial form:

$$V_T(n_{cT}) = f n_{cT}$$

In each period, his past arrest records depreciate at rate $1 - \delta$. If he commits a crime and gets caught, then his criminal record is augmented by unity. That is,

$$n_{ct+1} = \delta n_{ct} + 1$$

otherwise,

$$n_{ct+1} = \delta n_{ct}.$$

At age 18, we allow for a single period change in δ to δ_{18}. This allows us to capture the effect of juvenile records being sealed at adulthood. This leads us to expect a lower value for δ_{18} than δ.[8] Let $\mathbf{s}_t \in S_t$ be the state space vector for period t. This state space expands as an agent reaches maturity to reflect the additional choices made by an adult as opposed to a child.

In each period t, before the age 16, $\mathbf{s}_t = (t, n_{ct}, i_{ht}, \epsilon_{Nt}, \epsilon_{Ct})$, where $i_{ht} = 1$ if in the data the individual attends high school in period t and 0 otherwise. ϵ_{Nt} is the utility shock of not committing a crime and ϵ_{Ct} is the utility shock of committing a crime. We assume both of them follow the *i.i.d.* extreme value distribution. At or after the age 16, the individual starts working,

[8] As expected, our estimates show $\delta_{18} = 0.76$, while $\delta = 0.98$.

and the state vector is augmented by labor market information. Hence, $\mathbf{s}_t = (t, n_{ct}, i_{ht}, i_{ut}, W_t, \epsilon_{Nt}, \epsilon_{Ct})$ between the ages of 16 and 18, where $i_{ut} = 1$ if the individual is not employed in period t and 0 otherwise and W_t is the real wage rate. High school age unemployment is not exogenous and the probability of being unemployed at age 16 has the following logit form:

$$P_{hu} = \exp(\theta_{hu})/[1 + \exp(\theta_{hu})]$$

where

$$\theta_{hu} = h_0 + h_1 n_{ct}.$$

Then, after the first month of age 16, he experiences job transitions, and the probability of staying unemployed depends both on his past criminal history and the employment status. That is,

$$P_{ut+1} = \exp(\theta_{ut})/[1 + \exp(\theta_{ut})]$$

where

$$\begin{aligned}\theta_{ut} &= b_{00}I(age < 18) + b_{01}I(age \geq 18) + b_1 t + b_2 i_h + b_3 n_{ct} \\ &\quad + [b_{40}I(age < 18) + b_{41}I(age \geq 18)]i_{ut}.\end{aligned}$$

$I(age < 18)$ is an indicator function which equals 1 when the agent is below 18, and 0 otherwise. All the other indicator functions are analogously defined. The above specification allows us to have different unemployment probabilities and persistence before and after 18. At age 18, the individual either graduates or does not graduate from high school. We set $i_{hg} = 1$ if he graduates from high school, and 0 otherwise. Hence, the state vector at and after the age 18 is further augmented by high school graduation, i.e. $\mathbf{s}_t = (t, n_{ct}, i_{ht}, i_{hg}, i_{ut}, W_t, \epsilon_{Nt}, \epsilon_{Ct})$ after age 18. At the age 18, the individual graduates from high school with probability

$$P_g = \exp(\theta_g)/[1 + \exp(\theta_g)]$$

where

$$\theta_g = g_0 + g_1 n_{ct}.$$

The starting wage of the individual at the first month of employment follows the log normal distribution

$$\log(W_{t+1}) \ \sim \ N(\mu_b(n_{ct}), \sigma_b)$$

where

$$\mu_b(n_{ct}) = \mu_{b0} + \mu_{b1} n_{ct}.$$

Furthermore, the wage growth for the individual on a job is assumed to be log normally distributed such that

$$\log(W_{t+1}) - \log(W_t) \ \sim \ N(\mu_{gt}(.), \sigma_g),$$

where

$$\mu_{gt}(.) = \mu_{g01}I(16 < age \leq 19) + \mu_{g02}I(20 < age \leq 23) + \mu_{g03}I(20 < age) \\ +[\mu_{g11}I(16 < age \leq 23) + \mu_{g12}I(24 < age)]t + \mu_{g2}n_{ct}.$$

We solve for the optimal choice of whether to commit a crime or not.[9] The value of not committing a crime is

$$V_{Nt}(\mathbf{s}_t) = u_N(\mathbf{s}_t - \boldsymbol{\epsilon}_t) + \beta EV_{t+1}(\mathbf{s}_{t+1}|\mathbf{s}_t) + \epsilon_{Nt}$$

where $\mathbf{s}_t \in S_t$ is the state space vector, and $\mathbf{s}_t - \boldsymbol{\epsilon}_t$ denotes the variables in $\mathbf{s}_t$ having removed those in $\boldsymbol{\epsilon}_t = (\epsilon_{Nt}, \epsilon_{Ct})$ and $u_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t)$ is the deterministic component of the utility of not committing the crime. Of course, in the event of not committing a crime, $n_{ct+1} = \delta n_{ct}$.

The value of committing the crime is

$$V_{Ct}(\mathbf{s}_t) = u_C(\mathbf{s}_t - \boldsymbol{\epsilon}_t) + P_C\beta E[V_{t+1}(\mathbf{s}_{t+1})|\mathbf{s}_t] \\ +[1 - P_C]\overline{V}_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t) + \epsilon_{Ct}$$

where $\overline{V}_{Nt}$ is the deterministic part of the value of not committing the crime and P_C is the probability of getting caught after committing a crime and $u_C(\mathbf{s}_t - \boldsymbol{\epsilon}_t)$ is the deterministic component of the utility of committing a crime.[10] The probability of catching the offender is not identified, and we

[9] The main reason why we do not solve and estimate the jointly optimal choice of employment and crime is because of the high computational burden. Our horizon for the DP problem is from age 14 to age 33, which gives us 240 monthly periods for which we have to evaluate the value functions. This is already quite computationally demanding.

[10] The term $u_C(.)$ includes the expected loss from being caught and punished. For this reason there is no cost of punishment that multiplies the probability of being caught above. In any event, this expected cost of punishment would not be seperately identified.

therefore set it to be

$$P_C = 0.16.$$

This number is consistent with other facts. Clearance rates, that is the ratio of arrests to reported crimes varied from 92% for murder and non-negligent manslaughter to 20% for larceny in the *U.S.* in 1960. In 1991 the range for clearance rates was about 67% for murder and non-negligent manslaughter and 13.5% for burglary.[11] We chose 16% as a reasonable weighted average.[12] Note that we assume that when, despite committing a crime, an agent is not caught, it is as if he never committed it. It is not the crimes you committed, but the crimes for which you are arrested that affect future payoffs. Since crime and arrests are linearly related due to our specification, we use the words crimes and arrests interchangeably from here on.

We assume that the utility function takes the form

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[11]These numbers are based upon Table 1 in Ehrlich (1996).

[12]This specification ignores the possible endogeneity of the probability of getting caught which could vary with the seriousness of the crime. Those aspects are pointed out by Tauchen et. al. (1994) and others. Lochner (2000) estimates the manner in which beliefs about being apprehended are affected by past arrests and other information.

$$
\begin{aligned}
u_N(\mathbf{s}_t - \boldsymbol{\epsilon}_t) &= c_{01}I(age < 18) + c_{02}I(age \geq 18) + c_{03}I(age \geq 18)age + c_1 i_{ht} \\
&+[c_{l1}I_l(W_t) + c_{m1}I_m(W_t) + c_{h1}I_h(W_t)]I(age < 18) \\
&+[c_{l2}I_l(W_t) + c_{m2}I_m(W_t) + c_{h2}I_h(W_t)]I(age \geq 18) \\
&+c_5 i_{hg} + c_6(n_{ct})^{\alpha}.
\end{aligned}
$$

where $I_j(W_t),\ j = l, m, h$ are the indicator functions for low, medium and high wage groups[13] and $I(age < 18)$ is the indicator function for being below age 18. We introduce this differentiation before and after age 18 to reflect the differences in treatment of juveniles and adults under the law. In general, the criminal justice system treats individuals under and over age 18 quite differently. α allows for convexity or concavity in the effect of criminal history.

As is well known from the discrete choice econometric literature, we cannot separately identify the utility of not committing the crime and the utility of committing the crime just on the basis of data on criminal choice. Hence, we set

$$u_C(\mathbf{s}_t - \boldsymbol{\epsilon}_t) = 0.$$

After the utility shocks $\epsilon_{Nt}, \epsilon_{Ct}$ are realized in period t, the agent chooses

[13] Low wage group individuals are those with real wages below \$5. Medium wage group individuals are those with real wages between \$5 and \$8. High wage group individuals are those with real wages greater than or equal to \$8.

whichever option yields the higher value. Hence,

$$V_t(\mathbf{s}_t) = Max\{V_{Nt}(\mathbf{s}_t), V_{Ct}(\mathbf{s}_t)\}.$$

In the section on Bellman equations in the Appendix, we elucidate on the value functions of the individuals at various ages.

The unit of time in our paper is months. Since no individuals have multiple arrests in our data, we abstract from multiple crimes and assume that the individuals only have two choices, either to commit a crime or not to do so. Because of this, the effect of incarceration on crime/arrests is not identified. Incarceration is interpreted as being unemployed and at the same time, unable to commit any crimes.[14] The richer model incorporating aspects such as the severity of crimes is hard to put into an error structure that results in easy dynamic logit computation, such as that of Rust (1987), which we use below. The analysis of the richer dynamic model is, in our view, a very interesting topic for future research. In fact, some topics, such as the effects of alternative sentencing requirements can only be addressed in a model with multiple crime choices resulting in behavior which is affected by the sentencing structure. We see our work as a start in this direction.[15]

[14]Because of this, the effect of past crimes on unemployment will be biased upwards and the effect on crimes committed by the unemployed biased downwards. Since in our results, past crimes raise unemployment and past unemployment raises crimes, the former might change signs after the bias is removed, but the latter would not. However, in any case, we believe the bias to be small since the probability of incarceration in the data is small (see Fig. 5).

[15]While we see offenses with various severity - ranging from drunk driving to murder, we excluded minor offenses such as drunk driving and other traffic offenses. Offenses included are: homicide, rape, robbery, aggravated assault, burglary, theft, other assaults, arson, forgery. See appendix for the detailed description of the offenses.

We also include some unobserved heterogeneities. We take a minimalist stand and assume 2 criminal types and 2 unemployment types. We have crime type 1 and 2 and unemployment type 1 and 2. The agent's type is modeled as a random effect, and the probability of an agent's type is estimated so as to maximize the likelihood function. Crime type 1 and unemployment type 1 turn out to be the high crime/high unemployment types. As in other estimation exercises such as Keane and Wolpin (1997) or Eckstein and Wolpin (1999), we do not include any observed heterogeneity. As a check, we later look at the regression relationship between the unobserved heterogeneities and the observed differences in individual characteristics and conclude that the unobserved heterogeneities estimated from the data capture the observed differences in individual characteristics.

The Maximum Likelihood estimation involves a number of steps. Not only must the Dynamic Programs be solved, but the likelihood has to be computed. The steps are as follows.

Step 1 Solution of the Dynamic Programming problem. For any given parameters, and any state vector, $\mathbf{s}_t - \boldsymbol{\epsilon}_t \in S_t$, it is standard to solve the Dynamic Programming problem to obtain the values $\overline{V}_{Ntj}(\mathbf{s}_t - \boldsymbol{\epsilon}_t)$, $\overline{V}_{Ctj}(\mathbf{s}_t - \boldsymbol{\epsilon}_t)$, which are the deterministic components of the values of type j. As usual, the solution proceeds from the last period T backwards. As a result of this, for the given parameters, we know what the value of committing verses not committing the crime would be if we knew the state variables. Now, we want to get some idea of how likely the parameter chosen is with respect to the data. To do so, we compute the likelihood function.

Step 2 Computing the likelihood components. Given the data $\mathbf{s}_{it}^{d} = (t^{d}, n_{cit}^{d}, i_{hit}^{d}, i_{uit}^{d}, W_{it}^{d})$ for individual i and period t, and the parameters in θ, we integrate over the taste shocks $\boldsymbol{\epsilon}_t$ to calculate the probability of committing a crime. That is, we calculate

$$\begin{aligned} P_j(V_{Ct}(\mathbf{s}_t) &> V_{Nt}(\mathbf{s}_t)) \\ &= \int I[\overline{V}_{Ctj}(\mathbf{s}_{it}^{d}) + \epsilon_{Ct} > \overline{V}_{Ntj}(\mathbf{s}_{it}^{d}) + \epsilon_{Nt}]dF(\boldsymbol{\epsilon}_t). \end{aligned}$$

This gives the probability that individual i when he is of type j, commits a crime in period t . This is then done for each period t, and then repeated for each individual and type. The latter is required since each individual is not assigned a type, but rather a set of probabilities over types. This gives the 4 probabilities associated with the individual committing the crime if he was of the given type. Of course, the probability of being a particular type remains to be estimated. In this manner, we obtain the criminal choice component of the likelihood, $L_{itjC}(\theta_j)$. The other components of the likelihood are the probability of unemployment and the wage density component, which are jointly denoted by $L_{itjE}(\theta_j)$, and the high school graduation probability component denoted by $L_{i18jHS}(\theta_j)$ in the Appendix. As before, these probabilities are calculated for all individuals i, periods t and types j for the given parameter θ. Of course, the probability of high school graduation is only calculated at age 18. The probability of unemployment and the high school graduation probability components have the standard logit form. The wage density component also has the standard log-normal form.

Step 3 From the previous steps, we can get the values of the likelihood components for different parameter values. The likelihood function is the type probability weighted sum of the likelihood components.

Step 4 We choose the values of the parameters and the prior type probability parameters π_1, π_2, π_{11}, and π_{21}, namely the probability of the 2 crime types and the conditional probability of being an unemployment type 1 conditional on crime type, to maximize the likelihood. This gives us the parameter estimates. As usual in maximum likelihood estimation, standard errors are calculated from the inverse of the sample information matrix.

In general, solving and estimating dynamic discrete choice models, such as this, is computationally demanding. Recall that in order to solve for the Bellman equation described in more detail in the Appendix, we needed to solve for the expected values, $E[V_{t+1}(\mathbf{s}_{t+1})|\mathbf{s}_t]$. To derive these expected value functions, we needed to integrate over the shocks ϵ_{Nt} and ϵ_{Ct} and over the wage and employment shocks. This integration had to be done for each point in the state space $\mathbf{s}_t - \boldsymbol{\epsilon}_t$ at each period t. On top of this, the above Dynamic Programming problem had to be solved once at each likelihood evaluation, when we assume no heterogeneity, and several times when we introduce some unobserved heterogeneities. As a result, the programming and computation were non trivial. Details on model estimation are to be found in the section on the Solution Algorithm and the Likelihood in the Appendix.[16]

4 Estimation Results

Parameter estimates are presented in Table 2. Notice that the intercept of the net utility of not committing crime for both types is lower before age 18 ($c_{01}^i < c_{02}^i,\ i = 1,\ 2$). This together with $\delta_{18} < \delta$ is how our model explains the fact that in the data, arrest rates drop sharply at age 18. In the current criminal justice system, juvenile offenses have more lenient sentences, and juvenile records are sealed. Note that the estimated relationship between arrest rates and wages is not monotonic.[17] This could be why the wage coefficients of crime choice model in past research such as Lochner (1999), Grogger (1998) have been of mixed sign.

The depreciation rate $(1 - \delta)$ is about 2% per month, which amounts

[16]The FORTRAN programs used to implement the estimation is available upon request.
[17]The dummies for low, medium and high wages in the utility function are not necessarily increasing in wage levels.

to an annual depreciation rate of about 21%. Our estimates are consistent with past work such as Grogger (1995), Kling (1999), who have pointed out that the effect of past criminal history on current variables such as employment and wages is temporary. The depreciation rate of the juvenile criminal record at age 18, or $(1-\delta_{18})$ is about 24%. This, combined with the annual depreciation rate of 21% implies that juvenile crime records have a relatively small effect on the adult behavior.

Before age 18, the parameter estimates indicate that overall for low crime types, being employed increases crime, i.e., $c^1_{l1}, c^1_{m1}, c^1_{h1} < 0$, whereas for high crime types, being employed tends to decrease crime, i.e., $c^2_{l1}, c^2_{m1} > 0$, and $c^2_{h1} < 0$ but insignificant. Furthermore, attending high school decreases crime for the low crime type ($c^1_1 > 0$), but increases it for the high crime type ($c^2_1 < 0$). One would expect that employment and high school attendance would reduce crime. However, suppose the low crime types who work instead of going to high school tend to be the low achievement types, perhaps, because they are less academically gifted, and the high crime types who stay in high school rather than work tend to be lazy and hence low achievers. Then this result makes sense, since Eckstein and Wolpin (1999) show that the low achievers tend to be more criminally active. In short, we need to be more careful about the unobserved and observed characteristics in explaining the criminal, labor market and schooling behavior of youth together. Unfortunately, compared to the NLSY data used by Eckstein and Wolpin (1999), our panel data has only limited information on schooling as only the final year of school attendance is recorded.

Other parameters have either the expected signs or are not significant. For example, the state dependence effect indicates that a history of criminal activity reduces the utility of not committing a crime ($c_6 < 0$, $\alpha > 0$). While the high school graduation dummy has a negative sign, it is not significant. Nor is the negative sign of the arrest record coefficient in the initial unemployment probability ($h_1 < 0$). The criminal type (type 1) has higher probability of being of a high unemployment type as evidenced by $\pi_{11} > \pi_{21}$. π_{11} is the conditional probability of being a high unemployment type (type 1) given that the agent belongs to the high crime type (type 1) and π_{21} is the conditional probability of being a high unemployment type (type 1) given that the agent belongs to low crime type (type 2). Moreover, high school graduation reduces unemployment transition probability ($b_2 < 0$) while a longer criminal record increases it ($b_3 > 0$). Unemployment rate probability intercepts are lower for employment type 1, both before and after 18 ($b_{00}^1 < b_{00}^2$, $b_{01}^1 < b_{01}^2$). Also, for both employment types, the unemployment probability falls with age ($b_1^1 < 0$, $b_1^2 < 0$). This is also evident from the age unemployment profiles in Fig 2. Wage growth increases with age ($\mu_{g1i} < 0, i = 1, 2$) and decreases with past criminal records ($\mu_{g2} < 0$). The starting wage increases with past criminal records, but the coefficient is insignificant ($\mu_{b2} > 0$).

We follow Keane and Wolpin (1997) and Eckstein and Wolpin (1999) and do not include the observed characteristics in our model. Our results show that the criminally at risk type is about 28% of the sample. Moreover, these types clearly affect behavior, as is evident in the difference in their crime, unemployment and wage profiles depicted in Figures $6-8$. We argue that the unobserved types, in particular the unobserved criminal types, reflect the effect of the observed characteristics on the crime rate. In Table 3, we report the results of a logit type regression which relates the odds of the individual being of crime type 1 with several observed characteristics. That is, we estimated the following equation.

$$\ln[P_{c1}/(1-P_{c1})] = \beta_0 + \beta_1 X.$$

Most of the signs are reasonable. Being white increases the non-criminal type probability. So does the father and mother being in household from age 12 to 18, socioeconomic status of the family when young, growing up in a loving household. On the other hand, the father having been unemployed when young, ever being a gang member, any of the parents ever being arrested, all increase the probability of being the criminal type. Furthermore, the probability of being a criminal type increases with the number of friends who are arrested. It is interesting to note that mothers working outside the home when the individual grew up actually increases the probability of being a low crime type. The coefficients of the religion dummies are relative to the unknown religious beliefs. Being Jewish or being Catholic reduces the criminal type probability compared to other religious beliefs. But as the standard errors indicate, most of the coefficients are insignificant. Both R-squares and the adjusted R-squares are low, so that much unexplained heterogeneity remains.

5 Simulation Exercises

This section has two distinct components. The first deals with how well the data and the simulated model track each other. The second deals with the effects of some policy experiments.

5.1 Generated and Actual Data

In Figures 1 to 3 and Figure 9 vs. Figure 4, we compare the simulation results with the data. The model fits well with regard to the overall age arrest profile and the age unemployment profile. It fits the age *median* wage profile much better than the age *mean* wage profile. This is quite natural since maximum likelihood is robust against outliers, and tries to fit the distribution of wages instead of its mean. In contrast to most age wage profiles in empirical labor economics, real wage growth here is sluggish until the age 24, even showing occasional decreases. This, we suspect, is due to the fact that our panel data consists of a single cohort which experienced a business cycle downturn in the period 1978 to 1982. Figure 9 depicts the simulated age arrest profiles with different past criminal records. Notice that the simulated arrest profiles for individuals with more past arrest records lie above those with fewer ones.

This corresponds to the actual profiles, as depicted in Figure 4. That is, profiles indicate that repeat offenders commit more crimes than others. Thus, greater criminal activity by repeat offenders comes naturally from our setup.

Figure 6 plots the simulated age arrest profiles of the four types separately. Notice that there are large differences in arrest rates among the types. In particular, the arrest rate of the at-risk youths (criminal types with both low and high unemployment) seem to be 2 to 4 times as high as that of the others. This is also consistent with repeat offenders committing most crimes. Also, notice from Figure 6, that it is the arrest rate of the criminal types (criminal type 2) that shows a rapid decline after age 18 so that it is the criminally prone types who improve dramatically after age 18. This is consistent with the arrest rate decreasing with age after 18. Figures 7 – 8 plot the simulated unemployment and wage profiles for the 4 different types. The types do look different. Note that just as the difference in age arrest profiles is greatest for the criminal types in Figure 6, the difference between the age unemployment and age wage profiles are largest for the two unemployment types in Figures 7 and 8. Hence, there seems to be evidence of an interaction between being more prone to committing crimes and being unemployed. Both crime types for the high unemployment type lie above the low unemployment type, but there is more separation between the two crime types in the high unemployment group, and the separation increases with age. This is consistent with crime and unemployment reinforcing each other.

5.2 Simulation Exercises

Next, we conduct some counter factual simulations to better understand some policy issues of interest. First, we try and look at the extent of dynamic deterrence. As explained earlier, dynamic deterrence occurs to the extent that agents are deterred from crime by looking forward and considering the effects of their current actions on future outcomes. In the simulation, both static state dependence and dynamic deterrence are present. Criminal history affects employment outcomes as well as choices. At the same time, individuals take into account the effect of current choices on future outcomes. In order to get an idea of the extent of static state dependence versus dynamic deterrence, we conduct two experiments. In experiment A, we look at what the outcomes would have been if criminal history did not affect employment outcomes, though individuals expected it to do so. The difference between the original simulation and this counter factual exercise captures the extent of state dependence. We implement this counter factual exercise by setting the coefficients for the number of past offenses in the unemployment probit in the likelihood calculation to zero. Notice that in this exercise, to make the policy unanticipated, we still keep the coefficients in the DP routine unchanged.

In experiment B, in order to get an idea of the extent of dynamic deterrence, we look at what the outcomes would have been if criminal history did not affect employment outcomes, and individuals did not expect it to do so. The difference between the second simulation and this counter factual captures the extent of dynamic deterrence. We implement this counter factual exercise by setting both the coefficients for the past criminal history (in the unemployment probit in the likelihood calculation) and the coefficients in the DP routine corresponding to the anticipated effects of current criminal outcomes, to zero. A loose interpretation might be that experiment A corresponds to the case where all criminal records are destroyed, but no one knows about it. As a result, there would be no state dependence, employment opportunities of criminals would be better, and for this reason, we would expect crime to fall. However, if they know about it, which would correspond to experiment B, crime would rise because dynamic deterrence would be eliminated.

The results of experiment A are found in Figures $10-12$ where we plot the ratios of the profiles generated by this experiment to the original simulated profile. We see that as expected, the unemployment ratio lies below unity. This makes sense as the impact effect of this experiment reduces the unemployment rate. In addition, there is an induced effect on the arrest ratio and the wage ratio. The arrest ratio also falls as being employed reduces the probability of committing a crime after age 16. However, this effect is small. The arrest ratio can be seen as a measure of the extent of the state dependence effect, or the stigma effect, of past criminal records on current employment and consequently on current criminal behavior. Wages first fall then rise as does the wage ratio. This comes from lower wage agents accepting employment which pulls the wage down initially. As past employment raises wages, wage ratios in the future rise.

What if, in addition, this elimination of criminal records were anticipated? In Figures $10-12$ we can see that anticipated elimination also reduces unemployment because of the elimination of past arrest records. But the arrest rate rises. That is, erasing past criminal records to promote employment raises the incentives to commit crimes as there is no adverse effect expected on employment. The difference in the two crime ratios in experiment B and A gives an idea of the extent to which future unemployment induced by criminal acts prevents them. This is because B has no dynamic deterrence and A does, so that their difference (scaled by the original simulated profiles) gives the extent of the dynamic deterrence effect. This difference is large which indicates that the prospect of future unemployment works as a strong deterrence against committing crimes. This suggests that the dynamic deterrence effect is stronger than the static state dependence effect. Not only do they work in opposite directions, but the dynamic deterrence more than cancels out the static state dependence effect.[18]

As is well known, crime rates have fallen in the past decade but show

[18]The astute reader might ask whether the results are immune to changing the order of the experiments, i.e., whether the path matters. When this was checked, no substantive difference was found.

signs of levelling off. An important question in the policy arena is the extent to which this is due to the booming economy of the period. To get a partial handle on this, consider another policy experiment, where, given the current state variable, we reduce the one period ahead unemployment probability after the first month of age 18, by 5%. That is,

$$P_{ut+1} = 0.95 \times \exp(\theta_{ut})/[1 + \exp(\theta_{ut})]$$

The results on the unemployment, arrest rate and real wage ratios are plotted in Figures $13 - 15$. Because of the persistence of unemployment, unemployment rates are reduced by more than 5%. When the reduction is unanticipated, unemployment falls so the ratio is below unity. Since the employed commit fewer crimes, the induced effect on the arrest ratio also pulls it below unity. The wage ratio initially falls below unity and then rises for similar reasons as in experiment A. In contrast to this, if the policy is anticipated, the reduction in unemployment transition probability increases crime. Again this is due to the strong dynamic deterrence effect since it is the prospect of future unemployment which deters crime. This exercise thus makes it hard to argue that the boom in the $90's$ alone can be seen as responsible for the reduction in crime. However, to the extent that this boom, due to its length and depth managed to bring those at the very bottom into the labor force, our approach may be under-estimating the effect of crime reduction. Bringing such agents into the labor force, thereby providing some a dynamic deterrence effect where none existed before, could well reduce crime.

One way to obtain larger effects on the crime ratio is to consider the effects of an anticipated boom followed by a bust. In this case we get higher effects on crime ratios as depicted in Figure 16. Given the current state variable, we reduce the one period ahead unemployment probability by 5%, after the first month of age 20, for 2 years.[19] After this the unemployment transition probability is assumed to increase by 5%, compared to the original one for 2 years. Behavior is affected even before the onset of the reduction of the unemployment transition probability because individuals anticipate the reduction in future threat of unemployment. Before age 20, expectations of a good labor market, makes crime and hence arrest rise. As a result, the arrest rate ratio rises above unity, and once the boom begins, expectations of a slump to follow reduces crime, and hence, the arrest rate ratio drops below unity quite considerably to begin with. As the slump occurs, expectations of normal times raise crime and the arrest ratio. The policy maker, failing to understand the deterrence aspect of the unemployment effect, could erroneously conclude that low unemployment is the cure for crime. However, a permanent reduction in unemployment raises crime! Note that if this anticipated boom-slump were the reason for the observed decline in crime seen in the 90's, we should expect an increase once the slump comes.

[19]We choose the age of 20 so that the change in the behavior of adults as well as juveniles anticipating this boom and then slump can be iullustrated. It makes no difference to the earlier simulations if the same age (of 20) is used there.

What about the effect of greater enforcement? This policy, joint with harsher sentencing, has been the standard approach to combatting crime. In our next experiment, we increase the anticipated probability of being caught by 10%. As shown in Figures $17-19$, the effect is to raise the crime ratio for the young and reduce it for the old. This occurs as the young face weaker penalties as their criminal history depreciates at age 18, and they inter-temporally substitute towards crime. It reduces the unemployment ratio for adults below unity since adults commit fewer crimes. It reduces the wage ratio for the young and raises it for the old as a result of the effect of the policy on their criminal behavior.

We also look at the effect of not sealing juvenile records. This roughly corresponds to making $\delta_{18} = \delta$.[20] The arrest ratio is depicted in Figure 20. As expected, the young commit fewer crimes, realizing that their criminal record is more permanent. The old commit more crimes as they cannot get away from their juvenile records.

Finally we look at the what happens if we increase both δ and δ_1 by 0.1%. This corresponds to decreasing the depreciation rate of past criminal histories. There are large differences between countries in the extent to which an agent's past haunts him. In Japan for example, a criminal record is relatively permanent. In the U.S. on the other hand, criminal history is

[20] Of course, if juvenile records were completely eradicated, and there were no other effects such as differences in criminal and other human capital among juvenile offenders and others, then δ_{18} should be zero. This is why making $\delta_{18} = \delta$ only roughly corresponds to the opening of the juvenile records.

much easier to disguise. In fact, only in recent years have there been laws such as Megan's Law, on informing neighbors of sex offenders who move in. The results are shown in Figure 21. We notice that even a small decrease in depreciation rate generates a large decrease in the crime rate. This highlights the importance of dynamic deterrence. The work of Glaeser, Sacerdote and Scheinkman (1996), or Williams and Sickles (2000) on social human capital suggests that such effects could be important even though they do not directly look at depreciation as we do. Casual observations across different countries and regions reinforce this conclusion. In countries where people live in a closely knit communities, where it is often said that "everybody knows everybody", so that there is no depreciation, crime is lower. In these communities, even though legal consequences of offenses may be lenient and temporary, past misconduct of their members are not forgotten, and hence the long memory among the other community members work as a strong deterrent against crime. These are issues that could be further investigated by conducting international comparisons of criminal behavior.

In sum, our results emphasize the role of future unemployment as an important factor holding people back from committing crimes. Even though much attention has been paid to the relationship between labor market outcomes and crime, we think this dynamic deterrence aspect has been neglected. When researchers consider the effect of unemployment and wages on crime, they mainly focus on the direct state dependence effect on criminal behavior. Instruments and other methods are used to avoid endogeneity problems due to state dependence or heterogeneity. However, correcting endogeneity in this manner does not give all the structural parameters of interest, and hence only incompletely addresses the effect of government policy since expectational effects cannot be incorporated. Our results agree with many past results insofar as unemployment and wages have small direct effects on crime. What is new in our work is that despite such small direct effects, government employment and wage policies could change criminal behavior significantly, mainly through changing peoples' anticipations about their future.

As is the case with all structural estimation results, we need to interpret the above results with caution, and more work needs to be done to assess the robustness of the results with respect to various alternative model specifications. For example, we assumed that the individuals only choose between committing a crime and not committing a crime and we treated all crimes as the same. Obviously, the criminal justice system pursues the offenders of different crimes with different intensities, and punishes and records them with different degrees of severity. Hence, the both the state dependence and the deterrence effect should be different depending on the types of crimes committed. Such issues could be addressed in the future, with better data sets.

6 Concluding Remarks

Our estimation and simulation exercises show the following. First, note that our generated data match the actual age arrest, age unemployment and age median wage profiles remarkably well, despite the parsimonious model structure and parameterization. Second, the parameter estimates have the expected signs or are insignificant. Third, unobserved as well as observed heterogeneities are very important in explaining the data. In fact, the criminally prone type, which is about 27% of our population, is estimated to have an arrest rate up to 4 times as high as the rest of our population. In all of our simulation results, it is the criminally prone types who decrease their crime rates faster than the other types after the age 18. This runs counter to the assertions that criminal behavior cannot be corrected afterwards. Fourth, employment status has a negative, although small, direct effects on crime. It is the possibility of future unemployment which works as a strong deterrence against committing crime. Fifth, the simulation exercises show that the anticipated consequences of committing crimes are very important in understanding peoples' criminal behavior. For example, the increase in the arrest rate, the traditional deterrence measure, leads to both less crime and unemployment on average, though it raises youth arrest rates slightly while lowering the adult ones.

What are the implications of our work for the conduct of public policy towards crime? Our structural dynamic approach provides a unified understanding of a number of findings in the traditional literature. Kahan (1995) claims that effective anti-crime policies are those that change people's anticipation of future punishments. This is exactly our point, and these future punishments seem to come from the labor market! There have been several papers showing that early intervention programs such as the Job Corps, The Perry Preschool Program, The Syracuse University Family Development Plan and the Quantum Opportunity Program are very effective in reducing crime[21], see Lochner (1999) for a summary of such results. This is exactly what would be expected from our model, since anticipated later intervention allows criminals to look forward to negating the consequences of their actions. Hence, the dynamic deterrence effect via future employment is reduced. Early intervention has no such adverse effect on dynamic deterrence. This suggests that early prevention is more effective than redemption.

Much more needs to be done on this area of structural estimation of criminal behavior. First, more needs to be done in checking the robustness with respect to different specifications. In particular, in future work, we need to relax the assumption that individuals can only choose between committing and not committing crime, and to increase the degree of choice over the extent of crimes. It is natural to think that certain crimes carry more stigma than others, and putting all crimes into one category is undesirable, as they are bound to have different effects. In addition, this would allow us to include

[21] The Perry Preschool Program for disadvantaged minority children reduced arrests through age 27 by 50%.

sentencing policies in our model since sentencing variation is across a variety of crimes. Finally, the relationship between high school attendance, work behavior, and crime before age 18 needs to be better understood. Since our crime data only has years of last schooling, and lacks any measure of actual school attendance until then, or achievements with respect to grades, with our data set it is impossible to conduct an empirical exercise on youth behavior before the age 18 comparable to the kind of work done by Eckstein and Wolpin (1999).

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8 Appendix

8.1 Offense Categories

We did not count some offenses. These were:

1 Driving while intoxicated.

2 Drunkenness.

3 Disorderly conduct.

4 Vagrancy.

5 Cruelty to animals.

6 Selling fireworks.

7 Fortune telling.

8 Violation of cigarette tax act.

9 Scavenger.

10 Sunday law violation (except sale of liquor).

11 Traffic and motor vehicle violations.

8.2 Bellman Equations

The value function of the individual before the age 16 of not committing a crime is

$$V_{Nt}(\mathbf{s}_t) = u_{Nt}(\mathbf{s}_t) + \beta E[V_{t+1}(\mathbf{s}_{t+1})|\mathbf{s}_t] + \epsilon_{Nt}.$$

where

$$\mathbf{s}_t = (t, n_{ct}, i_{ht}, \boldsymbol{\epsilon}_t),$$

$$n_{ct+1} = \delta n_{ct},$$

$$\boldsymbol{\epsilon}_t = (\epsilon_{Nt}, \epsilon_{Ct}).$$

The value function of not committing a crime at or after the age 16 before age 18 is:

$$\begin{aligned} V_{Nt}(\mathbf{s}_t) &= u_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t) \\ &+[1 - P_u(\mathbf{s}_t)] \\ &\beta E[V_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 0, W_{t+1}, i_{h,}\boldsymbol{\epsilon}_{t+1})|\mathbf{s}_t] \\ &+P_u(\mathbf{s}_t)\beta E[V_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 1, W_{t+1} = 0, i_h, \boldsymbol{\epsilon}_{t+1})|\mathbf{s}_t] \\ &+\epsilon_{Nt}. \end{aligned}$$

That is, it is the utility of not committing a crime today and having an arrest record of δn_{ct} tomorrow. In the next period, you are unemployed with probability $P_u(\mathbf{s}_t)$ and have an expected payoff in present value of

$$\beta E[V_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 1, W_{t+1} = 0, i_h, \boldsymbol{\epsilon}_{t+1})|\mathbf{s}_t].$$

If you are employed in the next period, the analogous expression arises. The value function of committing a crime is similarly defined.

The value function of the individual at the first month of age 18 of not committing a crime is has 4 elements, which consists of the continuation payoffs from the 4 combinations of graduating or not, and being employed or not. That is,

$$\begin{aligned}
V_{Nt}(\mathbf{s}_t) &= u_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t) \\
&\quad + P_g(n_{ct})(1 - P_u(t, n_{ct}, i_{ut}, i_{hg} = 1)) \\
&\quad EV_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 0, W_{t+1}, i_{hg} = 1, \boldsymbol{\epsilon}_{t+1}|\mathbf{s}_t) \\
&\quad + P_g(n_{ct}) P_u(t, n_{ct}, i_{ut}, i_{hg} = 1) \\
&\quad EV_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 1, W_{t+1} = 0, i_{hg} = 1, \boldsymbol{\epsilon}_{t+1}|\mathbf{s}_t) \\
&\quad + (1 - P_g(n_{ct}))(1 - P_u(t, n_{ct}, i_{ut}, i_{hg} = 0)) \\
&\quad EV_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 0, W_{t+1}, i_{hg} = 0, \boldsymbol{\epsilon}_{t+1}|\mathbf{s}_t) \\
&\quad + (1 - P_g(n_{ct})) P_u(t, n_{ct}, i_{ut}, i_{hg} = 0) \\
&\quad EV_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 1, W_{t+1} = 0, i_{hg} = 0, \boldsymbol{\epsilon}_{t+1}|\mathbf{s}_t) + \epsilon_{Nt}.
\end{aligned}$$

After the first month of the age 18, the individual has either graduated from high school or not. Hence, the value of the individual not committing any crime is just a combination of the payoffs from being employed or not. That is,

$$
\begin{aligned}
V_{Nt}(\mathbf{s}_t) \quad = \quad & u_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t) \\
& +[1 - P_u(\mathbf{s}_t)]\beta E[V_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 0, W_{t+1}, i_{hg}, \boldsymbol{\epsilon}_{t+1})|\mathbf{s}_t] \\
& +P_u(\mathbf{s}_t)\beta E[V_{t+1}(t, n_{ct+1} = \delta n_{ct}, i_{ut+1} = 1, W_{t+1} = 0, i_{hg}, \boldsymbol{\epsilon}_{t+1})|\mathbf{s}_t] \\
& +\epsilon_{Nt}.
\end{aligned}
$$

8.3 The Solution Algorithm and the Log Likelihood

In order to solve for the dynamic programming problem at each DP solution step, we need to integrate the value function with respect to the taste shock $(\epsilon_{Nt}, \epsilon_{Ct})$ and the wage shock. We follow the steps described below.

1) Integration with respect to the taste shock: Rust (1987) suggests a method which allows for the analytical integration of the value function when we assume that the shocks ϵ_{Nt}, ϵ_{Ct} have *i.i.d.* extreme values distributions. In this event he points out that the expected value function in period t has the following expression

$$E_{\{\epsilon\}}[V_t(\mathbf{s}_t)] = log[exp(\overline{V}_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t)) + exp(\overline{V}_{Ct}(\mathbf{s}_t - \boldsymbol{\epsilon}_t))]$$

since they have been integrated over. $\overline{V}_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t)$, and $\overline{V}_{Ct}(\mathbf{s}_t - \boldsymbol{\epsilon}_t)$ are the value functions net of the taste shock $\boldsymbol{\epsilon}_t$ at period t and state vector $\mathbf{s}_t$. This eliminates the need to numerically integrate the value function with respect to the taste shocks ϵ_{Nt},ϵ_{Ct}.

2) Integration with respect to the wage shock: The expected value function at period t is

$E_{\{W,\epsilon\}}[V(\mathbf{s}_t)|\mathbf{s}_{t-1}] = E_{\{W\}}(\log[exp(\overline{V}_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t)) + exp(\overline{V}_{Ct}(\mathbf{s}_t - \boldsymbol{\epsilon}_t))]|\mathbf{s}_{t-1})$.

We approximate this integral by taking finite grid points over the wage distribution and evaluate the density weighted sum of the value function as the integral (See Rust 1998). That is,

$$
\begin{aligned}
& E_{\{W\}}(\log[exp(\overline{V}_{Nt}(\mathbf{s}_t - \boldsymbol{\epsilon}_t)) + exp(\overline{V}_{Ct}(\mathbf{s}_t - \boldsymbol{\epsilon}_t))]|\mathbf{s}_{t-1}) \\
= \; & (1 - P_u(\mathbf{s}_{t-1})) \int \log[exp(\overline{V}_{Nt}(., i_{ut} = 0, W_t, .)) \\
& + exp(\overline{V}_{Ct}(.i_{ut} = 0, W_t, .))] f(W_t|\mathbf{s}_{t-1}) dW_t \\
& + P_u(\mathbf{s}_{t-1}) \log[exp(\overline{V}_{Nt}(., i_{ut} = 1, W_t = 0, .)) \\
& + exp(\overline{V}_{Ct}(., i_{ut} = 1, W_t = 0, .))]
\end{aligned}
$$

$$
\begin{aligned}
= \; & (1 - P_u(\mathbf{s}_{t-1})) \sum_{m=1}^{M} \log[exp(\overline{V}_{Nt}(., i_{ut} = 0, W_t^m, .)) \\
& + exp(\overline{V}_{Ct}(.i_{ut} = 0, W_t^m, .))] f(W_t^m|\mathbf{s}_{t-1}) \\
& + P_u(\mathbf{s}_{t-1}) \log[exp(\overline{V}_{Nt}(., i_{ut} = 1, W_t = 0, .)) \\
& + exp(\overline{V}_{Ct}(., i_{ut} = 1, W_t = 0, .))].
\end{aligned}
$$

Since we assume that past criminal records depreciate at rate $(1-\delta)$, the past criminal history variable n_{ct} is a continuous one. Since we cannot evaluate the expected value function at infinite state space points of n_{ct}, we solve for the expected value function at finite q Chebychev grid points $(n_{ct,1},...,n_{ct,q})$ and then interpolate them using the Chebychev Polynomial Least Squares Interpolation (for details, see Judd (1999)).

After integrating out $\boldsymbol{\epsilon}_t$, the probability of committing a crime and getting caught for individual i under the parameter value θ given s_{it} is

$$P(i_C=1|\mathbf{s}_{it}-\boldsymbol{\epsilon}_t,\theta)=P_C\frac{\exp(\overline{V}_{Ct}(\mathbf{s}_{it}-\boldsymbol{\epsilon}_t))}{\exp(\overline{V}_{Nt}(\mathbf{s}_{it}-\boldsymbol{\epsilon}_t))+\exp(\overline{V}_{Ct}(\mathbf{s}_{it}-\boldsymbol{\epsilon}_t))}$$

where i_C is defined to be 1 if the person gets caught in committing the crime, and 0 otherwise. P_C is the probability of getting caught. If individuals are of different types, then the above needs to be indexed by type as well so that the likelihood increment for individual i of type j in period t is

$$L_{itj}(\theta_j)=L_{itjC}(\theta_j)L_{itjE}(\theta_j)L_{itjHS}(\theta_j)$$

where θ_j is the parameter vector of type j, and

$$
\begin{aligned}
L_{itjC}(\theta_j) &= [P_j(i_C = 1|\mathbf{s}_{it} - \boldsymbol{\epsilon}_t, \theta_j)]^{i_C}[1 - P_j(i_C = 1|\mathbf{s}_{it} - \boldsymbol{\epsilon}_t, \theta_j)]^{1-i_C}, \\
L_{itjE}(\theta_j) &= I(age < 16) + I(age \geq 16)[P(i_{ut}|\mathbf{s}_{it} - \boldsymbol{\epsilon}_t, \theta_j)^{i_{ut}}] \\
&\quad [[1 - P(i_{ut}|\mathbf{s}_{it} - \boldsymbol{\epsilon}_t, \theta_j)]f(W_t|\mathbf{s}_{it} - \boldsymbol{\epsilon}_t, \theta_j)]^{1-i_{ut}} \\
L_{itjHS}(\theta_j) &= I(age \neq 18) + I(age = 18)P(i_{hg}|\mathbf{s}_{it} - \boldsymbol{\epsilon}_t)^{i_{hg}}(1 - P(i_{hg}|\mathbf{s}_{it} - \boldsymbol{\epsilon}_t))^{1-i_{hg}}.
\end{aligned}
$$

$L_{itjC}(\theta_j)$ is the crime increment of the likelihood function. If the individual commits the crime, then the likelihood is given by the first term, and if he does not, by the second term. $L_{itjE}(\theta_j)$ is the employment and wage increment of the likelihood. If he is below 16, it equals unity. If he is above 16, and is unemployed, the likelihood increment is $P(i_{ut}|\mathbf{s}_{it}, \theta_j)$. If he is employed, then the likelihood increment is the product of the probability of employment and the wage density. $L_{itjHS}(\theta_j)$ is the high school graduation increment of the likelihood, which is defined similarly.

In our data, only employment spells of 6 months or more, and only unemployment spells of 2 months or more are recorded. Hence, if we just estimate the employment dynamics directly from the data, our results will be biased. Using the steps below, we try to recover the missing employment and unemployment spells through the model of employment dynamics.

1) Missing data after an employment spell must contain an immediate unemployment spell of less than 2 months. Had the unemployment spell not been immediate, it would have been recorded as employment. Had it been longer than or equal to 2 months, it would have been recorded as an unemployment spell. Similarly, missing data after an unemployment spell must contain an immediate employment spell of less than 6 months. If the blank data after an employment spell is of one period, then we infer it has to be an unemployment spell. If it is of 2 periods, it must be an unemployment spell followed by the employment spell of a month. If a blank data after an unemployment spell is of one month, it must be an employment spell. If it is more than one month, we cannot say.

2) In all other cases, we use the probability of employment in the entering state to run the employment/unemployment probabilities forward. To be consistent with the data, the augmented employment spells are restricted to not exceed 6 months and unemployment spells are restricted not to exceed 2 months.

The likelihood increment for individual i is the product of the likelihood increments for all quarters and types so that

$$L_i(\Theta) = \sum_j \pi_j \sum_l \pi_{jl} \prod_{t=1}^{T} [L_{itj}(\theta_j)]$$

where Θ is the vector of parameters for all types. Also π_j is the probability of the individual being of crime type j, while π_{jl} is the conditional probability of the individual being of unemployment type l, given he is of crime type j.

The total log likelihood is

$$l(\Theta) = \sum_{i=1}^{N} log[L_i(\Theta)].$$

9 Tables and Graphs

Table 1: Sample Statistics

% Whites	52.2
% Father present in childhood home	78.3
% Father unemployed during respondents childhood	14.8
% Mother present in childhood home	97.0
% Mother worked during respondents childhood	56.9
% High socioeconomic status	49.2
% Grew up in a not loving household	6.04
% Gang member before 18 years old	36.3
No. of friends arrested; average	1.53
% Parents arrested	2.47
% Protestant	42.3
% Catholic	31.3
% Jewish	1.92
% Other religion	1.92
% No religious beliefs	12.6
% Unknown on religion	9.89
% Of high school graduates	44.2
% Who obtained the high school equivalency degree	17.9
% Who are none of the above two	37.9

Table 2: Parameter Estimates

Utility of not committing crime

Utility parameters		Estimates	Std. errors			Estimates	Std. errors
Crime type 1							
Before 18				After 18			
Constant	c^1_{01}	1.1992	(2.890)		c^1_{02}	7.8973	(4.871)
High school attend.	c^1_1	0.33221	(1.611)	Age	c^1_{03}	0.03048	(0.932)
Low wage	c^1_{l1}	-4.9355	(2.069)		c^1_{l2}	1.9377	(1.729)
Medium wage	c^1_{m1}	-2.9786	(3.213)		c^1_{m2}	0.02457	(1.620)
High wage	c^1_{h1}	-4.4134	(2.928)		c^1_{h2}	2.29192	(1.370)
Final period value	f^1	-1.4023	(116.2)				
Crime type 2							
Before 18				After 18			
Constant	c^2_{01}	-3.6852	(2.724)		c^2_{02}	0.4878	(3.396)
High school attend.	c^2_1	-2.5499	(1.891)	Age	c^2_{03}	0.07621	(0.0565)
Low wage	c^2_{l1}	4.37584	(5.459)		c^2_{l2}	1.3222	(1.634)
Medium wage	c^2_{m1}	6.2710	(6.287)		c^2_{m2}	1.1418	(1.423)
High wage	c^2_{h1}	-0.59725	(4.961)		c^2_{h2}	-0.1438	(1.423)
All types, all ages							
Final period value	f^2	-16.4698	(82.15)				
High school grad.	c_5	-0.56415	(0.775)				
State dependence	c_6	-1.9171	(1.058)				
State dependence	α	0.09264	(0.0910)				
Discount factor	β	0.99022	(0.0134)				
Depreciation	δ	0.98046	(1.202E-3)				
Depreciation at 18	δ_{18}	0.76011	(0.0560)				
Crime type 1 prob.	π_1	0.7284	(0.0868)				

$$\begin{aligned} u_N(\mathbf{s}_t - \boldsymbol{\epsilon}_t) &= c_{01}I(age < 18) + c_{02}I(age \geq 18) + c_{03}age * I(age \geq 18) + c_1 i_{ht} \\ &+[c_{l1}I_l(W_t) + c_{m1}I_m(W_t) + c_{h1}I_h(W_t)]I(age < 18) \\ &+[c_{l2}I_l(W_t) + c_{m2}I_m(W_t) + c_{h2}I_h(W_t)]I(age \geq 18) \\ &+c_5 i_{hg} + c_6 n_{ct}^{\alpha} \end{aligned}$$

High school graduation parameters

Crime type1	g_0^1	0.47671	(0.252)
Crime type2	g_0^2	-1.6667	(1.087)
Criminal history	g_1	-0.32986	(0.164)

$$\begin{aligned} P_g &= \exp(\theta_g)/[1+\exp(\theta_g)] \\ \theta_g &= g_0 + g_1 n_{ct}. \end{aligned}$$

Initial unemployment probability

Employment type 1	h_0^1	-0.31411	(0.289)
Employment type 2	h_0^2	2.0465	(0.384)
Criminal history	h_1	-0.0031551	(0.210)

$$\begin{aligned} P_{hu} &= \exp(\theta_{hu})/[1+\exp(\theta_{hu})] \\ \theta_{hu} &= h_0 + h_1 n_{ct}. \end{aligned}$$

Unemployment probability

Employment type 1				Employment type 2			
Before 18	b^1_{00}	-3.149	(0.145)	Before 18	b^2_{00}	-1.399	(0.110)
After 18	b^1_{01}	-2.801	(0.190)	After 18	b^2_{01}	-1.876	(0.178)
Age	b^1_1	-0.0573	(9.884E-3)	Age	b^2_1	-0.0315	(9.52E-3)
All types							
High school grad.	b_2	-0.4347	(0.0506)				
Criminal history	b_3	0.1465	(0.0207)				
Before 18	b_{40}	3.9475	(0.139)				
After 18	b_{41}	5.1209	(0.0432)				

$$\begin{aligned} P_{ut+1} &= \exp(\theta_{ut})/[1+\exp(\theta_{ut})] \\ \theta_{ut} &= b_{00}I(age<18)+b_{01}I(age\geq 18)+b_1t+b_2i_h+b_3n_{ct} \\ &\quad +[b_{40}I(age<18)+b_{41}I(age\geq 18)]i_{ut}. \end{aligned}$$

Probability of being employment type l conditional on being crime type j (π_{jl})

Crime type 1	π_{11}	0.54428	(0.0589)
Crime type 2	π_{21}	0.40896	(0.110)

$$\pi_{j2} = 1-\pi_{j1},\ j=1,2$$

$$L_i(\Theta) = \sum_{j=1,2}\pi_j\sum_{l=1,2}\pi_{jl}\prod_{t=1}^{T}[L_{itjl}(\theta_j)]$$

Wage growth

16-19 dummy	μ_{g01}	0.014360	(7.580E-4)
20-23 dummy	μ_{g02}	-2.41926E-3	(9.950E-4)
24-26 dummy	μ_{g03}	-3.21734E-4	(6.542E-4)
16-23, age	μ_{g11}	1.35110E-4	(3.400E-5)
24-26, age	μ_{g12}	1.65710E-3	(2.394E-5)
Criminal history	μ_{g2}	-5.96896E-3	(2.647E-4)
Std. error	σ_g	0.070657	(4.746E-4)

$$\begin{aligned} \log(W_{t+1}) - \log(W_t) &\sim N(\mu_{gt}(.), \sigma_g), \\ \mu_{gt}(.) &= \mu_{g01} I(16 < age \leq 19) + \mu_{g02} I(20 < age \leq 23) + \mu_{g03} I(20 < age) \\ &\quad + [\mu_{g11} I(16 < age \leq 23) + \mu_{g12} I(24 < age)]t + \mu_{g2} n_{ct}, \end{aligned}$$

Starting wage

Const.	μ_{b0}	1.8006	(0.0445)
Criminal history	μ_{b1}	2.47055E-4	(0.0347)
Std. error	σ_b	0.58733	(7.815E-3)

$$\begin{aligned} \log(W_{t+1}) &\sim N(\mu_b(n_{ct}), \sigma_b) \\ \mu_b(n_{ct}) &= \mu_{b0} + \mu_{b1} n_{ct}. \end{aligned}$$

Table 3: Regression Results of Observable Characteristics on Posterior Probability of Crime Type 1

Variable	Estimates	Std. Error	t-Statistic	P-Value
Constant	.117779	.150838	.780828	.435
Race	.137260	.047429	2.89401	.004
Father at home	.032373	.050116	.645955	.519
Father unemployed	-.995937E-02	.055097	-.180760	.857
Mother at home	.102740	.118525	.866824	.387
Mother worked	.197234E-02	.040322	.048914	.961
Socioeconomic status	.063866	.039546	1.61497	.107
Loving household	.163008	.082119	1.98503	.048
Gang member	-.022921	.043140	-.531325	.596
No. friends arrested	-.020635	.015122	-1.36461	.173
Parents arrested	-.226739	.127177	-1.78286	.075
Rel: Protestant	-.096981	.069995	-1.38555	.167
Rel: Catholic	-.024396	.072846	-.334904	.738
Rel: Jewish	.154614	.154672	.999624	.318
Rel: other	-.109399	.156237	-.700214	.484
Rel: none	-.056244	.082521	-.681569	.496

R-Squared: .1173

Adjusted R-Squared: .0792

Figure 1: Age Arrest Profiles

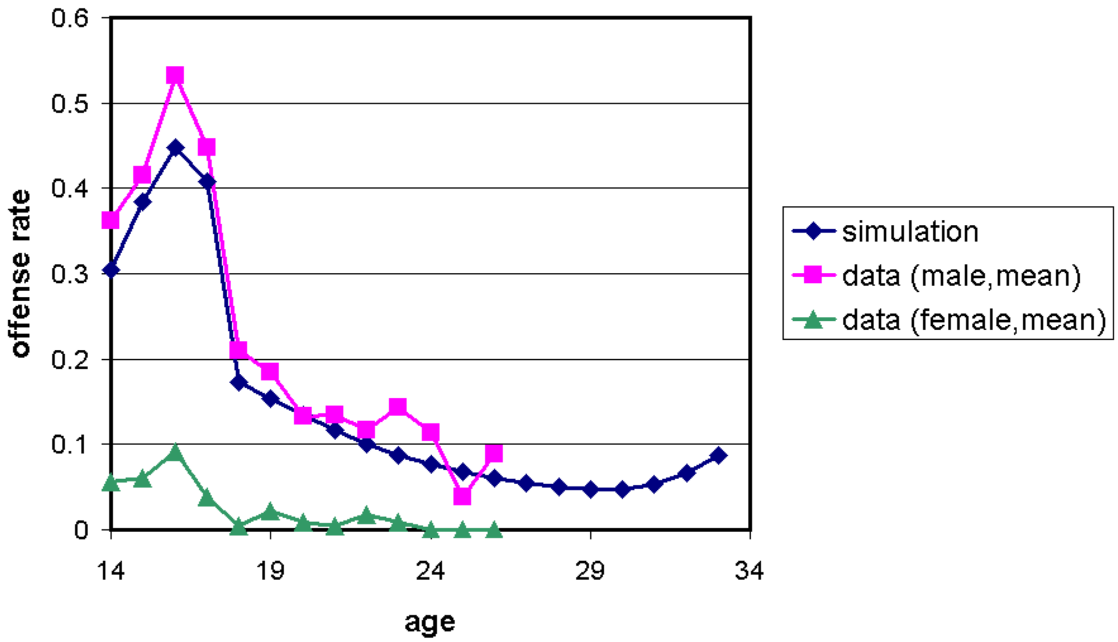

Figure 2: Age Unemployment Profiles

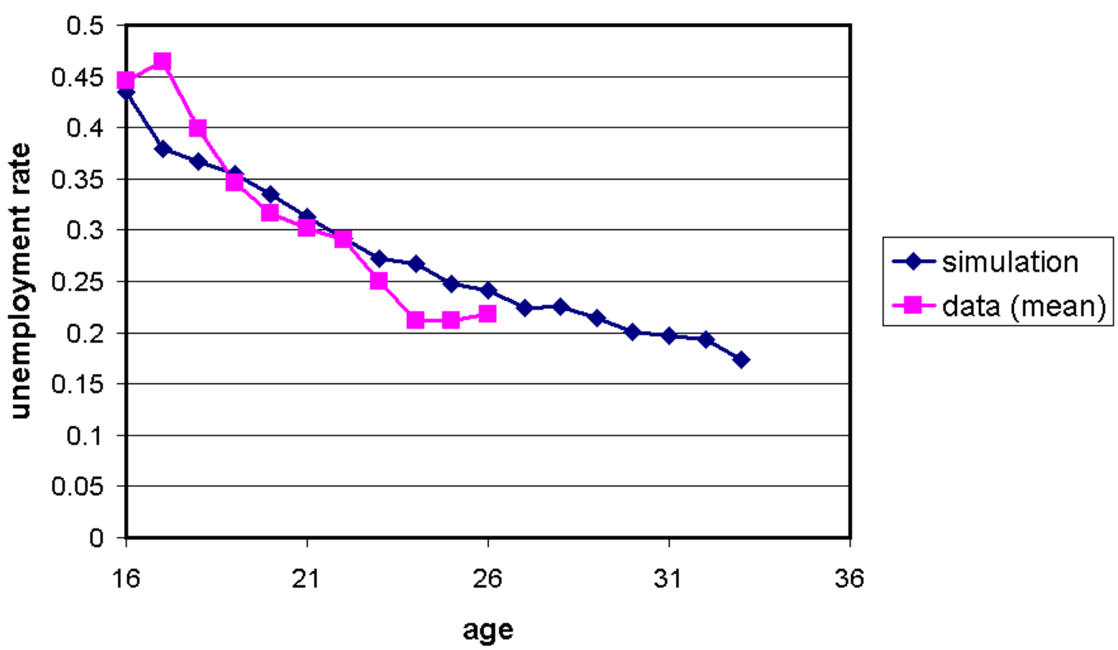

Figure 3: Age Wage Profiles

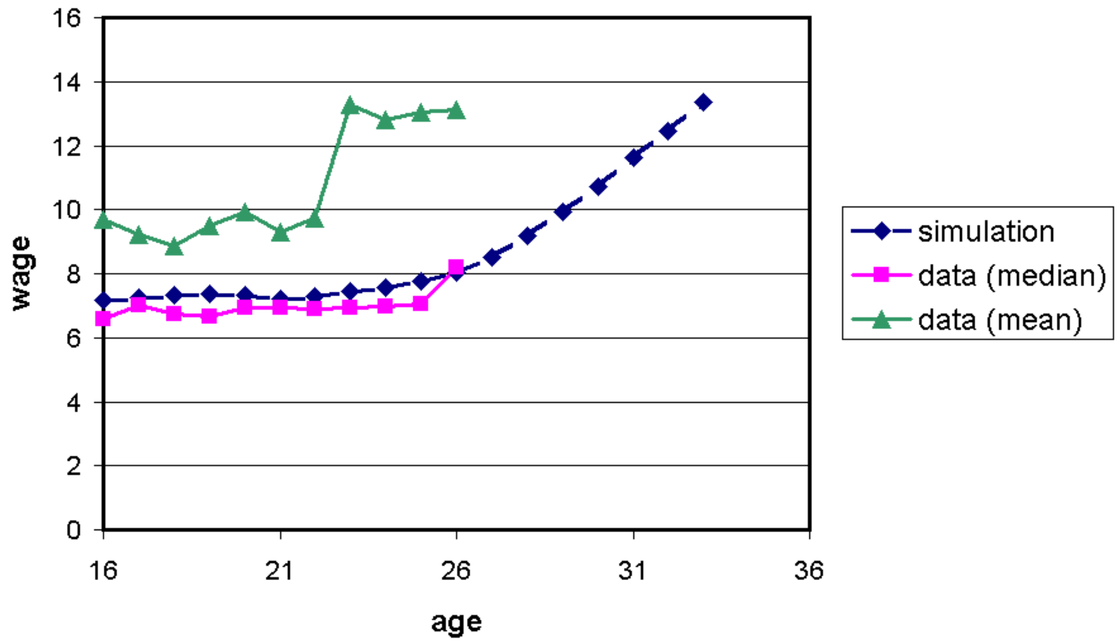

Figure 4: Age Arrest Profiles with Different Past Criminal Records

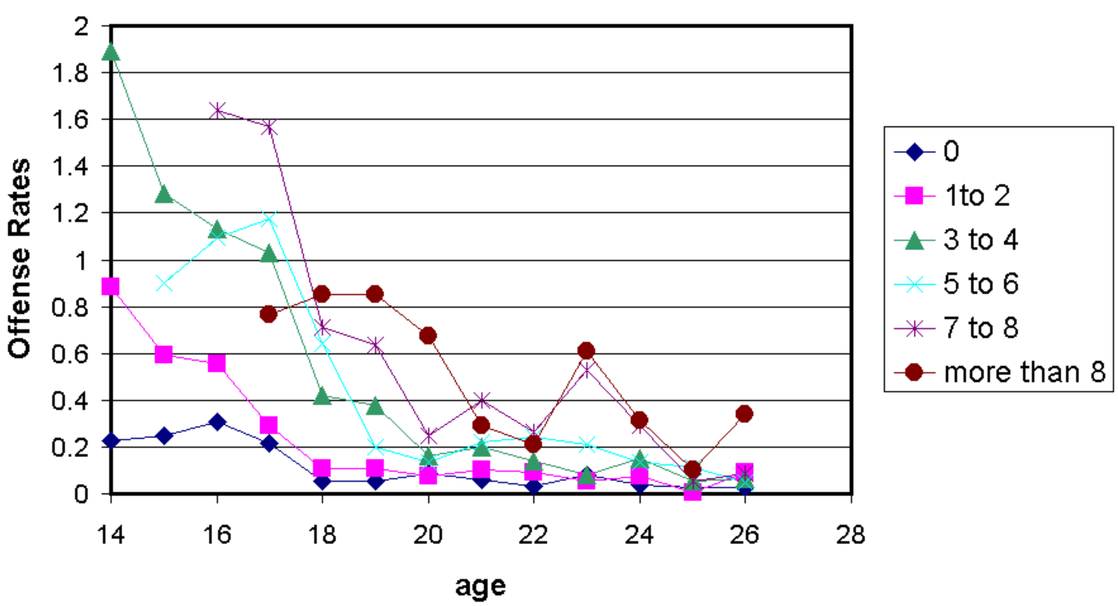

Figure 5: Age Incarceration Profile

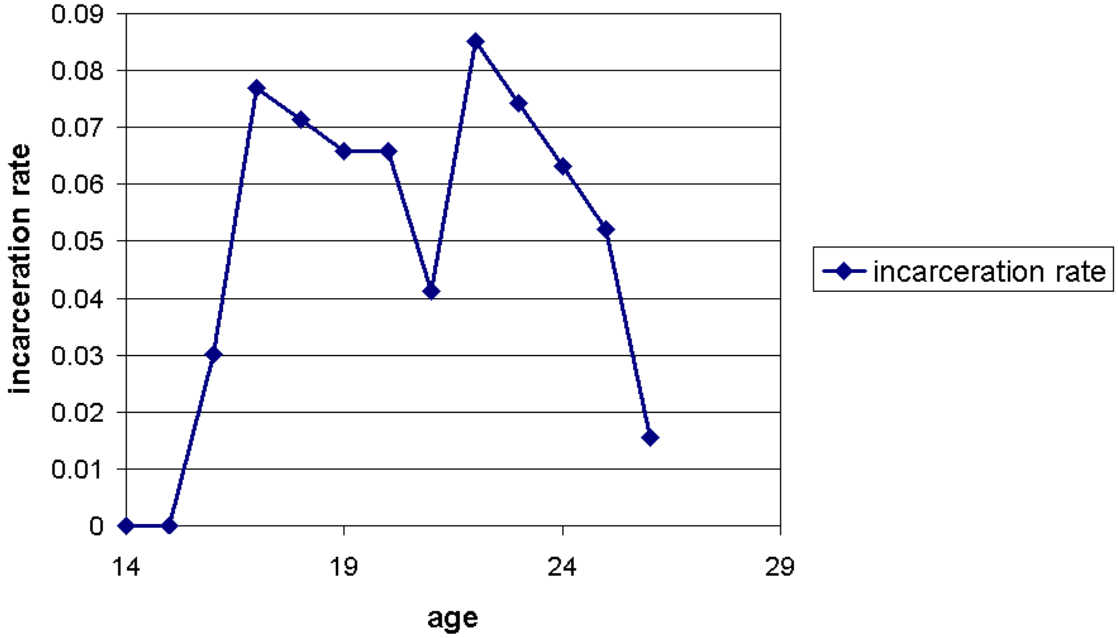

Figure 6: Simulated Age Arrest Profiles of Various Types

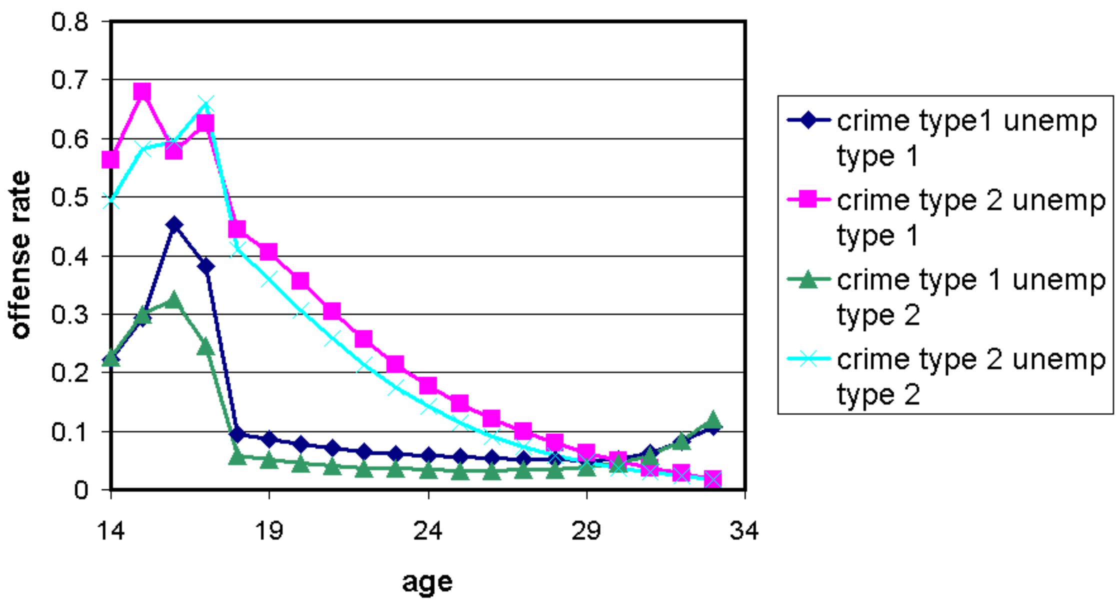

Figure 7: Simulated Age Unemployment Profiles of Various Types

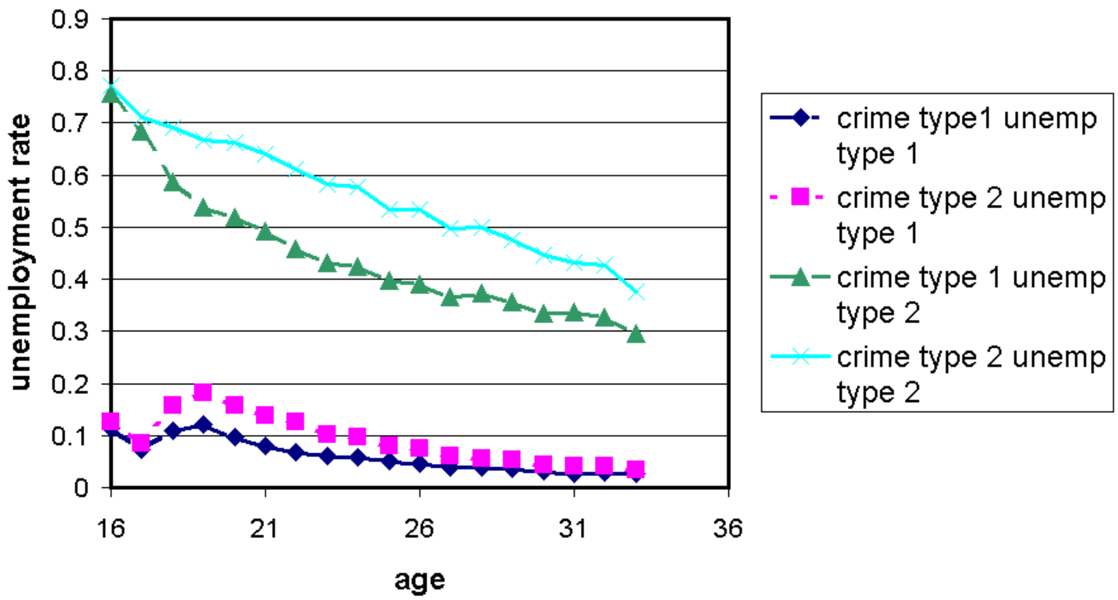

Figure 8: Simulated Age Wage Profiles of Various Types

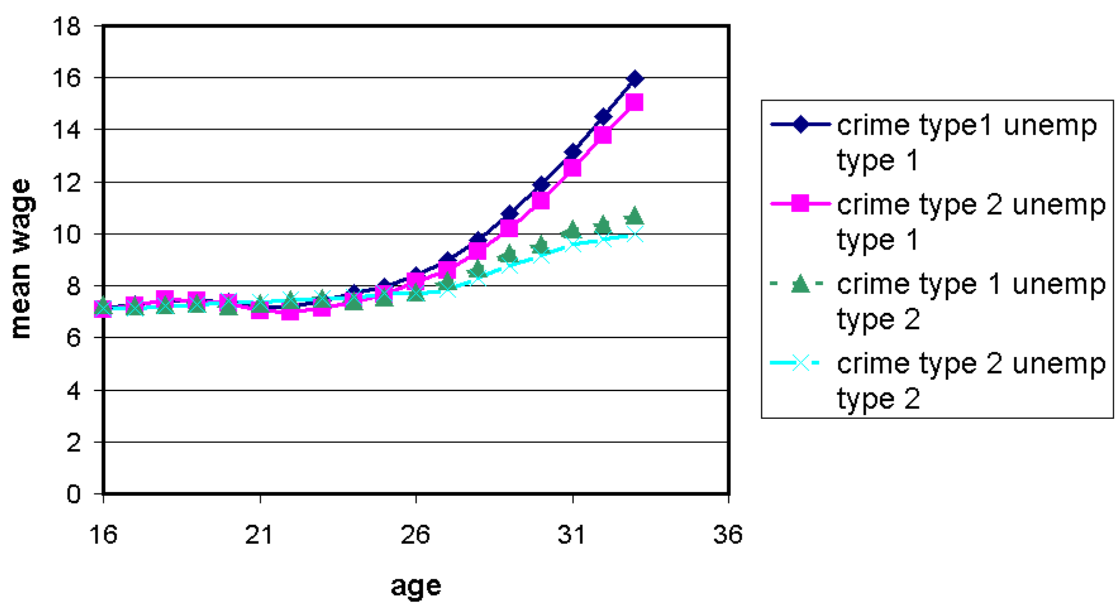

Figure 9: Simulated Age Arrest Profiles with Different Past Criminal Histories

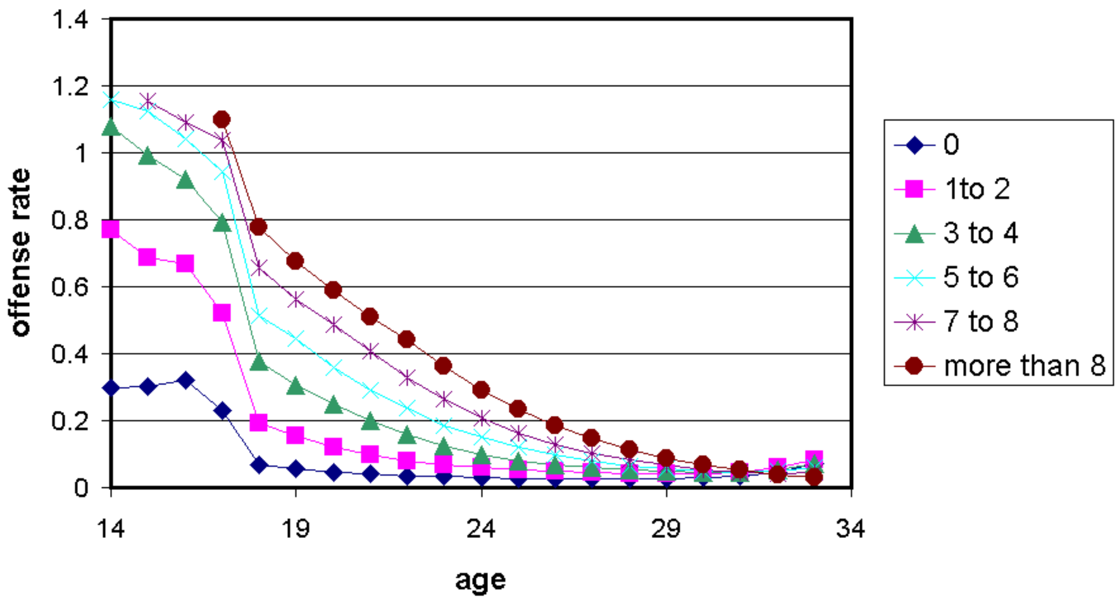

Figure 10: Ratio of Age Arrest Profiles:No Crime Effect on Unemployment Rate

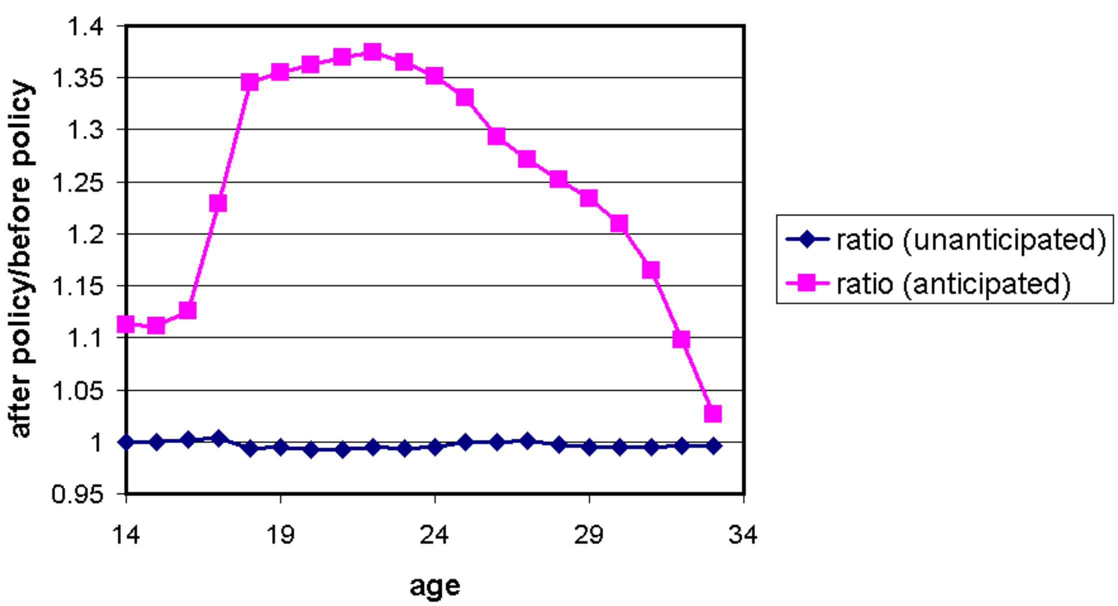

Figure 11: Ratio of Age Unemployment Profiles:No Crime Effect on Unemployment

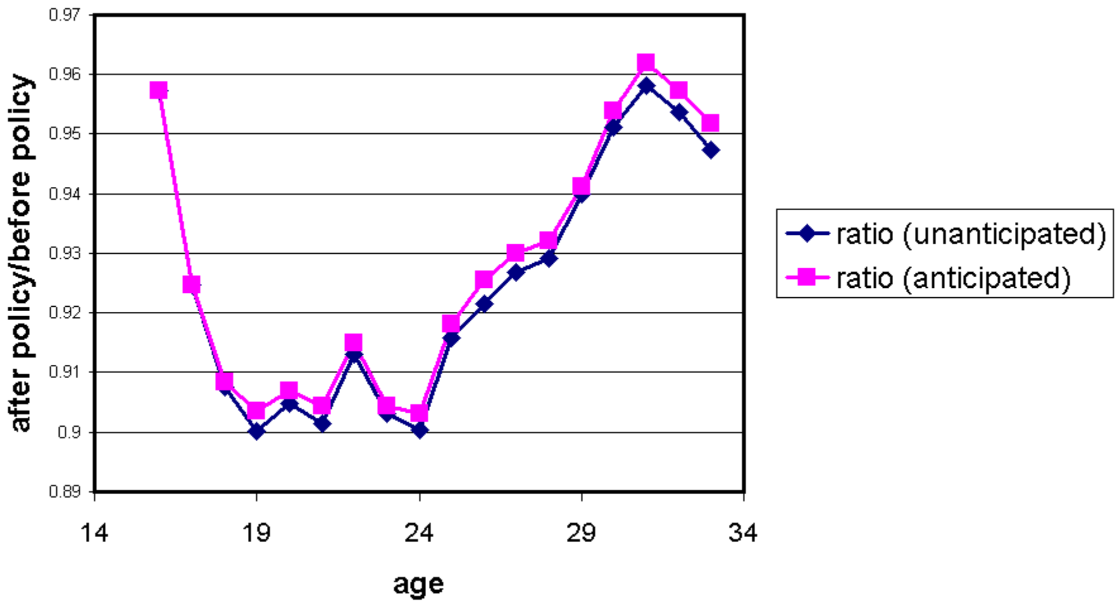

Figure 12: Ratio of Age Wage Profiles: No Crime Effect on Unemployment

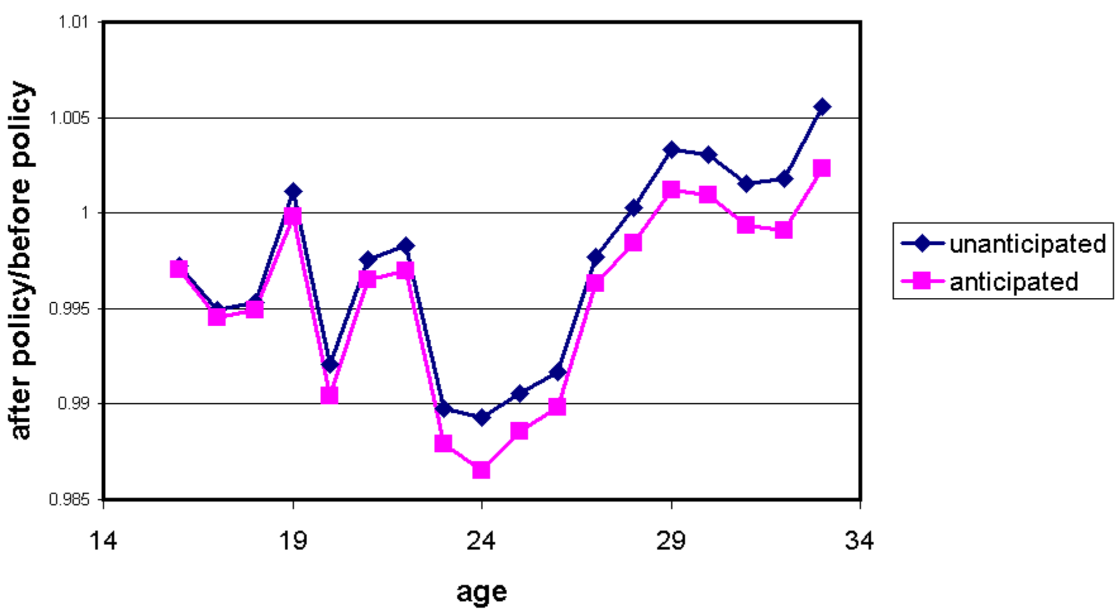

Figure 13: Ratio of Age Arrest Profiles:5% Decrease in Unemployment Transition Probability after 18

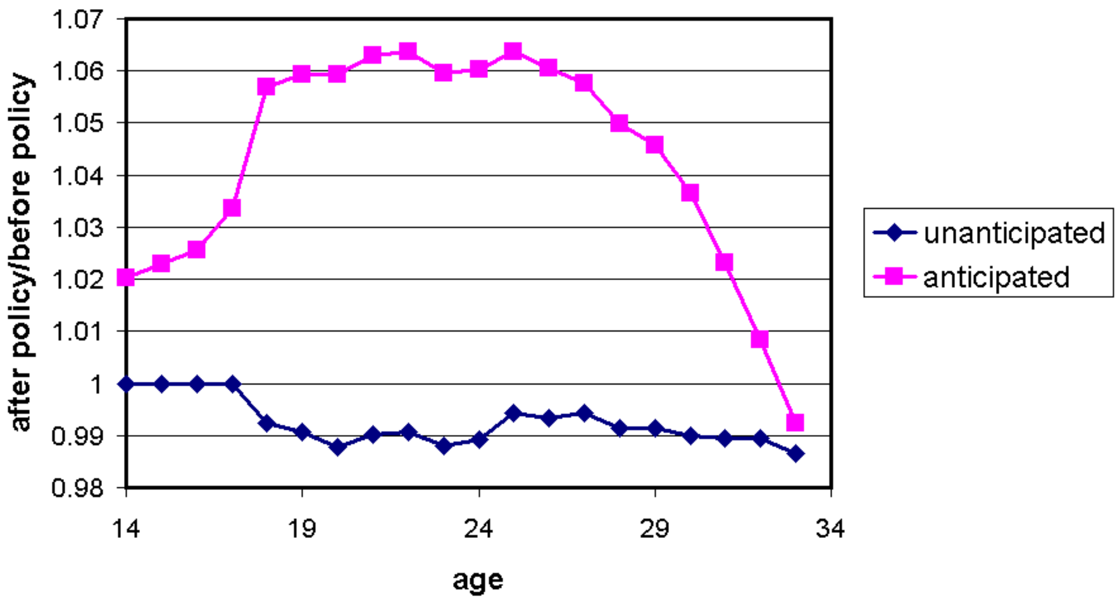

Figure 14: Ratio of Age Unemployment Profiles:5 % Decrease in Unemployment Transition Probability after Age 18

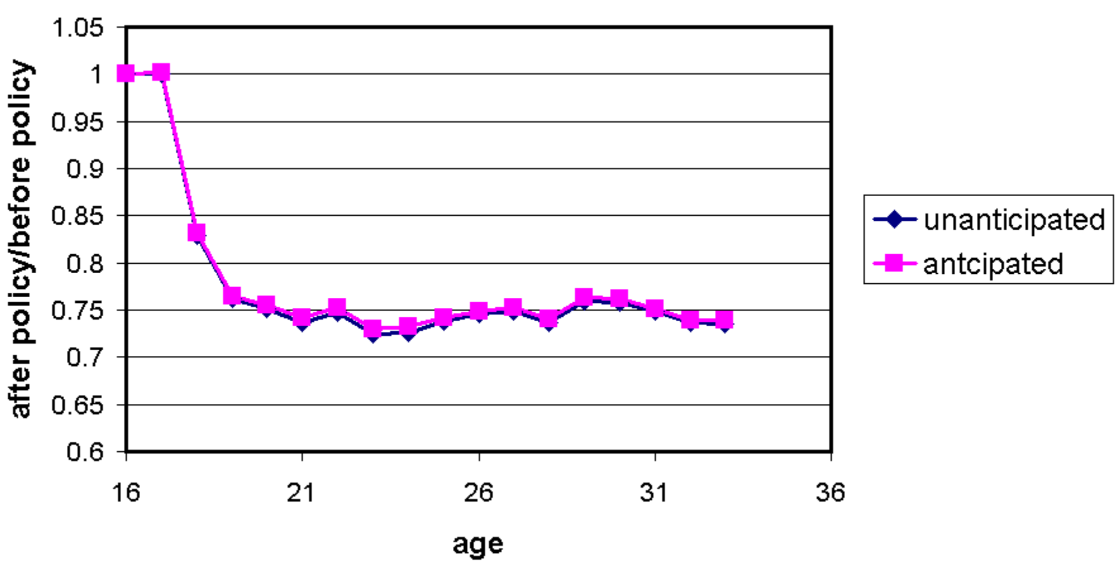

Figure 15: Ratio of Age Wage Profiles:5% Decrease in Unemployment Transition Probability after Age 18

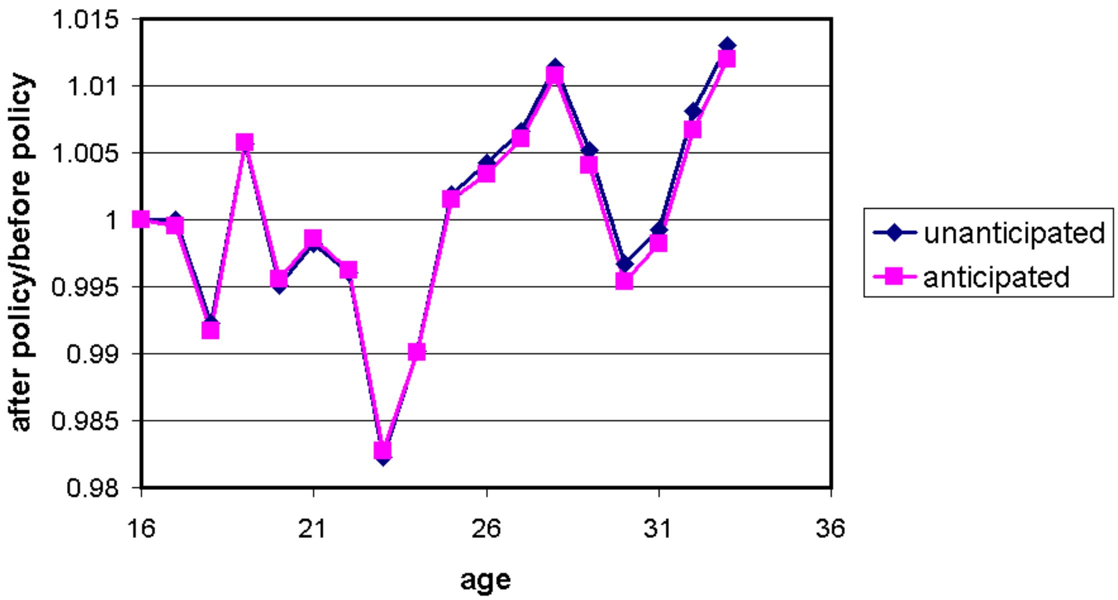

Figure 16: Ratio of Age Arrest Profiles: Anticipated Temporary Fluctuations in Unemployment Transition Probability

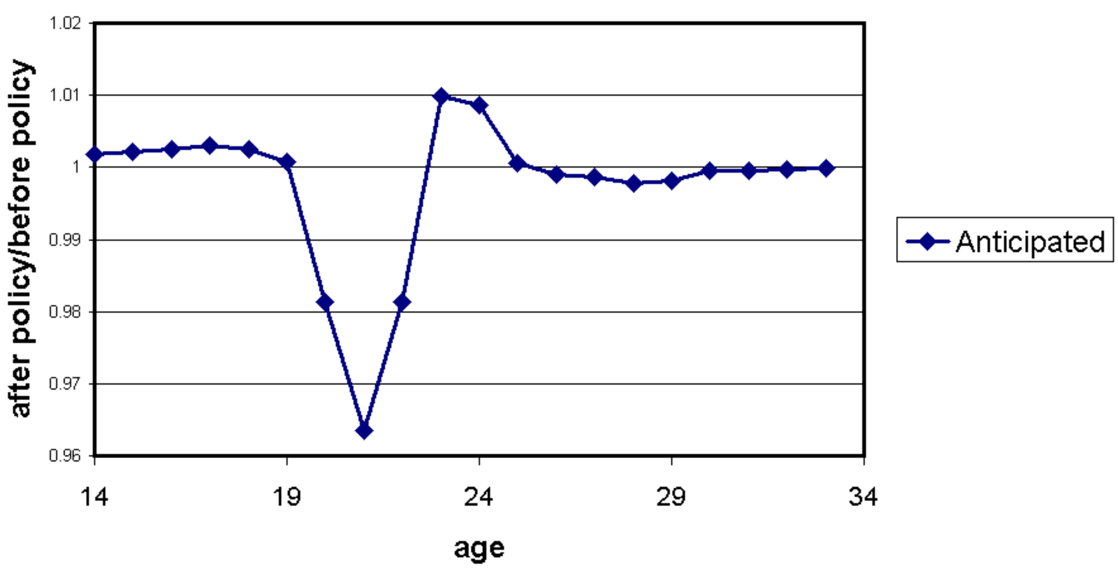

Figure 17: Ratio of Age Arrest Profiles: Anticipated 10% Increase in Probability of Getting Caught

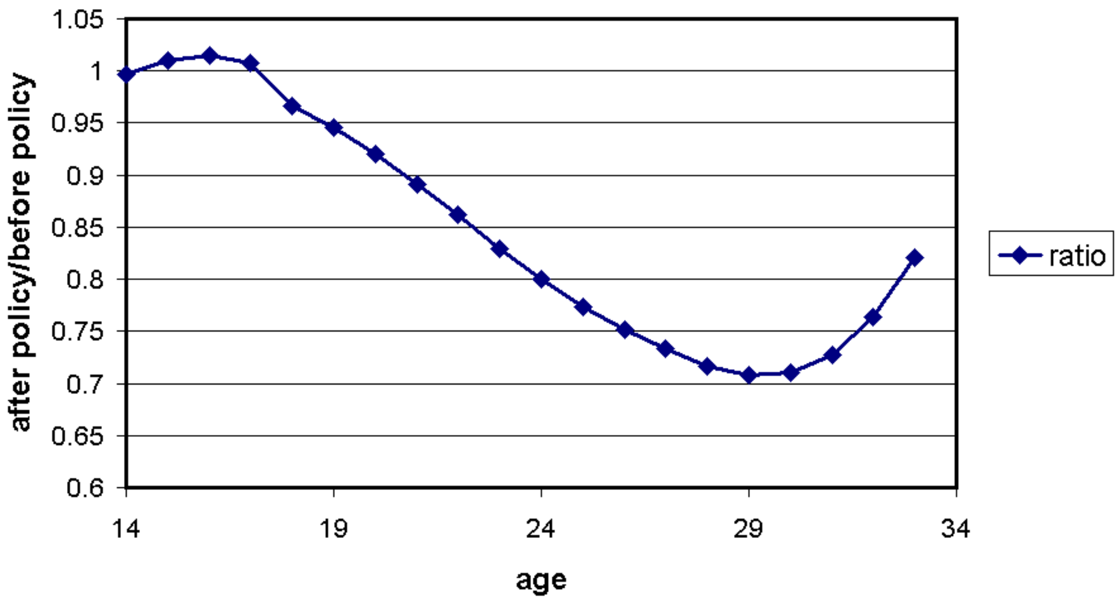

Figure 18: Ratio of Age Unemployment Profiles: Anticipated 10% Increase in Probability of Getting Caught

Figure 19: Ratio of Age Wage Profiles: Anticipated 10% Increase in Probability of Getting Caught

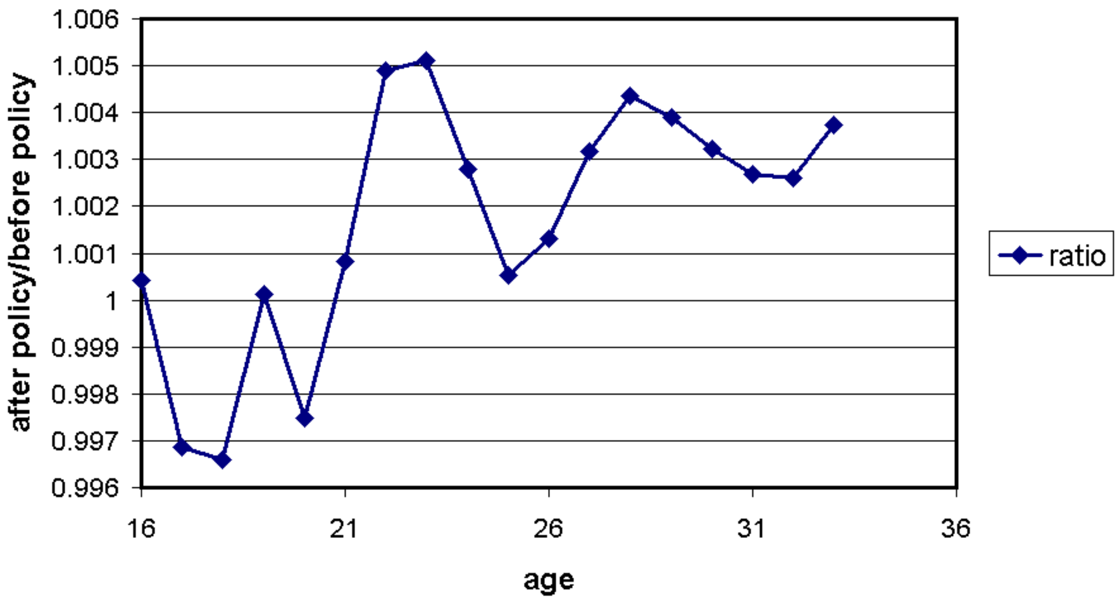

Figure 20: Ratio of Age Arrest Profiles: Anticipated Transformation of Juvenile Crime Records to Adult Records

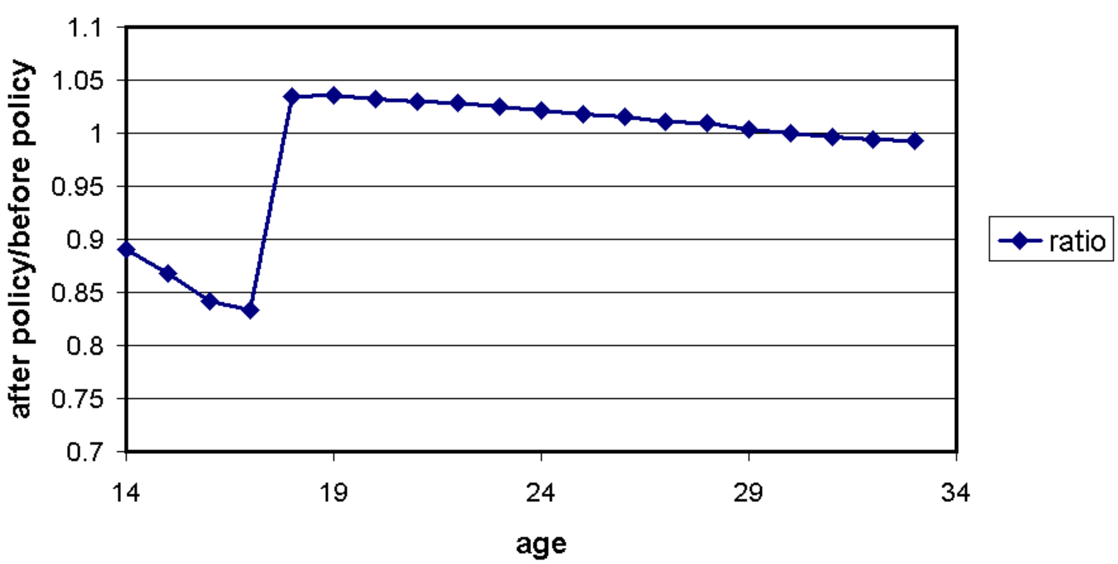

Figure 21: Ratio of Age Arrest Profiles: Anticipated 0.1% increase in delta and delta1