CHAPTER 1

The Economics of the Criminally Inclined

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Abstract

Only some people choose to commit crime. As a starting point, one might expect those desperate for money and with less to lose, such as the unemployed, to have a greater likelihood of offending. A well functioning social security system hopefully helps to reduce the incentives of the unemployed to commit crime. This paper considers an individual's criminal choice in such a setting, using a dynamic optimisation framework. The optimal choice of crime and job search is essentially a portfolio decision problem, which depends on an agent's tastes and opportunities. We also identify a link between unemployment, crime and gambling, even though the utility of consumption is assumed to be strictly concave. For the agent type we refer to as the "criminally inclined", gambling yields strictly positive value. The model then provides a framework to understand the associations between personal characteristics, economic circumstances and self-reports of offending in an unusually rich dataset: the Offending, Crime and Justice Survey (OCJS), 2003-2006.

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1.1. Introduction

Most people choose not to commit crime[1]; however, some people do. As a starting point, one might expect those desperate for money and with less to lose, such as the unemployed, to have a greater likelihood of offending. A well functioning social security system hopefully helps to reduce the incentives of the unemployed to commit crime. This chapter considers the criminal choice in a dynamic optimisation framework where agents are heterogeneous. The optimal choice of crime and job search is essentially a portfolio decision problem, which depends on an agent's tastes and opportunities. We also identify a link between unemployment, crime and gambling, even though the utility of consumption is assumed to be strictly concave. For certain agent types, whom we refer to as the "criminally inclined", gambling (say in a fair game of poker) yields strictly positive value. The model then provides a framework to understand the associations between personal characteristics, economic circumstances and self-reports of offending in an unusually rich dataset: the Offending, Crime and Justice Survey (OCJS), 2003-2006. In this dataset, covering England and Wales, an intuitive proxy for "integrity" is found to have a statistically significant negative relationship with the probability of offending. However, respondents' employment status and their self-assessments of financial position do not show consistently significant relationships with offending. Whilst the lack of relationship between employment status and offending is surprising, the theoretical model offers a number of explanations for this result.

[1]When we refer to crime we focus solely on economic crime. We define economic crime as an activity deemed illegal by society which leads to monetary benefit and/or makes extra non-monetary assets available for consumption. The more limited definition of the variable "Economic Crime" used in the empirical analysis is provided in Table 3.1 of section 3.7.2.

Viewing the criminal choice as a portfolio decision problem can be understood in the following way: committing economic crime, such as shoplifting, yields an instant financial pay-off but carries the risk of arrest and future time spent in jail. In contrast, job search while unemployed has the opposite structure: it is a costly investment made today whose financial return is deferred to the future (it takes time to find employment). An additional feature of the real world is incomplete insurance: a thief cannot purchase insurance against the risk of jail and an unemployed worker cannot purchase insurance against failing to find work. The optimal criminal choice is therefore the solution to a dynamic forward-looking decision problem based on an assessment of risks.

The heterogeneous agents differ regarding: (i) their labour market characteristics, such as wages earned, employment status, job search costs and expected duration of unemployment etc., (ii) their wealth[2] and (iii) their aversion to (disutility from) committing crime, a characteristic we refer to as "integrity". Given the assumption of rational decision making, many insights are immediate. For example, as one is not allowed to consume out of savings whilst in jail, going to jail has a higher opportunity cost for the rich. As such, a career in crime is an “inferior good” and one indulged in by the relatively poor. Similarly, a high wage worker has more to lose by going to jail and so has a reduced incentive to commit crime. At first glance, this statement suggests that, on average, the employed will commit less crime.

[2]A liquidity constraint requires agents’ asset holdings to be non-negative.

A central insight is that, depending on tastes and opportunities, agents sort (or self-select) into criminal behaviour or otherwise. Given such sorting, an interesting issue is how many individuals switch into and out of crime over time. If relatively few switch between crime and no-crime strategies over the business cycle, this would suggest the responsiveness of crime rates to cyclical changes in unemployment may be small in magnitude.

An agent who commands a high wage in the labour market and has high integrity will have little interest in committing crime while unemployed. If laid off, their optimal strategy is to invest in job search to find new employment and use a dissavings strategy to self-insure against the low income stream received whilst unemployed. Conversely, agents with low integrity and who can only earn, say, the minimum wage whilst (legally) employed, have a comparative advantage in "crime".[3] These low-integrity agents sort into criminal behaviour. Significantly, these "criminally inclined" agents may be just as likely to commit crime while employed and earning low wages as while unemployed and on benefits.

Despite the initial intuition that, on average, the employed will commit less crime, the OCJS data shows that the group reporting the highest offending rate[4] is those in routine and manual occupations. It is the high offending rate amongst these respondents which drives the surprising result that the offending rates for Theft and

[3]See Burdett et al (2003, 2004).

[4]In this chapter, the term offending rate refers to a percentage, calculated as the number of observations displaying a particular characteristic and where the respondent offended, divided by the total number of observations displaying the relevant characteristic.

Economic Crime are higher for the employed than for those looking for work.[5] To explain this, firstly, note that workers in this group are probably low paid and experience poor working conditions. Hence, the difference in their utility when employed and unemployed may be small.[6] The result is also explained by the high prevalence of workplace theft recorded. Once one controls for workplace and school theft, the offending rate of those looking for work is higher than for those employed in intermediate or higher occupations.

Additionally, that the survey period 2003-2006 was a period of benign economic conditions is important. It appears even "criminally inclined" individuals could find employment during this period.

Of course, there will be agents who do switch between committing crime whilst unemployed and not committing crime whilst employed. We refer to these types as "unfortunates". Again, the benign economic conditions when the OCJS was conducted probably meant that the number of unemployed "unfortunates" was small.

[5]The variable "Theft" represents all theft including vehicle theft, theft from work, theft from school, robbery and burglary (although there are few observations of these latter two crimes). "Economic Crime" is defined as Theft plus selling drugs, selling stolen goods and credit card fraud. Full details of the sample and offence categories are provided in section 3.7, whilst further detail about the employment status question is given in Table 3.13. All of the analysis uses a sub-sample of the OCJS data. The sub-sample covers respondents aged 17-25.

[6]Any difference in utility was probably further reduced, for the vast majority of respondents, as they lived with their parents. As such, transfers within family units may have provided an additional, informal, form of unemployment insurance.

In the model, those with an integrity high enough to never commit crime behave according to a standard job search model - the option to commit crime has no value. This chapter's novel contribution is the description of optimal dynamic behaviour by those agents with sufficiently low integrity that they are willing to commit crime. We identify three criminal types. These types share one common feature: each will commit crime when unemployed, but only when their liquidity constraint binds.

One criminal type has such a low return to labour that they never look for work, are permanently unemployed and always commit crime. These agents spend their lives in and out of jail. Being inactive in the labour market, their criminal activity is largely immune to business cycle variations in unemployment.

The "unfortunates" are more interesting. When unemployed and with a positive stock of assets, they use an optimal dissavings strategy to smooth consumption over time. If their asset stock is not too high, they will also search for employment. Only when their assets are exhausted do they switch to crime. However, even when this occurs they continue to look for work and, on finding employment, will stop committing crime.

The most interesting criminal type is the "criminally inclined". These agents search for jobs when unemployed, but will continue to commit crime when employed, if they have no assets. This criminal type also has non-standard financial incentives: when unemployed, these agents obtain a surplus by gambling in fair lotteries even

though their utility is strictly concave.[7] Gambling is optimal for this type, when unemployed, because it allows specialisation. If a "criminally inclined" agent gambles heavily and wins big, i.e. achieves a threshold level of assets, then, on finding employment, the agent goes straight and never commits crime again. If, instead, the agent loses everything so they have no assets, they immediately switch to a life of crime. For intermediate asset levels a smooth dissavings strategy while unemployed is not optimal. An unemployed "criminally inclined" agent with an intermediate level of assets will buy lottery tickets in the hope of a big win and, to maximise the probability of winning, will bet their total stock of assets. If they lose their shirt, they immediately switch to crime.

The OCJS data is consistent with this result. Figures 3.1 shows that those who favour risk are more likely to report offending. Also, offenders like taking risks.[8]

The positive value of gambling to the "criminally inclined" provides an additional explanation for the empirical link between gambling venues and increases in crime after their opening.[9] Not only risk-lovers, but also the "criminally inclined" will be drawn to locations where there are opportunities to gamble.

[7]This non-convexity issue also arises in the optimal unemployment insurance literature where unemployed individuals follow optimal job search and savings strategies: see, for example, Kocherlakota (2004), Booth and Coles (2007), Lentz and Tranaes (2005).
[8]For additional detail see section 3.7.2.
[9]See Grinols and Mustard (2006) and Wheeler et al (2011).

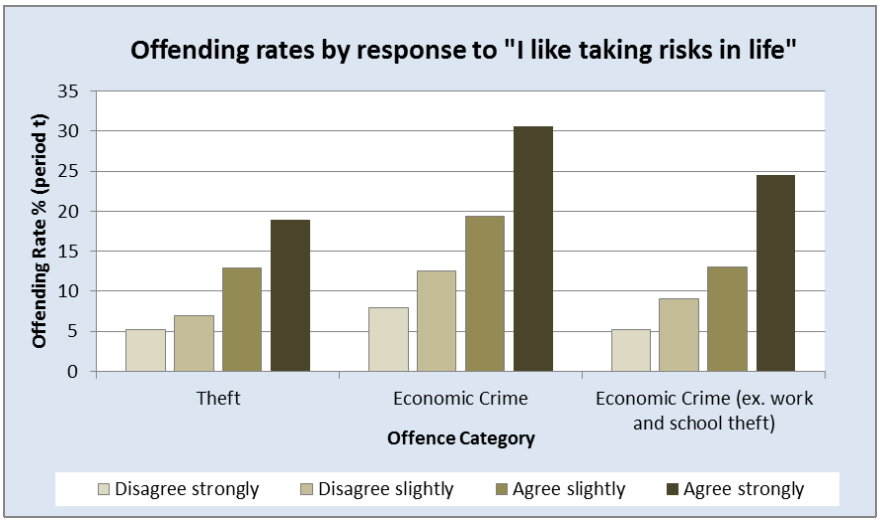

Figure 1.1: Offending rates in period t by attitude to risk at the end of period t-1.

The importance of "integrity" in identifying agent types drove the selection of the OCJS dataset. To the best of our knowledge, the OCJS is unique in allowing a comparison of individuals' attitudes towards breaking the law (a clear proxy for integrity) and subsequent offending. Figure 3.2 shows the strong positive association between our chosen measure of integrity and subsequent offending.

The strength of association between this integrity proxy and offending is confirmed by probit models of offending. In the preferred specification[10], an attitude shift from "Agree" to "Strongly disagree" is associated with a statistically significant average reduction in a respondent's offending probability of up to 9.9 percentage points.

[10]See Specification 1 in Table 3.6.

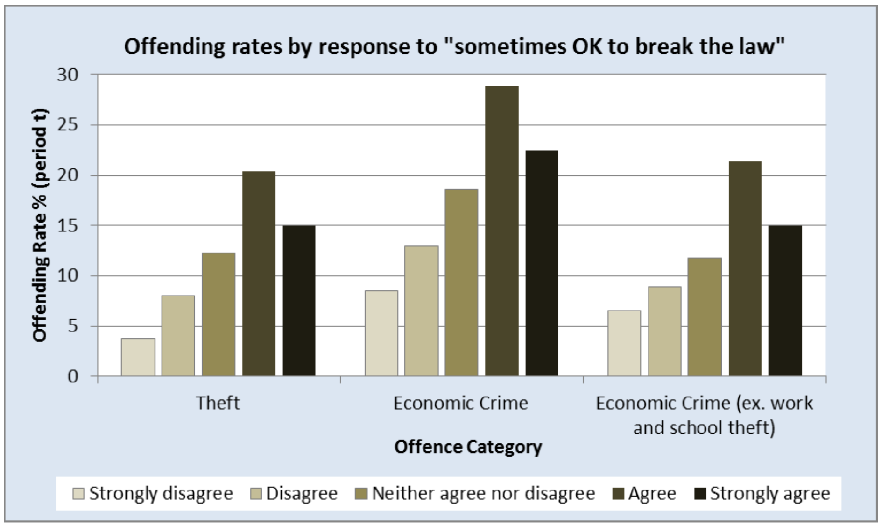

Figure 1.2: Offending rates in period t by attitude to breaking the law at first inteview.

The OCJS data also enables a control which proxies peer effects. The marginal effect of the integrity proxy reported above is robust to the inclusion of this control. Nevertheless, having friends in trouble with the police (our peer effects proxy) is associated with a statistically significant average increase in a respondent's offending probability of between 5.2 and 7.8 percentage points.

The variable which noticeably reduces the statistical significance of the integrity proxy's average marginal effects is a control for prior offending. However, the strength of association between prior offending and subsequent offending reports still supports the notion of agents specialising in crime. Previous offending can be interpreted as an additional signal of low integrity. Reporting an offence prior to first interview is associated with a statistically significant average increase of up to 12.2 percentage points in the offending probability.

The rest of the chapter comprises two parts. Sections 3.2 to 3.5 present the theoretical model and consider the optimal crime, job search, gambling and savings strategies of workers for a range of individual characteristics. Sections 3.6 to 3.9 use the theoretical model as a framework to analyse the OCJS data.[11] Section 10 concludes.

1.2. Theoretical Literature

Early theoretical contributions on the economics of crime include Becker (1968), Ehrlich (1973) and Block and Heineke (1975). These models emphasise the cost-benefit nature of the criminal decision with individuals comparing the expected benefits of crime against the expected costs of punishment. Whilst these papers do not specify the labour market in detail, they do highlight the importance of the earnings differential between legal and illegal sources of income in determining criminal activity. To some extent, all three papers, and in particular Block and Heinke (1975), also note the potential influence of "psychic" costs of crime, or individuals' varying aversions to committing crime. Thus, the need to accommodate integrity into economic models of crime has long been recognised.

More recently, Conley and Wang (2006) incorporate an individual's aversion to crime into a sorting model. Here, individuals choose a level of education to obtain and make a binary choice between legal employment and criminal activity. Individuals with lower integrity[12] and lower ability specialise in criminal activity.[13]

[11]Sections 3.3 to 3.5 are the work of Prof. Melvyn Coles, whilst Sections 3.6 to 3.9 are my work.
[12]Conley and Wang use the term "honesty".
[13]Fender (1999) also includes a simple notion of integrity by dividing the population he considers into "incorruptibles" who never commit crime and "corruptibles" whose criminal decision depends on the wage available.

The paper that introduced a criminal decision into a search theoretic model of the labour market was Burdett et al (2003). In contrast to the present chapter, Burdett et al (2003) develop an equilibrium model of the labour market. However, the present chapter is complementary, as it offers a significant increase in the complexity of the agent's decision problem. Whilst Burdett et al (2003) consider ex-ante identical workers, in our model there is significant agent heterogeneity. Also, our agents have to determine the optimal saving/dissaving strategy in the presence of liquidity constraints.

Engelhardt (2010) develops a search model incorporating agent heterogeneity regarding agents' flow utility whilst unemployed. Engelhardt finds that if this flow utility is sufficiently high, an agent will never commit crime due to the opportunity cost of jail. This result - that only a sub-section of the population commit crime - is similar to our model. However, as with Burdett et al, Engelhardt (2010) does not include an optimal savings problem with a liquidity constraint into his model.

Another search theoretic model is Engelhardt et al (2008). This paper adapts Pissarides (2000) to incorporate a criminal decision and an optimal employment contract. This model is then calibrated, using US data, to analyse the relative impacts of labour market policies and criminal justice policies in determining crime rates. Also, Huang et al (2004) considers the interplay of human capital investment with the legal and criminal sectors. Depending on the level of education obtained, individuals specialise in either legal or criminal activity.[14]

[14]Other theoretical papers linking the labour market and crime, but not involving search, are Lochner (2004) and İmrohoroğlu, Merlo and Rupert (2000, 2004).

1.3. The Model

The model extends the standard job search framework in continuous time where $t \in [0, \infty)$. Consider a representative agent who is infinitely lived, discounts the future at rate $r > 0$ and is characterised by the following parameters:

(i) the integrity parameter $k \geq 0$ describes the agent's (flow) disutility to committing crime;

(ii) if, while unemployed, the agent searches for a job with effort s, then λs describes the rate at which the agent receives a job offer, while ds describes the agent's flow disutility to search. Assuming search effort must be finite, there is no further loss in generality by assuming s is a binary choice variable $s \in \{0, 1\}$;[15]

(iii) w describes the market wage the worker enjoys once employed.

The agent obtains flow utility $u(c)$ from consumption $c \geq 0$, where $u(.)$ is a strictly increasing and strictly concave function. Each agent uses an optimal savings strategy where $A \geq 0$ denotes the agent's wealth and r also describes the market interest rate. There is a liquidity constraint: having no collateral when $A = 0$, the poor are unable to borrow from banks. As agents are liable to commit crime, and so go to jail, when $A = 0$, this crime margin reinforces the banks' decision not to lend.

There are incomplete insurance markets: the agent cannot insure against re-employment risk, nor against the risk of conviction. While unemployed, an agent

[15]Given linear costs and continuous time, the worker can search with effort $s = 1$ for a fraction σ of the next instant $dt > 0$, and so effectively searches with effort $\sigma \in [0, 1]$ at cost $\mathrm{d}\sigma dt$. Setting $s = 1$ as the upper bound is equivalent to re-normalising λ and d.

receives a constant social security benefit b. On re-employment, we simplify the problem by assuming a job is for life. Hence, employed workers do not have a precautionary savings motive.

As pointed out in the introduction, some "criminal" agents would like to gamble in fair lotteries. However, for the most part, gambling does not generate a positive return in the optimal crime/job search/savings strategy. For ease of exposition, we largely ignore the potential purchase of lottery tickets. Instead, we introduce this possibility only when it becomes relevant, i.e. when describing the optimal behaviour of the "criminally inclined".[16]

The agent can be in one of three states: $i \in \{J, U, E\}$ corresponding to being in jail, being unemployed and being employed. If not in jail, each agent can choose a criminal activity level $z \geq 0$ where z describes the resulting flow income from crime. Given current criminal activity z, $\gamma z dt$ describes the probability of being convicted over the next instant $dt > 0$. In an extended equilibrium framework, one might assume γ depends on police resources and on aggregate criminal activity. In this version, however, we fix γ as a parameter.

The agent is sent to prison if convicted of criminal activity; i.e. γ describes the conviction rate per unit of crime. During a prison spell, a prisoner cannot consume any of their savings. Instead he/she obtains a given flow utility u_J and simply waits until release. The prison spell is described by an exponential distribution with parameter μ. Hence $\frac{1}{\mu}$ describes the expected jail-term. Although μ potentially could be conditioned

[16] See Section 3.5.2.

on the level of crime committed, for simplicity, we assume μ is a constant.[17] On release from jail, the agent returns to the labour market as an unemployed individual.

We next describe the Bellman equations for the value functions in each state $i \in \{J, U, E\}$. The solution to these value functions depends on the agent's wealth, A, (a state variable) and their fixed characteristics $X = \{k, \lambda, d, w, b\}$. As X is held fixed throughout, we simplify notation by subsuming reference to X in the value functions below.

1.3.1. When In Jail

As a convicted individual with wealth A is given a jail term distributed according to an exponential distribution with parameter μ, the expected value of being convicted is:

$$V^J(A) = \frac{u_J + \mu V^U(A)}{r + \mu} \tag{1.1}$$

where, on release, the worker is unemployed with value $V^U(A)$. For simplicity, it is assumed the agent's assets, A, are frozen while in jail (perhaps hidden under the floorboards). As we shall show that agents only indulge in criminal activity when liquidity constrained, i.e. when $A = 0$, this assumption only involves a minor loss of generality.

[17] As in the light bulb example used to motivate Poisson processes, the court only observes that the light bulb has gone out, not the likelihood with which it was going to expire.

1.3.2. When Unemployed

At each point in time, the unemployed worker chooses consumption $c \geq 0$, criminal activity $z \geq 0$ and job search effort $s \in \{0, 1\}$ to maximise expected lifetime value. While unemployed, the agent's savings evolve according to:

$$\dot{A} \;=\; rA + b + z - c$$

Thus, given current assets A, the Hamilton/Jacobi/Bellman equation describing privately optimal behaviour while unemployed is:

$$rV^U(A) = \max_{\substack{c,z\geq 0 \\ s\in\{0,1\}}} \left[\begin{array}{c} u(c) - kz - ds + \frac{dV^U}{dA}\left[rA + b + z - c\right] \\ +z\gamma\left[V^J(A) - V^U(A)\right] + s\lambda\left[V^E(A) - V^U(A)\right] \end{array} \right] \tag{1.2}$$

subject to the constraint $A \geq 0$. $V^E(A)$ describes the agent's value from being employed with assets A. The integrity parameter, k, describes the agent's disutility from performing an illegal act while $d > 0$ describes the disutility of time spent looking for work.

1.3.3. When Employed

At each point in time, an employed agent chooses consumption $c \geq 0$ and criminal activity $z \geq 0$ but, as all firms pay the same wage w, we assume no on-the-job search and set $s = 0$. While employed, the agent's savings evolve according to:

$$\dot{A} \;=\; rA + w + z - c$$

Given current assets, A, the Hamilton/Jacobi/Bellman equation describing privately optimal behaviour while employed is:

$$rV^E(A) = \max_{c,z\geq 0} \left[\begin{array}{c} u(c) - kz + \frac{dV^E}{dA}\left[rA + w + z - c\right] \\ +z\gamma\left[V^J(A) - V^E(A)\right] \end{array} \right] \tag{1.3}$$

subject to the constraint $A \geq 0$.

1.3.4. Preliminary Comments and Insights

Describing optimal behaviour requires jointly solving the above Bellman equations for $V^i(.)$. The decision rules for the optimal choice of $\{c, s, z\}$ are functions of the state variable, A, and the underlying characteristics, X. The solution to these Bellman equations is non-trivial as insurance is incomplete: the optimal choice of $\{c, s, z\}$ depends on the mix of risks associated with the chosen portfolio of actions.

The simplifying assumption that the returns to crime are linear in z is empirically useful. If, instead, the cost of crime function, $k(z)$, were strictly convex with the Inada condition $k'(0) = 0$, all agents would commit a small amount of crime. The advantage of linear returns is that, consistent with the data, most citizens choose not to commit any crime. The central interest, of course, is understanding the interaction between job search incentives, criminal behaviour and the consumption choice.

The assumption of no lay-off risk once employed is critical for analytical tractability. It implies an employed agent has no precautionary motive to save. This, in turn, ensures the wealth state $A = 0$ is absorbing: when unemployed with $A = 0$ an agent

is liquidity constrained (unable to borrow further) and when employed with $A = 0$ an agent has no incentive to save for the future. Solving the Bellman equation for each $V^i(.)$ is then straightforward: we first characterise the optimal choice of $\{c, z, s\}$ and the corresponding $V^i(.)$ at $A = 0$. Given that solution, we can then iterate backwards to identify the optimal strategies for $A > 0$. Introducing lay-off risk would instead require computing these value functions numerically. As it is unlikely that adding lay-off risk per se would significantly change the model's insights, beyond marginally reducing the value of employment, we exclude this possibility and obtain analytical results.

This structure yields the following simplifications. First, we show that in the optimal solution, *no agent ever commits crime when* $A > 0$. The intuition for this is that an agent cannot consume out of wealth A whilst in jail, and this foregone consumption option implies a richer agent has a lower return to crime. Thus, the poor agent has a "comparative advantage" in committing crime relative to his/her wealthier self. The linear returns to crime then ensure all agents delay criminal activity until $A = 0$.

Second, an income gap $b < w$ ensures that it is strictly better to be employed than unemployed. As the agent has less to lose through committing crime when unemployed then, *if it is ever optimal to commit crime, the worker will commit crime when unemployed with* $A = 0$. Conversely, we show that if it is not optimal to commit crime when unemployed with $A = 0$, it is never optimal to commit crime. We classify this latter class of agents as "honest". Furthermore, as the option to commit crime

generates no surplus for "honest" agents, their behaviour reduces to that of a standard job search model (with savings).

The complementary group of "dishonest" agents, who commit crime when unemployed with $A = 0$, is our primary interest. A sufficiently large wage gap $w-b$, ensures these agents do not commit crime when employed (they have too much to lose). As employment is then an absorbing state, it follows straightforwardly that an agent consumes permanent income $w + rA$ while employed and so $V^E(A) = \frac{u(w+rA)}{r}$ for any $A \geq 0$. Given this solution for $V^E(.)$, it is relatively straightforward to characterise $V^U(.)$ and so describe job search and crime for this type of agent.

Life is much more complicated, and more interesting, for "dishonest" agents whose wage gap, $w-b$, is sufficiently small that the agent will commit crime when employed if $A = 0$, and whose search costs are sufficiently low that an unemployed agent with $A = 0$ will seek employment. The tension is that the agent is better off when employed, as $w > b$, but employment is no longer an absorbing state. At some point in time, the agent will be convicted and, after a prison spell, will be unemployed. This suggests that an employed agent has a precautionary savings motive: to accumulate savings while employed to self-insure against going to jail and subsequently being unemployed. However, this cannot describe optimal behaviour. Once an employed agent has accumulated $A > 0$, it is no longer optimal for them to commit crime. If they do not commit crime, then there is no risk of jail and, in turn, no precautionary savings motive.

The surprising result is that these agents wish to use gambling strategies while unemployed. We refer to these agents as "criminally inclined" and, given the non-standard nature of their optimal behaviour, we analyse this type separately (see section 3.5.2). Nevertheless it is important to note that, even for this type, we show $A = 0$ remains an absorbing state.

1.4. Optimal Job Search and Crime when $A = 0$ is an Absorbing State

Anticipating that $A = 0$ is an absorbing state, we first solve for the value functions $V^i(0)$ and find the corresponding optimal choices of $\{c, z, s\}$. The subsequent section uses backward iteration to characterise these functions and decision rules for all $A \geq 0$. Of course, we then verify that the solution to the Bellman equations does imply $A = 0$ is an absorbing state.

When unemployed and liquidity constrained with $A = 0$, consumption equals $b+z$, where z is the agent's crime rate in this state. Similarly, consumption while employed is $w + z$. Using (1.1) to substitute out $V^J(0)$, the Bellman equations (1.2) and (1.3), describing the values of being unemployed and employed with $A = 0$, reduce to:

$$rV^U(0) = \max_{\substack{z\geq 0 \\ s\in\{0,1\}}} \begin{bmatrix} u(b+z) - z\left(k + \gamma[\frac{rV^U(0)-u_J}{r+\mu}]\right) \\ +s\left(\lambda\left[V^E(0) - V^U(0)\right] - d\right) \end{bmatrix} \tag{1.4}$$

and

$$rV^E(0) = \max_{z\geq 0}\left[u(w+z) - z\left(k + \gamma\left[V^E(0) - \frac{u_J + \mu V^U(0)}{r+\mu}\right]\right)\right] \tag{1.5}$$

(1.4) and (1.5) are a closed pair of recursive equations for $V^U(0)$ and $V^E(0)$.

Define the No Crime Constraint, NCC, as the parameter values X where the unemployed worker with characteristics X, and $A = 0$, is just indifferent to committing crime. From (1.4), the NCC is identified by:

$$(NCC) \qquad u'(b) = k + \gamma[\frac{rV^U(0) - u_J}{r + \mu}]$$

where, in extended notation, $V^U(.) = V^U(.|X)$. Note the LHS of the NCC describes the marginal return to crime, whilst the RHS describes its marginal cost. Agents with sufficiently high integrity, i.e. those with $k \geq u'(b) - \gamma[\frac{rV^U(0)-u_J}{r+\mu}]$, do not commit crime when unemployed with $A = 0$. As we show such agents never commit crime, agents with integrity on or above the NCC are labelled "honest".

Agents with integrity below the NCC commit crime when unemployed and liquidity constrained. An important distinction, however, is that some of these agents also commit crime when employed. Define the No Crime Constraint (Employed), NCC_E, as the parameter values X such that an employed agent with $A = 0$ is indifferent to committing crime. From (1.5), this constraint is identified by:

$$(NCC_E) \qquad u'(w) = k + \gamma \left[V^E(0) - \frac{u_J + \mu V^U(0)}{r + \mu} \right]$$

As $w > b$ guarantees it is better to be employed than unemployed, i.e. $V^E(0) > V^U(0)$, it follows that the NCC_E lies below the NCC in (k, w) space. Those with integrity between these constraints are classified as "unfortunates": once employed they stop

committing crime as they then have too much to lose. In contrast, the "criminally inclined" - those with integrity below the NCC_E - commit crime even when employed.

The Job Search constraint, JS, in Figure 3.3 is defined as the parameter values X for which an unemployed agent with $A = 0$ is indifferent between $s \in \{0, 1\}$. From (1.4), this corresponds to the condition:

$$(JS) \qquad V^E(0) - V^U(0) = \frac{d}{\lambda}$$

Although only implicit in this equation, this constraint identifies a critical wage threshold where, ceteris paribus, an agent strictly prefers $s = 1$ for wages above the threshold.

A closed form solution for this partition requires solving for the endogenous values $V^i(0)$. To illustrate, consider the frictionless limit $\lambda \to \infty$. In this limit, an agent with $w > b$ chooses $s = 1$ and immediately finds work. For such w, the closed form solution for NCC_E is:

$$(NCC_E) \qquad k = u'(w) - \frac{\gamma}{r + \mu}\left[u(w) - u_J\right]$$

Note the marginal return to committing crime in this state is $u'(w)$, while the marginal loss includes the integrity cost k and the expected loss from conviction.

Again for $w > b$, which ensures job search is incentive compatible, the NCC has the closed form solution:

$$(NCC) \qquad k = u'(b) - \frac{\gamma}{r+\mu}\left[u(w) - u_J\right]$$

This time, when unemployed, the marginal return to committing crime is $u'(b)$ but, as the agent expects to be earning the wage w in the (very) near future, the marginal loss from conviction continues to depend on w. Both of these constraints are downward sloping, they intersect at $w = b$ and the NCC_E is below the NCC for all $w > b$.

For $w < b$, the agent does not look for work and so is a member of the long-term unemployed. The NCC in this case reduces to:

$$k = u'(b) - \frac{\gamma}{r+\mu}\left[u(b) - u_J\right]$$

as the worker expects to live on benefits, b, indefinitely and optimally selects to commit no crime, $z = 0$.

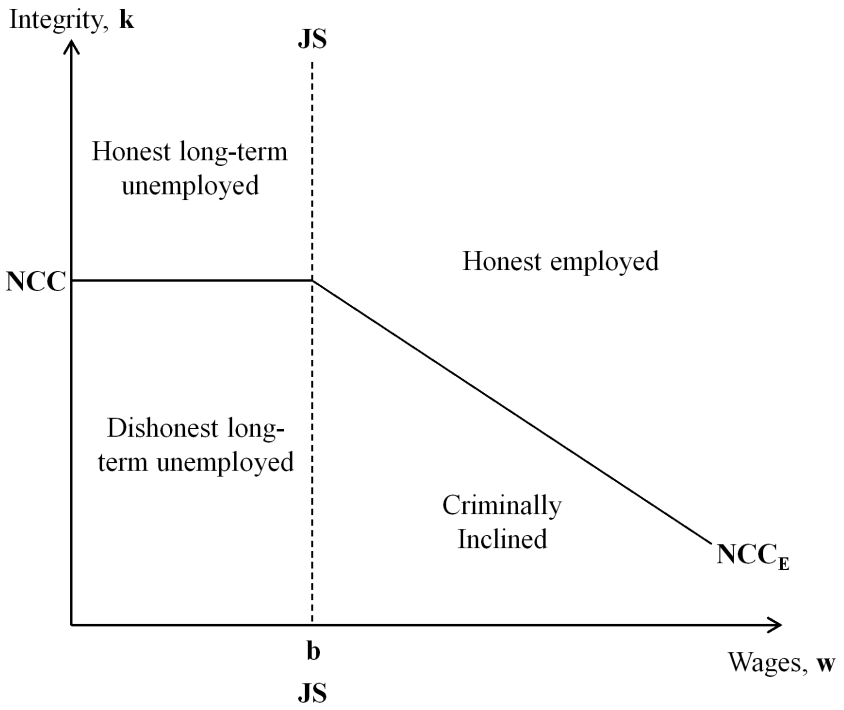

Figure 1.3: Agent types observed when job search frictions are absent.

As such, the frictionless limit identifies five possible types of behaviour when $A = 0$:

(i) **"honest" job seekers** who choose $s = 1$ and never commit crime;

(ii) **"unfortunates"** who choose $s = 1$ and only commit crime when unemployed;

(iii) the **"criminally inclined"** who choose $s = 1$ and commit crime both when employed and unemployed;

(iv) the **"honest" long-term unemployed** who choose $s = 0$ but live honestly on benefits b;

(v) the **"criminal" long-term unemployed** who choose $s = 0$ and commit crime.

In the frictionless limit, the number of unfortunates who commit crime is zero: they each find work arbitrarily quickly and do not commit crime when employed. In the frictionless limit, all crime is committed by the criminal long-term unemployed and by the criminally inclined. Hence, in Figure 3.3 only four types of behaviour are shown.

It is interesting to consider how the level of benefits, b, affects the structure of crime and unemployment. An increase in b shifts the JS constraint to the right and increases the set of long-term unemployed individuals. The NCC, however, shifts down and so there is an unambiguous increase in the number of "honest" individuals. Thus an increase in benefits reduces crime, but at the cost of increasing long-term unemployment.

Finally, note that the ability to earn a higher wage not only moves an agent out of long-term unemployment; it also switches an agent from being criminally inclined to being an "honest" job seeker. The worker switches away from crime once the value of employment is sufficiently high.

Even with labour market frictions, $\lambda < \infty$, the structure of this partition remains largely intact. It is easy to show that no agent has an incentive to look for work whenever $u(w) < u(b) + \frac{rd}{\lambda}$. For such types, the NCC is identified as:

$$k = u'(b) + \gamma \frac{u_J - u(b)}{r + \mu}$$

This is the same as before: for the long-term unemployed who choose $s = 0$, the return to crime does not depend on λ.

For $u(w) > u(b) + \frac{rd}{\lambda}$, active job search is potentially optimal. Whether the agent chooses to look for work, however, depends on their integrity, k. In essence, the unemployed agent is choosing between a portfolio of risky options: to seek employment at flow cost d (to obtain future wage, w, though such a position is only reached at rate λ) and/or to commit crime (which pays z immediately but incurs the cost of imprisonment at rate γz). The optimal portfolio choice depends on the agent's integrity, k, and the wage earned while employed, w.

A little algebra establishes the NCC is now given by:

$$\text{(NCC)} \qquad k = u'(b) - \frac{\gamma}{r+\mu}\left[u(b) - u_J + \frac{\lambda}{r+\lambda}\left[u(w) - u(b) - \frac{rd}{\lambda}\right]\right]$$

This condition is slightly more complicated than before as, whilst unemployed, the job seeker finds employment at rate λ, and $u(w) - u(b) - \frac{rd}{\lambda}$ describes the flow surplus whilst employed. However, the interpretation for the NCC is unchanged. The only difference is the cost of conviction now includes the foregone option value of looking for work. The NCC remains a downward sloping function of w. The intuition is that an increase in w raises the value of being employed which, at the NCC margin, causes the agent to switch away from crime as the loss from conviction is now too high. Thus, along the NCC, an increase in w causes the criminal to substitute from crime to legal employment; i.e. crime and job search are substitute activities.

It is straightforward to obtain an explicit solution for the JS constraint. For "honest" agents, i.e. those above the NCC, the JS constraint is identified by $u(w) = u(b) + \frac{rd}{\lambda}$. Agents with a potential wage above this threshold are active job seekers; the others are long-term unemployed. This threshold does not depend on k as "honest" agents always choose $z = 0$.

For the "dishonest" agents, who lie below the NCC, the expression for the JS constraint is very long and not particularly helpful. The key insight, as depicted in Figure 3.4, is that the JS constraint is downward-sloping for criminal agents. Thus along the JS constraint, an increase in integrity, k, would cause a criminal to invest in job search.

We establish this result using the Envelope Theorem. For "dishonest" agents with $A = 0$, let $z^U > 0$ denote the optimal crime rate when unemployed and $z^E \geq 0$ denote the optimal crime rate when employed. A useful result when $w > b$ (established in Proposition 3.1) is that $z^U > z^E \geq 0$; i.e. the "criminally inclined" choose a lower level of crime when employed. By the Envelope Theorem and for the parameter values X on the JS constraint, the Bellman equations (1.4) and (1.5) mean that an increase in integrity, k, implies:

$$r\frac{dV^U(0)}{dk} = -z^U - \frac{\gamma r}{(r+\mu)}\frac{dV^U(0)}{dk}$$

$$r\frac{dV^E(0)}{dk} = -z^E - \gamma z^E\left[\frac{dV^E(0)}{dk} - \frac{\mu}{r+\mu}\frac{dV^U(0)}{dk}\right]$$

As $z^U > z^E \geq 0$, simple algebra now establishes $\frac{dV^E(0)}{dk} > \frac{dV^U(0)}{dk}$; i.e. an increase in integrity has a greater downward impact on the value of being unemployed than on the value of being employed. This is largely because the agent commits more crime whilst unemployed. This implies the JS constraint is downward-sloping for "dishonest" agents: an increase in integrity increases the return to search, as $\frac{d}{dk}[V^E(0) - V^U(0)] > 0$, and so the wage earned whilst employed must fall to ensure the agent remains indifferent to job search. With market frictions, crime and job search are substitute activities: as integrity increases, the unemployed agent chooses less crime and switches to active job search.

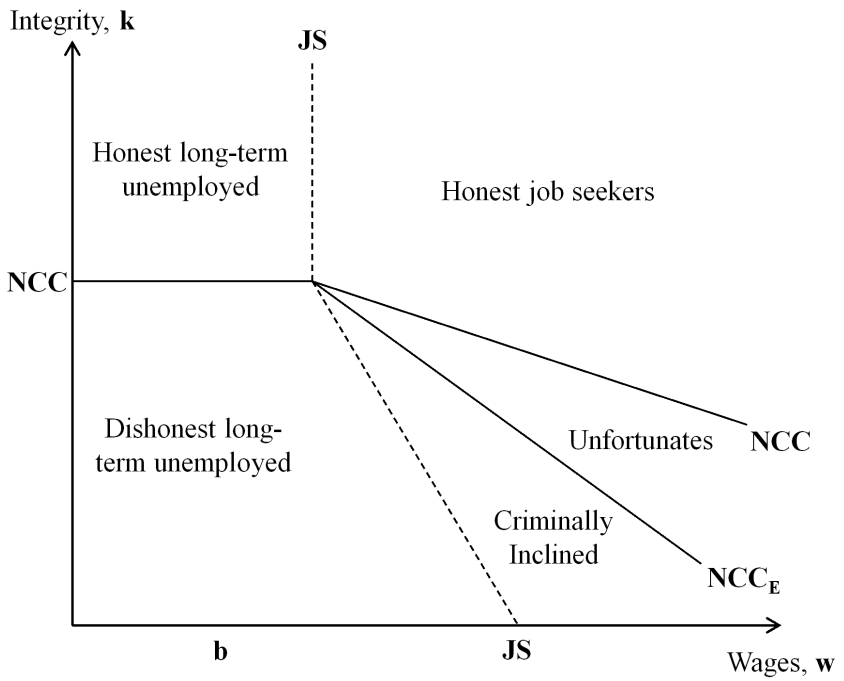

Figure 1.4: Agent types when job search frictions are present.

Note for wages, such that $u(w) > u(b) + \frac{rd}{\lambda}$, the NCC for active job seekers, given above, depends directly on the expected duration of unemployment, $\frac{1}{\lambda}$. An increase in the expected duration of unemployment (lower λ) shifts the NCC upwards and reduces the number of "honest" job seekers. A lower return to job search (it takes longer to find work) leads agents to switch to crime.

1.5. Optimal Savings Strategies when $A > 0$

The previous section described optimal behaviours when $A = 0$, for each possible type X. This section now uses an induction argument to describe optimal behaviours for all $A \geq 0$.

It is obvious that $V^U(.)$ is strictly increasing in A. Consider the Bellman equation (1.2), which describes the value of being unemployed with assets $A \geq 0$. As $u(.)$ is strictly concave, the optimal consumption choice is given by the standard first-order condition (FOC):

$$u'(c) = \frac{dV^U}{dA}$$

The solution of this FOC implies the optimal consumption rule $c = c^U(A)$.

As the return to search effort, s, is linear, optimality implies:

(JS Condition) $$s = 1 \text{ if } V^E(A) - V^U(A) \geq \frac{d}{\lambda}$$

where we assume a job seeker who is indifferent between $s = 0$ and $s = 1$ chooses $s = 1$. The jobless look for employment only if the return from doing so exceeds its cost. Below, we show this structure yields a critical asset level, A^P, where only the sufficiently poor, i.e. those with $A \leq A^P$, choose $s = 1$. Of course, this asset level A^P depends on agent characteristics X.

Substituting out $V^J(A)$ from the Bellman equation given by (1.2) implies that for any $A > 0$, the unemployed worker optimally chooses $z = 0$ when:

$$k > \frac{dV^U}{dA} + \gamma \left[\frac{u_J - rV^U(A)}{r + \mu} \right] \tag{1.6}$$

However, note that if crime whilst unemployed, $z^U > 0$, is optimal when $A = 0$, the optimal choice is given where:

$$u'(b + z^U) + \gamma \left[\frac{u_J - rV^U(0)}{r + \mu} \right] = k$$

This condition implies (1.6) only holds with equality at $A = 0$. Thus as long as $V^U(.)$ is an increasing concave function, then, if (1.6) holds with equality when $A = 0$, (1.6) must hold with strict inequality for all $A > 0$; i.e. crime is never optimal for $A > 0$. However, somewhat surprisingly, it is not immediate that $V^U(.)$ is concave. Indeed, the analysis is problematic for the "criminally inclined". Hence, we consider this case separately.

The Bellman equation (1.3) describes the value of being employed. The optimal consumption choice implies:

$$u'(c) = \frac{dV^E}{dA}$$

the solution of which gives the optimal consumption rule, $c = c^E(A)$. The return to criminal activity is linear, and the agent prefers not to commit crime whilst employed with $A > 0$ whenever:

$$k > \frac{dV^E(A)}{dA} + \gamma \left[V^J(A) - V^E(A)\right] \tag{1.7}$$

Given agent characteristics X and the corresponding solution for $V^U(.)$, $V^E(.)$ at $A = 0$, all that remains is to apply backward induction from this solution, using the optimal control rules described above. As the solution is standard for "honest" agents, we focus on the two most interesting cases, the "unfortunates" and the "criminally inclined". As the solutions are very different, we consider each case separately.

1.5.1. Optimal Behaviour for the "Unfortunates" ($A \geq 0$)

Fix parameter values X consistent with being an "unfortunate". Thus at $A = 0$, job search, $s = 1$, committing crime when unemployed, $z^U > 0$, and not committing crime whilst employed, $z^E = 0$, are all optimal. Given these choices, the payoffs V^U and V^E are determined by (1.4) and (1.5).

Now consider $A > 0$. Suppose for the moment that, given the characteristics X, crime is never optimal when employed. As employment is then an absorbing state, the agent optimally consumes permanent income, $c^E = w + rA$, and so:

$$V^E(A) = \frac{u(w + rA)}{r}$$

Given this conjectured solution for $V^E(.)$, we now characterise the corresponding solution for $V^U(.)$. We then verify in the proof of Theorem 3.1 that, for these parameters X, (1.7) is satisfied for all $A \geq 0$, implying that not committing crime, $z = 0$, is indeed optimal when employed. Hence, the expression $V^E(.)$ above solves the Bellman equation (1.3).

Now consider an "unfortunate" who is unemployed with $A > 0$. The previous section identifies an initial value for $c^U(0) = b + z^U$. The obvious approach is to identify the optimal consumption strategy, $c^U(.)$, given this initial value, whilst noting that $V^U(.)$ is the solution to the initial value problem:

$$\frac{dV^U}{dA} = u'(c^U(A)),$$

with the initial value $V^U(0)$ given by (1.4). It is important to recognise that, if consumption $c^U(.)$ increases with wealth, A, the value function $V^U(.)$ is necessarily concave. This latter result then establishes that committing crime, $z > 0$, is never optimal for $A > 0$.

Using the optimal consumption rule $u'(c) = \frac{dV^U}{dA}$ and the Envelope Theorem then, whilst $s = 1$ is optimal, the Bellman equation (1.2) implies the agent's optimal consumption smoothing strategy evolves according to the pair of differential equations:

$$[-u''(c)]\dot{c} = \lambda[u'(w + rA) - u'(c)] \tag{1.8}$$

$$\dot{A} = rA + b - c \tag{1.9}$$

(1.8) describes the optimal consumption smoothing strategy when the agent finds employment at rate λ, at which point the marginal utility of consumption falls to $u'(w + rA)$. The optimal strategy is forward looking: the "unfortunate" takes into account that at $A = 0$ he/she becomes liquidity constrained and consumes $c^U(0) = b + z^U$. Formally, the optimal consumption strategy $c^U(.)$ is the solution to the above dynamic system with the initial value $c^U(0) = b + z^U$. Figure 3.5 provides the corresponding phase diagram when $z^U < w - b$.

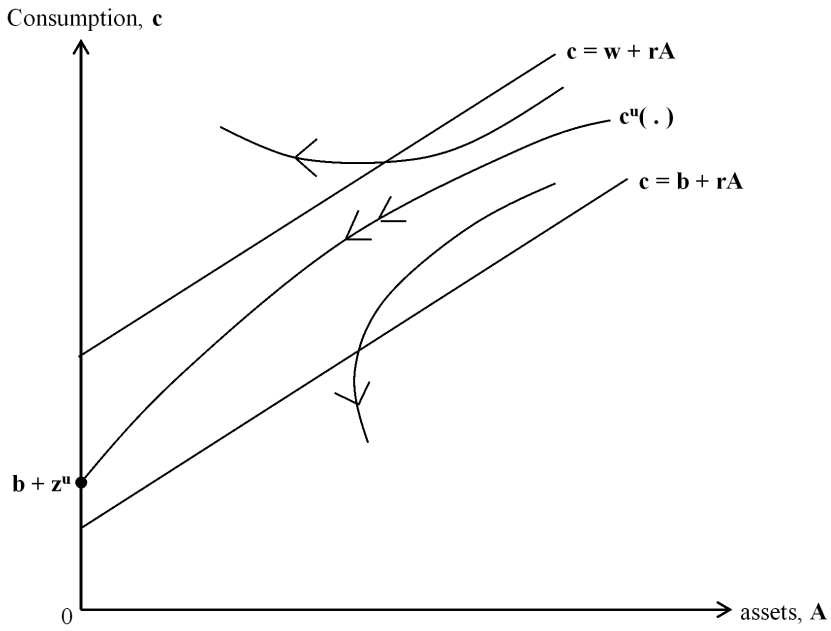

Figure 1.5: Phase diagram showing the optimal consumption strategy for an "unfortunate".

Whilst job search, $s = 1$, is optimal, a simple contradiction argument, using Figure 3.5, establishes the optimal consumption rule satisfies $c^U(A) \in (b + rA, w + rA)$ for all A and is a strictly increasing function. If $c^U(A)$ was not a strictly increasing function, the trajectory could not converge to the initial value $c^U(0)$ as $A \to 0$. Note

$c^U(A) > b + rA$ implies assets fall over time: the job seeker uses a dissaving strategy to reduce the consumption gap between c^U when unemployed and $c^E = w + rA$ when employed. Once $A = 0$, the worker is liquidity constrained and switches to crime, $z^U > 0$, to consume $c^U(0) = b + z^U$.

Of course, the phase diagram in Figure 3.5 only applies whilst $s = 1$ is optimal, which, in turn, requires $V^E(A) - V^U(A) \geq \frac{d}{\lambda}$. This inequality is satisfied at $A = 0$ since, by definition, the characteristics X of "unfortunates" imply $s = 1$ is optimal at this point. Furthermore, as optimal consumption, $c^U(A) < c^E(A) = w + rA$, the return to search, $V^E(A) - V^U(A)$, is continuous and strictly decreasing in A when $s = 1$ is optimal. Thus, there exists a critical asset level, say $A = A^P$, at which point $V^E(A) - V^U(A) = \frac{d}{\lambda}$. This asset level identifies the active job search region. For $A \in [0, A^P]$, the unemployed worker chooses $s = 1$ and, as consumption $c^U(.)$ is a strictly increasing function, it follows that $V^U(.)$ is strictly concave over this region. This confirms it is optimal not to commit crime, $z = 0$, in this region.

For $A > A^P$, we continue the induction process, noting that $s = 0$ and $z = 0$ are optimal in this range. Optimal consumption smoothing now implies $\dot{c} = 0$; i.e. c^U remains constant over time. As V^U is (weakly) concave, it follows that the no crime constraint continues to hold. Additionally, $c^U < c^E$ implies that $V^E(A) - V^U(A)$ continues to decrease as A increases and so $s = 0$ remains optimal. We now have enough information to complete the description of optimal behaviour for the "unfortunates".

Theorem 3.1: Optimal Behaviour of the "Unfortunates"

For characteristics X consistent with being an "unfortunate", whose optimal crime when unemployed is $z^U < w - b$, the optimal strategy is:

(1) Crime: the agent never commits crime except when unemployed and liquidity-constrained; i.e. when $A = 0$;

(2) Job search: the agent chooses $s = 1$ when $A \leq A^P$;

(3) Consumption when employed: the agent consumes their permanent income $c^E = w + rA$, which is an absorbing state.

(4) Consumption when unemployed:

(i) for low $A \in [0, A^P)$, consumption, $c^U(.)$, is strictly increasing in A and exceeds $b + rA$ so that assets fall over time;

(ii) for $A \in [A^P, A^R)$, where $A^R = \frac{c^U(A^P)-b}{r}$, consumption, $c^U = c^U(A^P)$, does not change with A but again exceeds $b + rA$ so that assets fall over time;

(iii) for $A \geq A^R$ the agent consumes permanent income $c^U = b + rA$, which is an absorbing state.

Proof. See the Technical Appendix.

This induction approach also applies when characteristics X are consistent with being an "honest" job seeker; i.e. someone who chooses $s = 1$ and $z^U = 0$ at $A = 0$. The phase diagram in Figure 3.5 continues to apply; the only difference is that the initial consumption value is now $c^U(0) = b$. The same argument as above applies: the optimal consumption smoothing strategy implies $\mathrm{c}^U(.)$ is an increasing function of wealth. As this implies $V^U(.)$ is a concave function, it follows that crime is never

optimal while unemployed. As the agent has even more to lose when employed, the agent also does not commit crime while employed. Finally, note that $A = 0$ is an absorbing state: when unemployed the agent is liquidity constrained and cannot borrow further, and when employed the agent consumes permanent income $c^E = w$. This approach thus identifies the solution to the Bellman equations.

An important feature of Theorem 3.1 is that it restricts attention to $z^U < w - b$. If instead $b + z^U > w$, then consumption whilst unemployed, $c^U(0) = b + z^U$, exceeds the wage earned when employed. Therefore, in this case, the agent has an incentive to also commit crime when employed. We now show that such agents, the "criminally inclined", have very different savings incentives.

1.5.2. Optimal Behaviour for the "Criminally Inclined" ($A \geq 0$)

From now on, we assume the presence of fair lotteries and show that the "criminally inclined" enjoy a strictly positive return from gambling. Of course, the presence of such lotteries ensures $V^U(.)$ is (weakly) concave. This, in turn, ensures that crime is never optimal for $A > 0$.

Fix parameter values X consistent with being "criminally inclined". Thus at $A = 0$, job search, $s = 1$, committing crime whilst unemployed, $z^U > 0$, and committing crime whilst employed, $z^E > 0$, are all optimal. The Bellman equations (1.4) and (1.5) imply the values $V^E(0)$ and $V^U(0)$ and the optimal crime rates z^E and z^U are jointly determined by:

$$rV^E(0) = u(w + z^E) - kz^E + z^E\gamma\left[V^J(0) - V^E(0)\right] \tag{1.10}$$

$$u'(w + z^E) = k + \gamma\left[V^E(0) - V^J(0)\right] \tag{1.11}$$

$$rV^U(0) = \begin{array}{c} u(b + z^U) - kz^U - d \\ +z\gamma\left[V^J(0) - V^U(0)\right] + \lambda\left[V^E(0) - V^U(0)\right] \end{array} \tag{1.12}$$

$$u'(b + z^U) = k + \gamma\left[V^U(0) - V^J(0)\right] \tag{1.13}$$

with $V^J(0)$ given by (1.1).

It is not surprising that the "criminally inclined" commit more crime when unemployed. Proposition 3.1, however, shows they commit significantly more crime when unemployed.

Proposition 3.1. *"Criminally inclined" agents with $A = 0$ choose $z^U > z^E + w - b$.*

Proof: The criminally inclined have $V^E(0) > V^U(0)$ since $s = 1$ is optimal. Equations (1.11) and (1.13) then imply $u'(w + z^E) > u'(b + z^U)$ which yields Proposition 3.1. ■

Having less to lose when unemployed, the crime rate of the "criminally inclined" when unemployed implies they actually consume more than when employed; i.e. $c^U(0) = b + z^U$ exceeds $c^E(0) = w + z^E$. As $w - b$ is typically small for the "criminally inclined" (see Figure 3.4), the difference in crime rates when employed and unemployed may not be particularly large. Nevertheless, this yields a non-standard result: an agent's marginal utility of consumption is higher when employed than when unemployed. Not surprisingly, this generates non-standard financial incentives.

The essential intuition for what follows is that crime and job search are substitute activities. Committing crime reduces the return to job search (being convicted implies a worker loses their job), while being employed reduces the return to crime (a worker has more to lose). Being substitute activities, an agent would prefer to specialise. The solution to the Bellman equations centres around an endogenously determined wealth level, denoted $A^S > 0$, such that an agent will never commit crime when employed with $A = A^S$. It is not optimal to accumulate this asset level A^S through crime. Instead, the "criminally inclined" attempt to win A^S through gambling.

For $A \in [0, A^S]$, where A^S is determined in Theorem 3.2 below, an unemployed agent uses the following gambling strategy: they bet all their assets so that a win yields wealth level A^S, while a loss yields zero wealth. A fair lottery implies they win with probability $p = \frac{A}{A^S}$. Thus, for such an A, the value of being unemployed is:

$$V^U(A) = V^U(0) + \frac{A}{A^S}\left[V^U(A^S) - V^U(0)\right],$$

which is linear and increasing in A. Furthermore, optimality of z^U at $A = 0$ requires:

$$u'(b + z^U) = \frac{dV^U(0)}{dA} = \frac{\left[V^U(A^S) - V^U(0)\right]}{A^S}, \tag{1.14}$$

while linearity of the value function over $[0, A^S]$ further implies $c^U(A^S) = b + z^U$.

In the optimal solution, the employed agent with $A \geq A^S$ never commits crime, consumes permanent income $c^E = w + rA$ and so obtains the value $V^E(A) = \frac{u(w+rA)}{r}$. Now consider the unemployed agent with $A \geq A^S$ but A small enough that $s = 1$ remains optimal. The agent's optimal consumption smoothing strategy again is described by the differential equations (1.8) and (1.9), but this time with the initial value $c^U = b + z^U$at $A = A^S$. Further, the proof of Theorem 3.2 below establishes that optimality requires $w + rA^S > b + z^U$. Figure 3.6 portrays the relevant phase diagram for the optimal consumption strategy.

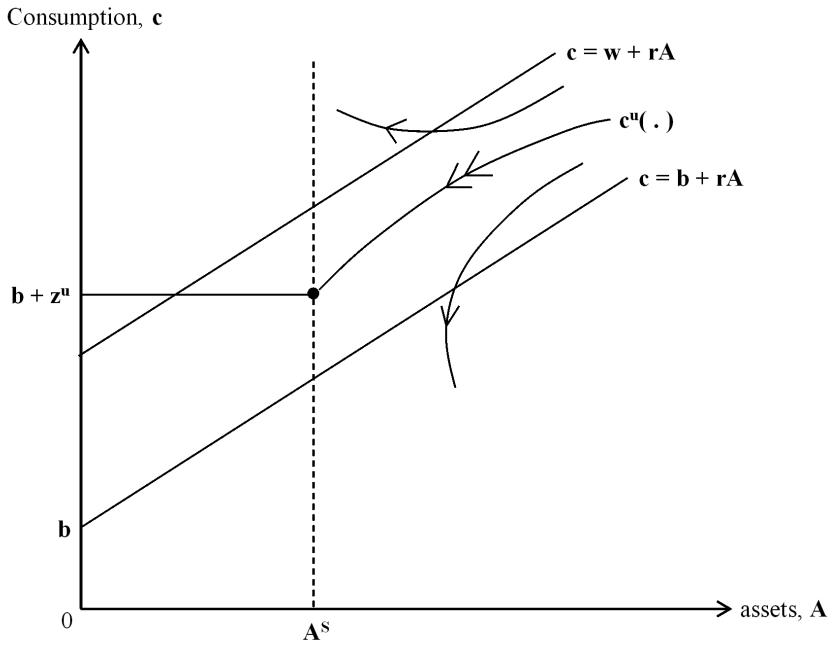

Figure 1.6: Phase diagram showing the optimal consumption strategy for a "criminally inclined" individual.

Whilst $A \geq A^S$, but A is small enough that $s = 1$ remains optimal, then, as before, optimal consumption is $c^U(A) \in (b + rA, w + rA)$ and assets fall over time. Once assets fall to the critical threshold $A^S > 0$, the agent consumes $c^U = b + z^U$ but, as consumption exceeds income $b+rA$, the agent has to finance this income shortfall. At $A = 0$, this shortfall is financed by switching to crime. At A^S, however, the shortfall is now financed through gambling. The job seeker bets their remaining wealth A^S which, in a fair lottery, is lost at a Poisson rate α such that $\alpha A^S = c^U(A^S) - b - rA^S$. We can give an explicit example supposing a fair roulette wheel. Over each (small) time period $\Delta > 0$, the agent bets $(c^U(A^S) - b - rA^S)\Delta$ on red. If they win, they walk away with their winnings and their assets are successfully maintained at A^S. If they lose, they double their bet. Whenever they win they walk away and the net winnings

cover their income shortfall, $(c^U(A^S) - b - rA^S)\Delta$. Of course, they keep doubling their bet every time they lose and, with probability $\alpha\Delta$, they lose everything. In the limit, as $\Delta \to 0$, this gambling strategy maintains wealth at A^S but the agent loses everything according to a Poisson process with parameter $\alpha = \frac{z^U}{A^S} - r$. Once penniless, the agent switches to crime, $z^U > 0$.

This gambling strategy yields the value:

$$rV^U(A^S) = u(b + z^U) - d + \lambda \left[\frac{u(w + rA^S)}{r} - V^U(A^S) \right]$$

$$+\alpha[V^U(0) - V^U(A^s)]$$

the solution of which is:

$$V^U(A^S) = \frac{u(b + z^U) - d + \alpha V^U(0) + \lambda \frac{u(w+rA^S)}{r}}{r + \lambda + \alpha}$$

Using this expression to substitute out $V^U(A^S)$ in (1.14), and noting $\alpha = \frac{z^U}{A^S} - r$, yields the following equation for A^S:

$$u(b + z^U) - d - (r + \lambda)V^U(0) - z^U u'(b + z^U) = \lambda u'(b + z^U)A^S - \frac{\lambda}{r} u(w + rA^S)$$

As (1.12)-(1.13) imply:

$$(r + \lambda)V^U(0) = u(b + z^U) - d - z^U u'(b + z^U) + \lambda V^E(0)$$

substituting out $V^U(0)$ in the previous expression yields:

$$\frac{u(w + rA^S)}{r} - A^S u'(b + z^U) = V^E(0) \tag{1.16}$$

Remarkably, this condition is equivalent to:

$$V^E(A^S) - V^U(A^S) = V^E(0) - V^U(0)$$

Hence, as job search, $s = 1$, is optimal at $A = 0$, it is also optimal at $A = A^S$.

The final step is to show that a solution for A^S exists, is unique, implies $w + rA^S > b + z^U$ (as depicted in Figure 3.6); and that when employed with $A \geq A^S$ the optimal strategy is never to commit crime. The proof of Theorem 3.2 in the Technical Appendix establishes this result.

Theorem 3.2: Optimal behaviour of the criminally inclined

The optimal strategy of a "criminally inclined" agent is:

(1) Crime: $z = 0$ *for all* $A > 0$, *but, at* $A = 0$, $z = z^U > 0$ *and* $z = z^E > 0$ *as identified by the solution to (1.10)-(1.13);*

(2) Gambling while unemployed: for $A \in [0, A^S]$ *the worker bets everything where, in the event of a win, the agent holds wealth* $A = A^S$;

(3) Optimal job search: $s = 1$ *when* $A < A^P$ *where* $A^P > A^S$;

(4) Consumption whilst unemployed:

(i) for $A \leq A^S$, *the worker consumes* $c^U = b + z^U$;

(ii) for intermediate asset levels $A \in [A^S, A^P]$, *consumption* $c^U(.)$ *is strictly increasing in* A *and exceeds* $b + rA$ *so that assets fall over time;*

(iii) for $A \in [A^P, A^R)$*, where* $A^R = \frac{c^U(A^P)-b}{r}$*, consumption* $c^U = c^U(A^P)$ *does not change with* A *but exceeds* $b + rA$ *so again assets fall over time;*

(iv) for $A \geq A^R$*, the worker consumes permanent income* $c^U = b + rA$ *which is an absorbing state;*

(5) Consumption while employed:

(i) for assets $A < \frac{z^E}{r}$ *, the worker consumes* $c^E = w + z^E$ *and, as assets fall over time, switches to crime when* $A = 0$*;*

(ii) for assets $A \geq \frac{z^E}{r}$*, the worker goes straight and consumes permanent income* $c^E = w + rA$*. As* $A^S > \frac{z^E}{r}$*, the employed worker with* $A = A^S$ *goes straight.*

Proof. See the Technical Appendix.

Finally, note that $A = 0$ is indeed an absorbing state. Hence, the above solution method is applicable.

1.6. Existing Empirical Evidence

The theoretical model now provides a framework to analyse data from the Offending, Crime and Justice Survey (OCJS). Before describing the OCJS data, the relationship between the theoretical model and existing empirical results is discussed.

1.6.1. Unemployment and Crime

A large empirical literature explores the link between unemployment and economic crime. Studies from the US consistently find a statistically significant link between unemployment and economic crimes. However, there is debate regarding whether

changes in unemployment rates are sufficient to explain the drop in property crime seen during the 1990s. Levitt (1996, 1997 and 2004), along with Donohue and Levitt (2001), consistently find an elasticity of around 1 between a percentage point change in the unemployment rate and percentage changes in the crime rate. Hence, Levitt (2004) argues that the 2 percentage point drop in the US unemployment rate between 1991 and 2001 was insufficient to explain the 28.8% drop in property crime over the same period. In contrast, other authors, including Raphael and Winter-Ebmer (2001), Gould et al (2002), Lin (2008) and Mocan and Bali (2010), report higher elasticities of crime with respect to unemployment. For example, Mocan and Bali (2010) find that a 1 percentage point increase in the unemployment rate increases the crime rate by 2-4%.[18]

Also concerning the US, Engelhardt (2010) structurally estimates a search model of the labour market which incorporates crime. Using individual-level data from the National Longitudinal Survey of Youth 79 (NLSY79), Engelhardt estimates that the incarceration rate for the unemployed is double that for low-wage workers and quadruple that for high-wage workers.

Turning to Europe, almost all studies find a statistically significant link between aggregate unemployment rates and economic crime. Using a panel of European countries, Altindag (2012) finds a significant positive relationship between unemployment and economic crime. Similarly, Fougere et al (2009), Edmark (2005) and Öster and

[18]Also, Mocan and Bali (2010) find property crime responds asymmetrically to unemployment changes across the business cycle. Crime is more sensitive to unemployment during periods of rising unemployment.

Agell (2007) all find significant positive relationships between unemployment and economic crimes. Fougere et al (2009) consider youth unemployment in France, whilst Edmark (2005) and Öster and Agell (2007) both consider Swedish data.

Using panels of UK police force areas (PFAs), Witt et al (1999) and Carmicheal and Ward (2001) find a significant positive relationship between the unemployment rate, or changes in the unemployment rate, and crime. However, Machin and Meghir (2004) fail to find a statistically significant link between unemployment and crime once PFA fixed effects are considered.

Whilst all of these results, apart from Machin and Meghir (2004), are in contrast to our empirical findings, they are consistent with the theoretical model when $w - b > 0$. Also, as many of these studies cover longer time periods than the OCJS, they can pick up business cycle fluctuations and include periods of higher unemployment.

1.6.2. Wages, Benefits and Crime

In the present model, when wages (benefits) are increased, the NCC_E (NCC) is met at lower values of k. Holding the distribution of k fixed, we would then expect a negative relationship between wages (benefits) and economic crime. This finding matches the empirical results. Grogger (1998) finds a negative relationship between the log of wages and economic crime using data from the NLSY79. The same relationship, again using US data, is also found by Gould et al (2002) and Mocan and Unel (2011).

Turning to England and Wales, Machin and Meghir (2004) find a negative relationship between wages at the 25th percentile in the wage distribution and economic crimes. Using a difference-in-difference estimation strategy which compares PFAs, Hansen and Machin (2002) show the introduction of the minimum wage in 1999 reduced economic crime rates. These findings fit with the evidence provided in the introduction that those in low-level occupations show the highest offending rates.

Switching to the role of benefits, Machin and Marie (2006) find that the introduction of the Job Seekers' Allowance in 1996, with its tougher eligibility criteria, led to increased economic crime. Lastly, Feinstein and Sabates (2008) find that the introduction of the educational maintenance allowance for 16-18 year olds, when combined with improved policing initiatives, was associated with a drop in burglaries.

1.6.3. Asset Holdings, Financial Constraints and Crime

More limited empirical research exists on the direct role of asset holdings and liquidity constraints in determining criminal behaviour.

Probably the most interesting work is Foley (2011). Foley compares daily reports of crimes in twelve US cities and considers their relationship to the monthly cycle of welfare payments. In cities where welfare payments occur at the start of each month an increase in crime is recorded towards the end of each month. This temporal crime pattern does not occur in cities where welfare payments are staggered across the month. The present model explains this temporal variation by viewing each welfare

payment as an endowment of assets, A. Individuals only commit crime once A has been exhausted, i.e. towards the end of the month.[19]

A number of other papers also provide some evidence of a relationship between liquidity constraints and crime. However, they either show mixed results or do not, themselves, argue that binding liquidity constraints cause individuals to commit crime. For example, Morse (2011) argues that payday lenders helped to mitigate increases in shoplifting following natural disasters in California. Also, Garmaise and Moskowitz (2006) show that neighbourhoods containing less banking competition had higher interest rates and subsequently experienced higher economic crime rates. However, Immergluck and Smith (2006) fail to find a statistically significant relationship between the foreclosure rate in Chicago neighbourhoods and economic crime.

Lastly, McIntyre and Lacombe (2012) consider data from London in 2004-2005 on county court judgements (CCJs). CCJs are issued when an individual has difficulties paying off debt. These authors find a statistically significant relationship between the total value of CCJs issued within a neighbourhood and robbery/personal theft.

1.7. Data and Descriptive Statistics

1.7.1. The Offending, Crime and Justice Survey

The OCJS is an individual-level panel data set covering England and Wales in the period 2003-2006. It is similar in structure to the British Crime Survey. However,

[19]Foley's own interpretation of the results is that the permanent income hypothesis is violated and individuals suffer from self-control problems.

in addition to information regarding crime victimisation and individuals' socioeconomic position, the OCJS includes self-reports of offending. The OCJS was explicitly selected due to its richness regarding personal attitudes. This richness includes questions directly asking respondents for their views on the acceptability of committing crime. We interpret respondents' responses to these questions as a strong proxy for k.

The survey ran for four waves. The first wave, in 2003, consisted of a representative cross-sectional sample of 6,892 individuals aged 10-65 plus a boost sample of 3,187 individuals aged 10-25. Subsequently, the survey ran as a panel study with fresh sampling in every wave. In the waves after 2003, only those considered most likely to offend, i.e. those aged 10-25, were interviewed. Sampling was conducted at the household level using modified random sampling of addresses from the Postcode Address File.[20]

Since the theoretical model focuses on the relationship between the labour market and crime, it is important to focus on those individuals who are no longer required to be in full-time education. As such, analysis is performed only using data for respondents aged 17-25.[21] To address concerns regarding reverse causality, offending behaviour in period t is estimated using values of independent variables in period $t-1$.[22] Hence, only respondents completing interviews in two consecutive waves, a

[20]The random sampling was modified to ensure that in each of England and Wales's 43 PFAs at least 100 individuals were surveyed.

[21]17 is the lowest age when information is used to form independent variables in period $t-1$. For the study period, the minimum school leaving age was 16.

[22]As much of the OCJS data is inherently backward-looking, this approach is equivalent to observing independent variables at the start of a time period and offending behaviour during the corresponding time period.

"paired-transition", are included in the main analysis.[23] Thus, the main results use a sub-sample of 3,268 paired-transitions involving 2,004 individuals. This sub-sample is a highly unbalanced panel with just over half of respondents featuring in only one paired-transition.[24] Further detail on the structure of the unbalanced panel is given in Table 3.9.

With self-reported offending data, under-reporting is a concern. The OCJS was specifically designed to minimise under-reporting. First, data collection was performed by independent research companies rather than by the Home Office.[25] Second, to reassure respondents about the confidentiality of their data, respondents received letters on headed paper from the Home Office stating that the Home Office would not know the identity of those interviewed. Last, the interviews were designed to minimise interviewer influence. Responses concerning offending, drug use, alcohol use, health and risk factor questions were completed using computer assisted self-interviewing (CASI).

[23]A minimum amount of further data cleaning was undertaken. Three individuals were dropped for age discrepancies. Also, records involving partial interviews, i.e. interviews not reaching the offending questions, were dropped. Additionally, in 2004, data concerning personal "risk" factors was lost for some respondents. Respondents who were re-interviewed for this "risk" data several months after their original interview have had their 2004 data dropped. Following advice, those who reported ever having taken heroin were dropped due to re-contact and reliability problems. Lastly, the sub-sample is reduced by the requirement for respondents to have answered all questions relating to the dependent and independent variables.

[24]At present, the data is analysed without applying sampling weights. The only weights provided are for cross-sectional analysis and for fully-balanced panel analysis. The value of analysing the observations forming a fully balanced panel is probably limited. The sample of respondents aged 17-25 who are present in all four waves consists of only 305 individuals and 915 paired-transitions. Also, using weights designed to make the sample representative of the 10-25 population may well be inappropriate, given that the population of interest is those aged 17-25.

[25]The Home Office is the government department with responsibility for the police/law and order in the UK.

A small number of academic papers, and a range of Home Office reports, have made use of the OCJS. For example, Papadopoulos (2010) considers links between immigration and crime. However, none of this work specifically considers the relationship between the labour market and crime. Also, the Home Office reports[26] take a broader criminological view of the OCJS data. Hence, they use data for all those aged 10 and above rather than focusing on older, more economically active, age groups.

1.7.2. Descriptive Statistics

Crime variables and offending rates

The OCJS includes very detailed offending questions with over 20 different main offence categories being considered and a separate section covering "white-collar" crime. However, the low number of reports in many offence categories makes it necessary to aggregate the data into broader offence groups. Table 3.1 provides definitions and offending rates for each of the aggregate offence categories used. For now, other than selling stolen goods and credit card fraud, analysis of data from the "white-collar" crime section is left for future research.

As a comparison to the main paired-transition sample, another "Contemporary Sample" is reported. The only difference between this much larger sample, and the paired-transition sample is that in the former, data for both independent and dependent variables comes from the period t interview. Hence, individuals only need to be in one sampling wave to be included. All percentages for the descriptive statistics use the total number of observations, N, as their base unless stated otherwise.

[26]See, for example, Budd et al (2005), Wilson et al (2006) and Hales et al (2009).

Crime Variable	Definition	Paired-Transition Sample		Contemporary Sample	
		Offending Rate (%)	Total Number of Reports[1]	Offending Rate (%)	Total Number of Reports[1]
Theft	Includes: vehicle theft, burglary, robbery, shoplifting, theft from work and theft from school	10.50	343	9.58	541
Economic Crime	As for Theft but adding drug selling, credit card fraud and selling stolen goods	16.43	537	16.32	922
Economic Crime (ex. work and school theft)	As for Economic Crime but excluding theft from work and school	11.47	375	11.35	641

Note: "Paired-Transition Sample" refers to a sample where respondents answered all questions regarding independent variables in period t-1 and all questions regarding dependent variables in period t. "Contemporary Sample" refers to a sample where respondents answered all questions for both independent and dependent variables in period t. All percentages have N as their base.

[1] For "Paired-Transition Sample" as up to three paired transitions are covered each individual could make a maximum of three reports per crime category. For "Contemporary Sample" as an individual could be sampled in up to four waves they could make up to four reports per crime category.

Table 1.1: Definition of offence categories and offending rates by sample type.

The offending rates in the current sub-sample are in line with the offending rates reported in the Home Office reports using the OCJS. For example, for the 18-25 age group, Wilson et al (2006) state that 11% of individuals reported committing some form of theft and 5% sold drugs. Also, Budd et al (2005) take the 2003 data and compare it to data from the Home Office's Offenders Index.[27] The Offenders Index showed that 9% of males had a conviction by the age of 18-20. In the OCJS, the percentage of individuals, in the same age range, admitting some form of offence prior to interview was 63%. As discussed by Smith (2002), in the criminology literature self-reported offending rates are consistently found to be higher than those based on official data.

[27] This is a database holding conviction histories for 7 million individuals that covers all major crime types.

That self-reports of offending exceed the number of convictions is not surprising as only some crimes are detected/reported, the police only arrest a proportion of criminals and only a proportion of those arrested are actually convicted. Also, regarding reporting, some of the offences may occur within families. Others, such as workplace theft, involve a wide spectrum of behaviour. As such, not all reports of offending, had they been discovered, would have warranted a response from the criminal justice system. Within the sub-sample currently analysed, the total admissions of serious crimes, such as burglary and robbery, was very low (18 and 2 reports respectively).

The category Economic Crime (excluding work and school thefts) is included to overcome the following problem: if the unemployed do not have the opportunity to commit workplace theft, using a crime variable including workplace theft could bias downwards estimates for unemployment's impact on offending. Indeed, the offending rate for workplace theft of the unemployed was 3.51%, but for the employed it was 8.73%. However, for this bias to be serious, and for Economic Crime (ex. work and school theft) to be a better indicator of the unemployment-crime relationship, unemployed individuals must not substitute from workplace theft to other crimes. Whilst substitution probably does occur, it is plausible that workplaces may offer favourable opportunities for theft. The opportunities may be higher, and the risks lower, to take items from your employer's warehouse than to force entry into a house, or to steal and dispose of a car.

Respondent Characteristics

Table 3.2 reports the socioeconomic background of respondents. That period t values of independent variables are used in the contemporary sample explains why the mean age is approximately one year higher than in the paired-transition sample. This age difference may also explain some of the other differences in respondent characteristics between the two samples. All the offender/non-offender breakdowns refer to the paired-transition sample.

Statistic	Non-Offenders (Economic Crime)	Offenders (Economic Crime)	Paired-Transition Sample	Contemporary Sample
Personal/Household Characteristics				
% Male	42.99	64.43	46.51	46.04
Mean Age	19.98	19.46	19.89	21.03
(standard deviation)	(2.36)	(2.20)	(2.34)	(2.33)
% Non-white ethnicity	8.97	6.89	8.63	8.85
% A-Levels or above	55.36	50.65	54.59	63.96
% Live with parents	77.85	85.29	79.07	70.46
% Married or co-habiting	14.21	9.68	13.46	18.04
% Have biological children	10.95	5.59	10.07	12.80
% From home without 2 natural parents	26.14	26.44	26.19	26.90
% Religious (at 1st interview)	56.32	50.84	55.42	53.79
% Ever Sought mental health help (before 1st interview aged over 16)	19.33	27.75	20.72	22.76
% Victim of personal crime in past year	24.20	43.76	27.42	24.88
% Victim of household crime in past year	37.53	47.49	39.17	37.75
N	**2,731**	**537**	**3,268**	**5,650**
i	**1,768**	**428**	**2,004**	**3,105**

Note: "Paired-Transition Sample" refers to a sample where respondents answered all questions regarding independent variables in period t-1 and all questions regarding dependent variables in period t. "Contemporary Sample" refers to a sample where respondents answered all questions for both independent and dependent variables in period t. All percentages have N as their base and, other than for "Contemporary Sample", refer to period t-1. The breakdown by offending refers to the "Paired-Transition Sample" with the Offender/Non-Offender classification determined by responses to offending questions in period t.

Table 1.2: Respondents' personal and household characteristics.

Differences in the characteristics of offenders and non-offenders are immediately apparent. The most noticeable are the greater proportions of offenders who are males and victims of crime. The percentage of males is 21.44 percentage points higher for offenders than non-offenders and the percentage of offenders who were victims of personal crime is 19.56 percentage points higher.

The other significant feature of the data is that 79% of respondents lived with their parents. Whilst teenagers and young adults are those most likely to offend,[28] it is an open question whether such individuals are economically independent of their parents. Thus, those in the age group with the greatest proportion of offenders may supplement unemployment benefits with resources from other family members.

The introduction noted the benign labour market conditions during the OCJS's survey period. Table 3.3 confirms a low unemployment rate amongst those surveyed. That the unemployment rate for offenders is 1.26 percentage points lower than for non-offenders can be explained by the inclusion of workplace theft in the category Economic Crime.

[28]See Levitt (1999), Hales et al (2009), Budd et al (2005) and Wilson and Herrnstein (1985). There is consistent evidence that the proportion of the population who offend/get arrested declines with age. However, for continuing offenders, whether the frequency of offending declines with age is less clear (see Piquero et al (2007)). If older offenders are more persistant offenders, it would suggest individuals sort between legitimate and criminal activity over their lifetime.

Statistic	Non-Offenders (Economic Crime)	Offenders (Economic Crime)	Paired-Transition Sample	Contemporary Sample
Economic Variables				
% Unemployment rate[1]	8.46	7.20	8.26	8.02
% NEET rate[2]	13.22	10.24	12.73	13.99
Median household income category[3]	£20,000-24,999	£20,000-24,999	£20,000-24,999	£25,000-29,999
% Respondents answering "Don't know/Refused" to household income question	23.58	25.51	23.90	25.08
% Received free school meals as child[3]	19.10	22.08	19.59	20.47
% Interviewer reports rundown houses "Fairly/Very Common" in area[3]	9.23	10.75	9.48	10.26
N	**2,731**	**537**	**3,268**	**5,650**
i	**1,768**	**428**	**2,004**	**3,105**

Note: "Paired-Transition Sample" refers to a sample where respondents answered all questions regarding independent variables in period t-1 and all questions regarding dependent variables in period t. "Contemporary Sample" refers to a sample where respondents answered all questions for both independent and dependent variables in period t. All percentages have N as their base and, other than for "Contemporary Sample", refer to period t-1. The breakdown by offending refers to the "Paired-Transition Sample" with the Offender/Non-Offender classification determined by responses to offending questions in period t.

[1] The definition of unemployment is designed to match that of the Labour Force Survey. Based on the OCJS's employment status question the numerator is defined as those looking for employment/government training plus those waiting to take up paid employment. The denominator is formed from these two groups plus those in paid employment/self-employment and those doing unpaid work in a family business.

[2] NEET is an acronym for "Not in Education, Employment or Training". Based on the OCJS's employment status question NEET is defined as all respondents other than those going to school; going to college; in paid employment/self-employed; doing unpaid work for a family business; or on a government training scheme.

[3] The base for these percentages/calculating the median excludes those answering "Don't Know" or "Refused".

Table 1.3: Respondents' economic circumstances.

Statistic	Non-Offenders (Economic Crime)	Offenders (Economic Crime)	Paired-Transition Sample	Contemporary Sample
Risky/Negative Behaviours				
% Taken drugs in past year[1]	25.12	59.96	30.84	29.75
% Taken 'Class A' drugs in past year[1]	7.73	21.97	10.07	11.33
% Ever expelled (before 1st interview)	1.83	4.28	2.23	2.44
% Report friends in trouble with police[2]	18.37	40.90	22.09	19.46
% Parents ever in trouble with police (before 1st interview)[2]	8.20	11.76	8.79	8.51
% Parents ever in prison (before 1st interview)[2]	1.47	4.32	1.94	1.94
% Ever arrested (before 1st interview)	7.84	18.44	9.58	11.45
% Ever been to court (before 1st interview)	2.93	5.40	3.34	4.58
% Ever sentenced (before 1st interview)	2.05	3.72	2.33	3.29
% Ever sent to prison (before 1st interview)	0.15	0.74	0.24	0.39
N	**2,731**	**537**	**3,268**	**5,560**
i	**1,768**	**428**	**2,004**	**3,105**

Note: "Paired-Transition Sample" refers to a sample where respondents answered all questions regarding independent variables in period t-1 and all questions regarding dependent variables in period t. "Contemporary Sample" refers to a sample where respondents answered all questions for both independent and dependent variables in period t. All percentages have N as their base and, other than for "Contemporary Sample", refer to period t-1. The breakdown by offending refers to the "Paired-Transition Sample" with the Offender/Non-Offender classification determined by responses to offending questions in period t.

[1] Individuals who reported ever taking heroin were dropped from the sample due to re-contact problems. As such heroin use is not included in these statistics. 'Class A' drugs include cocaine. Cannabis has a lower (less serious) classification.

[2] The base for these percentages excludes those who answered "Don't Know" or "Refused".

Table 1.4: Respondents' engagement in risky or negative behaviours.

As one would expect, Table 3.4 shows that those who report offending are far more likely to report previous contact with the criminal justice system and engagement in risky behaviours during period $t-1$. In particular, the percentage of offenders taking drugs is 2.4 times (2.8 times for Class A drugs) the percentage of non-offenders. This, and the fact that 60% of offence reports came from individuals reporting prior drug use, is consistent with the theoretical model. It seems reasonable to suppose that those dependent on drugs have a particularly high marginal utility of additional consumption due to the high utility provided by obtaining an extra "fix". Considering NCC and NCC_E, if $u'(b)$ and $u'(w)$ are particularly high, drug users will require particularly high integrity, k, not to offend.

Some might argue that any link between Economic Crime and drug use simply reflects a "drugs culture" which inherently connects drug consumption and drug supply. However, if offending and non-offending are classified by Theft, a crime category that excludes selling drugs, the proportion of offenders taking drugs in period $t-1$ is still more than double that for non-offenders (60.6% versus 27.4%).

That only 0.2% of respondents admitted a spell in prison reflects two things. The first is the greater emphasis placed on community sentencing in the UK compared to, say, the US. Secondly, as the OCJS is a household survey, it excludes individuals currently in prison. Thus, the empirical results are probably most representative of those at an early stage in their criminal careers, "successful" criminals[29] or those who engage in relatively low-level offending.

Risk attitude and offending

The full question providing data for Figure 3.1 in the introduction was "Do you agree or disagree? I like taking risks in life". Table 3.10 in the Empirical Appendix records the responses to this question. The data for Figure 3.1 shows that responses of "Agree strongly" for "I like taking risks in life" were associated with offending rates between 3.6 and 4.7 times the offending rates of those responding "Disagree strongly". Figure 3.7 shows that it is also the case that offenders show a preference for taking risks.

[29]By "successful" criminals we mean those who have escaped conviction.

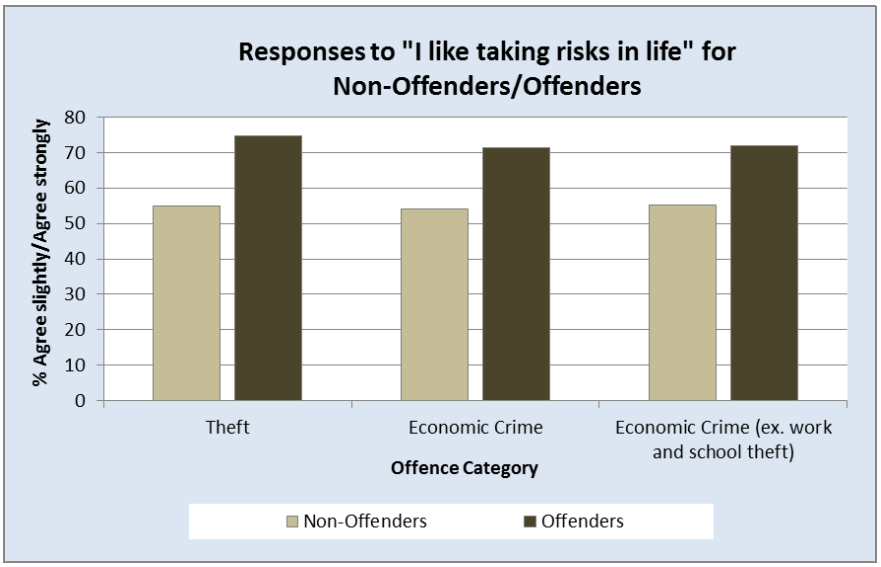

Figure 1.7: Attitude to risk at the end of period t by offending status during period t.

The data behind Figure 3.7 shows that, for each offence category, the percentage of offenders reporting "Agreed" or "Agreed strongly" to the risk taking statement was at least 16.8 percentage points higher than for non-offenders.

Integrity and offending

The theoretical model emphasises the central role that integrity, k, or the "psychic" cost of committing crime has on an agent's criminal decision. An original feature of the current chapter is access to data including clear proxies for k. The potential proxies are the responses to the following four questions:

"How much do you agree or disagree that....

- it is OK to steal something if you are very poor?

- it is OK to steal something from somebody rich who can afford to replace it?

- it is OK to steal something from a shop that makes a lot of money?

- it is sometimes OK to break the law?"

Respondents could answer each question on a five-point scale from "Strongly Agree" to "Strongly Disagree". If a respondent reported greater agreement with these statements, it is intuitive to interpret it as an indicator of their disutility from crime being lower. Table 3.5 highlights that responses were heavily skewed towards "Disagree" and "Strongly Disagree". Less than 0.5 percent of responses to the first three statements involved strong agreement.

Response	OK to steal if poor	OK to steal from rich	OK to steal from shop	OK to sometimes break the law
% Strongly agree	0.41	0.39	0.34	1.15
% Agree	3.26	1.13	0.94	18.28
% Neither agree nor disagree	8.94	3.42	3.61	21.79
% Disagree	39.89	44.02	43.08	36.34
% Disagree strongly	47.5	51.04	52.04	22.44
% Total[1]	**100.00**	**100.00**	**100.01**	**100.00**

Note: Attitudes to crime are held fixed at the value reported in the first interview to match the model. The base for the percentages is the total number of reports across all survey waves.

[1] Values that do not sum to 100% are due to rounding error.

Table 1.5: Responses regarding the acceptability of offending.

As is discussed in section 3.8, responses to the statement "it is sometimes OK to break the law" show the strongest relationship with offending. Hence, it is the responses to this question that have been used to form the integrity proxy. In the model, k is fixed through time and, to match this, the analysis fixes the responses to the crime attitude questions at the values given in a respondent's first interview. That offenders show disruptive/anti-social attitudes and behaviour from an early age has also been widely established in the criminology literature. For example, see Farrington (2002). Thus, when individuals enter our sub-sample at 17, their underlying views on offending are likely to be well established.

To reflect the slightly different spread of data for the "OK to steal" statements, Figure 3.8 shows offending rates by responses to the statement regarding theft when very poor. Figure 3.8 shows respondents reporting "Agree" have offending rates between 2.6 and 3 times higher than those reporting "Strongly disagree". For the breaking the law statement (Figure 3.2), the multiples are even higher being between 3.3 and 5.4. An exception to this pattern of increased offending when agreement with the statements increases is for respondents answering "Strongly agree". However, only a very small number of individuals, 9 in the case of the OK to steal if very poor statement, reported "Strongly agree". For the vast bulk of the data, a clear association exists between stronger agreement with crime being OK and subsequent offending.[30]

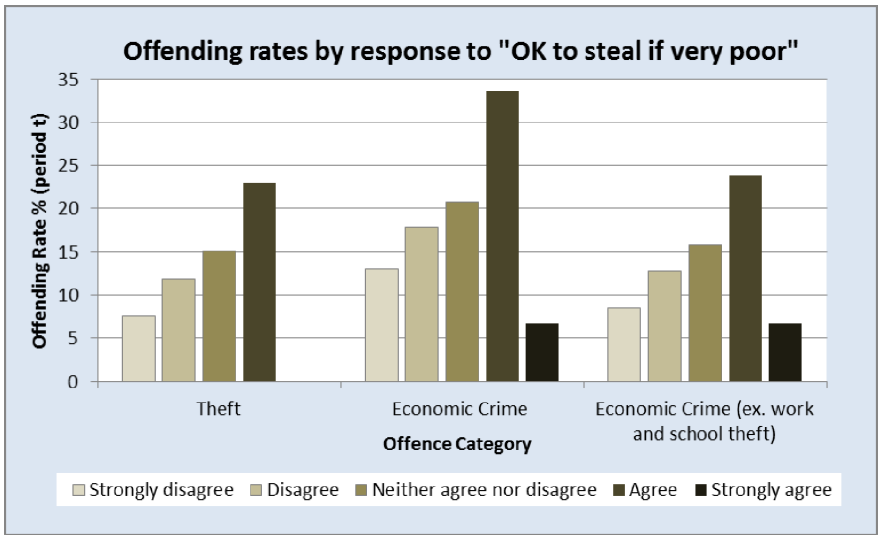

Figure 1.8: Offending rates in period t by attitude to stealing when poor, at first interview.

[30]The charts (not shown) for the other two stealing statements are very similar to the chart for the statement concerning stealing when very poor. The very low offending rate for those reporting strong agreement with the OK to steal statements seems related to religious belief. Of the 9 individuals who reported "Strongly agree" with it being OK to steal when very poor, 8 reported being a member of a religious group.

Liquidity constraints and offending

As a proxy for a binding liquidity constraint ($A = 0$) respondents' ratings of their household's financial position are used. Respondents were asked:

"Thinking of how your household is managing on your total income at the moment, would you say it was....

1. Managing quite well, able to save or spend on leisure,
2. Just getting by, unable to save if wanted to,
3. Getting into difficulties"

We interpret "Getting into difficulties" as a proxy for respondents approaching/having a binding liquidity constraint. Table 3.11 shows the proportion of responses in each category. Figure 3.9 shows the offending rates for those "Getting into difficulties" were between 4.9 and 9.3 percentage points higher than for those "Just getting by".

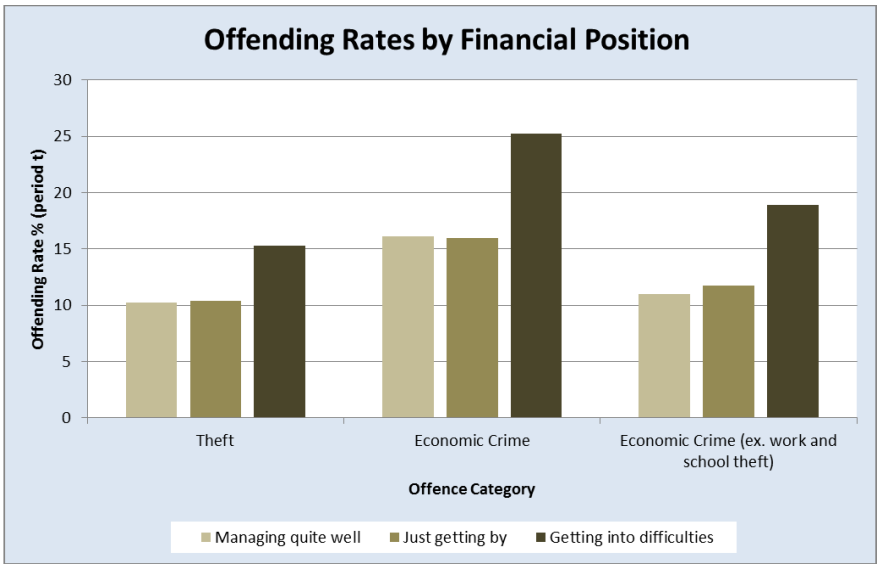

Figure 1.9: Offending rates in period t by financial position at the end of period t-1.

However, there were only 111 reports of "Getting into difficulties". So, whilst Figure 3.9 shows some support for the theoretical model's insight that liquidity constraints are linked to offending, it is unsurprising that the financial position dummies show only limited statistical significance in the econometric analysis.

Employment status and offending

Perhaps the most surprising feature of the OCJS data is the high level of offending reported by the employed. Indeed, for Theft and Economic Crime the offending rate for those in work is higher than for those out of work. This can be seen in Figure 3.10, below.

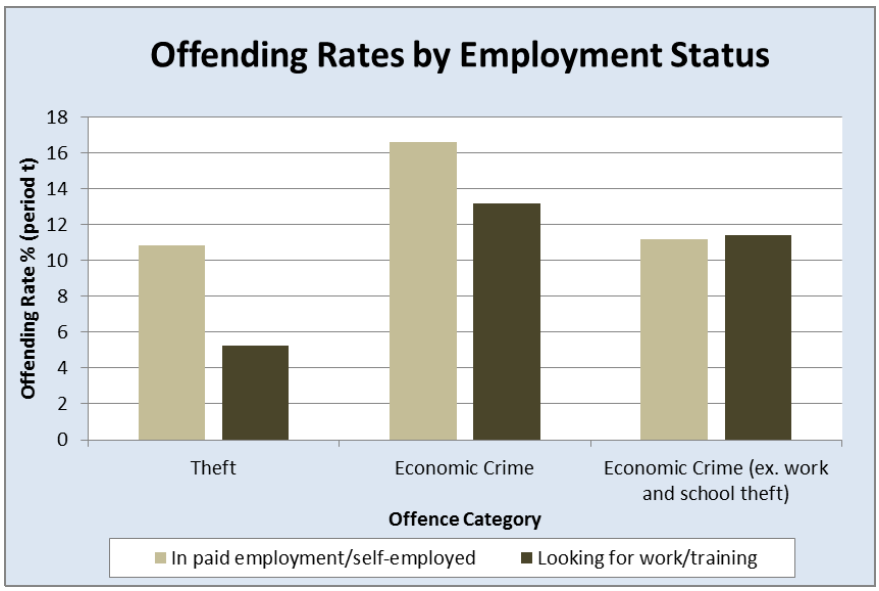

Figure 1.10: Offending rates in period t by employment status at the end of period t-1.

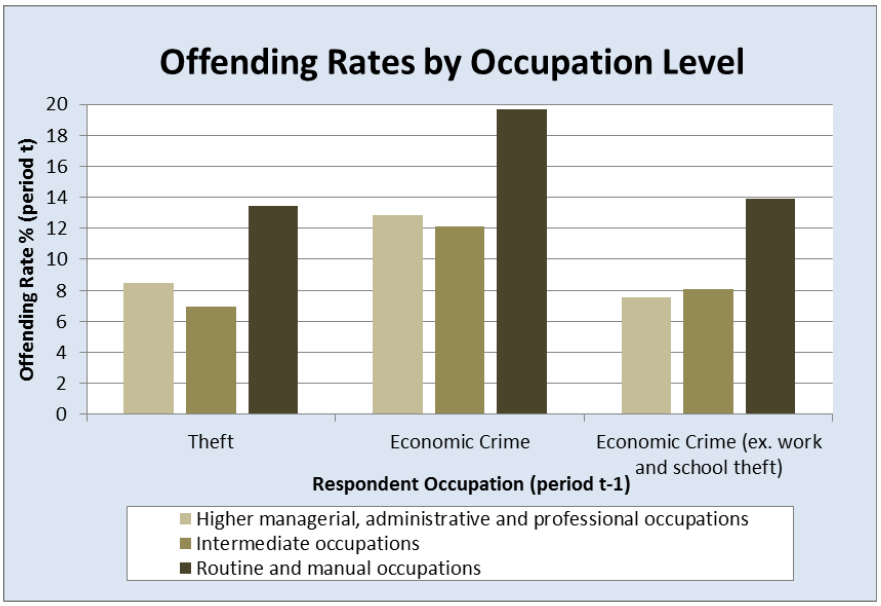

Figure 1.11: Offending rates in period t by occupation level at the end of period t-1.

Figure 3.10 show that, in the OCJS, the group reporting the highest offending rate is those in routine and manual occupations. It is the high offending rate amongst respondents in these low-level, presumably low-paid, occupations which drives the offending rates for Theft and Economic Crime to be higher for the employed than for those looking for work. This result is also explained by the high prevalence of workplace theft recorded. In 40.6% of interviews where the respondent reported committing Economic Crime, there was a report of stealing from work, and in 63.6% of interviews where Theft was admitted, this included stealing from work. Once one excludes workplace and school theft, the offending rate of those looking for work is over 3.3 percentage points higher than for those employed in intermediate or higher occupations.

As discussed earlier in this section, these results may reflect employed individuals having more opportunities for criminal activity. Beyond this, the survey period, 2003-2006, was a period of benign economic conditions. This fact is central to understanding these results. The unemployment rate for 18-24 year olds during 2003-2006 was in the range 9.9%-12.6%. This compares to 19.7% for the year ending June 2012.[31] In these favourable conditions, it appears even "criminally inclined" individuals could find employment. Also, note that for those under 20, being in employment, rather than in full-time education, may indicate low future earnings. The model suggests that for such individuals the opportunity cost of jail is probably low.

Some agents will switch between committing crime whilst unemployed and not committing crime whilst employed. Again, the benign economic conditions when the OCJS was conducted probably meant that the group of unemployed "unfortunates" was small.

Another possible reason why unemployed young adults did not report higher offending rates is that they lived with their parents. Almost 80% of respondents in the OCJS lived with their parents. For these individuals the difference in utility when employed and when unemployed may have been low. Their unemployment benefits may have been supplemented with other household resources; i.e. they may have used the "bank of mum and dad".

The full details of respondents' employment statuses are provided in Table 3.12. Given the high proportion of respondents living with their parents, Table 3.12 also

[31]These figures are based on Labour Force Survey data.

includes information regarding the Household Reference Person's (HRP's)[32] employment status.

Table 3.12 provides further context for Figure 3.11. Table 3.12 shows that a greater proportion of offenders than non-offenders previously reported activities which could represent "disguised" unemployment. For example, a higher percentage of offenders previously reported "intending to look for work but prevented by temporary sickness or injury".

Overall, Table 3.12 is consistent with the difference between $u'(b)$ and $u'(w)$ being low. In Table 3.12, over half of workers report being in routine and manual occupations. Not only are these jobs likely to be low paid, but they probably also have poor non-pecuniary characteristics.[33] Also, table 3.12 shows evidence regarding the capacity of HRPs to provide resource transfers to unemployed household members. In just over 80% of the paired-transitions, the HRP was in paid employment/self-employment. Additionally, in 36% of paired-transitions, the HRP was employed in a presumably well-paid, higher managerial, administrative or professional occupation.

[32]The HRP is identified as the person who owns/rents the household's accommodation. If accommodation is held in joint names, the individual with the highest income becomes the HRP. If individuals also share a common income level, then the HRP is the oldest individual in the household.
[33]If the value of being employed is low the opportunity cost of being in jail, $V^J(A) - V^E(A)$, is also reduced.

1.8. Econometric Analysis

1.8.1. Econometric Method

In all of the estimations, offending is modelled as a binary choice with the offending behaviour of individual i in period t being represented by O_{it}.[34] O_{it} takes a value of 1 when offending is reported and a value of 0 when no offending is reported. The probability of each outcome occurring is:

$$O_{it} = \left\{ \begin{array}{ll} 1 & \text{with probability } p_{it} \\ 0 & \text{with probability } 1 - p_{it} \end{array} \right\}$$

The aim is to model p_{it} as a function of time-invariant and time-varying independent variables. The baseline model is a straightforward probit estimation.[35] Beyond this, a fixed-effects logit model, a biprobit model with partial observability and a complementary log-log model have also been estimated.

As mentioned in Section 3.7, the time-varying independent variables are lagged by one period to reduce the risk of two-way causation biasing the results. Whilst the offending questions refer to the 12 months prior to interview, many of the independent variable questions relate to the respondent's position at the point of interview. Using dependent and independent variables from the same interview wave creates the following problem. Suppose someone at the end of period t reports offending during period

[34] A count data model is not used due to the low proportion of individuals who offend.
[35] The two baseline probit specifications, specifications 1 and 2, have also been estimated using the logit link function. The differences in the values of the maximised log-likelihood functions are always less than 1%. As such, there is no advantage in using a logit model over the probit model.

t and that, at present, they are unemployed. The question then arises of whether the respondent committed the offence after becoming unemployed, or, whether the offence led to the individual being sacked, implying that offending caused the unemployment? Taking the first lag of the unemployment indicator, removes this issue. Hence, p_{it} is modelled as:

$$p_{it} \equiv P(O_{it} = 1|\mathbf{x}_{it-1}, \mathbf{y}_i) = F(\mathbf{x}'_{it-1}\boldsymbol{\beta} + \mathbf{y}'_i\boldsymbol{\gamma})$$

where $\mathbf{x}_{it-1}$ is a vector of independent variables which vary by individual and time, $\mathbf{y}_i$ is a vector of time-invariant independent variables, and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of coefficients to be determined.

In the probit model, $F(.)$ is specified as the Normal cumulative distribution function. The transformation $F(.)$ ensures the estimated value of p_{it} lies between zero and one.

Using full panel data methods on the paired-transition sample does not appear feasible. Table 3.9 shows that 52% of respondents took part in only a single paired-transition. Instead, a pooled cross-section approach is used. Estimation is performed using maximum likelihood techniques. For a sample of N paired-transitions, the log-likelihood function which the estimators $\widehat{\boldsymbol{\beta}}$ and $\widehat{\boldsymbol{\gamma}}$ maximise is:

$$Q(\boldsymbol{\beta}, \boldsymbol{\gamma}) = \sum_{i=1}^{N} \sum_{t=2}^{T} \left[O_{it} \ln F(\mathbf{x}'_{it-1}\boldsymbol{\beta} + \mathbf{y}'_i\boldsymbol{\gamma}) + (1 - O_{it}) \ln \left(1 - F(\mathbf{x}'_{it-1}\boldsymbol{\beta} + \mathbf{y}'_i\boldsymbol{\gamma})\right) \right]$$

Recognising that the error terms for each individual i are almost certainly correlated through time, a cluster robust estimate for the variance-covariance matrix is used.

Each individual, i, is treated as a separate cluster. However, independence of the error terms between individuals is still assumed.

All the independent variables are described in Table 3.13. Separate estimations were performed for each crime category identified in Table 3.1. A variable representing attitude to risk is not included in the estimations, as the relationship between attitude to risk and offending emerges from the model endogenously. Including a regressor, which the model implies is endogenous, is unattractive as it leads to the maximum likelihood estimators being inconsistent.

Two versions of the baseline probit model were run. Compared to specification 1, specification 2 includes an extra variable recording whether individuals reported offending prior to their first interview. In the context of explaining why individuals offend, there is value in running the estimations without this prior offending variable. It seems natural for this prior offending variable to "swamp" the other independent variables' explanatory power without providing much insight about why individuals offend. However, the prior offending variable can also be interpreted as a further proxy for integrity. It indicates that previously a respondent's value of k was sufficiently low for it to lie below the NCC/NCC_E. Yet, since in reality wages, benefits and time spent in jail may vary through time, causing the NCC/NCC_E to also shift through time, there is perhaps a better interpretation. This prior offending variable is best used to identify all the unobservable characteristics that make an individual likely to commit crime. In this context, specification 1 identifies factors associated

with offending, whilst specification 2 indicates whether these factors are robust to including a control for individuals' unobservable characteristics.

1.8.2. Results

Table 3.6 reports the average marginal effects for the baseline probit using specifications 1 and 2. Along with the variables relating to financial position, employment status and integrity, other variables are reported which are consistently significant at the 1% level, or which have particular relevance to offending. Apart from "Age", all the independent variables are binary variables or categorical variables broken down into dummies. The values not in parentheses, therefore, report the average discrete change in the probability of offending, p_{it}, when a variable shifts from its "Null" position (shown in Table 3.13) to the position stated. The marginal effects for these binary/dummy variables are calculated using finite-difference methods. All statements regarding statistical significance relate to Wald tests.

Considering specification 1 first, the association between respondents' attitude to breaking the law and subsequent offending is statistically significant and in the expected direction. For all three crime categories, as one moves from "Agree" towards disagreement, the average marginal effects are negative and, in all but two cases, are statistically significant at the 1% level.[36]

[36]The other two cases are statistically significant at the 5% level.

Independent Variable	Specification 1 - Baseline Probit			Specification 2 - Prior Offending Control		
	Theft	Economic Crime	Economic Crime (ex. work and school theft)	Theft	Economic Crime	Economic Crime (ex. work and school theft)
Household just getting by on income	0.017	0.019	0.023*	0.015	0.017	0.022*
	(0.013)	(0.015)	(0.013)	(0.013)	(0.015)	(0.013)
Household getting into difficulties on income	0.048	0.074*	0.047	0.034	0.061	0.038
	(0.035)	(0.041)	(0.032)	(0.031)	(0.038)	(0.031)
Respondent employment status: intermediate	-0.005	-0.011	-0.009	-0.013	-0.017	-0.009
	(0.023)	(0.028)	(0.026)	(0.022)	(0.028)	(0.025)
Respondent employment status: routine and manual occupations	0.030	0.027	0.013	0.026	0.023	0.013
	(0.021)	(0.026)	(0.023)	(0.020)	(0.026)	(0.022)
Respondent employment status: looking for paid work/training	-0.046*	-0.049	-0.028	-0.042	-0.044	-0.026
	(0.026)	(0.035)	(0.030)	(0.027)	(0.035)	(0.030)
Strongly agree: sometimes OK to break the law (1st interview)	-0.051	-0.076*	-0.066*	-0.020	-0.049	-0.040
	(0.038)	(0.045)	(0.037)	(0.042)	(0.049)	(0.040)
Neither agree/disagree: sometimes OK to break the law (1st interview)	-0.039**	-0.044**	-0.045***	-0.021	-0.030	-0.030*
	(0.019)	(0.021)	(0.017)	(0.016)	(0.019)	(0.015)
Disagree: sometimes OK to break the law (1st interview)	-0.053***	-0.061***	-0.046***	-0.024	-0.031*	-0.023
	(0.017)	(0.020)	(0.016)	(0.016)	(0.018)	(0.015)
Strongly disagree: sometimes OK to break the law (1st interview)	-0.099***	-0.099***	-0.056***	-0.066***	-0.062***	-0.030*
	(0.017)	(0.020)	(0.017)	(0.016)	(0.020)	(0.016)
Taken drugs in past year (not 'Class A')	0.087***	0.134***	0.107***	0.058***	0.099***	0.079***
	(0.015)	(0.018)	(0.015)	(0.014)	(0.017)	(0.015)
Taken 'Class A' drugs in past year	0.076***	0.162***	0.153***	0.039**	0.112***	0.110***
	(0.021)	(0.027)	(0.024)	(0.017)	(0.024)	(0.022)
Friends in trouble with police in past year	0.059***	0.078***	0.052***	0.046***	0.064***	0.039***
	(0.013)	(0.016)	(0.013)	(0.012)	(0.015)	(0.012)
Victim of crime in past year	0.026**	0.026**	0.021**	0.018*	0.017	0.015
	(0.011)	(0.013)	(0.011)	(0.010)	(0.012)	(0.011)
Ever expelled (before 1st interview)	0.012	0.103**	0.090**	0.011	0.103**	0.080*
	(0.037)	(0.047)	(0.046)	(0.035)	(0.045)	(0.044)
Ever arrested (before 1st interview)	0.016	0.054**	0.052**	0.003	0.035	0.038*
	(0.020)	(0.024)	(0.022)	(0.018)	(0.023)	(0.021)
Ever sent to prison (before 1st interview)	0.084	0.230	0.191	0.039	0.167	0.127
	(0.111)	(0.194)	(0.181)	(0.087)	(0.167)	(0.151)
Ever committed economic crime (before 1st interview)[1]	-	-	-	0.114***	0.122***	0.093***
				(0.013)	(0.016)	(0.015)
Male	0.035***	0.063***	0.053***	0.026**	0.053***	0.047***
	(0.012)	(0.014)	(0.012)	(0.011)	(0.014)	(0.012)
Age	-0.003	-0.006	-0.007**	-0.001	-0.004	-0.007**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Ever sought help for mental health problems (before 1st interview over age 16)	0.044***	0.072***	0.055***	0.042***	0.068***	0.052***
	(0.016)	(0.019)	(0.016)	(0.015)	(0.018)	(0.015)
PFA: Derbyshire	-0.088**	-0.124***	-0.110***	-0.096***	-0.129***	-0.104***
	(0.036)	(0.041)	(0.032)	(0.033)	(0.039)	(0.032)

(continued on following page)

	Theft	Economic Crime	Economic Crime (ex. work and school theft)	Theft	Economic Crime	Economic Crime (ex. work and school theft)
PFA: Devon & Cornwall	-0.068*	-0.109***	-0.095***	-0.074**	-0.114***	-0.090***
	(0.036)	(0.042)	(0.035)	(0.036)	(0.040)	(0.033)
PFA: Essex	-0.109***	-0.157***	-0.131***	-0.117***	-0.159***	-0.123***
	(0.035)	(0.039)	(0.026)	(0.034)	(0.039)	(0.026)
PFA: North Yorkshire	-0.116***	-0.162***	-0.108***	-0.121***	-0.164***	-0.089**
	(0.032)	(0.040)	(0.035)	(0.031)	(0.039)	(0.041)
Sweep 3	-0.041**	-0.056**	-0.031	-0.044**	-0.053**	-0.030*
	(0.019)	(0.022)	(0.019)	(0.018)	(0.022)	(0.018)
N	**3,268**	**3,268**	**3,268**	**3,268**	**3,268**	**3,268**
i	**2,004**	**2,004**	**2,004**	**2,004**	**2,004**	**2,004**
Log likelihood	**-889.51**	**-1,166.84**	**-899.66**	**-839.44**	**-1,127.88**	**-874.45**
Median predicted probability of offending report	**0.062**	**0.106**	**0.059**	**0.047**	**0.095**	**0.054**
p-value for joint test of managing on income H_0: =0	**0.327**	**0.239**	**0.032**	**0.484**	**0.316**	**0.024**
p-value for joint test of employment status H_0: =0	**0.048**	**0.166**	**0.536**	**0.099**	**0.264**	**0.639**
p-value for joint test of 'OK to break the law' H_0: =0	**0.000**	**0.000**	**0.011**	**0.001**	**0.035**	**0.274**

Notes: Cluster robust standard errors are given in parentheses. Significance levels: * 10% significance, ** 5% significance and *** 1% significance. The p-values reported test whether the marginal effects are jointly different from zero for the set of independent variables stated. Specification 2 is the baseline probit estimation with an extra dummy variable indicating whether a respondent reports offending prior to their first interview. Independent variables which were frequently significant at the 5% level or above but not shown here for brevity are: Household income: £35,000-£44,999 (positive); Drinks alcohol 1-3 times a month (positive); Household size:1 (negative); PFA: Dyfed Powys (negative); PFA: Hampshire (negative); PFA: West Mercia (negative); PFA: Wiltshire (negative); Sports club/gym member (positive); and Not 100% truthful re: crime questions (positive). Many other independent variables were also significant in individual regressions at the 10% level or above.

[1] This variable varies by dependent variable. If the dependent variable is "Theft" then this variable is whether the respondent has ever committed "Theft" before their first interview.

Table 1.6: Average marginal effects for the baseline probits using specifications 1 and 2.

The average drop in offending probability also becomes larger as the level of disagreement with "it is sometimes OK to break the law" becomes stronger. For example, in the cases of Theft and Economic Crime, whilst moving from "Agree" to "Neither agree/disagree" is associated with an average fall in p_{it} of around 4 percentage points, moving from "Agree" to "Strongly disagree" is associated with a 9.9 percentage point drop. Also, Wald tests reject the null hypothesis that all the integrity proxy dummies are equal to zero. Whilst it is anomalous that the shift from "Agree" to "Strongly Agree" for "it is sometimes OK to break the law" is associated with a reduction in p_{it}, this result is only weakly significant.[37]

[37] Given the small sample, relationships significant only at the 10% level are likely to be particularly weak.

Not only is our proxy for k highly statistically significant, but the magnitudes of the average marginal effects for a shift from "Agree" to "Strongly disagree" also appear empirically relevant. For all three classifications of crime, the reduction in p_{it} is of a greater magnitude than the increases in p_{it} associated with reporting friends in trouble with the police, being male, being a victim of crime or having previously sought help for mental health problems. However, apart from for Theft, taking drugs has a noticeably greater impact on p_{it} than the integrity proxy. For the two Economic Crime variables, drug taking is associated with an increase in p_{it} of between 10.7 and 16.2 percentage points. Nevertheless, specification 1 provides strong support for the importance of integrity in individuals' criminal decisions.

The only other dummies that have statistically significant average marginal effects of a similarly large magnitude to drug taking, are those for some of the PFA fixed effects. Also, in specification 1 there are no PFAs that show an increase in p_{it} (compared to the Metropolitan PFA) significant at the 5% level. The PFAs which show large and statistically significant drops in p_{it} are all considerably more rural than London. However, as there were 41 PFA dummies, it is surprising that more did not have statistically significant marginal effects.[38]

In contrast to the integrity proxy, the associations of financial position and employment status with offending are both weak. Only rarely are the average marginal effects statistically significant at the 10% level.

[38]Beyond picking up rural-urban differences, the PFA fixed effects should also capture differences in policing methods/resources and local labour market/economic characteristics.

Looking in detail at the financial position dummies, the magnitude of the average increase in p_{it} when reporting "getting into difficulties" is reasonably large, being 7.4 percentage points for Economic Crime.[39] In addition, for Economic Crime (ex. work and school theft) the average marginal effects for the financial position variable, when tested jointly are significantly different from zero at the 5% level. This result remains true in specification 2. As previously suggested, the lack of statistical significance for "getting into difficulties" may be due to the small number of individuals in this category. Hence, overall, the data provides tentative signs that financial position may play a role in determining offending.

The number of unemployed individuals within the sample is also small. Nevertheless, for all three crime categories, the negative sign for the average marginal effect of looking for work/training is the opposite to our initial expectations. However, these negative marginal effects are only statistically significant for Theft, and here the significance is only at the 10% level.[40] Specification 1 has also been run using wider categories for unemployment and replacing the employment status of the respondent with that of the household head (HRP). Neither approach led to the average marginal effect becoming positive, although, when the widest definition of unemployment was used, the magnitude of the negative average marginal effect was reduced to 1.3-1.5 percentage points.[41]

[39]Also, the raw co-efficient for "getting into difficulties" in the probit estimation for Economic Crime using specification 1 is positive and significant at the 5% level.

[40]When the categories of those looking for work and those waiting to take up employment already obtained are combined to match the Labour Force Survey's definition of unemployment, the average marginal effect for Theft is no longer statistically significant.

[41]The widest definition of unemployment included those responses that might cover "disguised" unemployment. Beyond waiting to take up paid employment already obtained, the additional responses included were: being on a government training scheme, intending to look for work but prevented from doing so by sickness, and doing something else.

As expected, the average marginal effect in specification 1 with the largest magnitude is for spending time in prison prior to the respondent's first interview. However, as only 4 individuals reported spending time in prison, this average marginal effect is not significant. The average marginal effects for the Economic Crime variables of being expelled or being arrested, although of a lower magnitude, are both significant at the 5% level.

Given that the criminology literature's identifies a declining age-crime profile after the late teenage years, one slightly surprising finding is that Age only has a statistically significant negative relationship with Economic Crime (ex. work and school theft). There are a number of explanations for this. Firstly, the age variation being considered, 17 to 25, is relatively small. Secondly, there are other age-related variables, such as highest educational qualification obtained, living with parents and having a child which are included in the regressions. Lastly, and perhaps most importantly, as young adults age, they move out of education into employment. Using OCJS data, Hales et al (2009) note that in contrast to other forms of theft, the rate of workplace theft continues rising until age 20 (shoplifting peaks at around 14 to 15), and then falls only relatively slowly. This last reason can explain the difference in the significance of Age between the crime categories, i.e. only after workplace theft is excluded is a significant negative relationship found.

Moving to specification 2, which includes the prior offending control, many variables experience a loss of significance compared to specification 1. In particular, there are marked drops in the number of average marginal effects for the integrity proxy,

which are highly statistically significant. Nevertheless, a statistically significant relationship with offending does still exist for large shifts in respondents' attitude to crime. Also, for Theft and Economic Crime, Wald tests still reject the joint hypothesis that all the integrity dummies are equal to zero.

The average marginal effects of admitting offending prior to first interview are always significant at the 1% level. The magnitudes of these average marginal effects are also large. Admitting an offence prior to first interview is associated with a 9.3 to 12.2 percentage point increase in p_{it}. The general loss of significance for the integrity proxy suggests, unsurprisingly, that integrity and prior offending are highly correlated.

Whilst predicting the probability of offending for different individuals is not this study's purpose, it is worth considering how the magnitudes of the average marginal effects compare to the predicted probabilities of offending, $\widehat{p}_{it}$. Table 3.14 shows the predicted values of p_{it} are heavily skewed towards zero, i.e. not offending. In all specifications, over 48% of the predictions are for $\widehat{p}_{it} < 0.1$.[42] Whilst Table 3.14 and the median values of $\widehat{p}_{it}$ in Table 3.6 reinforce the empirically relevant magnitude of the average marginal effects, a note of caution should be struck. These average marginal effects are just that: averages. To gain a greater understanding of how the marginal effects vary by respondent, six hypothetical individuals have been considered. The characteristics of these individuals are described in Table 3.15. For each of these hypothetical individuals, marginal effects have been calculated using their

[42]The highest is 67%.

characteristics as representative values. These marginal effects are reported in Table 3.7.

Independent Variable	Successful Graduate	Single mother	A-Level Student	Family man	Rogue	Average Joe
Household just getting by on income	0.010	0.018	0.032	0.008	0.037	0.031
	(0.009)	(0.015)	(0.025)	(0.009)	(0.028)	(0.025)
Household getting into difficulties on income	0.037	0.062	0.114*	0.027	0.130*	0.109*
	(0.023)	(0.048)	(0.059)	(0.027)	(0.067)	(0.061)
Respondent employment status: intermediate occupation	-0.006	-0.011	-0.020	-0.005	-0.023	-0.019
	(0.017)	(0.028)	(0.050)	(0.012)	(0.057)	(0.048)
Respondent employment status: routine and manual occupations	0.014	0.024	0.043	0.010	0.049	0.041
	(0.014)	(0.025)	(0.044)	(0.013)	(0.050)	(0.043)
Respondent employment status: looking for paid work/training	-0.031	-0.052	-0.095	-0.022	-0.108	-0.091
	(0.027)	(0.046)	(0.071)	(0.026)	(0.085)	(0.071)
Strongly agree: sometimes OK to break the law (1st interview)	-0.039	-0.066	-0.121	-0.028	-0.138	-0.116
	(0.030)	(0.052)	(0.084)	(0.031)	(0.095)	(0.084)
Neither agree/disagree: sometimes OK to break the law (1st interview)	-0.021	-0.036	-0.065**	-0.015	-0.074**	-0.062*
	(0.013)	(0.022)	(0.033)	(0.015)	(0.036)	(0.033)
Disagree: sometimes OK to break the law (1st interview)	-0.031**	-0.052*	-0.095***	-0.022	-0.108***	-0.091**
	(0.014)	(0.030)	(0.034)	(0.021)	(0.035)	(0.037)
Strongly disagree: sometimes OK to break the law (1st interview)	-0.054**	-0.091**	-0.167***	-0.039	-0.190***	-0.160***
	(0.024)	(0.046)	(0.045)	(0.035)	(0.046)	(0.052)
Taken drugs in past year (not 'Class A')	0.067**	0.112**	0.205***	0.048	0.234***	0.196***
	(0.026)	(0.053)	(0.048)	(0.042)	(0.043)	(0.053)
Taken 'Class A' drugs in past year	0.077**	0.130**	0.238***	0.056	0.271***	0.228***
	(0.031)	(0.061)	(0.054)	(0.049)	(0.050)	(0.065)
Friends in trouble with police in past year	0.039**	0.066*	0.121***	0.028	0.138***	0.115***
	(0.017)	(0.035)	(0.034)	(0.025)	(0.033)	(0.040)
Victim of crime in past year	0.014*	0.024	0.044*	0.010	0.050*	0.042**
	(0.008)	(0.015)	(0.023)	(0.010)	(0.026)	(0.021)
Ever expelled (before 1st interview)	0.049*	0.082*	0.151**	0.035	0.172**	0.144**
	(0.028)	(0.047)	(0.064)	(0.034)	(0.068)	(0.069)
Ever arrested (before 1st interview)	0.027*	0.046*	0.084**	0.020	0.096**	0.080**
	(0.016)	(0.027)	(0.036)	(0.019)	(0.042)	(0.038)
Ever sent to prison (before 1st interview)	0.096	0.162	0.297	0.070	0.338	0.283
	(0.077)	(0.138)	(0.217)	(0.077)	(0.248)	(0.208)
Male	0.034**	0.058*	0.106***	0.025	0.121***	0.101***
	(0.015)	(0.031)	(0.032)	(0.023)	(0.032)	(0.034)
Age	-0.003	-0.005	-0.010	-0.002	-0.011	-0.010
	(0.002)	(0.005)	(0.006)	(0.002)	(0.007)	(0.006)
Ever sought help for mental health problems (before 1st interview over age 16)	0.037**	0.062*	0.114***	0.027	0.130***	0.109***
	(0.016)	(0.033)	(0.033)	(0.024)	(0.037)	(0.037)

(continued on following page)

	Successful Graduate	Single mother	A-Level Student	Family man	Rogue	Average Joe
PFA: Derbyshire	-0.077*	-0.129	-0.236**	-0.055	-0.269**	-0.226**
	(0.046)	(0.080)	(0.102)	(0.053)	(0.112)	(0.107)
PFA: Devon & Cornwall	-0.064	-0.107	-0.196**	-0.046	-0.224**	-0.187*
	(0.040)	(0.070)	(0.092)	(0.045)	(0.103)	(0.096)
PFA: Essex	-0.111*	-0.187*	-0.342**	-0.080	-0.390***	-0.327**
	(0.063)	(0.106)	(0.135)	(0.075)	(0.149)	(0.146)
PFA: North Yorkshire	-0.119*	-0.200*	-0.366**	-0.086	-0.416**	-0.349**
	(0.068)	(0.120)	(0.153)	(0.079)	(0.169)	(0.162)
Sweep 3	-0.031*	-0.053*	-0.097**	-0.023	-0.110**	-0.092**
	(0.017)	(0.032)	(0.043)	(0.021)	(0.049)	(0.044)
N	**3,268**	**3,268**	**3,268**	**3,268**	**3,268**	**3,268**
i	**2,004**	**2,004**	**2,004**	**2,004**	**2,004**	**2,004**
Predicted probability of reporting Economic Crime	**0.054**	**0.107**	**0.195**	**0.039**	**0.607**	**0.257**
p-value for joint test of managing on income H_0: =0	**0.382**	**0.570**	**0.224**	**0.795**	**0.215**	**0.302**
p-value for joint test of employment status H_0: =0	**0.765**	**0.809**	**0.340**	**0.990**	**0.383**	**0.585**
p-value for joint test of 'OK to break the law' H_0: =0	**0.241**	**0.403**	**0.007**	**0.868**	**0.001**	**0.051**

Notes: Cluster robust standard errors are given in parentheses. Significance levels: * 10% significance, ** 5% significance and *** 1% significance. The p-values reported test whether the marginal effects are jointly different from zero for the set of independent variables stated.

Table 1.7: Marginal effects on the probability of Economic Crime, for six hypothetical individuals.

Table 3.7 shows the marginal effects' magnitudes, as well as their significance, varies considerably between the hypothetical individuals. The general pattern is for the hypothetical individuals with higher values of $\widehat{p}_{it}$ to have marginal effects of a higher magnitude and greater statistical significance. The clearest illustration of this is the contrast between the marginal effects for a hypothetical "Family Man" and a hypothetical "Rogue". For the hypothetical, "Family Man", none of the reported variables are statistically significant, whereas 15 of the reported variables are statistically significant at the 5% or 1% levels for the hypothetical "Rogue". This exercise suggests that for a typical non-offender to switch to being an offender, a range of factors must change.

Overall, these probit estimations provide strong support for the notion that an individual's attitude to crime, which we interpret as a clear proxy for k, is related to subsequent offending. Even though the statistical significance of attitude to crime drops once a control for prior offending is included, this control itself could be taken as another proxy for integrity. Also, the prior offending variable demonstrates the role individuals' unobservable characteristics play in determining their offending decisions.

There is also some tentative evidence that those individuals experiencing financial difficulties are more likely to offend. Where the results and data are more surprising, is in the lack of relationship between employment status and offending. This appears to be driven, in part, by the prevalence of workplace theft reported in the OCJS, which suggests most crime was being committed by the "criminally inclined". It is also plausible that the benign economic conditions during the survey period meant that few individuals with the characteristics of an "unfortunate" were actually out of work.

Whilst it is difficult to make direct comparisons between studies, due to the different samples and estimation techniques used, the work of Hales et al (2009), which also uses the OCJS, suggests a similar pattern of significance across the variables common to both studies. As in the present study, showing approval for criminal activities, being a victim of crime, being excluded from school, having friends in trouble with the police and being male all increased p_{it}.

1.9. Robustness

A wide range of alternative specifications have been estimated to ensure the robustness of the results reported in Table 3.6. Much of this testing involved running modified versions of specification 1. The exceptions to this were attempts to control for zero inflation by estimating a fixed effects logit model and a bivariate probit model with partial observability. More detail regarding these alternative estimation approaches is provided in the Empirical Appendix.

Robustness of the baseline specification

Due to the lack of significance of age in specifications 1 and 2, these specifications were re-run with terms for age squared and age cubed added. In neither specification were these extra variables significant. Additionally, to test for possible misspecification, RESET tests were performed. The RESET test includes squared and cubed terms of the fitted values of the index, $\mathbf{x}'_{it-1}\widehat{\boldsymbol{\beta}} + \mathbf{y}'_i\widehat{\boldsymbol{\gamma}}$, as additional regressors. If the terms are significant, it suggests the model is potentially mis-specified or, for the probit model, the error terms are non-Normal. The results in Table 3.8 suggest that the Theft regressions could be mis-specified. However, as predicting offence probabilities is not the focus of the paper, the importance of this result should not be overstated.

Given the large number of dummy variables in the regressions, tests were also performed to check for multicollinearity. In no case was multicollinearity identified.

Regression Term	Specification 1 - Baseline Probit			Specification 2 - Prior Offending Control		
	Theft	Economic Crime	Economic Crime (ex. work and school theft)	Theft	Economic Crime	Economic Crime (ex. work and school theft)
Index squared	0.129	0.293	0.186	0.001	0.071	0.501
Index cubed	0.573	0.545	0.236	0.008	0.095	0.553
Joint test squared and cubed terms	0.003	0.284	0.414	0.000	0.194	0.790

Notes: The figures reported are p-values for Wald tests of the null hypothesis that the co-efficient for the variable stated is equal to zero.

Table 1.8: P-values from RESET tests.

The baseline probit model has also been run for two additional specifications. The average marginal effects for these specifications are reported in Table 3.16. In specification 3, dummy variables representing all four crime attitude questions are included. Including this additional information does not alter the overall pattern of significance. It also shows that only dummies for the "sometimes OK to break the law" statement have average marginal effects consistently significant at the 5% level. This supports the choice of the "sometimes OK to break the law" statement as the integrity proxy used in specifications 1 and 2.

Since the distribution of responses is heavily skewed towards not offending, $O_{it} = 0$, it is sensible to assess whether the assumed symmetry of the error terms in the probit model is reasonable. To evaluate this assumption, specification 1 was also run using a complementary log-log link function. The complementary log-log model allows the error terms to be asymmetric around zero. The pattern of significance for the variables and their relative magnitudes was similar to that in specification 1. More

importantly, the difference between the maximised log-likelihood for the probit and complementary log-log models was always less than 1%, suggesting little difference in the suitability of the two models.

Additionally, specification 1 was re-run using explanatory variables recorded in period t rather than in period $t-1$. This introduces the issue of two-way causation, however, there is a big increase in sample size, from 3,268 to 5,650 observations. This increase in observations is because respondents only have to be present for one interview wave.

The average marginal effects for this contemporary sample are reported in Table 3.17. Compared to the average marginal effects for the paired-transition data in Table 3.17 there are some changes. The average marginal effects for the looking for paid work variable are now all positive, although none of them are statistically significant. Also, the magnitudes of the average marginal effects for the financial position variable drop, often to near zero.[43] However, importantly, the strong significance of the "OK to sometimes break the law" variable is repeated.

Under-reporting and attrition

As already mentioned, a concern with any econometric model of crime is under-reporting. The OCJS allowed respondents to answer "Don't know" and "Don't want to answer" to each offending question. A control for under-reporting would recognise that offenders might strategically answer "Don't know" or "Don't want to answer" to avoid admissions of offending. It is difficult to think of a situation where genuine

[43]This may be because a successful offender can materially improve their financial position.

non-offenders would have an incentive not to report their non-offending behaviour. As a first step to controlling for this strategic answering, specification 4 re-runs specification 1 after re-coding responses of "Don't Know" and "Don't want to answer" as reports of offending. This re-coding led to 68 extra reports of Theft, 71 extra reports of Economic Crime and 27 extra reports of Economic Crime (ex. work and school theft).[44]

Table 3.16 shows that in this under-reporting specification, the magnitude and significance of the variables are generally reduced. Most noticeably, significance is reduced for smaller shifts in attitudes to breaking the law. Nevertheless, the shift from "Agree" to "Disagree" remains significant at the 5% level, and the shift to "Strongly disagree" remains significant at the 1% level.

Using a bivariate probit model would be another, more sophisticated, way to control for under-reporting. In the spirit of Heckman (1979), Greene (2008) describes how one of the two binary processes estimated in the bivariate probit model could be a control for sample selection. Here, the sample selection process would represent whether an individual answered affirmatively, i.e. "Yes" or "No", to the offending questions, or whether they answered "Don't Know" or "Don't want to answer". However, implementation of this model is left for further work. Also, the effectiveness of this approach may be limited due to only a small number of individuals not answering affirmatively.

[44]The slight rise in sample size for specification 4 occurs because in specifications 1, 2 and 3, non-offenders answering "Don't know" or "Don't want to answer" to an offending question were dropped from the sample.

An additional issue is attrition. Attrition may cause bias if respondents drop out of the sample due to factors other than those described by the independent variables. It is certainly possible that offenders, may drop out of the sample at a higher rate than non-offenders due to the former group's increased risk of jail. However, in the full 10-25 sample, the number of respondents confirmed as being in prison when a re-interview was attempted was very low, being 1, 4 and 1 respondents in 2004, 2005 and 2006 respectively. The full re-interview rates for the 10-25 sample were fairly high, being 74.5%, 83% and 85% in 2004, 2005 and 2006 respectively.[45]

To understand how offending reports varied with time spent in the sample, a sweep variable was included in all the estimations. For Theft and Economic Crime, interviewees reporting independent variables in their third sweep showed a statistically significant drop in p_{it} of 4 to 6 percentage points. This suggests that those more likely to offend did drop out for factors other than those measured by the independent variables. As further work, one could formally model the attrition process by using information available in sweep s to model the probability of respondents completing the survey in sweep $s + 1$.

1.9.1. Controlling for zero-inflation

The fixed effects logit model that uses the contemporary sample, and the bivariate probit model with partial observability that uses the paired-transitions sample, are

[45]These figures come from the survey documentation of Hamlyn et al (2005), Phelps et al (2006) and Phelps et al (2007). It should be noted that the figure for 2004 is lower because it excludes those cases, not used in our sub-sample, where some data was lost and a second interview was required. Including these cases would increase the 2004 re-interview rate to 81%.

now discussed. Further detail regarding these models' structures is provided in the Empirical Appendix. Both models attempt to overcome the issue of zero-inflation by controlling for the presence of those who never offend, i.e. the "honest" individuals. This interprets "integrity" as a broader characteristic than just the attitude to crime picked up by our integrity proxy. The aim is to understand with greater clarity the impact of time-varying characteristics, in particular economic circumstances, on the offending of those agents whose time invariant characteristics suggest they are at a high risk of offending.

As the fixed effects logit model is a conditional logit model, it requires there to be variation in the dependent variable, O_{it}. Hence, individuals included in its estimation must offend at least once within the sampling period.

This requirement for variation in the dependent variable significantly reduces the sample size. The sample size drops from 3,105 individuals in the main contemporary sample to only 236 for the Theft regression. As with standard fixed effects models, the estimation focuses on the within variation, i.e. the variation in the behaviour of each individual over time. However, after conditioning on variation in O_{it}, over 40% of respondents were in the sample for only two waves. This limits the variation in the independent variables.

The consistent lack of significance for the independent variables shown in Table 3.18 is, therefore, perhaps unsurprising.[46] The only consistently significant variable

[46]For comparison, the co-efficients from logit regressions using the contemporary sample are also reported in Table 3.18.

is the dummy for taking Class A drugs. However, the lack of statistical significance could also support a sorting story. Once an individual's time-invariant characteristics (both observable and unobservable) have been controlled for, other factors no longer have strong relationships with offending. Individuals sort according to their fixed characteristics to be either a criminal or a non-criminal.

The bivariate probit model with partial observability was introduced by Poirier (1980). It models the observed binary outcome - to offend or not offend - as the outcome of two correlated but unobserved binary processes. In the current setting, the first unobserved binary process is whether a respondent is an "honest" type or not. The second binary process is interpreted as whether or not a respondent's economic circumstances would induce someone "dishonest" to offend. Only if an individual is both "dishonest" and their circumstances make it attractive to offend, will offending be observed.

From Poirier's original work, it is known that identification can be problematic. Identification appears to be an issue in the current setting. Estimation was only possible for Theft and Economic Crime, and only if no independent variables were common to both the "honest/dishonest" regression and the economic circumstances regression. As such, all the time-invariant variables were used to estimate the "honest/dishonest" regression and all the time-varying variables were used to estimate economic circumstances regression. Hence, one obtains the average marginal effects of the time-varying variables conditional on the time-invariant variables indicating that a respondent is "dishonest".

The estimation results for this model are shown in Table 3.19. Considering the conditional average marginal effects, there is a general lack of significance for the time varying characteristics. This again fits a sorting story where a changing environment has only a weak relationship with offending. It is further evidence that within the OCJS sample the proportion of "unfortunates" compared to the "criminally inclined" appears low. The only variable with conditional average marginal effects statistically significant for both Theft and Economic Crime was having friends in trouble with the police. Also, for Economic Crime, conditional on being "dishonest", taking drugs was associated with an increase in the probability of offending. However, given the estimation issues encountered and the very specific model specification used, these results should be treated with a degree of caution.

1.9.2. Further Work

There are a range of possibilities for further work. The most interesting is to investigate further the relationship between asset holdings, a binding liquidity constraint and economic crime. In the model individuals only commit crime once their liquidity constraint binds, i.e. $A = 0$. When unemployed, low-integrity individuals will run down their asset holdings before offending. As such, a logical hypothesis is that as unemployment duration increases, individuals become more likely to offend. The information in the OCJS data on unemployment duration is too limited for this type of analysis.

Two alternative datasets present themselves for this future work. One is the JUVOS cohort, which is a 5% sample of those claiming unemployment benefit in the

UK. This dataset includes the destination of those leaving the claimant count between 1996 and 2006. The possible destinations include going to prison or appearing in court.[47] The other potential dataset is the US's National Longitudinal Survey of Youth 97 (NLSY97). The NLSY97 is a general panel survey. It includes more labour market information than the OCJS, but lacks questions regarding attitude to crime.

The longer sampling periods of these studies also allow the theoretical model to be considered in an environment including business cycle fluctuations. Most significantly, this would help to identify whether the apparent low number of "unfortunates" observed in the OCJS is due to the economic environment when the sampling took place, or a more general empirical result.

Staying with the OCJS data, it seems sensible to run multinomial probit models to obtain further information regarding the determinants of attitude to crime, employment status and financial position. The purpose is twofold. Firstly, it may suggest instruments that could be used to address any concerns about endogeneity in the estimations. Secondly, by identifying variables linked with attitude to crime, it should provide information about alternative integrity proxies which could be used in other, less detailed, datasets. As such, estimating a multinomial probit model for attitude to crime would be a useful precursor to any work using the NLSY97.

Lastly, a number of further robustness checks could be carried out. In particular, information regarding the frequency of offending and the monetary value of items

[47]This dataset has been suggested by Prof. Eric Smith.

stolen could prove important. The former would identify the number of prolific offenders within the sample. The latter would identify the seriousness of the crimes committed.

Another extension could be to use the geographic information identifying a respondent's PFA to link the survey data with other contextual information about areas. Incorporating information regarding labour market conditions could prove valuable. Such data could help identify individuals' expectations regarding the job finding rate and the wages available. If expectations of the returns to job search are low, the theoretical model suggests offending will appear relatively attractive.

1.10. Conclusion

Both the theoretical and empirical sections of the paper highlight the interplay between personal characteristics and economic circumstances that determine individuals' criminal decisions. In a dynamic framework, the optimal crime, job search, gambling and saving decisions of heterogeneous agents are derived. It is shown that an individual's aversion to crime is key to their criminal decision, and to whether employment status has an impact on this criminal decision.

In broad terms, the data provides support for this view. The results show that fixed personal characteristics and the immediate social environment are more important than employment status and financial position in determining offending behaviour. This fits with a notion of individuals sorting by integrity. High-integrity

"honest" agents choose never to offend and low-integrity agents, the "criminally inclined", offend regardless of employment status.

In the OCJS data, the prevalence of workplace theft and the lack of relationship between unemployment and offending suggest that the "criminally inclined" are dominant amongst the offenders observed. In contrast, those with slightly higher integrity, the "unfortunates", whose offending behaviour depends on employment status, seem rare. Either this group is inherently small, or, the benign labour market conditions in 2003-2006 meant that these individuals were employed, had assets remaining or perceived good future earnings opportunities. It is the unusual detail of the OCJS data that makes these conclusions possible.

In conclusion, this chapter provides a rich theoretical model in which the heterogeneity of individuals and labour market conditions combine to determine individuals' choice between legitimate employment and crime. Many of the insights are novel, such as the relationship between asset holdings and crime, or provide alternative explanations for existing empirical relationships, such as the value of gambling to otherwise risk-averse offenders. The empirical analysis uses the richness of the OCJS to explore the theoretical framework highlighting, in particular, the link between individuals' initial attitude towards criminal activity and subsequent offending. Taken together, the model and data emphasise that any relationship between employment status and offending is likely to be complex. Not only do they emphasise that only a sub-section of the general population has the necessary inclination to offend, but also that some individuals will offend both when unemployed and employed. Lastly, the chapter

provides avenues for further research, most notably, investigating the prediction of a positive relationship between unemployment duration and offending.

1.11. Technical Appendix

Proof of Theorem 3.1. The text has characterised optimal behaviour for $A \in [0, A^P]$. For the interval $A \in (A^P, A^R)$ the agent chooses $s = 0$ and $z = 0$, whilst optimal consumption smoothing implies $c = c^U(A^P)$ in this region. Thus, there is perfect consumption smoothing but $\dot{A} < 0$ implies the agent switches to job search, $s = 1$, and the consumption rule, $c^U(.)$, once $A \leq A^P$. As c does not change, $V^U(.)$ has a constant slope $u'(c^U)$ in this region.

A^R is identified where $b + rA^R = c^U(A^P)$. At $A = A^R$, the agent consumes $c = c^U(A^P)$ indefinitely; i.e. $\dot{A} = 0$ and the worker is sufficiently rich that never looking for work is an absorbing state. For $A > A^R$, the agent is retired: they choose $s = 0$ and $c^U = b + rA$. As $V^U = \frac{u(b+rA)}{r}$, V^U is increasing and concave.

As V^U is increasing and concave, the NCC is satisfied for all $A > 0$ whilst unemployed. Further, as $V^E(A) = \frac{u(w+rA)}{r} > V^U(A)$ and $\frac{dV^E}{dA} < \frac{dV^U}{dA}$ for all $A \geq 0$, it follows that the NCC_E holds for all $A \geq 0$. Thus consuming $c^E = w + rA$ while employed is indeed optimal. ■

Proof of Theorem 3.2. We first establish a solution for A^S exists and is unique. The LHS of (1.16) is a concave function of A^S whose maximum occurs at $\frac{b+z^U-w}{r}$. Furthermore, at this maximum, the LHS of (1.16) is:

$$\frac{u(b+z^U)}{r} - \frac{(b+z^U-w)}{r}u'(b+z^U)$$

As Proposition 3.1 and $z^E > 0$ imply $b+z^U-w > 0$, this latter term is a decreasing function of z^U. Hence:

$$\frac{u(b+z^U)}{r} - \frac{(b+z^U-w)}{r}u'(b+z^U) >$$

$$\frac{u(w+z^E)}{r} - \frac{z^E}{r}u'(w+z^E) = V^E(0)$$

by (1.10) and (1.11). Thus, strict concavity of $u(.)$ and continuity imply there exist two solutions for A^S satisfying (1.16). The smaller solution implies $A^S < \frac{b+z^U-w}{r}$, and, thus, $w + rA^s < b + z^U$ which is not the relevant case (consumption would then decrease for some A and as V^E is not then concave, the solution is not consistent with fair lotteries). Instead, a unique solution for A^S exists which satisfies (1.16) and $A^S > \frac{b+z^U-w}{r}$.

Optimal consumption smoothing implies that when employed, an agent with $A < \frac{z^E}{r}$ consumes $c^E = w_i + z^E$ and A will fall over time until $A = 0$. At $A = 0$, the agent switches to crime. For $A \geq \frac{z^E}{r}$, the agent instead consumes $w + rA$ in perpetuity and so never commits crime. As the solution for A^S implies $A^S > \frac{b+z^U-w}{r}$, and as $b+z^U > w+z^E$ from Proposition 3.1, we therefore have $A^S > \frac{z^E}{r}$: an employed agent with A^S never commits crime.

Finally, note the parameter space for the "criminally inclined" implies $V^E(0) - V^U(0) \geq \frac{d}{\lambda}$. It follows from (1.14) that:

$$V^E(A^S) - V^U(A^S) = V^E(0) - V^U(0)$$

and thus $V^E(A) - V^U(A) \geq \frac{d}{\lambda}$ for all $A \in [0, A^S]$. Thus $s = 1$ is optimal at $A = A^S$. The arguments used to characterise optimal behaviour for $A > 0$ in the proof of Theorem 3.1, now characterise optimal behaviour here, when $A > A^S$ and the initial value $c^U(A^S) = b + z^U$ at $A = A^S$. ■

1.12. Empirical Appendix

Number of Individuals	Percentage of Individuals	Paired-Transitions
551	27.50	. . 1
450	22.46	. 1 1
305	15.22	1 1 1
257	12.82	. 1 .
237	11.83	1 . .
184	9.18	1 1 .
20	1.00	1 . 1
2,004	**100.01**	**-**

Note: The percentage does not sum to 100% due to rounding error.

Year	Number of Paired-Transitions	Percentage of Paired-Transitions
2003-2004	746	22.83
2004-2005	1,196	36.60
2005-2006	1,326	40.58
Total:	**3,268**	**100.01**

Note: The percentage does not sum to 100% due to rounding error.

Table 1.9: Structure of the unbalanced panel and number of paired-transitions by year.

"I like taking risks in life"	Non-Offenders (Economic Crime)	Offenders (Economic Crime)	Paired-Transition Sample	Contemporary Sample
% Agree strongly	5.49	12.29	6.61	6.64
% Agree slightly	48.19	58.66	49.91	49.31
% Disagree slightly	29.70	21.60	28.37	28.67
% Disagree strongly	14.87	6.52	13.49	13.79
% Don't know/Refused	1.76	0.93	1.62	1.59
% Total[1]	**100.01**	**100.00**	**100.00**	**100.00**

Note: "Paired-Transition Sample" refers to a sample where respondents answered all questions regarding independent variables in period t-1 and all questions regarding dependent variables in period t. "Contemporary Sample" refers to a sample where respondents answered all questions for both independent and dependent variables in period t. All percentages have N as their base and, other than for "Contemporary Sample", refer to period t-1. The breakdown by offending refers to the "Paired-Transition Sample" with the Offender/Non-Offender classification determined by responses to offending questions in period t.

[1] Values that do not sum to 100% are due to rounding error.

Table 1.10: Responses to "I like taking risks in life".

Financial Assessment	Non-Offenders (Economic Crime)	Offenders (Economic Crime)	Paired-Transition Sample	Contemporary Sample
% Managing quite well	67.15	65.74	66.92	66.71
% Just getting by	28.38	27.37	28.21	28.48
% Getting into difficulties	3.04	5.21	3.40	3.70
% Don't know/Refused	1.43	1.68	1.47	1.12
% Total[1]	**100.00**	**100.00**	**100.00**	**100.01**

Note: "Paired-Transition Sample" refers to a sample where respondents answered all questions regarding independent variables in period t-1 and all questions regarding dependent variables in period t. "Contemporary Sample" refers to a sample where respondents answered all questions for both independent and dependent variables in period t. All percentages have N as their base and, other than for "Contemporary Sample", refer to period t-1. The breakdown by offending refers to the "Paired-Transition Sample" with the Offender/Non-Offender classification determined by responses to offending questions in period t.

[1] Values that do not sum to 100% are due to rounding error.

Table 1.11: Respondents' assessments of their financial position.

Table 1.12: Employment status of respondent and HRP.

Activity in Past Week	Respondent				Household Reference Person[1]			
	Non-Offenders (Economic Crime)	Offenders (Economic Crime)	Paired-Transition Sample	Contemporary Sample	Non-Offenders (Economic Crime)	Offenders (Economic Crime)	Paired-Transition Sample	Contemporary Sample
% Going to school (including on holiday)	4.10	3.54	4.01	1.22	0.18	0.19	0.18	0.09
% Going to college (includes 6th form and university) full-time (including on holiday)	36.80	39.66	37.27	29.82	3.70	2.61	3.52	5.17
% In paid work - higher managerial, administrative and professional occupations	10.18	7.64	9.76	13.79	36.21	37.06	36.35	35.03
% In paid work - intermediate occupations	11.17	7.82	10.62	13.04	16.11	16.20	16.13	16.00
% In paid work - routine and manual occupations	23.76	30.17	24.82	27.27	27.68	29.80	28.03	27.86
% On a government scheme for employment training	0.73	0.93	0.76	0.83	0.18	0.00	0.15	0.19
% Doing unpaid work for a family business	0.04	0.00	0.03	0.04	0.07	0.00	0.06	0.09
% Waiting to take up paid work already obtained	0.55	0.74	0.58	0.69	0.18	0.74	0.28	0.32
% Looking for paid work or a government training scheme	3.63	2.79	3.49	3.86	1.43	0.56	1.29	1.47
% Intending to look for work but prevented by temporary sickness or injury	0.48	1.12	0.58	0.71	0.44	0.74	0.49	0.37
% Permanently unable to work because of long-term sickness or disability	0.26	0.37	0.28	0.34	2.38	1.86	2.29	2.16
% Retired from paid work	0.00	0.19	0.03	0.02	3.59	4.10	3.67	3.93
% Looking after home or family	6.85	2.79	6.18	6.90	7.36	5.21	7.01	6.65
% Doing something else	1.46	2.23	1.59	1.47	0.48	0.93	0.55	0.67
Total[2]	**100.01**	**99.99**	**100.00**	**100.00**	**99.99**	**100.00**	**100.00**	**100.00**

Note: "Paired-Transition Sample" refers to a sample where respondents answered all questions regarding independent variables in period t-1 and all questions regarding dependent variables in period t. "Contemporary Sample" refers to a sample where respondents answered all questions for both independent and dependent variables in period t. All percentages have N as their base and, other than for "Contemporary Sample", refer to period t-1. The breakdown by offending refers to the "Paired-Transition Sample" with the Offender/Non-Offender classification determined by responses to offending questions in period t.

[1] Household Reference Person is defined as the person who is the owner/renter of the household's accomodation. If the accomodation is in joint names it is the person with the highest income. If incomes are the same it is the older person.

[2] Values that do not sum to 100% are due to rounding error.

Independent Variables	Categories used in Regression	Notes	"Null" Category
Managing on income	Just getting by, Getting into difficulties and Don't Know/Refused		Managing quite well
Employment status	In full time education/training, Intermediate occupations, Routine and manual occupations, Looking for work/training, Looking after home/family, Other (specified) and Doing something else	Formed from responses to several questions. The first question asks individuals to specify, from a list of 12 options, their main activity in the past week. Options with few responses, such as unable to work due to sickness, were grouped into "Other (specified)". For those individuals replying that they were in paid work a variety of other questions were asked regarding their job title, responsibilities and employer. Respondents' occupational level was then classified according to the National Statistics Socio-economic Classification. This classification was provided as part of the original dataset.	Higher managerial, administrative and professional occupations
Household income group	Under £4,999, £5,000-£14,999, £15,000-£24,999, £25,000-£34,999, £35,000-£44,999, Don't know/Refused	Original question involved 12 income groups. Respondents were provided with annual, monthly and weekly income equivalents.	£45,000+
Housing tenure	Paying off mortgage and Renting		Own outright/Live rent-free
Highest educational qualification obtained	A/AS-Levels or equivalent, GCSE grades A*-C/Trade apprenticeships or equivalent, GCSE grades D-G or equivalent	Compared to other variables a relatively high number of respondents had this data marked as missing.	A higher education qualification
Gender	Male		Female
Relationship status	Single	Respondents who were separated but not divorced are grouped as being "In a relationship".	In relationship
Drug use in past year	Taken 'Class A' drugs, Taken drugs (not 'Class A')	Class A' drugs include cocaine. Cannabis is not a 'Class A' drug. It has a lower (less serious) classification.	Not taken illegal drugs
Alcohol consumption	Most days, Once or twice a week, 1-3 times a month		Less often than "Once a month"
Has biological children	Yes		No
Lives with parents	Yes		No
Friends in trouble with the police in past year	Yes	Exact question wording: "Thinking about your closest friends. About how many of them, if any, have been in trouble with the police in the last 12 months?" Respondents could answer: none, a few, quite a lot, nearly all, all. All responses other than "None" are classified as "Yes".	No

Independent Variables	Categories used in Regression	Notes	"Null" Category
Age	Treated as continuous variable		-
Sometimes OK to break the law	Strongly agree, Neither agree nor disagree, Disagree, Strongly disagree	During interview asked prior to questions regarding crime victimisation and offending.	Agree
OK to steal if you are very poor	Strongly agree, Neither agree nor disagree, Disagree, Strongly disagree	During interview asked prior to questions regarding crime victimisation and offending.	Agree
OK to steal from somebody rich	Strongly agree, Neither agree nor disagree, Disagree, Strongly disagree	During interview asked prior to questions regarding crime victimisation and offending.	Agree
OK to steal from shop	Strongly agree, Neither agree nor disagree, Disagree, Strongly disagree	During interview asked prior to questions regarding crime victimisation and offending.	Agree
Household size	1 person, 2 people and 6+ people		3-5 people
Police Force Area	Dummies for the 41 Police Force Areas (other than Metropolitan/City of London) in England and Wales	Police Force Areas often, but not always, cover the same areas as county councils. Some police forces cover multiple counties and some cover specific conurbations.	Metropolitan/City of London
Belongs to a religious group	Yes	The survey does not ask whether individuals are active in their faith e.g. actually go to church.	No
Member of ethnic minority	Yes	Ethnic majority defined as white from any background.	No
Interview wave	Wave 2, Wave 3 and Wave 4	Wave 4 only features in the "Contemporary" regressions. In the baseline regressions as the lag of the wave is used Wave 3 is the last wave of data used for the independent variables.	Wave 1
Victim of crime in past year	Yes	Victimisation questions cover the same range of offences as the offending questions. Crimes against the respondent and the physical household are considered.	No
Safety of walking alone in area after dark	Fairly safe, Fairly unsafe and Very unsafe	Exact question wording: "How safe would you feel walking alone in this area after dark. Would you feel..."	Very safe

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Table 1.13: Description of the independent variables used.

Independent Variables	Categories used in Regression	Notes	"Null" Category
Belongs to sports club/gym	Yes	Original survey question identified 9 different types of groups/clubs/organisations to which a respondent could belong. Respondents could also specify other types of groups to which they were members.	No
Answered all crime questions truthfully	Yes	Exact question wording: "When you answered the questions about committing crimes, how truthful were you?" Only respondents agreeing with the statement "I answered ALL questions truthfully" are treated as "Yes".	No
Interview sweep	Sweep 2, Sweep 3 and Sweep 4	Sweep 4 only features in the "Contemporary" regressions. In the baseline regressions, as the lag of the sweep is used, Sweep 3 is the last sweep of data used for the independent variables.	Sweep 1
Parents spent time in prison (before 1st interview)	Yes, Don't Know/Refused		No
Ever expelled (before 1st interview)	Yes		No
Ever arrested (before 1st interview)	Yes	Note that in the UK being arrested does not necessarily lead to a court appearance or even being charged with an offence.	No
Ever sentenced (before 1st interview)	Yes		No
Ever spent time in prison (before 1st interview)	Yes		No
Ever sought help for mental health problems (before 1st interview over age 16)	Yes	Question only asked of those aged over 16.	No
Ever committed offence (before 1st interview)	Yes	The classification of offence varies by regression to match the dependent variable being estimated. For the Economic Crime variables the relevant "Ever committed offence" variables do not include the offences of credit card fraud and selling stolen goods. This is because only those over the age of 18 were asked about these offences.	No

Predicted Probability of Offending Thresholds	Percentage of Predictions Below Threshold					
	Specification 1			Specification 2		
	Theft	Economic Crime	Economic Crime (ex. work and school theft)	Theft	Economic Crime	Economic Crime (ex. work and school theft)
Below 0.01	12.09	3.89	12.33	18.18	5.72	14.44
Below 0.05	43.15	27.48	45.62	51.01	32.71	48.13
Below 0.10	63.92	48.07	64.14	66.62	51.41	65.15
Below 0.25	88.4	77.63	86.51	86.44	76.81	85.95
Below 0.50	98.53	94.31	96.94	97.86	93.18	96.14
Below 0.75	100.00	99.24	99.51	100.00	99.02	99.57
Below 0.90	100.00	99.91	99.97	100.00	99.88	99.97
Below 1.00	100.00	100.00	100.00	100.00	100.00	100.00

Note: The cumulative percentages are as a percentage of the total number of predictions. The total number of predictions is 3,268.

Table 1.14: Distributions of predicted offending probabilities.

Independent Variable	Successful Graduate	Single mother	A-Level Student	Family Man	Trouble maker	Average Joe
Managing on income	Managing quite well	Getting into difficulties	Managing quite well	Just getting by	Just getting by	Managing quite well
Employment status	Higher managerial, administrative and professional occupations	Looking after home/family	In full time education/ training	Intermediate occupation	Looking for paid work/ training scheme	Routine/ manual occupation
Sometimes OK to break the law	Disagree	Neither agree nor disagree	Neither agree nor disagree	Strongly disagree	Agree	Neither agree nor disagree
Household income group	£35,000-£44,999	Under £5,000	£25,000-34,999	£25,000-34,999	£15,000-24,999	£15,000-24,999
Housing tenure[1]	Rent	Rent	Mortgage	Rent	Mortgage	Mortgage
Highest educational qualification obtained	Higher education qualification	GCSEs grades D-G or equivalent	GCSEs grades A*-C or equivalent	Higher education qualification	GCSEs grades A*-C or equivalent	A Levels or equivalent
Gender	Female	Female	Male	Male	Male	Male
Relationship status	In relationship	Single	Single	In relationship	Single	In Relationship
Drug use in past year	None	None	Yes - Not 'Class A'	None	Yes - 'Class A'	None
Alcohol consumption	Once or twice a week	Once to three times a month	Once or twice a week	Once or twice a week	Once or twice a week	Once or twice a week
Has biological children	No	Yes	No	Yes	No	No
Lives with parents	No	No	Yes	No	Yes	Yes
Friends in trouble with the police in past year	No	Yes	Yes	No	Refused to answer	No
Age	24	19	18	24	20	20
Household size	2 people	3-5 people	3-5 people	3-5 people	6+ people	3-5 people
Police Force Area	Metropolitan (London)	Greater Manchester	Nottinghamshire	Wiltshire	West Midlands	Northamptonshire
Belongs to a religious group	No	Yes	No	Yes	No	No
Member of ethnic minority	No	No	Yes	No	No	No
Interview wave	2	2	2	2	2	2
Victim of crime in past year	No	Yes	Yes	No	No	No
Safety of walking alone in area after dark	Fairly unsafe	Very unsafe	Fairly unsafe	Very unsafe	Fairly safe	Fairly safe
Belongs to sports club/gym	Yes	No	Yes	Yes	No	Yes
Answered crime questions truthfully	Yes	Yes	Yes	Yes	No	Yes
Interview sweep	2	2	2	2	2	2
Parents spent time in prison (before 1st interview)	No	Don't Know	No	No	Yes	No
Ever expelled (before 1st interview)	No	No	No	No	Yes	No
Ever arrested (before 1st interview)	No	No	No	No	Yes	No
Ever sentenced (before 1st interview)	No	No	No	No	No	No
Ever spent time in prison (before 1st interview)	No	No	No	No	No	No

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	Successful Graduate	Single mother	A-Level Student	Family man	Rogue	Average Joe
Ever sought help for mental health problems (before 1st interview over age 16)	No	Yes	No	No	No	No
Admits committing Economic Crime (before 1st interview)	No	No	No	No	Yes	No
Excluding prior offending variable						
Predicted probability of reporting Theft in following time period[2]	**0.042**	**0.032**	**0.229**	**0.019**	**0.263**	**0.173**
Predicted probability of reporting Economic Crime in following time period[2]	**0.054**	**0.107**	**0.195**	**0.039**	**0.607**	**0.257**
Predicted probability of reporting Economic Crime (ex. work and school theft) in following time period[2]	**0.014**	**0.093**	**0.170**	**0.010**	**0.502**	**0.106**
Including prior offending variable						
Predicted probability of reporting Theft in following time period[2]	**0.026**	**0.014**	**0.084**	**0.008**	**0.303**	**0.072**
Predicted probability of reporting Economic Crime in following time period[2]	**0.040**	**0.063**	**0.111**	**0.022**	**0.639**	**0.149**
Predicted probability of reporting Economic Crime (ex. work and school theft) in following time period[2]	**0.011**	**0.066**	**0.126**	**0.007**	**0.560**	**0.066**

[1] The statement "Mortgage" does not imply that the respondent has a mortgage. Instead it implies the household reference person pays a mortgage.

[2] These predicted probabilities should be treated with a degree of caution. The confidence intervals are very wide, often over twenty percentage points, indicating that the predictions are imprecise. Also recall that the model is not causal. The predicted probabilities are included for illustrative purposes only.

Table 1.15: Description of hypothetical individuals.

Independent Variable	Specification 3 - All Integrity Proxies			Specification 4 - Under-Reporting Control		
	Theft	Economic Crime	Economic Crime (ex. work and school theft)	Theft	Economic Crime	Economic Crime (ex. work and school theft)
Household just getting by on income	0.016	0.019	0.024*	0.008	0.009	0.021
	(0.013)	(0.015)	(0.013)	(0.013)	(0.015)	(0.013)
Household getting into difficulties on income	0.041	0.066*	0.044	0.045	0.074*	0.048
	(0.034)	(0.040)	(0.032)	(0.035)	(0.041)	(0.031)
Respondent employment status: intermediate occupation	-0.010	-0.014	-0.010	-0.008	-0.017	-0.017
	(0.023)	(0.029)	(0.026)	(0.024)	(0.029)	(0.026)
Respondent employment status: routine and manual occupations	0.028	0.026	0.013	0.026	0.020	0.008
	(0.021)	(0.026)	(0.023)	(0.021)	(0.026)	(0.023)
Respondent employment status: looking for paid work/training	-0.046*	-0.048	-0.028	-0.037	-0.043	-0.038
	(0.027)	(0.035)	(0.030)	(0.030)	(0.037)	(0.031)
Strongly agree: sometimes OK to break the law (1st interview)	-0.062*	-0.063	-0.057	-0.036	-0.048	-0.047
	(0.033)	(0.046)	(0.037)	(0.043)	(0.052)	(0.041)
Neither agree/disagree: sometimes OK to break the law (1st interview)	-0.031*	-0.035*	-0.037**	-0.028	-0.030	-0.037**
	(0.018)	(0.021)	(0.016)	(0.020)	(0.022)	(0.017)
Disagree: sometimes OK to break the law (1st interview)	-0.040**	-0.048**	-0.034**	-0.046**	-0.052**	-0.040**
	(0.018)	(0.020)	(0.016)	(0.018)	(0.020)	(0.016)
Strongly disagree: sometimes OK to break the law (1st interview)	-0.078***	-0.074***	-0.031	-0.098***	-0.092***	-0.046***
	(0.019)	(0.022)	(0.019)	(0.018)	(0.021)	(0.017)
Strongly agree: OK to steal if you are very poor (1st interview)[1]		-0.122	-0.073	-	-	-
		(0.147)	(0.117)			
Neither agree/disagree: OK to steal if you are very poor (1st interview)	-0.064*	-0.108***	-0.067**	-	-	-
	(0.035)	(0.040)	(0.032)			
Disagree: OK to steal if you are very poor (1st interview)	-0.045	-0.070*	-0.035	-	-	-
	(0.035)	(0.039)	(0.031)			
Strongly Disagree: OK to steal if you are very poor (1st interview)	-0.050	-0.074*	-0.056	-	-	-
	(0.037)	(0.042)	(0.035)			
Strongly agree: OK to steal from somebody rich (1st interview)	0.123	-0.123*	-0.115*	-	-	-
	(0.121)	(0.071)	(0.066)			
Neither agree/disagree: OK to steal from somebody rich (1st interview)	0.006	0.040	0.012	-	-	-
	(0.049)	(0.066)	(0.064)			
Disagree: OK to steal from somebody rich (1st interview)	0.008	0.008	-0.027	-	-	-
	(0.043)	(0.055)	(0.056)			
Strongly Disagree: OK to steal from somebody rich (1st interview)	0.006	0.004	-0.037	-	-	-
	(0.046)	(0.058)	(0.059)			
Strongly agree: OK to steal from shop (1st interview)	0.195	0.121	0.103	-	-	-
	(0.145)	(0.264)	(0.231)			
Neither agree/disagree: OK to steal from shop (1st interview)	0.068	-0.024	-0.059	-	-	-
	(0.069)	(0.083)	(0.069)			
Disagree: OK to steal from shop (1st interview)	-0.033	-0.078	-0.081	-	-	-
	(0.060)	(0.078)	(0.067)			
Strongly Disagree: OK to steal from shop (1st interview)	-0.053	-0.099	-0.083	-	-	-
	(0.063)	(0.081)	(0.070)			

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	Theft	Economic Crime	Economic Crime (ex. work and school theft)	Theft	Economic Crime	Economic Crime (ex. work and school theft)
Taken drugs in past year (not 'Class A')	0.088***	0.134***	0.106***	0.091***	0.138***	0.110***
	(0.015)	(0.018)	(0.015)	(0.015)	(0.018)	(0.016)
Taken 'Class A' drugs in past year	0.074***	0.160***	0.150***	0.088***	0.175***	0.155***
	(0.021)	(0.027)	(0.023)	(0.023)	(0.028)	(0.024)
Friends in trouble with police in past year	0.056***	0.076***	0.050***	0.062***	0.081***	0.057***
	(0.013)	(0.016)	(0.013)	(0.014)	(0.017)	(0.013)
Victim of crime in past year	0.028***	0.027**	0.022**	0.022*	0.020	0.024**
	(0.011)	(0.013)	(0.011)	(0.011)	(0.013)	(0.011)
Ever expelled (before 1st interview)	0.024	0.114**	0.106**	0.025	0.114**	0.097**
	(0.041)	(0.050)	(0.048)	(0.041)	(0.049)	(0.047)
Ever arrested (before 1st interview)	0.011	0.050**	0.051**	0.001	0.043*	0.049**
	(0.020)	(0.024)	(0.022)	(0.021)	(0.025)	(0.022)
Ever sent to prison (before 1st interview)	0.084	0.232	0.175	0.100	0.247	0.181
	(0.121)	(0.198)	(0.170)	(0.130)	(0.199)	(0.178)
Male	0.033***	0.063***	0.055***	0.030**	0.061***	0.056***
	(0.012)	(0.014)	(0.012)	(0.013)	(0.015)	(0.012)
Age	-0.002	-0.006	-0.007**	-0.004	-0.007*	-0.008**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Ever sought help for mental health problems (before 1st interview over age 16)	0.043***	0.072***	0.056***	0.045***	0.074***	0.057***
	(0.016)	(0.019)	(0.015)	(0.016)	(0.019)	(0.016)
PFA: Derbyshire	-0.080**	-0.118***	-0.103***	-0.045	-0.085**	-0.103***
	(0.036)	(0.041)	(0.032)	(0.039)	(0.043)	(0.031)
PFA: Devon & Cornwall	-0.067*	-0.111***	-0.094***	-0.057	-0.099**	-0.080**
	(0.036)	(0.040)	(0.033)	(0.039)	(0.043)	(0.036)
PFA: Essex	-0.103***	-0.153***	-0.127***	-0.121***	-0.170***	-0.128***
	(0.035)	(0.039)	(0.027)	(0.035)	(0.040)	(0.027)
PFA: North Yorkshire	-0.109***	-0.155***	-0.100***	-0.075	-0.123**	-0.109***
	(0.033)	(0.041)	(0.036)	(0.049)	(0.055)	(0.035)
Sweep 3	-0.046**	-0.060***	-0.034*	-0.040**	-0.056**	-0.033*
	(0.018)	(0.022)	(0.019)	(0.020)	(0.024)	(0.019)
N	**3,253**	**3,268**	**3,268**	**3,341**	**3,341**	**3,341**
i	**1,995**	**2,004**	**2,004**	**2,025**	**2,025**	**2,025**
Log likelihood	**-875.94**	**-1,154.99**	**-888.54**	**-1,024.85**	**-1,287.21**	**-960.35**
Median predicted probability of offending report	**0.061**	**0.104**	**0.057**	**0.080**	**0.124**	**0.064**
p-value for joint test of managing on income H_0: =0	**0.370**	**0.297**	**0.028**	**0.267**	**0.308**	**0.111**
p-value for joint test of employment status H_0: =0	**0.068**	**0.182**	**0.313**	**0.037**	**0.073**	**0.286**
p-value for joint test of 'OK to break the law' H_0: =0	**0.001**	**0.021**	**0.133**	**0.000**	**0.000**	**0.069**

Notes: Cluster robust standard errors are given in parentheses. Significance levels: * 10% significance, ** 5% significance and *** 1% significance. The p-values reported test whether the marginal effects are jointly different from zero for the set of independent variables stated. Specification 4 uses the same independent variables as specification 1. However, in an attempt to control for under-reporting, in specification 4 responses of "Don't Know" and "Don't Want to Answer" to the offending questions have been recorded as reports of offending. This also explains the small increase in sample size as individuals reporting "Don't Know" and "Don't Want to Answer" to offending questions were dropped in the other specifications. Independent variables which were frequently significant at the 5% level or above but not shown here for brevity are: Household income: £35,000-£44,999 (positive); Drinks alcohol 1-3 times a month (positive); Household size:1 (negative); PFA: Dyfed Powys (negative); PFA: Hampshire (negative); PFA: West Mercia (negative); PFA: Wiltshire (negative); Walking alone in local area at night fairly unsafe (negative); Sports club/gym member (positive); and Not 100% truthful re: crime questions (positive). Many other independent variables were also significant in individual regressions at the 10% level or above.

[1] A co-efficient is not reported for "Strongly agree: OK to steal if you are very poor" since no respondent reporting this attitude reported an offence in the following period. As a result these observations were dropped from the regression. This also explains the drop in N and i for the "Theft" regression in specification 3.

Table 1.16: Average marginal effects for the baseline probits using specifications 3 and 4.

Independent Variable	Specification 1 - Baseline probit		
	Theft	Economic Crime	Economic Crime (ex. work and school theft)
Household just getting by on income	0.011	0.004	-0.001
	(0.009)	(0.012)	(0.010)
Household getting into difficulties on income	0.000	-0.002	0.011
	(0.021)	(0.025)	(0.022)
Respondent employment status: intermediate occupation	0.009	0.008	0.004
	(0.014)	(0.019)	(0.017)
Respondent employment status: routine and manual occupations	0.025*	0.015	0.001
	(0.013)	(0.017)	(0.015)
Respondent employment status: looking for paid work/training	0.026	0.005	0.011
	(0.022)	(0.026)	(0.023)
Strongly agree: sometimes OK to break the law (1st interview)	-0.053*	-0.048	-0.003
	(0.030)	(0.047)	(0.044)
Neither agree/disagree: sometimes OK to break the law (1st interview)	-0.038***	-0.051***	-0.049***
	(0.014)	(0.017)	(0.014)
Disagree: sometimes OK to break the law (1st interview)	-0.061***	-0.073***	-0.046***
	(0.013)	(0.016)	(0.013)
Strongly disagree: sometimes OK to break the law (1st interview)	-0.085***	-0.094***	-0.056***
	(0.014)	(0.017)	(0.014)
Taken drugs in past year (not 'Class A')	0.079***	0.118***	0.090***
	(0.012)	(0.014)	(0.012)
Taken 'Class A' drugs in past year	0.131***	0.227***	0.190***
	(0.017)	(0.021)	(0.019)
Friends in trouble with police in past year	0.042***	0.066***	0.042***
	(0.011)	(0.013)	(0.010)
Victim of crime in past year	0.046***	0.054***	0.039***
	(0.008)	(0.009)	(0.008)
Parents spent time in prison (before 1st interview)	0.065*	0.099**	0.083**
	(0.039)	(0.042)	(0.037)
Ever expelled (before 1st interview)	0.002	0.063*	0.058*
	(0.026)	(0.033)	(0.030)
Ever arrested (before 1st interview)	-0.007	0.016	0.024*
	(0.013)	(0.016)	(0.014)
Ever sent to prison (before 1st interview)	0.064	0.119	0.029
	(0.067)	(0.076)	(0.056)
Male	0.030***	0.053***	0.042***
	(0.009)	(0.012)	(0.010)
Age	-0.004*	-0.008***	-0.008***
	(0.002)	(0.003)	(0.002)

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	Theft	Economic Crime	Economic Crime (ex. work and school theft)
Ever sought help for mental health problems (before 1st interview over age 16)	0.026**	0.042***	0.037***
	(0.011)	(0.013)	(0.011)
PFA: Derbyshire	-0.002	-0.023	-0.047
	(0.037)	(0.040)	(0.030)
PFA: Devon & Cornwall	-0.064***	-0.068**	-0.049*
	(0.024)	(0.031)	(0.027)
PFA: Essex	-0.075***	-0.134***	-0.108***
	(0.027)	(0.029)	(0.020)
PFA: North Yorkshire	-0.059*	-0.101**	-0.062*
	(0.034)	(0.041)	(0.035)
Sweep 3	0.008	-0.002	-0.013
	(0.013)	(0.016)	(0.014)
N	**5,650**	**5,650**	**5,650**
i	**3,105**	**3,105**	**3,105**
Log likelihood	**-1,463.42**	**-2,069.76**	**-1,609.46**
Median predicted probability of offending report	**0.055**	**0.108**	**0.064**
p-value for joint test of managing on income H_0: =0	**0.652**	**0.981**	**0.949**
p-value for joint test of employment status H_0: =0	**0.356**	**0.902**	**1.000**
p-value for joint test of 'OK to break the law' H_0: =0	**0.000**	**0.000**	**0.001**

Notes: Cluster robust standard errors are given in parentheses. Significance levels: * 10% significance, ** 5% significance and *** 1% significance. The p-values reported test whether the marginal effects are jointly different from zero for the set of independent variables stated. Independent variables which were frequently significant at the 5% level or above but not shown here for brevity are: PFA: Gwent (negative); PFA: South Wales (negative); Wave 2 (positive); and Sports club/gym member (positive). Many other independent variables were also significant in individual regressions at the 10% level or above.

Table 1.17: Average marginal effects for the baseline probits (specification 1) using the contemporary sample.

Fixed Effects Logit (Conditional Logit) Model

The fixed effects logit model removes all the characteristics of individuals that are fixed through time, including those which are unobservable. Using the fixed effects logit model, a consistent estimator of β can be obtained without any assumptions regarding the relationship between individuals' fixed characteristics and the other explanatory variables. As Wooldridge (2002) describes, this is possible due to the logit link function's specific functional form. To understand why this is possible,

firstly, denote the individual fixed effect α_i and $\mathbf{x}_i = (\mathbf{x}_{i1}, ..., \mathbf{x}_{iT})$. The next step is to find the joint distribution of $\mathbf{O}_i \equiv (O_{i1}, ..., O_{iT})'$ conditional on $\mathbf{x}_i$, α_i and $\eta_i = \sum_{t=1}^{T} O_{it}$ (η_i is the total number of offences reported within the sampling period).

The following is adapted from Wooldridge (2002) with changed notation. It demonstrates the key insight that the conditional distribution described does not depend on α_i and that, hence, $\boldsymbol{\beta}$ can be estimated using conditional maximum likelihood techniques.

Consider the simplest case of $T = 2$. When $\eta_i = 0$ or $\eta_i = 2$, the conditional distribution of $(O_{i1}, O_{i2})'$ given η_i cannot be informative for estimating $\boldsymbol{\beta}$ because the value of η_i completely determines the value of $\mathbf{O}_i$. Hence, to estimate $\boldsymbol{\beta}$, only cases where there is variation in O_{it} are used, i.e. $\eta_i = 1$. This means, by definition, only those individuals who offend at some point during the sampling period will be included in the estimation and the most persistent offenders will be excluded.

Suppose the probability of offending in period 2 is being estimated. Assuming conditional independence, so that O_{i2} is independent of O_{i1}, and after conditioning on $\mathbf{x}_i$ and α_i it is possible to write:

$$P(O_{i2} = 1|\mathbf{x}_i, \alpha_i, \eta_i = 1) = \frac{P(O_{i2} = 1 \cap \eta_i = 1|\mathbf{x}_i, \alpha_i)}{P(\eta_i = 1|\mathbf{x}_i, \alpha_i)}$$

$$= \frac{P(O_{i2} = 1|\mathbf{x}_i, \alpha_i) P(O_{i1} = 0|\mathbf{x}_i, \alpha_i)}{P(O_{i2} = 1 \cap O_{i1} = 0|\mathbf{x}_i, \alpha_i) + P(O_{i2} = 0 \cap O_{i1} = 1|\mathbf{x}_i, \alpha_i)}$$

As the logit function is being used:

$$P\left(O_{it}|\mathbf{x}_i, \alpha_i\right) = \frac{\exp\left(\mathbf{x}'_{it}\boldsymbol{\beta} + \alpha_i\right)}{1 + \exp\left(\mathbf{x}'_{it}\boldsymbol{\beta} + \alpha_i\right)}$$

which, in turn, means:

$$\frac{P\left(O_{i2} = 1|\mathbf{x}_i, \alpha_i\right) P\left(O_{i1} = 0|\mathbf{x}_i, \alpha_i\right)}{P\left(O_{i2} = 1 \cap O_{i1} = 0|\mathbf{x}_i, \alpha_i\right) + P\left(O_{i2} = 0 \cap O_{i1} = 1|\mathbf{x}_i, \alpha_i\right)} =$$

$$\left(\frac{\exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta} + \alpha_i\right)}{1 + \exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta} + \alpha_i\right)} \times \frac{1}{1 + \exp\left(\mathbf{x}'_{i1}\boldsymbol{\beta} + \alpha_i\right)}\right) \times$$

$$\left[\begin{array}{c} \left(\frac{\exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta}+\alpha_i\right)}{1+\exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta}+\alpha_i\right)} \times \frac{1}{1+\exp\left(\mathbf{x}'_{i1}\boldsymbol{\beta}+\alpha_i\right)}\right) + \\ \left(\frac{1}{1+\exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta}+\alpha_i\right)} \times \frac{\exp\left(\mathbf{x}'_{i1}\boldsymbol{\beta}+\alpha_i\right)}{1+\exp\left(\mathbf{x}'_{i1}\boldsymbol{\beta}+\alpha_i\right)}\right) \end{array}\right]^{-1}$$

Cancelling all the denominators gives:

$$P\left(O_{i2} = 1|x_i, \alpha_i, \eta_i = 1\right) = \frac{\exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta} + \alpha_i\right)}{\exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta} + \alpha_i\right) + \exp\left(\mathbf{x}'_{i1}\boldsymbol{\beta} + \alpha_i\right)}$$

$$= \frac{\exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta}\right)}{\exp\left(\mathbf{x}'_{i2}\boldsymbol{\beta}\right) + \exp\left(\mathbf{x}'_{i1}\boldsymbol{\beta}\right)} = \frac{\exp\left[\left(\mathbf{x}'_{i2} - \mathbf{x}'_{i1}\right)\boldsymbol{\beta}\right]}{1 + \left[\exp\left(\left(\mathbf{x}'_{i2} - \mathbf{x}'_{i1}\right)\boldsymbol{\beta}\right)\right]}$$

and

$$P\left(O_{i1} = 1|\mathbf{x}_i, \alpha_i, \eta_i = 1\right) = \frac{1}{1 + \left[\exp\left(\left(\mathbf{x}'_{i2} - \mathbf{x}'_{i1}\right)\boldsymbol{\beta}\right)\right]}$$

The probability of offending in each period depends only on the first differences of the independent variables. For higher T, equivalent manipulations can be performed. Since the resulting expressions do not contain α_i, the individual fixed effects are not estimated. Also, as the first differences are being used, coefficients for the time-invariant independent variables are not identified.[48]

[48]Additionally, the Sweep variable has to be dropped. This is because, by definition, one period changes in the Wave variable and the Sweep variable are identical.

That α_i drops out of the estimation means only probabilities of offending conditional on η_i can be estimated and marginal effects cannot be computed. Due to this, Table 3.18 reports coefficients rather than marginal effects.

	Contemporary Logit			Contemporary Fixed Effects Logit		
Independent Variable	**Theft**	**Economic Crime**	**Economic Crime (ex. work and school theft)**	**Theft**	**Economic Crime**	**Economic Crime (ex. work and school theft)**
Household just getting by on income	0.147	0.024	-0.040	-0.252	-0.192	-0.187
	(0.126)	(0.105)	(0.123)	(0.328)	(0.250)	(0.317)
Household getting into difficulties on income	-0.072	-0.030	0.093	-1.403	-0.791	-0.139
	(0.288)	(0.234)	(0.262)	(1.248)	(0.697)	(0.769)
Respondent employment status: intermediate	0.110	0.069	0.072	0.354	0.206	0.300
	(0.217)	(0.173)	(0.215)	(0.597)	(0.435)	(0.621)
Respondent employment status: routine and manual occupations	0.303	0.122	0.034	0.119	-0.183	-0.100
	(0.187)	(0.152)	(0.191)	(0.542)	(0.377)	(0.513)
Respondent employment status: looking for paid work/training	0.296	0.047	0.172	2.139	0.766	0.692
	(0.282)	(0.232)	(0.274)	(1.729)	(0.621)	(0.871)
Strongly agree: sometimes OK to break the law (1st interview)	-0.566	-0.359	-0.035	-	-	-
	(0.389)	(0.371)	(0.402)			
Neither agree/disagree: sometimes OK to break the law (1st interview)	-0.381**	-0.354***	-0.488***	-	-	-
	(0.154)	(0.125)	(0.145)			
Disagree: sometimes OK to break the law (1st	-0.710***	-0.580***	-0.492***	-	-	-
	(0.151)	(0.122)	(0.139)			
Strongly disagree: sometimes OK to break the law (1st interview)	-1.158***	-0.796***	-0.619***	-	-	-
	(0.202)	(0.146)	(0.164)			
Taken drugs in past year (not 'Class A')	1.017***	0.964***	1.052***	0.359	0.280	0.394
	(0.130)	(0.103)	(0.121)	(0.408)	(0.282)	(0.365)
Taken 'Class A' drugs in past year	1.444***	1.573***	1.723***	1.315**	1.085**	1.150**
	(0.150)	(0.120)	(0.136)	(0.550)	(0.425)	(0.548)
Friends in trouble with police in past year	0.509***	0.530***	0.455***	0.548	0.381	0.149
	(0.121)	(0.096)	(0.108)	(0.335)	(0.253)	(0.317)
Victim of crime in past year	0.646***	0.505***	0.489***	0.300	0.249	0.315
	(0.111)	(0.087)	(0.102)	(0.323)	(0.209)	(0.259)
Parents spent time in prison (before 1st interview)	0.738**	0.715**	0.733**	-	-	-
	(0.366)	(0.287)	(0.319)			
Ever expelled (before 1st interview)	0.058	0.509**	0.565**	-	-	-
	(0.343)	(0.231)	(0.258)			
Ever arrested (before 1st interview)	-0.129	0.115	0.250	-	-	-
	(0.188)	(0.137)	(0.152)			
Ever sent to prison (before 1st interview)	0.754	0.842*	0.280	-	-	-
	(0.603)	(0.458)	(0.514)			
Male	0.424***	0.490***	0.534***	-	-	-
	(0.133)	(0.105)	(0.121)			
Age	-0.057*	-0.075***	-0.103***	-0.888	0.034	0.052
	(0.032)	(0.026)	(0.030)	(2.511)	(0.493)	(0.528)
Ever sought help for mental health problems (before 1st interview over age 16)	0.343**	0.379***	0.448***	-	-	-
	(0.137)	(0.106)	(0.118)			
PFA: Derbyshire	-0.094	-0.226	-0.602	-	-	-
	(0.421)	(0.349)	(0.457)			

(continued on following page)

	Theft	Economic Crime	Economic Crime (ex. work and school theft)	Theft	Economic Crime	Economic Crime (ex. work and school theft)
PFA: Devon & Cornwall	-0.958**	-0.618*	-0.618	-	-	-
	(0.452)	(0.331)	(0.409)			
PFA: Essex	-1.300*	-1.676***	-2.032***	-	-	-
	(0.674)	(0.520)	(0.673)			
PFA: North Yorkshire	-0.855	-1.041*	-0.789	-	-	-
	(0.608)	(0.564)	(0.569)			
Sweep 3	0.089	-0.028	-0.167	-	-	-
	(0.187)	(0.148)	(0.172)			
Constant	-2.484***	-1.215*	-1.700**	-	-	-
	(0.934)	(0.732)	(0.843)			
N	**5,650**	**5,650**	**5,650**	**653**	**1,033**	**765**
i	**3,105**	**3,105**	**3,105**	**236**	**377**	**280**
Log likelihood	**-1,461.47**	**-2,066.16**	**-1,607.09**	**-200.02**	**-322.98**	**-231.61**
Median predicted probability of offending report[1]	**0.053**	**0.104**	**0.062**	-	-	-
p-value for joint test of managing on income H_0: =0	**0.608**	**0.987**	**0.925**	**0.670**	**0.698**	**0.941**
p-value for joint test of employment status H_0: =0	**0.397**	**0.878**	**0.999**	**0.946**	**0.566**	**0.842**
p-value for joint test of 'OK to break the law' H_0: =0	**0.000**	**0.000**	**0.000**	-	-	-

Notes: Standard errors are given in parentheses. For the basic logit regression the standard errors are robust to clustering. Significance levels: * 10% significance, ** 5% significance and *** 1% significance. For the fixed effects logit co-efficients are only obtained for time-varying independent variables as all time-invariant variables are conditioned out. Time-invariant variables have co-efficients marked "-". Far lower values of N and i are reported for the fixed effects logit are reported since only individuals with variation in their offending status across time are included in these estimations. The p-values reported test whether the marginal effects are jointly different from zero for the set of independent variables stated. Independent variables which were frequently significant at the 5% level or above in the basic logit estimations but not shown here for brevity are: PFA: South Wales (positive); Wave 2 (positive); Wave 3 (positive); and Sports club/gym member (positive). Many other independent variables were also significant in individual regressions at the 10% level or above.

Table 1.18: Co-efficients from logit and fixed effects logit estimations using the contemporary sample.

One point to note is that the command to implement the fixed effects logit model in Stata does not provide a cluster robust variance-covariance matrix. Hence, the standard errors reported in Table 3.18 for the fixed effects logit estimation are not robust to each individual's error terms being correlated through time. The standard errors reported are likely to be significantly smaller than if this correlation was taken into account. Cameron and Trivedi (2010) suggest this problem can be mitigated by bootstrapping over clusters. Bootstrapping was undertaken with re-sampling occurring 4,000 times; however, convergence of the standard errors did not occur. Yet, for

the results in Table 3.18, that the standard errors are biased downwards does not affect the interpretation of the results. If the standard errors increased in size, it would not alter the conclusion that financial position and employment do not show a statistically significant association with offending.

Bivariate Probit Model with Partial Observability

The following description of the bivariate probit model with partial observability is taken from Poirier (1980) with changed notation.

Suppose there are two latent variables: k_i^{**} representing integrity and BC_{it}^{*} representing the benefit of crime in period t, (BC_{it}^{*} is akin to the RHS of the NCC). Each of these latent variables can be described as:

$$k_i^{**} = \mathbf{y}_i'\boldsymbol{\gamma}_1 + \varepsilon_{1i}$$

$$BC_{it}^{*} = \mathbf{x}_{it-1}'\boldsymbol{\beta} + \mathbf{y}_i'\boldsymbol{\gamma}_2 + \varepsilon_{2it}$$

Now suppose that the variable k_i^{*} represents an individual's integrity type such that:

$$k_i^{*} = \left\{ \begin{array}{lll} 1 & \text{(low-integrity)} & \text{if } k_i^{**} \leq 0 \\ 0 & \text{(high-integrity)} & \text{if } k_i^{**} > 0 \end{array} \right\}$$

where a high-integrity individual will never offend and a low-integrity individual's offending decision depends on their circumstances. In turn, define BC_{it} as a variable splitting the benefit of crime into high and low categories:

$$BC_{it} = \left\{ \begin{array}{ll} 1 \quad \text{(high benefit)} & \text{if } BC_{it}^{*} > 0 \\ 0 \quad \text{(low benefit)} & \text{if } BC_{it}^{*} \leq 0 \end{array} \right\}$$

As in a standard bivariate probit model, the error terms for each of the latent variables, ε_{1i} and ε_{2it}, are jointly normally distributed with a correlation coefficient ρ. Where Poirier (1980) and the bivariate probit model with partial observability depart from the standard probit model is that k_i^* and BC_{it} are both unobservable. The only outcome which is observed is O_{it}, i.e. whether or not an individual offends within a given time period. The probability of an individual offending in a given time period is:

$$p_{it} = P\left(O_{it} = 1\right) = P(k_i^* = 1 \cap BC_{it} = 1) = F\left(\mathbf{y}_i'\boldsymbol{\gamma}_1, \mathbf{x}_{it-1}'\boldsymbol{\beta} + \mathbf{y}_i'\boldsymbol{\gamma}_2; \rho\right)$$

whilst the corresponding probability of not offending is:

$$1 - p_{it} = P(k_i^* = 0 \cup BC_{it} = 0) = 1 - F\left(\mathbf{y}_i'\boldsymbol{\gamma}_1, \mathbf{x}_{it-1}'\boldsymbol{\beta} + \mathbf{y}_i'\boldsymbol{\gamma}_2; \rho\right)$$

That not offending occurs when either $k_i^* = 0$ or $BC_{it} = 0$ means an observation of no offending could result from three different situations: $(k_i^* = 0, BC_{it} = 0)$, $(k_i^* = 1, BC_{it} = 0)$ and $(k_i^* = 0, BC_{it} = 1)$. The current chapter's theoretical model suggests that financial position and employment status only affect the offending decision for low-integrity individuals. Hence, there is an issue similar to zero-inflation in count data models, as many people will never offend simply because $k_i^* = 0$. Using the bivariate probit model with partial observability, allows the marginal effects for financial position and employment status to be estimated conditional on being a low-integrity individual, i.e. $k_i^* = 1$.

Problems were encountered running the model described above in Stata. However, imposing the restriction $\boldsymbol{\gamma}_2 = \mathbf{0}$, it was possible to estimate the model for Theft and Economic Crime. Clearly the restriction $\boldsymbol{\gamma}_2 = \mathbf{0}$ is a strong one, as it implies that the time-varying benefits of crime are not influenced by individuals' fixed characteristics. The unconditional average marginal effects and the average marginal effects conditional on $k_i^* = 1$ are reported in Table 3.19.[49]

[49]Note the time-invariant explanatory variables influence the average marginal effects for BC_{it} even after conditioning on $k_i^* = 1$. This point can be understood by considering the standard definition of conditional probabilities:

$$P\left(BC_{it} = 1 | k_i^* = 1, \mathbf{x}_{it-1}, \mathbf{y}_i\right) = \frac{P\left(BC_{it} = 1 \cap k_i^* = 1 | \mathbf{x}_{it-1}, \mathbf{y}_i\right)}{P\left(k_i^* = 1 | \mathbf{y}_i\right)} = \frac{F\left(\mathbf{y}_i'\boldsymbol{\gamma}_1, \mathbf{x}_{it-1}'\boldsymbol{\beta}; \rho\right)}{F_k\left(\mathbf{y}_i'\boldsymbol{\gamma}_1, \rho\right)}$$

The conditional probability is still a function of $\mathbf{y}_i$. This statement is adapted from Greene's (2008) discussion of the standard bivariate probit model.

Independent Variable	Unconditional Theft	Unconditional Economic Crime	Conditional on k*=1 Theft	Conditional on k*=1 Economic Crime
Strongly agree: sometimes OK to break the law (1st interview)	-0.017	-0.049	0.008	-0.019
	(0.041)	(0.043)	(0.045)	(0.026)
Neither agree/disagree: sometimes OK to break the law (1st interview)	-0.011	-0.027	0.005	-0.010
	(0.018)	(0.019)	(0.025)	(0.012)
Disagree: sometimes OK to break the law (1st interview)	-0.016	-0.028	0.007	-0.010
	(0.017)	(0.018)	(0.038)	(0.012)
Strongly disagree: sometimes OK to break the law (1st interview)	-0.055***	-0.056***	0.029	-0.022
	(0.020)	(0.020)	(0.150)	(0.023)
Ever expelled (before 1st interview)	0.002	0.088**	-0.001	0.031
	(0.101)	(0.044)	(0.044)	(0.032)
Ever arrested (before 1st interview)	0.006	0.035	-0.003	0.013
	(0.021)	(0.024)	(0.019)	(0.017)
Ever sent to prison (before 1st interview)	0.080	0.309***	-0.033	0.096
	(0.205)	(0.083)	(0.242)	(0.099)
Ever committed economic crime (before 1st interview)[1]	0.117***	0.126***	-0.052	0.047
	(0.014)	(0.016)	(0.283)	(0.046)
Male	0.032**	0.051***	-0.016	0.020
	(0.015)	(0.015)	(0.089)	(0.020)
Ever sought help for mental health problems (before 1st interview over age 16)	0.034*	0.068***	-0.016	0.025
	(0.019)	(0.018)	(0.087)	(0.024)
PFA: Derbyshire	-0.098***	-0.125***	0.054	-0.055
	(0.036)	(0.039)	(0.297)	(0.057)
PFA: Devon & Cornwall	-0.067	-0.111***	0.032	-0.047
	(0.045)	(0.040)	(0.179)	(0.047)
PFA: Essex	-0.121***	-0.158***	0.080	-0.080
	(0.041)	(0.037)	(0.446)	(0.078)
PFA: North Yorkshire	-0.111***	-0.153***	0.067	-0.075
	(0.039)	(0.041)	(0.361)	(0.078)
Household just getting by on income	0.008	0.015	0.040	0.039
	(0.016)	(0.014)	(0.064)	(0.038)
Household getting into difficulties on income	0.035	0.048	0.173	0.130
	(0.037)	(0.035)	(0.261)	(0.098)
Respondent employment status: intermediate occupation	-0.016	-0.015	-0.077	-0.038
	(0.022)	(0.027)	(0.141)	(0.069)
Respondent employment status: routine and manual occupations	0.018	0.025	0.091	0.067
	(0.025)	(0.025)	(0.102)	(0.067)
Respondent employment status: looking for paid work/training	-0.057*	-0.040	-0.269	-0.102
	(0.029)	(0.035)	(0.339)	(0.088)

(continued on following page)

	Theft	Economic Crime	Theft	Economic Crime
Taken drugs in past year (not 'Class A')	0.055***	0.097***	0.266	0.261***
	(0.016)	(0.018)	(0.178)	(0.068)
Taken 'Class A' drugs in past year	0.037**	0.102***	0.181	0.273***
	(0.018)	(0.023)	(0.134)	(0.069)
Friends in trouble with police in past year	0.043	0.070***	0.210***	0.188***
	(0.031)	(0.016)	(0.078)	(0.063)
Victim of crime in past year	0.012	0.011	0.059	0.030
	(0.014)	(0.013)	(0.059)	(0.033)
Age	-0.002	-0.004	-0.009	-0.009
	(0.003)	(0.003)	(0.017)	(0.009)
Sweep 3	-0.047*	-0.051**	-0.225	-0.133**
	(0.025)	(0.023)	(0.182)	(0.061)
N	**3,268**	**3,268**	**3,268**	**3,268**
i	**2,004**	**2,004**	**2,004**	**2,004**
Log likelihood	**-838.49**	**-1,126.54**	**-838.49**	**-1,126.54**
Median predicted probability of offending report	**0.048**	**0.095**	**-**	**-**
Median predicted probability of being a criminal type	**-**	**-**	**0.130**	**0.322**
Median predicted conditional probability of reporting offending given respondent is a criminal type	**-**	**-**	**0.446**	**0.323**
p-value for joint test of managing on income H_0: =0	**0.722**	**0.393**	**0.78**	**0.429**
p-value for joint test of employment status H_0: =0	**0.123**	**0.184**	**0.516**	**0.421**
p-value for joint test of 'OK to break the law' H_0: =0	**0.047**	**0.078**	**-**	**-**

Notes: Cluster robust standard errors are given in parentheses. Significance levels: * 10% significance, ** 5% significance and *** 1% significance. The p-values reported test whether the marginal effects are jointly different from zero for the set of independent variables stated. Independent variables which were frequently significant at the 5% level or above in the unconditional regression but not shown here for brevity are: Drinks alcohol 1-3 times a month (positive); PFA: Dyfed Powys (negative); PFA: Wiltshire (negative); and Sports club/gym member (positive). Many other independent variables were also significant in individual regressions at the 10% level or above. The horizontal line in the table indicates the split between independent variables used to estimate a respondent being a potential offender and independent variables used to estimate a respondent committing an offence within a given time period. The variables above the line are used in the potential offender estimation.

[1] This variable varies by dependent variable. If the dependent variable is "Theft" then this variable is whether the respondent has ever committed "Theft" before their first interview.

Table 1.19: Average marginal and conditional average marginal effects for a bivariate probit model with partial observability.

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