Crime Prospects and Prospect Theory

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Abstract

This paper models criminal behavior in a dynamic optimization setting where psychological factors such as subjective risk perception and time preferences play a key role in inducing illegal actions. When psychological perceptions over the actual magnitude of the reward and over the subjective risks of finding a victim or of being caught are dynamic, their influence on crime efforts could vary. Specifically, increasing punishment over rewards, ceteris paribus, deters crime, but increasing punishment and monitoring simultaneously, may encourage crime in the long term. It is also demonstrated that it may not be possible to distinguish between the impacts of hyperbolic discounting and probability weighting on criminal behavior.

Keywords: Crime Economics, Prospect Theory, Risk Dynamics, Time Preference, Hyperbolic Discounting
Introduction

Traditionally economic theory has concentrated mostly on rational decision makers maximizing utility. However, in real life examples of irrational actions abound. This is especially reflective of a group of people that have significant, albeit, adverse impact on the society-- those who take to illegal or criminal actions. There is a large body of literature on crime economics but most of it assumes rationality in behavior. This approach has been inspired by Becker (1974) who postulated that criminals are motivated by the considerations of relative costs and benefits of crime in deciding between whether or not to commit an offence. Based on this, Becker (1993) argues that as the probability of imprisonment increases with monitoring, crime rate should fall. Becker (1974) also shows that social welfare increases with penalty thus arguing for higher penalties.

The literature on crime economics is replete with theories over how to control crime rates through adequate punishment incentives and over factors influencing criminal behavior. Saha and Poole (2000) show that non-maximal penalties too can maximize social welfare as long as the regulator’s objective function does a joint maximization of the probability of monitoring and a minimization of the probability of transgression.

Yet crime rates in countries such as the US and UK haven’t gone down over time despite tougher punishment disincentives, the primary reason being the lack of incorporation into societal disincentive mechanism of psychological aspects that influence individual decisions. Psychological abnormalities may alter the perception of both the magnitude of rewards and punishment and the associated risks, thus altering behavior. When punishment rules are based solely on cost-benefit criteria they may fail to provide effective deterrence. Consequently, there is a need for delving deeper into the
criminal psychology to better understand the influence of societal disincentives on criminal behavior.

It is debatable whether criminals maximize utility over a long or a short time horizon. Perhaps they maximize utility over a very short time span, as has been argued in the ‘visceral needs’ hypothesis for explaining time discounting behavior. Alternatively, they may actually be maximizing their utility over the long term; however, their perceptions of rewards and punishments from actions may be highly skewed by their distorted psychological needs. Perception of the magnitude of rewards is not a static phenomenon but evolves with time, individual’s needs and difficulty in achieving those rewards. This is especially true if the rewards are non-monetary.

The perception of severity of punishment has been found to be negatively correlated with the level of crime. The ‘broken windows’ hypothesis claims that tougher penalties for minor crimes lower both minor and major crime rates (Wilson and Keling 1982). Lochner (2005) finds that lower perceived probability of arrest amongst youth leads to a higher rate of crime. The perception of punishment severity has also been found to vary with age, older individuals perceiving the punishment to be much higher than their younger counterparts. Hjalmarsson (2007) finds that perceived chances for jail increases by at least six points when the individual turns into an adult. However, the perception of severity of punishment is also influenced by the guilt consciousness of the offender (Indermaur 1994). If the offender does not feel remorse for his crimes even a high level of punishment (e.g. longer jail term) may not deter him from committing the crime. But from the society’s point of view punishment is a combination of both the time spent behind bars and the guilt feeling it induces in the offender.
Risk plays an important role too in motivating criminal behavior, both in terms of chances of finding a victim and getting caught. The role of subjective perceptions of risk of crime and punishment remains largely unexplored so far (Cameron 19897). Risk perception in the prospect theory literature has been found to be skewed upwards or downwards depending upon the level of risk. Further, under-(over) weighting of risks has been assumed to be static over time. In reality, the levels of risks above (below) which individual’s subjective perceptions are higher (lower) than the objective risks could change over time due to external or internal factors surrounding the individual. When this happens, regions of risk which were under-weighted in the past might get over-weighted in the future, thus leading to reversal in their behaviors. This possibility has not been considered so far in the literature but could play an important role in influencing crime behavior as is argued in this paper.

Risk perception is not the only significant determinant for criminal behavior. Time preference may be equally important\(^1\). For instance, an individual may perceive the subjective risk of being caught to be higher than the objective risks, thereby inducing him not to commit the crime. However, if his time preferences are skewed and he has a high cost of waiting for his reward, he might be forced to commit the crime earlier despite the risk being large. Time preferences have been found to be influenced by visceral needs. Visceral influences such as hunger and sexual desire might cause fluctuations in the tastes and therefore in the utility function. These visceral states have been argued to be endogenous, implying that the longer the time from past consumption (or crime), the higher the current need for food (or crime) (Frederick et al. 2002 ).

\(^{1}\) There are several other factors that influence criminal behavior. These include, but are not limited to, intelligence, character, self perception, personality and neurological disorders, etc. Here we do not include cases with neurological disorders.
This brings up the question of whether perception of the magnitude of rewards itself is malleable and could vary over time or with psychological influences. The higher the difficulty (or visceral need), the higher may be the perceived reward in overcoming it. It may happen that the expected increase in punishment is always balanced out by an increase in the perceived expected reward from the act. Under such a circumstance, criminal acts may actually increase with enforcement. An associated consequence of this possibility is that criminal acts may increase even as punishment exceeds the perceived rewards, provided the risks of attaining the rewards are lower than the risks of getting caught. Further, higher enforcement under these situations might postpone short term crimes but increase crime efforts in the long term. We demonstrate these possibilities under an inter-temporal utility maximizing framework for the offender.

In this paper the role of probability weighting in influencing criminal behavior is explored in a dynamic optimization setting where the only options available to the criminal are search efforts associated with the criminal act. There is an impatience cost of waiting leading to hyperbolic discounting, which makes the reward from crime more desirable as time passes. Following this framework, it is shown that the psychological perceptions over the actual magnitude of the reward and over the subjective risks of finding a victim or of being caught are changeable over time thereby introducing irrational actions on the part of individuals. Specifically, when the exogenous chances of getting caught increase, the individual increases his efforts to find a victim rather than decreasing them. Further, it is also demonstrated that it is not possible to distinguish between the impacts of hyperbolic discounting and probability weighting on criminal behavior.
1. Model

In this section we develop a model of criminal behavior that involves search efforts which influence both the chances of finding a victim and getting caught. The chances of finding a victim are influenced by the level of search efforts and some exogenous parameters. Searching for victims also increases the chances of being caught. For instance, potential sex offenders may be laid into traps by monitoring authorities and therefore prosecuted on the basis of their intent to commit the crime. Criminals may get caught even after committing the crime, but we assume that they incorporate this possibility in their search efforts so that they believe that once they get away with the crime they will never get caught. This is especially true of crimes that involve consensual sex with minors as the victims may not be aware that they are being victimized. In such situations, the chances of getting caught are the highest during or before the crimes are committed and decline over time. Same goes for illegal trade in drugs.

Finding a victim leads to a one-off reward, whereas getting caught leads to a one-off punishment. The inter-temporal optimization problem for the criminal is to balance the expected benefits of crime to the expected costs of incarceration. The analysis can be extended to repeated acts of crime without any loss of generality. Repeat offenders may learn from their past mistakes and successes thereby allowing them to evolve and keep up with the monitoring strategies of the enforcement agencies. However, in this paper we confine our attention to the evolution of psychological and behavioral trends such as risk weighting and impatience that play a role in inducing criminal behavior.
Consider that the criminal searches for his victims through an effort level $s(t)$ that costs him $c(s(t))$. The probability of getting a victim is a Poisson process with hazard rate $\dot{p}(t)$. This assumption allows for increasing chances of getting a victim over time. The probability of getting caught is also modeled as a Poisson process with hazard rate $\dot{q}(t)$. When the criminal gets the victim before getting caught he earns a one-off reward. When he is caught before getting a victim he gets a punishment in terms of jail time. More specifically, the probability density function of finding a victim is defined as:

$$f(p(t)) = \dot{p}(t) \cdot \exp(-p(t))$$

It is possible to find a victim even without doing any search which could be a function of the environment (city, suburb type, etc.) and we incorporate this possibility in the numerical simulation section ahead. The probability density function of getting caught is given by:

$$f(q(t)) = \dot{q}(t) \cdot \exp(-q(t))$$

The long term value for the criminal before attaining either of the two possibilities is defined as $v_0$, where:

$$v_0 = \left\{ \int_0^\infty (-c(s(t)) - c(w(t))) \cdot \exp(-\rho \cdot t)dt \right\}$$

$\rho$ is the discount rate, $c(s)$ is the cost of search and $c(w)$ is the impatience cost of waiting, which is increasing in the time that it takes to find a victim. More specifically, the impatience cost of waiting is modeled as an exponentially increasing function of time:

$$c(w) = \exp(\theta \cdot t)$$

Similarly, the search cost is modeled as:
(5) \( c(s) = cs_0 \cdot s(t)^{cs_1} \)

Where \( cs_0 \) and \( cs_1 \) are parameters influencing search cost. When a victim is found, the value function is defined as:

(6) \( v_1 = v_1(t) \cdot \exp(-\rho \cdot t) \)

Where \( v_1 \) is the one-off reward from the criminal act. Impatience may also be factored in by introducing a time component to the value function so that his valuation may increase over time. Next, if the criminal gets caught, his penalty function is:

(7) \( v_2 = v_2(t) \cdot \exp(-\rho \cdot t)dt \)

Where \( v_2 \) could be the jail term offered for that crime. Now, let \( t \) be the time when a victim is found. Then the value to the criminal until such an event occurs is given by:

(8) \( v_{crime} = \left\{ \int_0^t \hat{p} \cdot \exp(-p(t)) \cdot \exp(-q(t)) \cdot \int_0^t (-c(s) - c(w)) \cdot \exp(-\rho \cdot t)dt \right\} \)

where \( \hat{p} \cdot \exp(-p(t)) \cdot \exp(-q(t)) \) is the probability that the victim is found at time \( t \) and criminal is caught after time \( t \). After integration by parts, this can be further written as:

(9) \( v_{crime} = \left\{ \int_0^t \frac{\hat{p} \cdot \exp(-p(t)-q(t))}{\hat{p}(t) + \hat{q}(t)} \cdot (-c(s) - c(w)) \cdot \exp(-\rho \cdot t)dt \right\} \)

Similarly, if \( t \) is the time when the criminal is caught, and a victim is not found until then, the value to the criminal before such an event is given by:

(10) \( v_{caught} = \left\{ \int_0^t \hat{q} \cdot \exp(-q(t)) \cdot \exp(-p(t)) \cdot \int_0^t (-c(s) - c(w)) \cdot \exp(-\rho \cdot t)dtdt \right\} \),

where \( \hat{q} \cdot \exp(-q(t)) \cdot \exp(-p(t)) \) is the probability that the criminal is caught at time \( t \), and the victim is found later than time \( t \). Note that the criminal could be caught in the
search and does not have to commit the actual crime for the cops to nab him. After
integration by parts, this can be further written as:

\[
(11) \quad v_{0\text{caught}} = \left\{ \int_0^\infty \hat{q} \cdot \frac{\exp(-p(t) - q(t))}{\dot{p}(t) + \hat{q}(t)} \cdot (-c(s) - c(w)) \cdot \exp(-\rho \cdot t) dt \right\}
\]

Therefore, the expected value to the criminal, before any of these two events occur is
given by:

\[
(12) \quad v_0 = v_{0\text{caught}} + v_{0\text{crime}} = \left\{ \int_0^\infty \hat{p} \cdot \frac{\exp(-p(t) - q(t))}{\dot{p}(t) + \hat{q}(t)} \cdot (-c(s) - c(w)) \cdot \exp(-\rho \cdot t) dt \right\} + \left\{ \int_0^\infty \hat{q} \cdot \frac{\exp(-p(t) - q(t))}{\dot{p}(t) + \hat{q}(t)} \cdot (-c(s) - c(w)) \cdot \exp(-\rho \cdot t) dt \right\}
\]

After simplification, (11) can be further re-written as:

\[
(13) \quad v_0 = \left\{ \int_0^\infty \exp(-p(t) - q(t)) \cdot (-c(s) - c(w)) \cdot \exp(-\rho \cdot t) dt \right\}
\]

Similarly, the expected value at the instant of getting reward \( v_1 \) can be defined as:

\[
(14) \quad v_1 = v_1 \cdot \hat{p} \cdot \exp(-p(t)) \cdot \exp(-\rho \cdot t) dt
\]

and the expected value at the instant of getting caught \( v_2 \) can be defined as:

\[
(15) \quad v_2 = v_2 \cdot \hat{q} \cdot \exp(-q(t)) \cdot \exp(-\rho \cdot t) dt
\]

The criminal’s problem is to maximize the expected sum of \( v_0, v_1 \) & \( v_2 \) given the
constraints posed by the equations of motion for the hazard functions for finding a victim
and getting caught. The current value Hamiltonian is given by:

\[
(16) \quad \exp(-p(t) - q(t)) \cdot (-\exp(\alpha t) - c(s)) + v_1 \cdot \exp(\alpha \cdot t) \hat{p} \cdot \exp(-p) - v_2 \cdot \hat{q} \cdot \exp(-q) + \lambda_1 \cdot \alpha \cdot \log(k_0 + s(t)) + \lambda_2 \cdot \beta \cdot \log(k_0 + s(t))
\]
Where $\lambda_1, \lambda_2$ are the shadow prices of stock of cumulative probability of crime and stock of cumulative risk of getting caught. In the above equation we assume that the hazard rates follow the following functional forms:

\begin{align}
(17) \quad \dot{p} &= \alpha \cdot \log(k_0 + s(t)) \\
(18) \quad \dot{q} &= \beta \cdot \log(k_0 + s(t))
\end{align}

Note that the chances of finding a victim and getting caught are both primarily influenced by the search effort. The other term $k_0$ is a small exogenous parameter that determines the exogenous chances of getting caught or finding a victim even without any search efforts. First order condition for optimization requires that:

\begin{align}
(19) \quad -c'(s) \cdot \exp(-p(t) - q(t)) + \frac{\alpha}{k_0 + s} \cdot (\lambda_1 \cdot \alpha + v_1 \cdot \exp(\alpha \cdot t) \cdot \exp(-p)) - \frac{\beta}{k_0 + s} \cdot (\lambda_2 \beta + v_2 \cdot \exp(-q)) = 0
\end{align}

The marginal cost of search is equated to the expected net reward from that effort.

Further, no-arbitrage conditions require that the shadow prices of the risks evolve as:

\begin{align}
(20) \quad \dot{\lambda}_1 &= \exp(-p(t) - q(t)) \cdot (-\exp(\alpha \cdot t) - c(s)) + v_1 \cdot \exp(\alpha \cdot t) \cdot \dot{p} \cdot \exp(-p) + d \cdot \lambda_1 \\
(21) \quad \dot{\lambda}_2 &= \exp(-p(t) - q(t)) \cdot (-\exp(\alpha \cdot t) - c(s)) + v_2 \cdot \dot{q} \cdot \exp(-q) + d \cdot \lambda_2
\end{align}

In the numerical simulations section we explore further underpinnings of risk tradeoffs over the implications for search efforts. However, before that we introduce the concept of risk weighting in crime behavior.

### 2.1 Risk Weighting

Prospect theory allows for subjective weighting of risks in order to explain away the observed behavioral anomalies that defy expected utility maximization. The same could be used to delve into the criminal mind in order to analyze the risk taking behavior of
repeat-offenders. The key idea explored here is over risk weighting by individuals and the psychological factors that influence the dynamics of risk perception over time.

The behavioral element of our model is based on accumulated evidence in economics and psychology literature (see summary in Hurley and Shogren, 2005). Assume that the criminal assigns higher weights to low probabilities of being caught (or finding a victim) and lower weights to high probabilities of being caught (also see Starmer, 2000). We add these weights to the hazard rates. Let the weighting function follow an inverse S-shape. Following Prelec (1998), we use a two-parameter weighting function as:

\[ w(p, q) = e^{-\theta (\ln p - q)^\gamma} \]

where \( \theta \) is the parameter that primarily determines elevation, and \( \gamma \) is the parameter that primarily determines curvature. \textit{Elevation} reflects the inflection (reference) point at which a criminal switches from overestimating low probability events to underestimating high probability events, i.e., the degree of over- and underestimation; \textit{curvature} captures the idea that the criminals become less sensitive to changes in probability the further they are from the inflection point (Tversky and Kahneman, 1992; Gonzales and Wu, 1999).

Probability weighting theory so far only deals with regions of under and over weighting of subjective probabilities. It is, however, silent on the possibility that these regions could themselves change over time as individual perceptions are influenced by the success or failure of efforts. Though a psychological issue, it can be argued that just like drug addiction, the time distance from the last crime could play a key role in under-weighting of risks involved and as this distance increases, a point is reached where the
expected rewards from the crime far exceed the almost sure penalties given the high real risks. The diagram below depicts this idea.

*Insert Figure 1 here.*

In the above figure \( w(p(t_1)) \) is the probability weighting of getting caught committing the crime at time \( t_1 \) from the last crime and \( w(p(t_2)) \) is the weighted probability of getting caught committing the same crime at time \( t_2 \) from the last crime where \( t_1 < t_2 \). Note that as time from last crime increases this probability weighted curve shifts leftwards until the reference frame \( (O) \) reaches the origin. It is possible that with the shift in reference frame, a point is reached when the perceived expected risk from the crime makes the benefits outweigh the punishment, thus prompting the crime. The functional forms of the weighted hazard rates are now given as:

\[
(23) \quad \dot{q} = e^{-\theta_e \cdot (-\log(\beta \cdot \log(2.71828 \cdot \log(s(t)))))^2}
\]

\[
(24) \quad \dot{p} = e^{-\theta_q \cdot (-\log(\alpha \cdot \log(2.71828 \cdot \log(s(t)))))^1}
\]

3. **Numerical Simulation**

The parameters used for numerical simulation are presented in Table 1 in the appendix. Note that for the base case we assume that the reward and punishment have the same value. This captures our basic notion that the perceived rewards from a criminal act are always revised to bring them in line with the punishment from getting caught. However, we do simulate over cases where punishment exceeds rewards. Search efforts are restricted between 0 and 1. First set of simulations involve the case when there is no probability weighting. In figure 2, notice that when the parameter \( \beta \), which is the exogenous component of the hazard rate is lowered from its base case value of .5 to .4,
the hazard rate is lowered all throughout\(^2\). This is achieved through a reduction in search long term efforts. This is a very surprising result as it says that the lower the exogenous chances of getting caught, the lower would be the search effort. However, notice that the base case gives equal reward and punishment of 500 from getting a victim or getting caught. Therefore, the objective of the criminal is to equalize his expected benefits from a victim to the expected costs from incarceration. This is achieved through a reduction in search effort. Whereas, when \(\beta\) is increased to .6, long term search efforts increase compared to the base case (as shown in figure 3). Notice that under this scenario search effort is also postponed until the fourth time period. That is search effort is actually discouraged in the beginning, but is spread out over a longer time period once it is started in order to make up for an increase in the incarceration hazard. The higher the exogenous element of risk of getting caught (say through increased monitoring), the higher is the search effort\(^3\). However, when punishment is increased (to 700) keeping all other parameters constant, search effort falls to zero. Whereas, if punishment is increased (to 700) along with the exogenous component of the risk of getting caught (raised to .6) search effort increases considerably. This implies that raising both monitoring and the punishment may be counter-productive.

The apparent irrationality of the criminal mind here can be analyzed here if it is realized that the criminal sees no other options apart from the act of crime. Therefore, an increase in the expected punishment from an increased risk of getting caught must be balanced by an increase in the expected rewards. Therefore, even though higher

\(^2\)Note that while the value of .5 for exogenous component of risk might seem large, the results remain the same for even very low values such as .01.

\(^3\)Another result worth mentioning is that even though search effort gets postponed with an increase in \(\beta\), the relationship between an increase in \(\beta\) and the time until search is postponed is negative. That is, the higher the \(\beta\), the lower is the time until search is postponed.
punishments may deter crime in the short term crime rate must increase in the long term to compensate for the higher chances of incarceration. This implies that increase in policing efforts actually is counter-productive if perception of rewards increases with difficulty so as to equate the reward with punishment. Figure 4 shows the corresponding incarceration probabilities.

*INSERT figures 2-4 here.*

When we introduce probability weighting, as shown in figure 5, some additional insights emerge. The 45 degree line from the origin depicts the un-weighted hazard rate. Two inverted shaped curves denoted the weighted hazard rates for different values of $\theta_2$. Notice that when $\theta_2$ is .7, there is a higher overweighting of low risks and lower underweighting of high risks, where as opposite is true for the case when $\theta_2$ is .8. Higher overweighting of risks leads to a positive search efforts, whereas lower overweighting of risks leads to zero search efforts by the criminal. This implies for the same level of objective risks, one criminal might go ahead and commit the crime, whereas the other whose perception is not skewed would not do it.

Finally, we also evaluate the case of dynamic risk perception that is borne out by the impatience factor or other psychological factors which lead to a shift in the risk perception for the criminal as time passes by without finding a victim. The decline in risk perception is modeled as:

\[
\theta_2(t+1) = \theta_2(t) + .6 \cdot (1 - \exp(-\xi \cdot t))
\]

for the base case where $\theta_2$ starts at .4. Note that a high $\theta_2$ implies a higher overweighting of risks. Therefore, overtime, $\theta_2(t)$ increases in value and leads to
underweighting of risks. That is, point O as shown in figure 1 shifts to left. Figure 6 shows three cases; a slower decline in $\theta_2(t)$ is achieved through $\xi = .05$, medium decline is achieved through $\xi = .1$ and a faster decline is achieved through $\xi = .2$. Slow decline leads to the highest search efforts, whereas a fast decline leads to the lowest search effort. This implies that someone who grows more impatient over time (a faster rate of decline) would actually pose the least threats of committing the crime as his expected benefits and costs make it optimal for him to refrain as risks fall over time.

3.1 Time Discounting and Risk Weighting

It is hard to separate the effects of the two mathematically, as we will discover in this section, but whether a criminal behaviour is influenced by time discounting or by risk weighting is a very important question --as the former is purely a psychological aspect of his personality whereas the latter is influenced to a certain extent by how society affects risks and its idiosyncratic perceptions. Hyperbolic discounting of time has been found to be a significant phenomenon in experiments and reflects the impatience associated with forgoing current consumption. There is a higher level of impatience associated with immediate tradeoffs (consuming a good today versus consuming tomorrow) as compared to future period tradeoffs (a month later versus two months later). Risk weighting as explored above, on the other hand, has the same influence on individual decisions as time discounting, however, it is yet to be seen how someone with a hyperbolic discounting behaves when his risk preferences could fall in the low weighting type range or high weighting type range. In this section we explore some of these combinations. Previously
we have indirectly modelled the hyperbolic time discounting component through impatience costs. Notice that the term \( \exp(\theta t) \) effectively lowers the discount rate over time thereby leading to hyperbolic discounting. However, we specifically introduce a fall in the discount rate component into our discount factor, which (in discrete time steps in GAMS) now reads as:

\[
(26) \quad (1 + \rho / (0.5 \cdot t))^{-\theta(t-1)}
\]

We combine hyperbolic discounting with two cases of dynamic risk perception. The slower decline in risk perception is now re-defined as:

\[
(27) \quad \theta_2(t + 1) = \theta_2(t) + 0.6 \cdot (1 - \exp(-0.18 \cdot t))
\]

Notice that as time progresses \( \theta_2 \), starting from its initial value of 0.4, converges to a value of 1. The faster decline in risk perception of being caught is re-defined as:

\[
(28) \quad \theta_2(t + 1) = \theta_2(t) + 0.6 \cdot (1 - \exp(-0.2 \cdot t)).
\]

Notice that slower decline in risk perception leads to a longer search effort than the faster decline as previously found. Also, in figure 8, hyperbolic discounting leads to a longer search effort when combined with a slower or faster decline in risk perception case. However, now notice that it is hard to distinguish between the search efforts for the case when there is a slower decline in risk perception and the case when there is a faster decline in risk perception coupled with hyperbolic discounting. This demonstrates that it may not be easy to separate the effects of time discounting from risk weighting judging solely by search efforts. This may have important policy implications as increased monitoring increases the risk component only without altering the time discounting component of individual decision making.
4. Conclusion

In this paper we explored the possibility of simultaneous probability weighting and time discounting in order to explain seemingly irrational acts on the parts of criminals. The key findings indicate that crime rate does not necessarily go down in the long term with the level of enforcement, a fact that has been empirically ascertained. Another outcome of the modelling exercise was the realization of that fact that probability weighting and time preference both have a significant influence on a criminal’s search behaviour. Yet, it is not possible to separate the effects of the two. This may have implications for public policies related to crime monitoring and punishment as time preference corresponds to visceral needs whereas probability weighting corresponds to perception of expected rewards and punishments. Increased monitoring may influence the latter, leaving the formal uncontrolled. The components of time preference and visceral needs in a criminal’s utility function would then determine the effectiveness of policing efforts.

The analysis in this paper considers one-off rewards and punishments. However, in reality criminals may find several victims before they are nabbed. Further, once released from prison they may take to crime, perhaps having become more hardened than before. The implications of excluding such considerations on our results should not be very strong. This is because it is improbable that criminals consider the possibility of repeated rewards and incarcerations before deciding on a particular crime. Neither is the term of incarceration known in advance, nor is known the possibilities of getting a second chance and emerging out smarter from the past experiences. It is more likely that individuals consider each crime as a one-off possibility with expected rewards and punishments. However, much research is needed to understand the influence of societal
punishment structure that might influence the time horizon of criminals. A very strong punishment scheme with no second chances might reinforce criminal behaviour if visceral needs are too strong. Whereas, second chances and lower punishment might discourage crime if probability weighting is a significant component as has been demonstrated in this paper.
References

Figure 1: Probability Weighting and its Dynamics
Figure 2: Probability of finding a victim under various scenarios
Figure 3: Search efforts under various scenarios
Figure 4: Probability of getting caught under various scenarios
Figure 5: Search efforts under weighted probabilities
Figure 6: Search efforts under dynamic perception

Faster Decline of risk perception: $\theta_2(t + 1) = \theta_2(t) + .6 \cdot (1 - \exp(-2) \cdot t))$

Slower Decline of Risk Perception: $\theta_1(t + 1) = \theta_1(t) + .6 \cdot (1 - \exp(-.05) \cdot t))$

Medium Decline of Risk Perception: $\theta_1(t + 1) = \theta_1(t) + .6 \cdot (1 - \exp(-.1) \cdot t))$
Figure 7: Search Effort with Hyperbolic Discounting
Figure 8: Search Effort with Hyperbolic Discounting and Subjective Weighting of Risks

Faster Decline of risk perception:  \( \theta_1(t + 1) = \theta_1(t) + 0.6 \cdot (1 - \exp(-0.2 \cdot t)) \)

Slower Decline of Risk Perception:  \( \theta_2(t + 1) = \theta_2(t) + 0.6 \cdot (1 - \exp(-0.18 \cdot t)) \)

Hyperbolic Discount Factor  

\[ \gamma(t) = (1 + \rho \cdot t) \cdot (\gamma(t-1))^{-1-\rho} \]
Table 1: Parameter Values

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$\rho$</td>
<td>.1</td>
<td>Discount rate</td>
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<td>$\alpha$</td>
<td>.5</td>
<td>Constant component of the victimization hazard function</td>
</tr>
<tr>
<td>$\beta$</td>
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<td>Constant component of the incarceration hazard function</td>
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<td>Probability weighting function parameter</td>
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<td>punishment</td>
<td>500</td>
<td>Punishment from getting caught</td>
</tr>
</tbody>
</table>